Safe Haptics-enabled Patient-Robot Interaction for Robotic and Telerobotic Rehabilitation of Neuromuscular Disorders: Control Design and Analysis

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Abstract

Motivation: Current statistics show that the population of seniors and the incidence rate of age-related neuromuscular disorders are rapidly increasing worldwide. Improving medical care is likely to increase the survival rate but will result in even more patients in need of Assistive, Rehabilitation and Assessment (ARA) services for extended periods which will place a significant burden on the world’s healthcare systems. In many cases, the only alternative is limited and often delayed outpatient therapy. The situation will be worse for patients in remote areas. One potential solution is to develop technologies that provide efficient and safe means of in-hospital and in-home kinesthetic rehabilitation. In this regard, Haptics-enabled Interactive Robotic Neurorehabilitation (HIRN) systems have been developed.

Existing Challenges: Although there are specific advantages with the use of HIRN technologies, there still exist several technical and control challenges, e.g., (a) absence of direct interactive physical interaction between therapists and patients; (b) questionable adaptability and flexibility considering the sensorimotor needs of patients; (c) limited accessibility in remote areas; and (d) guaranteeing patient-robot interaction safety while maximizing system transparency, especially when high control effort is needed for severely disabled patients, when the robot is to be used in a patient’s home or when the patient experiences involuntary movements. These challenges have provided the motivation for this research.

Research Statement: In this project, a novel haptics-enabled telerobotic rehabilitation framework is designed, analyzed and implemented that can be used as a new paradigm for delivering motor therapy which gives therapists direct kinesthetic supervision over the robotic rehabilitation procedure. The system also allows for kinesthetic remote and ultimately in-home rehabilitation. To guarantee interaction safety while maximizing the performance of the system, a new framework for designing stabilizing controllers is developed initially based on small-gain theory and then completed using strong passivity theory. The proposed control framework takes into account knowledge about the variable biomechanical capabilities of the patient’s limb(s) in absorbing interaction forces and mechanical energy. The technique is generalized for use
for classical rehabilitation robotic systems to realize patient-robot interaction safety while enhancing performance. In the next step, the proposed telerobotic system is studied as a modality of training for classical HIRN systems. The goal is to first model and then regenerate the prescribed kinesthetic supervision of an expert therapist. To broaden the population of patients who can use the technology and HIRN systems, a new control strategy is designed for patients experiencing involuntary movements. As the last step, the outcomes of the proposed theoretical and technological developments are translated to designing assistive mechatronic tools for patients with force and motion control deficits.

This study shows that proper augmentation of haptic inputs can not only enhance the transparency and safety of robotic and telerobotic rehabilitation systems, but it can also assist patients with force and motion control deficiencies.

Keywords: Safe Physical Patient-Robot Interaction, Rehabilitation Robotics, Haptics, Telerobotics, Time delay, Passivity Theorem, Small-gain Theorem, Kinesthetic Strategy Regeneration Through Modeling, Manipulation of Haptic Perception, Assistive Robotics, Medical Technologies, Tele-rehabilitation.
Co-Authorship Statement

The dissertation presented here has been written by Seyed Farokh Atashzar under the supervision of Dr. Rajni V. Patel. Parts of the materials in this thesis have been published in peer-reviewed journal and conference papers or are under review for publication. The research published in each paper has been mainly conducted and written by the principal author (S. F. Atashzar) under the supervision of Dr. Rajni V. Patel.

Chapter 1:
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• R.V. Patel was the project leader. All aspects of this work (including idea development, theoretical and experimental evaluations and paper writing) were conducted under his supervision and guidance and were based on his direct input and leadership. He contributed to all aspects of the planning and execution of the research and provided input and assistance at each step of the writing of various of the paper and responses to reviewers.

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S. Farokh Atashzar (principal author) was the primary contributor in developing the theory, implementating the E-BMFLC filter, conducting the engineering experiments for the AHR architecture, data analysis and writing the paper.

M. Shahbazi (supervisor: R.V. Patel) contributed in the design of the engineering experiments and the resulting data analysis.

O. Samotus contributed by conducting the patient-based study, data collection and revising the paper.

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M. Jog was the clinical collaborator. Patient-based data collection was conducted under his supervision. He also contributed in paper revision.

R.V. Patel was the project leader. The engineering aspects of this work (including idea development, theoretical and experimental evaluations and paper writing and revising) were conducted under his supervision and direction. He contributed to all aspects of the planning and execution of the research and provided input and assistance during the writing and revision of the paper.

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N. Jafari prepared the evaluation protocol, and conducted the experiments and data collection.
M. Shahbazi (supervisor: R.V. Patel) contributed in preparing the experimental setup, and in the engineering tests.

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M. Tavakoli was an academic collaborator and contributed in developing the idea, system implementation, and revising the paper.

R.V. Patel was the supervisor of the principal author. All engineering aspects of this work (from idea development to paper writing and revision) were conducted under his supervision and direction.

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∗ M. Shahbazi (supervisor: R.V. Patel) contributed to development of the idea, protocol design and experiment preparation, system testing, conduct of the longitudinal patient-based study, and data collection.

∗ C. Ward’s contribution was in the design and implementation of the actuated pen.

∗ O. Samotus’s contribution was in conducting the patient-based study, system preparation, data collection and study management.

∗ M. Delrobaei contributed in conducting the patient-based study, protocol design/preparation, and data collection.

∗ F. Rahimi contributed to system implementation, idea development and protocol design/preparation/implementation.

∗ J. Lee contributed in system testing, data collection, protocol design, and study management.

∗ M. Jackman contributed in conducting the patient-based study, data collection, and study management.

∗ M. Jog was the clinical investigator and contributed to idea development, protocol design/preparation/implementation, conducting the patient-based study, delivering the treatment, patient assessment, and study organization and management.

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List of Acronyms

ADLs  Activities of Daily Living

AHR  Augmented Haptic Rehabilitation

ARA  Assistance, Rehabilitation and Assessment

AT  Assistive Therapy

BMFLC  Band-limited Multiple FLC

BoNT-A  Botulinum toxin injection

CAT  Coordination Assistive Therapy

CIS-M  CNS Input Sensing Modalities

CNS  Central Nervous System

CP  Cerebral Palsy

DOF  Degrees of Freedom

DS  Dystonia Severity

D-WAP  Dystonia Writing Assistance Pen

E-BMFLC  Enhanced-BMFLC

EIST  EMG-based Indirect Supervised Training

ELFC  Extended Lawrence Four-Channel

EOP  Excess of Passivity

ET  Essential Tremor

FDEs  Functional-Differential Equations

FHD  Focal Hand Dystonia
FLC  Fourier Linear Combiner

fMRI  functional Magnetic Resonance Imaging

FRG function  Force Reflection Gate function

GMFCS-E and R  Gross Motor Function Classification System Expanded and Revised

GP  Grip Pressure

GPS  Grasp-based Passivity Signature

HIRN  Haptics-enabled Interactive Robotic Neuro-Rehabilitation

HITN  Haptics-enabled Interactive Telerobotic Neuro-Rehabilitation

HRR  Haptics-enabled Robotic Rehabilitation

HTR  Haptics-enabled Telerobotic Rehabilitation

HTST  Haptics-enabled Teleoperated Supervised Training

INP  Input NonPassive

Input-to-Output Stability  IOS

ISP  Input Strictly Passive

LMS  Least-Mean-Square

LOP  Lack of Passivity

LTI  Linear Time-Invariant

MACS  Manual Ability Classification System

M-TDPC  Modulated TDPC

Multi-Input Multi-Output  MIMO

NM-DDD  Neuromuscular Motor Disorder, Deficit, and Disability
NN Neural Network
NP Neural Plasticity
NRM Neuro-Rehabilitation Mechatronics
NW Normal Writing
ONP Output NonPassive
OSP Output Strictly Passive
OTP Old Tremor Projection
PAT Power Assistive Therapy
PD Parkinson’s Disease
PMD Post-stroke Motor Disability
P-PMI Physical Patient-Machine Interaction
PTDPC Power-domain TDPC
PVT Programmable Virtual Therapist
QIT Quick Interpolation Technique
RAMIS systems Robotics-assisted Minimally Invasive Surgical systems
RAW Robotics-Assisted Writing
RG Relaxed Grasp
RMS Root Mean Square
RT Resistive Therapy
RTM Regeneration through Modeling
SA Signed Area
SD  Standard Deviation

SG  Stiff Grasp

SGC  Small-Gain Controller

SMI  Sensorimotor Integration

SOP  Shortage of Passivity

SPT  Strong Passivity Theorem

STD  Supervised Therapy Demonstration

TA  Tremor Amplification

TDPC  Time-domain Passivity Control

TSPL  Two-Segment Piecewise Linear

VE  Virtual Environment

VR  Virtual Reality

**Weakly Input-to-Output Stable**  WIOS

WFLC  Weighted-frequency FLC

WHO  World Health Organization

WE  Windowed Energy

WPT  Weak Passivity Theorem

WVC  Wave-Variables Control
Chapter 1

Introduction

1.1 Society Aging and the Need

Based on official numbers and statistics from the World Health Organization (WHO) as well as existing demographic data, the world’s population is aging rapidly. The population of senior adults worldwide over the age of 60 is expected to more than double by 2050 (from 841 million in 2013 to more than 2 billion by 2050). It is anticipated that by 2047 the number of senior adults will exceed the number of children. This trend is expected to continue due to increased life expectancy, and reduced fertility rate. It can become a global public health challenge in the near future and have significant social and economic effects on healthcare systems worldwide [1-4].

The rapid aging of our society is likely to increase the incidence of age-related neuromuscular and sensorimotor degeneration and corresponding disabilities and adverse events. Many of these age-related disorders such as post-stroke disabilities [5], Parkinson’s disease (PD) [6], disabilities caused by brain tumors, and essential tremor (ET), in addition to musculoskeletal impairments (such as osteoporosis [7], sarcopenia [8] and spinal cord problems [9]), result in sensorimotor dysfunction and impaired mobility in addition to long-lasting motor disabilities. This directly affects the health-related quality of life of senior adults [10].

Among age-related neuromuscular and sensorimotor problems, stroke is the leading cause of major motor disabilities [11-14] and results in excessive economic pressures on health-care systems. For example, stroke costs the Canadian economy $3.6 billion per year. Annually,
patients with stroke spend more than 639,000 days in acute care in Canadian hospitals and 4.5 million days in residential care facilities [15], [16]. A similar trend has been reported globally.

Repetitive, task-specific, interactive and goal-oriented motor rehabilitation is a key factor that helps patients to accelerate neural plasticity (NP) in their brain and consequently regain some of their lost motor functions. In fact, NP is a phenomenon that helps recovery of brain functions at the synaptic and non-synaptic levels. It is believed that NP can enhance damaged neural pathways of the brain and activate redundant, less-damaged pathways. This results in an increase in the quality of mobility and ultimately higher quality of life and level of independence. [17], [18].

Improving rehabilitation, together with pharmaceutical care is likely to increase the survival rates of patients with age-related neuromuscular problems and reduce hospital costs but will result in even more patients in need of Assistance, Rehabilitation and Assessment (ARA) services. Particularly, many stroke survivors experience permanent or long-lasting motor disabilities and often require labor-intensive motor therapy as early as possible and for extended periods. This places a significant burden on the healthcare system. The likely outcome is that, with a healthcare system that is already under-resourced, many patients suffering from a major functional deficit would not receive sufficient ARA services.

One potential solution is to develop intelligent Neuro-Rehabilitation Mechatronic (NRM) technologies that provide interactive, efficient, effective, safe and affordable means of ARA services for patients with neuromuscular disabilities, in clinics and ultimately in their homes [19].

In this chapter we review the existing categories of NRM technologies which have been developed for the above-mentioned goals. The specific focus of this review is Haptics-enabled Interactive Robotic Neuro-Rehabilitation (HIRN) systems which are being used in modern clinics to provide patients with an intelligent interactive repetitive computerized environment to accelerate NP and ultimately enhance the patient’s quality of mobility and life.

The rest of this chapter is organized as follows. In Section 1.2 the relevant definitions regarding NRM technologies are provided to highlight the main differences between the two major categories of NRM systems and better define the category which is studied in this chapter, i.e., HIRN technologies. In addition, some of the major commercialized NRM technologies
are introduced in Section 1.2. Details about the design and effectiveness of HIRN systems are given in Section 1.3. In Section 1.4 the existing challenges and the possible future vision of HIRN technologies are presented. In Section 1.5 scope, structure and the focus of this thesis are provided. Finally, in Section 1.6 the main contributions of this project are briefly presented.

1.2 Neuro-Rehabilitation Mechatronic Systems: Definition and Categories

This section introduces the definition of Neuro-Rehabilitation Mechatronic Systems and provides the existing categorizes.

1.2.1 Definition

The science of design and implementation of NRM systems falls within an overlapping region between two relatively new interdisciplinary fields of applied sciences, namely Neural Engineering (NE) and Bio-Mechatronics (BioM), whose definitions are given below. This concept is shown in Fig. 1.1.

Neural Engineering: The definition of NE given in the literature is “an interdisciplinary research area that brings to bear methods from neuroscience and engineering to analyze neurological functions and to design solutions to problems associated with neurological limitations and dysfunctions” [20].
Figure 1.2: Patient-Robot Interaction Information Flow for NRM technologies. In this figure, PMA-M refers to “Patient-Machine Action Modalities” which are generated by the patient and include Position, Force, EMG, EEG, Gaze modalities. In addition, PMR-M refers to “Patient-Machine Reaction Modalities” which are generated by the mechatronic system and include Position, Force and Electrical Muscle Stimulations. Also, CIS-M refers to “CNS Input Sensing modalities” which include Force, Rigidity, Tactile and Visual perceptions in addition to Proprioception. Also, NM-DDD refers to Neuromuscular Motor Disorder, Deficit, and Disability which affects the patient’s sensorimotor system. In addition, P-PMI refers to “Physical Patient-Machine Interaction”.

**Bio-Mechatronics**: The definition of BioM in the literature is “an applied interdisciplinary science that aims to integrate mechanical elements in the human body, both for therapeutic uses (e.g., artificial hearts) and for the augmentation of existing abilities” \[27\].

Considering the above definitions, NRM can be defined as the science of designing and implementing mechatronic solutions to help patients with Neuromuscular Motor Deficits, Disorders and Disabilities (NM-DDD) in rebuilding and regaining their lost motor functions. An NRM system has three major components (mechanical, electrical and computerized systems) which are fused to address the above-mentioned goal. Consequently, systems such as neural sensors and electrical nerve stimulators can be considered as components of an NRM system but they are not standalone NRM technologies. The diagram shown in Fig. 1.2 represents the information flow between a patient and an NRM technology. Consequently, a technology which cannot be modeled using the diagram given in Fig. 1.2 is not an NRM technology.

It should be noted that all NRM systems include a close physical interaction between a disabled patient and a powerful source of mechanical stimulation. If the interaction modalities (such as force, velocity, acceleration) go beyond certain limits, they can cause bone, joint
and/or soft tissue damages. This is why \textit{Physical Patient-Machine Interaction (P-PMI) safety} is an important requirement of NRM systems and, for safety purposes, may result in conservative restrictions on the amount of allowable forces that can be generated by the system \[22–24\]. High limitations in generating therapeutic and assistive forces can result in reduced performance (such as slow guidance or low-intensity interaction). Consequently, guaranteeing the safety of physical patient-machine interaction while maximizing the allowable force generation is an ongoing field of research which will be explained in more details in this chapter.

1.2.2 Categories

As shown in Fig. 1.1 there are two major categories for NRM systems, namely:

- Haptics-enabled Interactive Robotic Neuro-Rehabilitation (HIRN) Systems,
- Assistive Neural Technologies (Smart Active Prosthetics and Orthotics).

Although the main focus of this chapter is HIRN technologies, the authors believe that it is essential to have a good understanding of the boundaries of each category to allow for better interpretation of the main mission of HIRN technologies in comparison to that of the second category. The two categories are briefly introduced below and examples are provided.

\textbf{Haptics-enabled Interactive Robotic Neuro-Rehabilitation (HIRN) Systems}: The main purpose of HIRN technologies is to provide patients with a force-enabled interactive medium (mostly based on virtual-reality environments) that either assists or resists a patient’s upper-limb or lower-limb movements while performing a repetitive tasks. Examples for upper-limb HIRN systems can be found in \[25–27\] and examples for lower-limb HIRN systems can be found in \[28–31\].

For upper-limb rehabilitation, conventional tasks include reaching motions where the user needs to track and reach a moving target in a Virtual Reality (VR) environment. The target switches (a) if the user reaches it, or (b) if a specific task completion time limit has elapsed. There are more sophisticated game-like virtual environments designed to keep the patient engaged during a rehabilitation session. Widely used commercialized examples of the upper-limb HIRN robots include the InMotion ARM\textsuperscript{TM} system (Interactive Motion Inc. Watertown, MA,
6 CHAPTER 1. INTRODUCTION

Figure 1.3: Commercialized HIRN systems: (a) The Armeo system [36], (b) The InMotion ARM™ system [37, 38].

United States), which is the clinical version of the MIT-Manus [25, 32], and the Armeo technology (Hocoma AG, Zurich, CH) [33, 34] (which is based on ARMIN [35] technology). These systems are shown in Figs. 1.3a and 1.3b respectively.

The situation is slightly different for lower-limb HIRN systems which have two subcategories. The first type of lower-limb HIRN systems work in a similar manner as the above-mentioned upper-limb technologies. The patient needs to be in a sitting or a lying position, and the robot is connected to a part of their lower-extremity (which is usually their ankle) and the patients should perform a task in a virtual reality environment. Examples are the Rutgers Ankle system [39, 40] and the Anklebot [41] shown in Fig. 1.4. Other examples can be found in [42, 43].

* [Figure 1.3(a)] Copyright ©Hocoma AG, Switzerland, www.hocoma.com
**[Figure 1.3(b)] Copyright ©Bionik Laboratories Corp.
The second subcategory of lower-limb HIRN technology is treadmill based robotic gait trainers [28, 31]. This category aims to rehabilitate cyclic gait motion and the patients should be in the walking position while wearing the robot. The patient walks on a treadmill while their weight is usually supported to prevent falls. The robot provides assistive, coordinative or resistive forces while the patient walks. A virtual reality environment might be used for providing visual cues. An Example of this subcategory is Lokomat system (Hocoma AG, Switzerland) [46, 47] shown in Fig. 1.5.

The main targeted populations for HIRN technology is post-stroke patients and the major use is to harness neural and muscular plasticity and recovery over time. However, the same technology has been applied for other neuromuscular conditions, such as for assessment and better understanding of Parkinson’s Disease in adults [49–51], and for rehabilitation of Cerebral Palsy in children [52–55].

It should be noted that HIRN technologies do not aim to instantly assist a patient in performing Activities of Daily Livings (ADLs) through augmenting their movement capabilities.

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** [Figure 1.4(b)] Copyright ©1999, ASME. [M. Girone, G. Burdea, M. Bouzit, “The Rutgers ankle orthopedic rehabilitation interface,” Proceedings of the ASME, Dynamic Systems and Control Division, vol. 67, pp. 305–312, 1999.]
Instead, this technology aims to accelerate neural and muscular recovery and enhance motor performance of patients over time \[56\]. This is discussed further in the next section and is the main difference when compared with the second category of NRM systems.

**Assistive Neural Technologies (ANT), Smart Active Prosthetics and Orthotics:** In contrast to HIRN technologies, the mission of the second category is to provide instant active assistance for patients with neuromuscular deficits to help them in performing their ADLs. The control strategy for proper tuning of the functionality of this technology is usually complicated and requires fusion of data collected from the patient’s body (such as muscles, brain, nerves and the kinematics of motion) in addition to interactive data (such as measured forces from the walking surface). This data fusion is required to properly and actively tune the mechanical characteristics of the device (such as impedance of the robot’s joints) and the generated forces while performing tasks. In \[57, 58\], examples of existing control strategies and existing ANT technologies can be seen.

In this regard, active intelligent prosthetics (artificial limbs) have been designed for both upper-limb \[59, 60\] and lower-limb \[61\] deficits to help amputees in performing ADLs. An example of this technology for the lower-limb is the active emPOWER Ankle (from BionX\textsuperscript{TM}}
1.2. Neuro-Rehabilitation Mechatronic Systems

**Figure 1.6:** (a)† An example of a lower-limb Active Prosthetic, the emPOWER Ankle system from BionX™ Medical Technologies, Inc. [63]; (b)** Two examples of upper-limb active prostheses (from left to right) the Bebionic hand from RSL Steeper, the Vincent hand from Vincent Systems GmbH, and the i-LIMB Ultra system from Touch Bionics [62].

Medical Technologies, Inc., Bedford, MA, USA). In addition, some examples for upper-limb active prosthetics are the Bebionic hand (RSL Steeper, United Kingdom), the Vincent hand (Vincent Systems GmbH, Germany), and the i-LIMB Ultra (Touch Bionics, United Kingdom) [62]. The above-mentioned examples are shown in Fig. 1.6.

In addition to active prosthetics, smart assistive orthoses have been developed to instantly augment the capabilities of disabled patients (such as those with post-stroke impairments and spinal cord injuries) in performing ADLs, using their own limbs. An example of this technology is the Vanderbilt Lower-limb Exoskeleton that is designed for patients with paraplegia [65]. More examples can be found in [66]. In contrast to the assistive prosthetics, active orthoses are wearable exoskeleton-like mechatronic devices which aim to manipulate the limbs of patients to perform ADLs. In this regard, the EKSO GT™ system has been commercialized as an active orthosis which is claimed to be the first FDA-approved exoskeleton to be used for patients with post-stroke impairments and spinal cord injuries [67, 68]. The EKSO system is shown in Fig. 1.7.

†[Figure 1.6(a)] Copyright ©BionX Medical Technologies, Inc.
**[Figure 1.6(b)] Copyright ©2013, IEEE. T. Tommasi, F. Orabona, C. Castellini, B. Caputo, “Improving control of dexterous hand prostheses using adaptive learning,” IEEE Transactions on Robotics, vol. 29, no. 1, pp. 207-219, 2013.]
1.3 HIRN Technology: Design and Effectiveness

1.3.1 Design

Conventional HIRN systems have three major components whose definition and functionality are explained below [20, 25, 69, 70]. A representative schematic is given in Fig. 1.8 which shows how the components are interconnected.

(a) A Powerful Haptic Device: The first components of a HIRN system is an active medical robotic device which usually can provide multi-directional high-amplitude and high bandwidth kinesthetic forces in order to enable delivery of various type of kinesthetic rehabilitation exercises for patients with neuromuscular deficits. The medical robotic component used in HIRN systems should be powerful-enough to allow for generating high-intensity forces for patients with a wide-range of biomechanics and neuromuscular deficits. For example, patients may show strong imbalanced muscular tone symptoms (such as the one in post-stroke patients with spasticity and hypertonia [71, 72]), and the system should be capable of manipulating and stretching the affected muscles. In addition, the kinematic and biomechanical characteristics of the patients’ limbs can be very different. A patient may have a small workspace of motion...
with light-weight and compliant limbs and with no involuntary movement, while another patient may have a large workspace of motions and/or have heavy rigid limbs and/or tremor-like involuntary movements.

In addition to the above, the robot should be responsive-enough (having high bandwidth) to provide a transparent feel of interaction and to minimize potential latencies which can affect the quality of force feedback. In other words, “the robot should be invisible” for the patient. The concept of transparent haptic interaction has been investigated in depth in the area of haptic and telerobotic systems.

In addition, the electromechanical parts of the robot should be able to accommodate the generation of repetitive force-enabled tasks over a long period of time, while mechanically tolerate the uncoordinated external disturbances applied by patients with sensorimotor deficits. Also, the robot should provide various hardware and software safety features to avoid dangerous situations for disabled patients who are usually attached to the device (sometimes using velcro-like constraints). Detailed discussions on safety is provided in Section IV.

The above-mentioned notes represent considerable existing technical and technological challenges and the need for particular attention to the design of HIRN systems. As a result, electromechanical design of HIRN technologies is a distinct area of research which requires close communication and partnership between engineers and clinicians to optimally meet the requirements.
In order to reduce the complexity of the design, some of HIRN systems have targeted a limited number of joints and provided limited degrees of freedom for delivery of rehabilitation therapies. In this regard, rehabilitation robots have been separately designed for finger, wrist, arm and shoulder therapies. Commercial examples for different segments of the upper-extremity can be found in [79–82]. Modular designs have also been considered which allow for combining two standalone devices (for example wrist and arm robots) into one system [81]. In addition, pediatric rehabilitation systems have been separately designed and optimized to make them compatible with specific needs of pediatric patients and their kinematics and force capabilities [52].

Regarding the functionality of HIRN technologies, it should be noted that, two low-level control schemes have been commonly utilized in the literature [27, 73, 76], namely: (a) Impedance-Domain Control (IDC), such as the one used in the MIT-Manus system [83]; and (b) Admittance-Domain Control (ADC), such as the one used in the HapticMaster system [84].

For the case of IDC schemes, the robot measures the movement of the patient and provides therapeutic forces in response. If the scheme uses only the kinematic calculations of the robot to generate end-point forces by applying the calculated torques at the joints, the controller is called open-loop IDC. If the robot utilizes a closed-loop force control algorithm (based on the measured forces) to accurately tune the end-point force, it is called closed-loop IDC. An impedance-controlled robot is naturally in free-motion. For the case of open-loop IDC, the user may feel residual dynamics (such as friction in the joints and inertia) of the robot when the commanded force is zero. For this reason, the mechanical design of IDC-based robots is usually light-weight, back-drivable, low-friction and low-inertia [27, 85, 86]. The other solution to deal with the residual dynamics of the robot, in the case of open-loop IDC, is to utilize an inverse dynamics algorithm to compensate for the residual dynamics of the robot [27]. For the case of ADC schemes, the robot measures the forces applied by the patient and provides therapeutic motion profiles in response. In other words, the robot is naturally locked due to an inherently-implemented position control loop in ADC schemes.

In theory, the aforementioned low-level control schemes are identical from the point of view of rendering similar quality of kinesthetic interaction for a user. However, from a practical point of view, in ADC schemes, force measurement is an inherent feature of the system
which cannot be avoided. This can increase the cost of the system in comparison to the open-loop IDC-based robots that do not require force measurement. In addition, as mentioned above, ADC schemes have inevitable internal position control loops which command the robot to track a position profile with respect to the measured forces. This may challenge the stability and the complexity of the control strategy since it increases the number of control loops. The stability concern will be more serious in the presence of noise, delay, and latency of the force measurement system. In summary, mechanical designs of IDC-based robots are more complicated (in comparison to ADC-based robots) to minimize the residual haptic effect (resulting from the robot’s dynamics); however, it requires less complicated control designs and provides a more robust behavior for rendering a kinesthetic feeling for the patient \[27, 85, 86\]. In general, using IDC, more responsive and accurate interaction \[85\], and better stability \[86\] can be expected. It should be noted that when high forces are needed, for example for lower-limb rehabilitation, ADC schemes might be more appropriate.

(b) Game-like Virtual Reality Environment: Due to significant progress in the field of real-time 2D/3D video rendering software and gaming technology during the last two decades, task-oriented VR environments have become an inherent component of HIRN technologies \[78, 87\]. The purpose of these VR environments is to provide the patient with multi-modal (mostly visual and auditory) cues during tasks performed by patients. Research has shown that the use of VR environments can significantly augment the effectiveness of robotic rehabilitation systems. This has been done by comparing VR-based and non-VR-based robotic training systems \[88, 89\]. A recent systematic review of the effectiveness of VR environments for upper-limb post-stroke recovery reports strong supporting scientific evidence \[90\]. Further reports can be found in \[91\].

The first generation of VR environments was mostly 2D and the tasks were usually simple reaching movements where the patient was required to track a moving object or to reach several stationary targets one-by-one. However, the recent generation of VR environments used in HIRN technologies, provide more sophisticated interaction allowing the user to perform tasks in the simulated environments similar to normal ADLs. In addition, taking advantage of existing relatively-inexpensive 3D rendering technologies, the recent generation of VR environments can provide the user with visual depth information, as well. One of the main purposes
of using VR environments in HIRN technologies is to maximize the engagement and participation of the patient. For the case of pediatric rehabilitation, the design of the VR environments is more challenging and it should be motivating and interesting-enough to keep the pediatric patient engaged in the loop of rehabilitation [76, 78, 91–93].

(c) Programmable Virtual Therapist (PVT) algorithm: The third component of a HIRN system is an algorithm responsible for calculating the needed therapeutic forces to be applied by the robot to the patient’s limb in order to deliver kinesthetic rehabilitation exercises. The algorithm is called a “high-level” control strategy in some articles. The main goal of this algorithm is to enhance motor capabilities of patients by (a) stimulating motor plasticity and neuromuscular recovery, and (b) preserving the health of the musculoskeletal system of patients [25, 27, 70].

The possible types of rehabilitation exercises generated using PVT algorithms can be categorized into two major groups of high-level control algorithms (a) passive movement therapy and (b) interactive therapy. For the first category, the patients’ motor control and their decision making procedure are not involved. Instead, the robot controls the position of the patient’s limb to track a desired trajectory. In other words, the control algorithm of the robot considers the patient’s inputs as disturbing forces that should be compensated for to enable tracking the predefined motion trajectory. Although, this therapy can be useful mostly for preserving and enhancing the health of joints and muscles (for example through muscle stretching exercises), it is not expected to significantly enhance motor learning since it does not allow the patient to (a) be engaged in the procedure of motion control and task accomplishment, and (b) make mistakes (which is a key factor in motor learning). It should be noted that, for extremely-impaired or completely disabled patients who are not capable of providing the minimum required motor capabilities that can be registered by the robot (this is needed for the second category), this option is still useful and can help the patient to regain some minimum motor capabilities which might be enough to make the patient a candidate for the second category of robotic therapy that is directly aimed at neural recovery [94, 95].

The second category is mostly considered for brain rehabilitation and neural recovery. This category has been specifically designed to allow patients to be involved in task performance. In this regard, the patient needs to track a trajectory while the robot provides interactive therapeu-
tic forces. There are two major types of widely-used and commercialized therapeutic actions under the second category: (a) Resistive Therapy (RT), and (b) Assistive Therapy (AT).

The functionality of RT is to challenge patients’ motor capabilities during task performance and to urge them to generate more muscle activities and contractions and more forceful motor control during task performances. This can help patients to enhance their motor capabilities and equalize their muscle activation. During RT, the robot may damp out or oppose the mechanical power generated by the patient to make the tasks (motion generation and target tracking) kinesthetically difficult and challenging for the patient. On the other hand, AT (denoted as “sensorimotor robotic therapy” or “coordinative therapy” in some articles) is designed to amplify the mechanical power of the patient’s hand and help to finish several repetitions of the task. In general, candidates of RT need to have considerable residual motor capability and it is not possible to perform this type of rehabilitation for severely-disabled patients. However, highly-disabled patients with minimum residual mechanical power can take advantage of interactive rehabilitation exercises through AT. This is why robotic rehabilitation is known as a tool which has significantly broaden the range of patients who can take advantage of receiving interactive exercises (which is a key factor for triggering brain plasticity). Clinical studies support effectiveness of both RT and AT. However, statistically-significant differences have not been reported yet between the effectiveness of RT and AT for those patients who can undergo both types of interactive robotic therapy (RT and AT) [27, 70, 96-98].

Although, the design of high-level control algorithms of RT is relatively straightforward, the situation is not the same for AT, as explained next. For RT, the high-level controller usually works like a viscoelastic or viscous environment which restricts or challenges the patient’s movement when they try to move the robotic handle away from the origin and towards the target for task performance. The intensity (forcefulness) of the environment is usually tuned by a clinician after some trials. In addition to viscosity-based resistive therapies, there are simpler formats of RT that only generates constant resistive forces (independent of the patient’s movement) during task performance. A clarifying example for the constant resistive forces is gravity which always resists the hand motion in one direction and the intensity of it is independent of the kinematic characteristics of the movement. In addition, it should be noted that generally RT algorithms do not require a desired trajectory. The above-mentioned notes represent relatively
straightforward design of RT algorithms [27, 94, 96, 99, 100].

In contrast to RT, for the case of AT, the design of the high-level control algorithm is more complicated. There are several ways to assist a patient for tracking a trajectory. Novel techniques have been and are being developed and/or are under clinical trials. This is a top line of research and is still under new development. In this regard, a major goal of the ongoing studies is to find the best way of intelligently assisting severely-disabled patients to enable them to perform tasks while maximizing their engagement and participation. Active involvement and participation of the patient is a key factor which can promote neural plasticity and has been enabled using task-oriented assistive therapies. The goal of AT is to help severely-disabled patients in recovering their motor performance as quickly and permanently as possible [95, 96, 101].

As mentioned above, for the case of AT the high-level control algorithm may be designed in different ways. One existing possibility is an error-reducing force field which does not apply forces if a patient follows a trajectory/path within an acceptable time/position threshold. However, once the patient deviates from the trajectory/path the force field starts pushing the patient towards the needed trajectory/path. The force can be proportional to the amount and derivative (velocity) of deviation. This strategy is called “impedance-based assistive therapy” or “active-assistance” in some articles. It should be noted that the difference between the path-control techniques and trajectory-control techniques is the “time” factor. For path control, the time factor is not considered. However, for trajectory control, the timing of movement is taken into account. This means that for the trajectory-control strategies, if a patient moves towards the target, even in the correct path, but deviates from the timing profile, the force-field starts assisting the patient and pushes them towards the correct trajectory considering the defined timing of the motion. The existence of the above-mentioned time/position thresholds is one of the main difference between interactive AT and the first category, mentioned earlier in this section, i.e., passive movement therapy. The use of the aforementioned thresholds allows patients to make mistakes and follow their own pattern of target tracking within an acceptable window. As mentioned above, being involved in generating the pattern of motion and being allowed to make mistakes during motor execution are important factors for stimulation motor learning and neural plasticity. Although, the AT can address several issues for promoting
neural plasticity, tuning of the thresholds and the characteristics of the considered impedance of the generated force field (the dependency of the therapeutic forces on the deviation from the desired path/trajectory) is questionable and in some cases has been approached using adaptive algorithms. This topic is discussed further in the next section. The relevant citations regarding the discussion given above are [95, 96, 102–106] and the references therein.

The other type of AT has been called “counter-balancing” or “gravity-compensation” strategies in some references. The main purpose of this type of AT is to compensate for the weight of the patient’s limb to make tasks easier and allow patients to conduct more repetitions. In other words, the basic aim of this type of high-level control strategy is not to guide a patient’s arm towards a trajectory or path. The aim is to help the patient in using the residual motor capabilities to perform repetitive tasks instead of using the capabilities to compensate for the weight of the musculoskeletal system. This type of AT has been motivated by classical passive counterbalancing devices used for rehabilitation therapies. The amount of compensation may be tuned to modify the level of assistance. Consequently, this type of AT can increase motion capabilities of patients by partially or totally counterbalancing the weight of their limbs. The conventional designs could not help patients with considerable increased muscle tone and agonist muscle weakness who are in need of considerable kinesthetic help in performing movement tasks. There are however hybrid designs of this type of AT which allow for balancing forces more than the weight of a patient’s limb to account for other symptoms such as increased muscle tone or to provide some level of impedance-based guiding forces. [107–111].

The other type of AT is power-assistive therapy which is also called “negative-viscosity assistance”, “negative-damping assistance”, “self-directed movement”, “energetic assistive therapy” and “positive feedback control” in various articles. The main concept of this type of assistive strategy is to directly amplify the mechanical power generated by the patient. For this purpose, the rehabilitation robot may generate forces in the same direction of the velocity provided by the patient. In other words, the robot can register the direction in which the patient intends to move and amplify the patient’s power by reflecting back the assistive forces to the patient’s limb in the intended direction of motion. This is done to help the patient in completing the intended movement task in a faster and easier manner. This type of assistive strategy is relatively new compared to conventional impedance-based assistance. Recent studies have sup-
ported the effectiveness of this type of AT in enhancing motor learning and motor performance for post-stroke patients. This high-level control technique allows patients to utilize their own motion strategies and residual motor capabilities for task accomplishment. The strategy enables patients to achieve “greater agency over their sensorimotor interactions” through active involvement which is an essential factor supported by motor learning studies, instead of relying on external control from a robot. It should be noted that this type of high-level control strategy has also been viewed as a tool which brings more awareness of the existing motor control errors for the patient, which is also an important factor for motor learning. The aforementioned viewpoint considers this type of AT as a new kinesthetic tool which provides “error enhancement” or “error augmentation”. This is a well-studied and widely-accepted strategy in the literature for motor-learning. Relevant discussions on this can be found in [106, 112–119].

The concept of detecting the patient’s intention of motor control and amplifying the intended motion has also been realized and clinically validated using surface EMG measurements of the muscle activities (instead of using kinematic measurements, such as velocity and acceleration) for detecting the intention of motion. The motivation is similar to the above-mentioned negative-damping AT and is to provide active involvement through direct motor agency for the patient. For this purpose, the EMG-based motion amplification assistive strategy analyzes the EMG activities of the corresponding muscles; then, it identifies the patient intention of movement (and possibly the direction of the intended motion) and finally, it amplifies the detected motion. Hybrid techniques which use EMG measurements in order to trigger impedance-based AT have also been developed and validated [120–122].

Although there are several clinical studies supporting the effectiveness of the above-mentioned high-level control strategies (i.e., AT and RT), there are many parameters which need to be tuned properly considering the rehabilitation need, the biomechanical characteristics of the patient’s limbs, in addition to the pattern of neuromuscular deficits and the progress of the motor learning. Examples of those parameters are the kinesthetic and kinematic characteristics of the desired trajectory to be tracked by the patient, and the strength/forcefulness (extent of reaction) of the RT and AT strategies. Improper tuning of these parameters and inappropriate choice of the rehabilitation strategy can convert a potentially effective robotic rehabilitation treatment to an ineffective therapy. This topic is further discussed in the next part.
1.3.2 Effectiveness

Programmable VR-based HIRN technologies have shown a great potential in accelerating neural recovery and has resulted in enhancing the quality of motor performance for post-stroke patients \[25, 123-125\]. There are several contributing factors which may have attracted a great deal of interest for using HIRN technology to enhance motor performance of neurologically-impaired patients. Some examples are given below:

a) Robots can be programmed to repeat an interactive task for several iterations while keeping patients engaged in the loop of rehabilitation.

b) Robots are powerful and precise, so they can generate accurate high- and low-intensity assistive and resistive force fields to deliver kinesthetic therapy for a wide range of patients with different biomechanics, over a long period of time.

c) Robots are computerized and can measure and log kinematic and kinesthetic data (such as motion and force profiles in different parts of the workspace) during rehabilitation therapies. This enables precise and repeatable objective assessment of motor performance that is important for clinicians to tune the dose, strategy, type, and intensity of therapy, while monitoring the progress of motor enhancement.

d) VR environments coupled with HIRN systems provide interactive visual and auditory cues, enable goal-oriented sensorimotor tasks which keep patients engaged and urge them to use their decision making capabilities. This is a key factor for stimulating neural recovery in comparison with passive limb movement therapy \[25, 126\].

The effectiveness of HIRN systems in enhancing neural recovery has been widely accepted in the literature \[25, 127\]. In this regard, the American Heart Association (AHA) has endorsed upper-limb robotic therapy in its guidelines as a standard for post-stroke therapy \[52, 127, 128\]. However, there are two major controversial questions about the performance of HIRN systems.

**The first question is:** Does the enhanced motor performance achieved by the use of HIRN technology remains for a significant period of time after robotic rehabilitation? This question has been investigated in the literature \[56, 129, 130\] and it is shown that motor enhancement benefits remain even for three years after robotic therapy.
The second question is: *Can the trained skills be translated and generalized in performing ADLs?* In other words, the question is whether patients subjected to robotic therapy only adapt to the trained exercises (which may result in better performance of the trained tasks), or they learn motor skills and can generalize them for better performance of ADLs? To answer this question, a clinical study has been conducted including 158 recovering post-stroke patients [56]. The outcome of this study shows promising results regarding the functionality of HIRN systems in enhancing motor skills. In particular, the results show that kinematic enhancement achieved by robotic rehabilitation can be generalized to untrained tasks (in a similar workspace). This means that motor performance enhancement “*better resembles motor learning than motor adaptation* [56].”

In addition to the above two conventional questions, there is a third research question which is a current major line of research: *Can HIRN technologies and the corresponding concept of virtual therapist be a “replacement” for conventional manual rehabilitation therapies delivered through interpersonal kinesthetic interaction between a human therapist and a patient?* [131]. Based on the current state of HIRN technologies and conducted research in this area, it can be interpreted that the current available technology has not been accepted as a replacement for conventional therapy [131, 132]. However, it is widely accepted for enhancing the outcomes (as an adjunct to conventional rehabilitation therapy) through (a) increasing the hours of rehabilitation that a patient may receive and (b) exposing the patient to an interactive rehabilitation environment where their decision making procedure is involved for task accomplishment. In addition, it is believed that this technology can provide more independence for patients during rehabilitation, and has the potential to save the therapist’s time and ultimately reduce some burden on the healthcare systems [92, 128, 131–134]. This has been the motivation for (a) recent modern robotic gyms developed for upper-extremity rehabilitation [55, 127, 134], and (b) the current rising tendency towards developing in-home kinesthetic rehabilitation, tele-rehabilitation and cyber-rehabilitation systems. These systems have the potential to considerably increase the duration for which a post-stroke patient receives interactive kinesthetic rehabilitation and can also result in more accurate objective assessment of patients’ motor performances during a larger time window [78, 92, 134, 135]. This topic is discussed in the next section.
In summary, after 30 years of research in the area of robotic rehabilitation, the current trend is not anymore towards replicating or replacing manual therapies [69], but is targeting development of novel means of therapy and assessment that can be safely supervised by clinicians and can be performed by robots because of their unique features including advanced, interactive, repetitive, multi-modal, computerized, power-full and kinesthetic environment which has been realized by HIRN technologies. This trend is now targeting future homes of patients, in the context of smart modern homes. Further discussion is provided in the next section.

1.4 HIRN Technology: The Journey, Challenges and Future Vision

In this section, the existing challenges concerning the use and implementation of HIRN technologies are introduced and the future of this technology is discussed while looking at the ongoing journey of development that started around 30 years ago.

1.4.1 Background on the Evolution of HIRN Technologies

The earliest designs of HIRN technologies were published between 1992 and 1995 [32, 136–138] and a version of the technology was patented by researchers from Massachusetts Institute of Technology in 1995 [139]. Clinical studies have been conducted from the earliest stages of generation (reported around 1997 [83, 140]) until now (such as [141] published in 2015), in order to evaluate different aspects of the effectiveness of this new paradigm of rehabilitation. The goals of the conducted clinical studies have been mostly targeted towards answering research questions such as the ones below.

a) Are rehabilitation robots effective in accelerating neural recovery?

b) Can rehabilitation robots replace manual therapy?

c) Can robots augment the effectiveness of conventional interpersonal therapies?

d) What type of robotic rehabilitation is more effective?

e) How can the effectiveness of a robotic therapy regime be increased?

f) How can the functionality of rehabilitation robots be adapted to the needs of patients?
g) Can rehabilitation robots be used in patients’ homes?

The list given above shows some examples of important research questions. Although, some of these questions (such as (a) and (c)) have been deeply investigated during the last two decades of clinical research and the results have convinced several associations (such as AHA) to endorse the effectiveness of this technology, other questions (such as (b), (f) and (g)) are still under investigation and form the ongoing lines of research.

As mentioned in the previous section, although, the effectiveness of robotic rehabilitation systems has been widely accepted (at least as an effective adjunct therapy for manual rehabilitation), there are still conflicting clinical studies with contradictory conclusions (this will be explained more in the rest of this section). One possible reason for this controversy can be an improper generalization of the term “robotic rehabilitation”. In fact, due to the current large and growing size of the corresponding market and research effort there are several different commercialized and experimental rehabilitation robots with different implementations and modes of operation. Even for one specific product, there are several modes and parameters to be tuned in order to deliver a kinesthetic rehabilitation regime. As mentioned earlier, improper tuning of robotic therapy, or improper choice of the robot, or the strategy of rehabilitation can totally change the outcomes. It may even convert a possibly effective regime of rehabilitation to an improper or ineffective exercise. One well known example in this regard is an improper choice of parameters for impedance-based AT (introduced earlier in this chapter) which can result in excessive reliance of the patient on the actions of the robot that can reduce the engagement of the patient in the therapy and ultimately degrade the results of the prescribed regime of rehabilitation. Consequently, the existence of different opinions about HIRN technology might be translated into the fact that (a) the results from one specific evaluation cannot be generalized to all possible uses and formats of this technology; and (b) properly tuning the parameters which match the patient’s biomechanics and needs is a challenging procedure which can affect the outcomes. The aforementioned issues have been discussed in [103] and several other publications which focus on adaptive algorithms for therapy (as explained in the next subsection).

It is expected that we will shortly face the second major movement in the field of HIRN technologies during the following decade. Major goals would be (a) to make robots more
1.4. HIRN Technology: The Journey, Challenges and Future Vision

Flexible and intelligent to better match the patients’ needs and biomechanics, and (b) to move rehabilitation robots into patients’ homes which will increase the duration for which a patient can be exposed to an interactive rehabilitation environment and thereby improve the outcomes while reducing the cost of rehabilitation. The latter goal comes under the umbrella of cyber-medicine and tele-rehabilitation which has recently been introduced and is a growing field of research. Relevant discussions about these issues can be found in [77, 135, 142–145].

With the use of smart and portable technologies, a significant increase in the exposure of patients to intelligent, interactive rehabilitation environments is envisioned. It can be expected that this will have a considerable effect on the rate at which patients regain their lost motor functions and will reduce the burden on healthcare systems. There are several challenges facing this area of research and further development of HIRN technologies. In the next subsections we introduce the two major challenges together with possible solutions which form current and the future lines of research in the field of HIRN technologies.

1.4.2 Adaptability Challenge

As explained in the previous section, the current state of robotic rehabilitation technology has been accepted mostly just as an optional adjunct strategy for manual therapy and not as a replacement or a replication. One of the major challenges which contributes to this viewpoint is the compatibility issue of the robotic therapy with the needs and biomechanical characteristics of patients. It is still uncertain how to optimize robotic rehabilitation strategies for patients in need [56] considering the fact that stroke affects patients in different manners and the effect of stroke is different for each patient. “There is no reason to believe that a one-size-fits-all optimal treatment exists [102].” To move towards a possible solution for this issue and enhance the performance of robotic rehabilitation systems, adaptive algorithms have been suggested, as discussed below.

The need for making the assigned motor learning task compatible with the requirements of each user has been identified in several publications, for example in [95], [96], and references therein. As discussed in [95], a research question which is under investigation by several research teams is how to design the characteristics of high-level control algorithms for rehabilitation robots to match the sensorimotor requirements of each user. Some examples of the
characteristics are: (a) the strength/forcefulness of robotic therapy, (b) the allowed threshold for making errors and deviation from a desired trajectory during impedance-based assistive therapy, and (c) the amount and strength of power amplification provided during power-assistive therapy. These factors directly correlate with the choice of the parameters of the utilized high-level control strategy. The conventional choice of parameters is usually fixed values for the whole workspace of motion and might be changed (not frequently) by an operator after some trials. This has not been seen in the literature as an optimal solution. In the field of motor learning and rehabilitation sciences, it is widely accepted that the parameters of a robotic training system should be adapted (preferably in an automated manner and in real-time) considering (i) the motor control capability, kinematics and biomechanical characteristics of the patient, (ii) the characteristics of the neuromuscular deficits, and (iii) the rate and pattern of motor improvement. These three factors are denoted as Three Key Factors of Motor Training in this section and have been identified in the corresponding literature such as [96, 102, 103], and the references therein.

As an example for the above-mentioned compatibility need, it should be noted that high level of assistance during impedance-based assistive therapy can result in excessive reliance of the patient on the movement of the robot. This can result a phenomena called “slacking” which means that the patient reduces the participation and tries to minimize the needed effort for accomplishing the task over time, by relying on the robot and allowing it to “take over” and finish the task. This reduces stimulation of neural plasticity and may have an inverse effect on the progress of improvement. In fact, it is believe that a robotic device may result in decelerating recovery if it results in the slacking phenomena. The reason is that slacking may decrease the level of motor output and the generated mechanical power by a patient, and their involvement in task accomplishment. On the other hand, high level of resistance can make the task too difficult to accomplish for a patient. Relevant discussions regarding the above issues can be found in [95, 96, 146], and references therein.

The lack of “flexibility” in tuning the parameters of robotic therapy have been discussed in [95] as a possible factor affecting some studies (such as [147, 148]) which have not reported statistically-significant benefits of using robots over manual interpersonal therapy where the therapist has full authority to instantly and directly modify the strategy and the extent of kines-
thetic guidance in different parts of the workspace [95, 96]. This authority for the therapists which allows them to properly tune the therapy is known as a key factor in rehabilitation studies [149]. If the issue of flexibility is not resolved, robots can only be seen as an optional adjunct therapy whose performance might be uncertain to some extent. However, the existence of extensive clinical studies reporting significant benefits of rehabilitation robots under some specific circumstances has motivated research on ways to deal with this challenge and to ultimately allow for using this technology with minimum concern about how to manually tune the parameters.

Accordingly, an accelerated trend of research and development for designing high-level control algorithms is to determine how to design intelligent adaptive techniques which automatically (or semi-automatically) tune the parameters and match the three key factors of motor training. Motivated by this, adaptive control techniques such as “assist-as-needed”, “fading force feedback”, “progressive-based assistive/resistive therapy” have been proposed in the literature to autonomously or semi-autonomously tune the control parameters of the robots (considering some measures such as completion time, motion characteristics and/or quality of task accomplishment). Some of the developed adaptive techniques include algorithms such as “forgetting factors” (which decrease the assistance level after each successful task accomplishment or gradually over time) or “regions of no action in space-time coordinate” (in which the robot does not apply therapeutic forces) to keep challenging the patient for maximizing the participation and engagement. In summary, the common goal for adaptive high-level control techniques is to tune the strategy of therapy (considering (a) the biomechanical, kinesthetic and kinematic state of the patient over the workspace of the task, (b) performance of the task accomplishment and (c) the rate of progress in acquiring motor skills) to maximize the engagement of the patient, while addressing the concern of subjective manual tuning of the parameters. In this regard, assist-as-needed techniques are well known for adaptively tuning the assistance and keeping it at the minimum level that is just enough to allow the patient to finish the task while keeping the patients engaged in the loop and avoid slacking. In this regard, it is envisioned that more intelligent and flexible adaptive techniques may result in better outcomes of robotic therapy. Relevant discussions in this regard which support the above-mentioned issues can be found in [95, 96, 150-152].
Although the use of adaptive techniques is promising, and there are clinical studies supporting the effectiveness of these techniques (such as [102]), there are still several concerns which indicate the need for a more flexible, and perhaps more intelligent algorithm [146]. One of the issues with the widely-used conventional adaptive techniques is the requirement of numerous observations of motor performance (sometimes distinct observation for each separate task is needed) before identifying an appropriate base level of assistance/resistance to be used for tuning the parameters of the adaptive technique. This is a time consuming strategy and can depend on the subjective opinion of the operator (who runs the system for a patient) and may not result in a close-to-optimal or accurate tuning of the parameters. In addition, most of the existing techniques do not consider the biomechanical characteristics of the patient’s limb and do not take into account the amount of kinesthetic effort provided by the patient during task completion, though they are important factors which can define the extent of therapeutic forces to be applied. In addition to the above, the motor capabilities of the patient may vary in different parts of the workspace and a position-independent performance measure (which is commonly used in adaptive techniques) may not be the best representation of the patient’s need in different parts of the work space. These challenges clarify the need for developing more intelligent and more flexible techniques that minimize the required number of observations and subjective hand tuning of the control parameters of the adaptive techniques. It should be noted that resolving these challenges in this regard is a step towards moving HIRN technologies to the homes of patients. The ultimate goals of the ongoing research in this field are (a) enhancing the performance of the system in enhancing neural recovery and (b) making the effectiveness of the robots less dependent to the tuning of settings and fine modifications provided by a system operator. This is an ongoing line of research and new controllers and algorithms are being developed to handle the mentioned issues by considering new measures such as a patient’s limb biomechanical characteristics, kinesthetic efforts during task accomplishment and motor capabilities in different parts of the workspace. Relevant examples and discussions regarding the above-mentioned issues can be found in [24, 146, 153–156]. It can be envisioned that using advanced artificial intelligent techniques, the next generation of HIRN technologies will represent better compatibility to patients’ needs and impairments while showing higher autonomy.
In addition to the use of intelligent adaptive techniques, the other alternative which can help to deal with the above-mentioned compatibility issue is to directly bring the knowledge of a human therapist into the loop of kinesthetic robotic rehabilitation through development of Haptics-enabled Interactive Telerobotic Neuro-Rehabilitation (HITN) systems. This technology allows a human therapist to kinesthetically interact with the patient and intervene in a robotic therapy regime through a haptics-enabled telerobotic medium, while also cooperatively working with the patient on a shared VR environment. This concept is motivated by the reported lack of interpersonal interaction between human therapists and patients through the use of HIRN technologies which has resulted in the need for adaptive algorithms, as discussed earlier in this section. Considering the fact that no adaptive technique can replace or replicate knowledge of a human therapist, implementation of HITN systems makes it possible to fuse the capabilities of robotic rehabilitation systems (such as power, data logging, computerized assessment, repetition) and the knowledge and expertise of trained human therapists. In contrast to the HIRN systems, HITN technology avoids bypassing the knowledge of human therapists. In other words, through the use of HITN systems it is possible to deliver augmented therapy instead of virtual therapy. It is believed that HITN systems will play an important role in the future of robotic rehabilitation technologies and will be able to offer the following benefits:

A) Enabling kinesthetic interaction between a human therapist and a patient (through the use of a haptics-enabled telerobotic medium) for (i) allowing therapists to directly tune the difficulty and strategy of therapeutic force generation based on their knowledge; and (ii) allowing therapists to directly feel the patient’s motor performance during robotic therapy sessions besides the use of conventional computerized metrics.

B) Enabling remote interaction between a clinic-based therapist and a home-based patient. This will resolve the accessibility issues and comes under the umbrella of tele-medicine. In other words, haptics-enabled telerobotic rehabilitation can become a modality of tele-rehabilitation which has been identified in the literature as a possible future line of development for modern healthcare systems and can significantly increase the number of hours in which a remote patient can have access to ARA services.

C) Enabling hybrid techniques which can use a HITN platform to correct or intervene in the
therapy delivered by a HIRN system. The system can also learn from the intervention
delivered by the therapist and can correct the pattern of force generation to better match
the therapist's intention with regard to therapy.

The concept of haptics-enabled telerobotic rehabilitation, and in general, modern tele-rehabilitation
systems have been recently proposed and the number of papers published on this topic is grow-
ing due to the envisioned capabilities. Relevant discussions supporting the above-mentioned
notes and examples regarding telerobotic rehabilitation systems (including the publications
associated with this thesis) can be found in [157–168]. In addition, the potential of tele-
rehabilitation systems in the context of smart-home environments has been explained in [169–
174], and the references therein.

1.4.3 Safety Challenge

Patient-robot interaction safety is an an absolutely necessary criterion which cannot be violated
under any circumstances. In this regard, the following points should be specifically considered:

a) Users of rehabilitation robotic technologies are usually disabled patients who work very
closely with robotic devices and may even be physically attached to them. They share a
common workspace with the robot.

b) Rehabilitation robots are powerful mechatronic devices with high bandwidth in force
generation (that is needed to provide responsive, transparent and sufficient therapeutic
efforts).

As a result, it is very important to evaluate and guarantee physical patient-robot interaction
safety and stability for this technology.

Although, unsafe systems are not acceptable for use in close contact with patients, conserva-
tive designs of algorithms for providing safety can also affect the performance and effective-
ness of this technology, as discussed below. The safety concern is more serious for exoskeleton
HIRN technologies where a patient’s limbs are partially enclosed by the robot’s components.
The need for addressing the safety challenge in rehabilitation robotic systems is one of the most
important top lines of research and has been identified and discussed in the recent literature,
such as [23][161][175][178] and the references therein.
The concern of safety is a major obstacle for moving HIRN and HITN technologies into homes of patients in need. As mentioned, in-home robots can significantly extend the intensity (duration in which a patient is exposed to rehabilitation exercises) of interactive therapy which can accelerate motor recovery. However, since robotic rehabilitation systems are sources of high mechanical power, they can be dangerous if they are used in homes of patients and under minimal, indirect or remote supervision [22, 176, 179–181].

An accident due to safety issues during robotic therapy can result in incompatible, unplanned and out of control growth of interaction modalities (such as force, velocity and acceleration) beyond certain limits. The unacceptable increase in the interactive modalities results from injection of high mechanical energy into the patient-robot interaction which cannot be damped by the biomechanics of the patient’s limb. Due to the close physical interaction between the patient’s musculoskeletal system and the powerful source of mechanical energy generated by rehabilitation robots, an unsafe accident can cause serious injuries including bone, joint and soft tissue damage [22–24, 182].

Despite the importance of patient-robot interaction safety, current rehabilitation robots lack specific standard safety techniques and frameworks. The field is still under development and is an ongoing line of research. In this regard, some of the active topics of research are aimed at answering the following questions: (a) how to enhance robustness and safety using compliant or partially-compliant mechanical design of actuators and smart actuators [182–186], (b) how to monitor an inherently unsafe device to be used for rehabilitation purposes (e.g., [177]), and (c) how to guarantee the safety and stability of patient-robot interaction by intelligently controlling or limiting the transferred mechanical energy to the patient’s limb while maximizing performance (e.g., [23, 161, 187, 188]).

It should be noted that for industrial robots, ISO 10218 standard was established in 1992 which highlighted that robots “should to be isolated from humans and that they must be turned off when they cannot be isolated”. Unfortunately, this type of standard frameworks cannot be implemented for rehabilitation robots since these robots work in direct kinesthetic contact with disabled patients [22, 175]. New standards which can specifically standardize techniques to address safety challenges for rehabilitation robots are under development at present. An example is the IEC/NP 80601-2-78 standard which will address “particular requirements for
basic safety and essential performance of medical robots for rehabilitation, compensation or alleviation of disease, injury or disability [189].

The technique to include safety in most of the existing rehabilitation systems is to limit the amount of force, acceleration, and velocity applied to a patient’s hand (such as the one suggested in [188] or that in [126]). Although, these techniques can enhance safety, they have some restrictions as mentioned below.

The first challenge is that a high amplitude of force generated by a robot is not always equivalent to an unsafe situation. For example, for a patient with hypertonia (high muscular tone after stroke) or heavy limbs, the robot should apply high forces to be able to deliver a prescribed therapeutic regime. For such a patient, limiting the force can affect the performance and effectiveness of the system. On the other hand, a patient may show involuntary movements (such as post-stroke hand tremor), which can result in high acceleration, high-frequency and high-amplitude interactive forces which would be applied by the patient to the robot (and not in the opposite direction). This condition is not equivalent to instability or an undesirable event, while it can be misleading for conventional safety techniques. In addition to the above, limiting just the interactive forces or just the accelerations is not enough when an unsafe event occurs. In other words, an adverse event can result from an unsafe increase in only one of the mentioned interaction modalities while the other modality can remain within the predefined acceptable threshold. Consequently, both force and acceleration need to be limited. This can however result in excessive conservatism. In addition, the acceptable threshold(s) is not a particular identifiable value and can be different for each patient considering their neuromuscular deficits and biomechanical characteristics and can even be different in different parts of the workspace of the patient. Relevant discussions for this are given in [22] which evaluates a conventional risk assessment and risk reduction technique (initially developed for machinery, i.e., ISO/TR 12100-1 and ISO 14121:1999 standards). As discussed in [22], the definition and calculation of “risk” in the context of rehabilitation is very dependent on the state of the patient. This is an obstacle for generalizing conventional standards for rehabilitation robots.

The above issues, can result in a conservative choice of techniques for guaranteeing safety which can affect the performance of the rehabilitation system. For example, the following phrase is taken from [70] where a fixed 28 N force limit is considered to enhance safety while
the study compares the performance of an assistive and a resistive therapy for a population of post-stroke patients: “The absence of any difference between groups receiving progressive-resistance therapy and active-assistance therapy may simply mean that this robotic form of progressive-resistance exercise was not optimal in terms of duration, repetition, or intensity; for example, one limitation of this study was the relatively modest amount of resistance provided by the robot (for safety reasons). [70]”. In this regard, [22] has also defined potential challenges affecting the performance of HIRN technologies (such as limited power and velocity) raised by implementing conventional safety enhancing mechanisms.

In addition to the above, it should be highlighted that for in-home and remote rehabilitation systems, communication delays can give rise to an additional stability concern. The potential delay-induced instability is known in the literature of classical telerobotic and haptic systems and there are several stabilizers which have been proposed in the literature to deal with this instability by modifying the feedback of forces. Examples can be found in [190]. Two well-known state-of-the-art conventional control schemes developed for classical haptic and telerobotic systems are Wave-Variables Controller (WVC) [191] and Time-Domain Passivity Control (TDPC) [192, 193].

Although there are several existing techniques in the literature to stabilize haptics-enabled robotic and telerobotic systems, the performance of these controllers should be evaluated, customized and possibly enhanced in the context of rehabilitation robotics. The reason is that there are distinct differences between the components and requirements of a haptics-enabled robotic/telerobotic rehabilitation system and those for the classic and general-purpose telerobotic and haptic systems.

The first difference can be observed by investigating the energy characteristic of the environment component (the component that generates forces in response to the motion provided by the user). In a haptics-enabled robotic/telerobotic rehabilitation system, the therapy terminal (which can be assistive or resistive) plays the role of the environment component. The therapy terminal can be non-passive (generates more energy than it consumes) particularly when the goal is set to be assistive therapy which requires the robot to amplify the mechanical power of the patient by providing assistive forces. However, in classical systems, the environment is usually a passive remote/local object which either only consumes energy or consumes
more energy than it generates. The energy characteristics of the impaired human user (the other component) of robotic/telerobotic rehabilitation systems is also different compared to the conventional users of haptics-enabled systems who are usually unimpaired and maybe experts (such as surgeons). Conventionally, the user is assumed to behave in a passive manner and does not challenge the stability of the system (such as the assumptions made in [193, 194]). However, the passivity assumption cannot be made for neurologically-impaired patients particularly for those who have “abnormal reflex feedback and altered muscle mechanics [187]”. Relevant discussions in this regard can be found in [161,187] and [195].

Considering the above discussion, the assumption of passivity, which is a fundamental requirement for most of the conventional stabilizers, is not always valid in the context of rehabilitation robotics.

The other difference can be explained as follows. In classical haptics-enabled robotic and telerobotic systems, non-passivity and energy amplification is usually treated as an undesirable phenomena which occurs due to the phase lag caused by the communication delay and should be damped out to guarantee stability for a wide range of users [196]. In the context of rehabilitation robotics, however, this is not straight forward. A relevant example is given in [183] where it has been shown that guaranteeing passivity requirements for a lower-extremity rehabilitation robot with compliant actuators, can directly affect the performance, mechanical capabilities and bandwidth of the system. Further discussions on this topic are as follows. First of all, damping the amplified assistive energy, generated by the therapy terminal, is equivalent to canceling all the assistive and active behavior of the therapist. This defeats the very purpose of the system. Secondly, adding damping forces to the reflected force from the therapy terminal is equivalent to sacrificing the quality of force reflection (and transparency) of the system to guarantee stability. This could be acceptable when direct force feedback is an optional source of sensory information, such as in surgical robots where the direct force feedback may be even turned off (for example in commercialized examples) or substituted by other novel formats of sensory feedback [197-200]. However, in the context of rehabilitation, direct force feedback is the key factor which is needed to accomplish the very purpose of the system, i.e., delivering kinesthetic rehabilitation. Consequently, the frequency of occasions in which force is modified and the intensity of force modification and subsequently the conservatism of transparency
manipulation should be minimized in the context of rehabilitation robotics.

There is therefore a need for an intelligent safety technique and an advanced control strategy which can guarantee patient-robot interaction safety while maximizing the performance of rehabilitation robots, avoiding excessive conservatism, and relaxing the conventional assumptions on the energy behavior of the human limbs and the interactive environment. This is an ongoing line of research. In this regard, it can be envisioned that by taking into account the biomechanical characteristics of a patient’s limb, it may be possible to automatically and intelligently customize the parameters of the safety and control schemes of rehabilitation systems and enhance their performance in delivering interactive kinesthetic exercises. Realizing this aim will enable us to move towards equipping homes with safe haptics-enabled in-home robotic and telerobotic rehabilitation systems. Relevant discussions on this can be found in [24, 161, 167, 187, 195, 201, 202].

1.5 Thesis Scope, Structure and Focus

1.5.1 Scope

The work described in this thesis is developed based on the common impedance-based design of Haptics-enabled Interactive Robotic Neuro-Rehabilitation (HIRN) systems and specifically directed towards solving the challenges mentioned in Sections 1.3 and 1.4 (i.e. safety concern for in-clinic and in-home HIRN technologies and the lack of direct kinesthetic interaction between a human therapist and a patient during robotic rehabilitation). In this thesis, guaranteeing stability of patient-robot interaction and avoiding amplification of the energy of involuntary movements are two major factors which we consider for guaranteeing patient-robot interaction safety. In parts of this thesis, a brief title is used for HIRN technology which is Haptics-enabled Robotic Rehabilitation (HRR). As a result, both HIRN and HRR abbreviations refer to the same technology. In a similar manner, the term Haptics-enabled Telerobotic Rehabilitation (HTR) is used as a shorter terminology for HITN systems.

As mentioned in the previous section, HIRN technologies are usually connected to virtual reality environments which provide patients with repetitive tasks to be accomplished. We have implemented a simple point-to-point target reaching task in a virtual reality environment de-
veloped in this project. The use of more sophisticated virtual environments and modalities of interaction other than kinesthetic and visual are not considered in this work. In the rest of this thesis, the term “haptics” is used to denote kinesthetic inputs which are in fact forces applied by the robot to the patient’s limb for delivering rehabilitation exercises and in response to the patient’s movements. The study presented in this thesis focuses on upper-extremity interaction, while parts of the results can be extended to lower-extremity interaction, as well. All the theoretical developments in this project are for general multi-dimensional interactions. The experimental system used provides two degrees of freedom for the interaction.

1.5.2 Structure

Chapter 2: The goal is to bring the direct kinesthetic supervision of a human therapist into the interaction between a patient and a rehabilitation robot through a telerobotic medium. This is a move from virtual therapy toward augmented therapy.

Chapters 3 and 4: In these chapters, we investigate and guarantee safety of patient-robot interaction for robotic/telerobotic rehabilitation systems while maximizing the performance and fidelity of force feedback regardless of the unconventional existing restrictions which are associated with this category of haptic systems;

Chapter 5: This chapter is concerned with maximizing the use of a therapist’s time through learning the kinesthetic behavior of the therapist and to replicate it for the patient during several repetitions when the therapist is not in the loop.

Chapter 6: Here the goal is to expand the population of patients who can take advantage of robotic and telerobotic rehabilitation technologies. The outcome of this chapter allows patients with pathological tremors to benefit from non-passive robotic assistive/coordinative therapy in a safe manner.

Chapters 7 and 8: In these chapters, we extend the theoretical and technological findings of the thesis not only for rehabilitation purposes but also for assisting patients with force and motion control deficits (particularly individuals living with Cerebral Palsy and Focal Hand Dystonia).

Chapters 9: Concluding remarks on the research described in the thesis and suggestions for future research directions are provided.
1.5.3 Focus

In this project, we consider patient-robot interaction safety as the highest priority while we try to enhance the performance of robotic and telerobotic rehabilitation systems. In this regard, we aim to relax several restrictive assumptions such as passivity, linearity, time-independent behavior of the patient and the therapist, together with an assumption of the absence of involuntary movements and time delays. This allowed us to realize a safety-guaranteed patient-robot interaction platform to be used under direct, indirect, or recorded supervision of a therapist.

In addition, the second highest priority of this project is to maximize the quality of force feedback under the safety-guaranteed condition. This topic is known in the literature as enhancing transparency and fidelity of haptic systems. The reason is that in the context of rehabilitation robotics, the quality of force feedback is a key factor which directly correlates with the effectiveness of the system. As discussed before, utilizing conservative safety-guaranteeing techniques can affect the performance of these systems. The proposed framework can guarantee the stability of interaction; and in contrast to the existing stabilizers it takes into account the variable biomechanical capabilities of the patient’s limb to maximize the transparency. To achieve the above-mentioned goals, we have developed a new theoretical framework based on small-gain theory and strong passivity theory.

The theoretical and technological findings of this project can not only be used for any haptics-enabled robotic and telerobotic systems but they can also help to develop new assistive systems for patients with force and motion control deficits. The aforementioned topic is studied at the end of this thesis for two specific applications (one is developed for individuals living with cerebral palsy and the other for focal hand dystonia patients).

1.6 Main Contributions

The contributions of this thesis are briefly explained in this section. In this regard, chapter outlines are also included.
1.6.1 Contribution 1:

In Chapter 2, the design of a novel bilateral telerobotic architecture for tele-rehabilitation purposes is proposed, and the feasibility, stability and control challenges are studied. The objective of the proposed tele-rehabilitation framework is to incorporate the supervision of a local or remote human therapist into haptics-enabled rehabilitation systems and to allow the therapist to provide non-passive nonlinear assistive/resistive forces in response to the patient’s movements. The proposed architecture is a new paradigm for delivering motor therapy that gives therapists direct kinesthetic supervision over robotic rehabilitation procedures and is a step towards in-home supervised kinesthetic rehabilitation therapy. This can address a challenge of conventional software-based rehabilitation systems, i.e., limited capability in adjusting the therapy and the lack of direct kinesthetic interaction between a human therapist and the patient. As a result, the proposed framework can fuse the capabilities of conventional robotic therapy systems and the knowledge of a human therapist. To guarantee patient-robot interaction safety, a new design framework and a stabilizing controller are developed based on the small-gain theory. System stability and transparency are analyzed in the presence of the non-passive, nonlinear, nonautonomous behavior of the terminals (the therapist and the patient) and time-varying delays for the case of remote and cloud-based therapy. The proposed framework shows mathematically what particular conditions the system should have to preserve transparency and stability even in the presence of time-varying delays. Based on the developed framework a new stabilizer is proposed and is denoted as the Small-Gain Control (SGC) technique. Practical considerations have been considered to match the clinical needs and minimize the implementation cost.

1.6.2 Contribution 2:

In Chapter 3, the main focus is to increase the performance of the proposed telerobotic rehabilitation system. The result of Chapter 3 is developed for a general case and can also be used to enhance the transparency and performance of conventional robotic rehabilitation systems. It should be noted that although the stabilizer proposed in Chapter 2 can ensure system stability, under some specific conditions, it may result in conservative behavior in adjusting the forces reflected to the hand of a patient. More accurately, the SGC technique stabilizes the system
regardless of the passivity of the terminals, the type of therapy and the existing delay in the communication network. This has been done to relax the conventional assumption of passivity on the behavior of the terminals which are not always valid particularly (a) for a neurologically-impaired patient, and (b) for an active human therapist who injects energy into the interconnection to deliver assistance. However, since the SGC technique indirectly observes the loop gain (and not the energy characteristics of the terminals), under low delay values and when the therapy terminal is highly passive, the force modulation component of the SGC technique may become active and modify the reflected forces while the terminal does not challenge stability. This can result in a conservative behavior in the context of tele-rehabilitation. Motivated by this, in Chapter 3 a novel passivity-based technique is proposed to (a) develop a new stability analysis technique and (b) guarantee the stability of haptics-enabled robotic/telerobotic rehabilitation systems. The proposed approach can be used for robotic, cloud-based, and remote rehabilitation systems together with conventional haptic systems. The objective of the controller is to perform as little alteration as possible to the system transparency, in a dynamic and patient-specific manner. The technique utilizes a quantifiable biomechanical capability of the user’s limb (i.e., excess of passivity) in absorbing interactive therapeutic energy to guarantee patient–robot interaction safety, in the context of the strong passivity theory. The proposed controller is called Modulated Time-Domain Passivity Control (M-TDPC) approach.

**Remark 1.1.** The designs of the proposed stabilizers (SGC and M-TDPC) are supported by recent literature which denotes that (a) the assumption of passivity might be questionable for post-stroke patients; and (b) guaranteeing passivity may lead to concerns about “excessively conservative” behavior, and (c) “less conservative designs can be achieved if a quantitative knowledge of human interactive dynamics is available” [187]. The outcome of the stability analysis developed in this thesis is in agreement with the results reported in [201] which denotes the effect of linear damping of an operator’s arm on the stability margin of a teleoperated system. In this thesis, we identify and utilize a quantitative lower bound for a biomechanical characteristic of the patient’s limb in absorbing therapeutic forces (for the SGC technique), and energy (for the M-TDPC technique). A major difference between the conventional controllers and stabilizers proposed in this thesis is the consideration of the mentioned characteristics with the goal of enhancing the transparency of the system while guaranteeing stability.
1.6.3 Contribution 3:

It should be noted that, a human operator usually changes the biomechanical characteristics during task execution. In addition, in various directions of interaction, different biomechanical characteristics can be expected. As a result, considering the constant lower bound for the capability of the patient’s limb in absorbing therapeutic energy can still result in some degrees of conservatism. Relaxing this however requires extensive theoretical development but can significantly enhance the performance of the system. In Chapter 4, the variability in biomechanical capabilities of the human upper-limb in absorbing physical interaction energy is analyzed. The outcome is a graphical map that can quantitatively correlate (a) the extent of grasp pressure and (b) the geometry of interaction to the extent of hand passivity. For this purpose, a user study has been conducted for 11 healthy human subjects to characterize energy absorption capability in their arms and wrists. The above correlation is statistically confirmed. The identified user-specific Grasp-based Passivity Signature (GPS) map can be used as a graphical tool to assess the biomechanical capabilities of the upper-limb. In Chapter 4, the proposed GPS map is utilized in the design of a novel augmented nonlinear stabilizer, for haptics-enabled robotic and telerobotic rehabilitation systems. The controller, called a GPS-map Stabilizer, takes into account the variation in energy absorption during haptic task execution.

1.6.4 Contribution 4:

Chapter 5 proposes a new framework for supervised training of intensity and strategy for haptics-enabled robotic rehabilitation systems. Two alternative approaches are proposed, namely: (a) Haptics-enabled Teleoperated Supervised Training (HTST) and (b) EMG-based Indirect Supervised Training (EIST). The design of both techniques includes two phases: (a) to characterize and learn the required therapeutic intensity and strategy when a therapist delivers robotics-assisted rehabilitation to a patient (demonstration phase), and (b) to enable regeneration of the learned therapeutic behavior when the therapist is out of the loop (regeneration phase), e.g., when the therapist is working with another patient. This work is motivated by the existing challenges regarding the need for tuning the strategy and intensity of robotic therapy in a patient-specific manner. The framework is also expected to be beneficial for under-resourced
1.6. Main Contributions

healthcare systems because it enables therapists to share their time between several patients.

1.6.5 Contribution 5:

The outcome of Chapter 6 allows patients with pathological tremors to take advantage of non-passive robotic and telerobotic rehabilitation systems in a safe manner. This would not be possible using conventional systems due to the possibility of tremor amplification in an energetically active environment. The new haptics-enabled rehabilitation strategy, called Augmented Haptic Rehabilitation (AHR), is capable of delivering therapeutic forces while keeping hand tremor under control and avoiding unsafe amplification of tremor energy. To implement the AHR architecture, a new adaptive filter (Enhanced Band-limited Multiple Fourier Linear Combiners (E-BMFLC)) is proposed to characterize pathological tremors. The accuracy, robustness and effectiveness of the designed filter is statistically confirmed through a patient-based study involving data from 14 PD and 13 ET patients. The proposed filter is then used to develop a safe haptics-enabled robotic rehabilitation architecture (i.e., AHR), designed for patients having hand tremors.

Remark 1.2. The results presented in Chapters 2-6 include the main theoretical and technological developments of this thesis with a focus on safe patient-robot interaction in the context of telerobotic rehabilitation. The results can be used for conventional robotic rehabilitation systems as well as general purpose haptics-enabled systems. In Chapters 7 and 8 we show that the outcomes obtained have the potential to be used for developing assistive technologies and strategies for patients with force and motion control deficits. For this purpose, two specific case studies were conducted, as discussed below.

1.6.6 Contribution 6:

The first specific application (reported in Chapter 7) directly utilizes the results of Chapter 6 to design and implement a new telerobotics-assisted platform for enhancing interaction with physical environments for people living with cerebral palsy. The main objective is to modulate the capabilities of individuals through the proposed telerobotic medium and to enhance their control over interaction with objects in a real physical environment. The proposed platform
is motivated by evidence showing that lack of interaction with real environments can develop further secondary sensorimotor and cognitive issues for people who grow up with CP. The proposed telerobotic system assists individuals by (a) mapping their limited but convenient motion range to a larger workspace needed for task performance in the real environment, (b) transferring only the voluntary components of the hand motion to the task-side robot, and (c) kinesthetically dissipating the energy of their involuntary motions using a viscous force field implemented in the high frequency domain. The voluntary and involuntary components are extracted based on the design of the BMFLC filter described in Chapter 6. Consequently, using the proposed telerobotic system, an individual with CP will be capable of providing smooth and large-scale motions while presenting enhanced coordination during task performance.

1.6.7 Contribution 7:

The second specific application (reported in Chapter 8) utilizes the basic concept behind the theoretical developments given in Chapters 2 regarding the performance of an interconnected system and the concept of the loop gain. Increasing the loop gain increases the sensitivity to small changes which increases the sensitivity to potential abnormalities. To control an interconnected system, the loop gain can be reduced such as in the technique shown in Chapter 2. This concept can be applied to many interconnected systems. In Chapter 8, we considered the sensorimotor integration loop in humans during task execution (conducted by neuromuscular system) as an interconnected system. Here, the first subsystem is the human brain which generates motor commands (outputs) based on the received sensory data (inputs). The second subsystem is the physical environment (such as a writing surface during a writing task) on which we apply mechanical energy generated by our muscular system. As a result, we hypothesized that by reducing the loop gain we may be able to assist patients with sensorimotor integration deficits. For this goal, patients with Focal Hand Dystonia (FHD) participated in the study. Abnormality of sensorimotor integration in the basal ganglia and cortex has been reported in the literature for FHD patients. In this application, we investigated the effect of manipulation of kinesthetic input with the goal of reducing the loop gain. For this purpose, severity of dystonia was studied for 11 participants while the symptoms of 7 participants were tracked during 5 sessions of assessment and Botulinum toxin injection (BoNT-A) therapy. In
each session, the tasks were repeated twice when (a) a participant used a normal pen, and (b) when the participant used a robotics-assisted system which provides a compliant virtual writing surface to reduce the loop gain. The results show that reducing the writing surface rigidity significantly decreases the severity of dystonia and results in better control of grip pressure (an indicator of dystonic cramping). It was also shown that using the proposed strategy, it is possible to augment the effectiveness of BoNT-A therapy. The outcome was then used in the design of an actuated pen as an assistive tool that can provide compliant interaction during writing for FHD patients.

To conclude this chapter, it is worth mentioning that the work presented in this thesis shows that proper augmentation of haptic information can not only enable new modalities for supervised therapy and enhance the transparency and safety of robotic/telerobotic rehabilitation systems, but also has the potential to assist patients with force and motion control impairments.
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Chapter 2

A Small-Gain Approach for Non-Passive Bilateral Telerobotic Rehabilitation: Stability Analysis and Controller Synthesis

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2.1 Introduction

Haptics-enabled robotic rehabilitation has attracted a great deal of interest during the last decade [1]. It is anticipated that the population of people suffering a stroke worldwide each year will reach 23 million by 2030 [2]. This population will require motor rehabilitation to lead a normal life. Haptics-enabled robotic therapy is a candidate that can provide a better quality of life for this increasing population. There are significant advantages with the use of haptics-enabled robotic rehabilitation systems such as accelerating recovery of disabled patients [1], [3] and helping therapists in quantifying the severity of movement disorders [4], [5].
Commercially available robotic rehabilitation systems use a haptics-enabled software-based environment equipped with a Programmable Virtual Therapist (PVT) [1,4,6,7]. The PVT is an interactive virtual-reality-based environment that can provide the patient with assistive and resistive therapeutic forces during various tasks [1,8]. The forces are applied by the robotic device to the affected part of the patient’s body [4,5,1]. Considerable research has been conducted to evaluate the effectiveness of PVT-based systems [1,3,4].

One of the problems of PVT-based systems is how to modify the assistive/resistive exercises. Research has shown that the key to an effective therapy is to modify the therapy considering the state and progress of the patient [9]. Since there is no direct supervision and physical-interaction by a human therapist during PVT-based exercises, considerable research has focused on how to program flexibility, for a virtual therapist, to adjust the level of assistance/resistance for different patients with various states of impairment, body dynamics and needs for rehabilitation [10–12]. As a result, improved motor performance has been reported using adaptive virtual therapy techniques [13,14]. However, although the adaptive techniques provide some degree of flexibility, they cannot replace the advantages of having a direct physical interaction between a skilled therapist and patient during rehabilitation/assessment exercises. As a result, the main goal of the proposed architecture is to fuse the advantages of an expert therapist in-the-loop with the specific features of robotic systems such as force amplification and data logging.

To achieve the above-mentioned goal, in this chapter, a novel haptics-enabled telerobotic rehabilitation framework is designed and analyzed as a new paradigm for delivering resistive/assistive motor therapy (locally/remotely) that gives the therapist full supervision over the rehabilitation procedure while taking advantages of robotic technology. The proposed bilateral telerobotic rehabilitation architecture deals with the aforementioned main challenge of conventional assistive/resistive robotics-assisted rehabilitation, which is the lack of direct force/position exchange and intuitive supervision by an experienced human therapist during the therapy. The structure of the proposed bilateral telerobotic rehabilitation system, implemented in this chapter, is shown in Figure 2.1. In this system, the patient provides motion trajectories by moving a master device to complete a reaching task which is given to him/her through a shared virtual reality environment. The generated movements will be then copied by
the slave robot at the therapist’s side. As a result, the therapist can either kinesthetically feel the movements generated by the patient or visually see the corresponding trajectories in the shared virtual environment. The therapist can then provide the patient with resistive/assistive therapeutic forces (through the proposed telerobotic rehabilitation system) in response to the motion trajectories generated by the patient. Depending on the particular goal of the therapy, the therapist can either help the patient to perform the task by applying assistive/coordinative forces or make the task more difficult by applying resistive forces. It should be noted that the proposed design also makes it possible to perform remote rehabilitation under the direct supervision of a skilled therapist. This is a need for the current state of healthcare systems especially for delivering therapies to patients far from sophisticated rehabilitation centres.

It should be mentioned that the environment of the proposed telerobotic rehabilitation architecture (the human therapist) has a non-passive, nonlinear, non-autonomous dynamical behavior that is needed to deliver various types of complex therapies and also inject non-passive
energy into the interconnection for providing assistance and coordination. Also, both the patient’s and the therapist’s dynamics will be subjected to nonlinear non-autonomous mutual adaptation which cannot be modeled by linear time-invariant systems. In addition, the communication system could be exposed to time-varying delays which would be the case for remote and cloud-based rehabilitation. The above mentioned points can challenge the stability, performance and safety of the human-robot interaction, which will be addressed in this chapter.

Regarding the dynamical behavior of the therapist, it should be noted that if the therapist performs assistive therapy (or mixed assistive-resistive therapy), she/he essentially supplies the power/energy to the teleoperator (to guide/coordinate the patient towards the correct path of motion) thus behaving as a nonlinear active (non-passive) network. There is, therefore, a need for a method to analyze and guarantee the stability and safety of the proposed telerobotic rehabilitation system.

In this chapter, we develop a small-gain framework for the analysis and design of such systems. The stability and transparency properties of the proposed tele-rehabilitation system is analyzed for the case of intrinsically non-passive, nonlinear, non-autonomous behavior of the therapist and the patient. The proposed technique is also capable of dealing with potential instability induced by irregular time-varying delays (which exists for remote/cloud-based rehabilitation). The framework also demonstrates the possibility of a “perfectly transparent” and “stable” telerobotic system while the environment behaves as a non-passive nonlinear network and the communication is subjected to time-varying delays. Finally, we present a stabilization scheme, denoted by the Small-Gain Controller (SGC), which guarantees stability regardless of the specific actions of the therapist. The proposed SGC technique utilizes the available resources in the system (in terms of the capability of the patient’s hand in absorbing forces) to reduce the frequency and intensity of transparency manipulation (performed during episodes of having the controller active) while guaranteeing stability and having a positive stability margin. In other words, if during a time episode, it is determined that the stability margin can remain positive, the SGC technique does not degrade the transparency, even if the communication and the terminals are non-passive, nonlinear and time-varying. The results can be extended to conventional haptic and telerobotic systems. In this work, the two terminals of the “networked telerobotic” systems are called the patient and therapist terminals. In addition, the
term “viscoelasticity” refers to a system with both “viscosity” and “elasticity” components.

Remark 2.1. The contributions of this chapter are as follows:

_Theoretical Contributions:_

(1) A new framework is proposed to analyze the stability of haptics-enabled systems, regardless of linearity, time-dependence and passivity requirements and in the presence of time-varying delays. The framework shows mathematically what particular conditions a teleoperated interaction should have to preserve transparency and stability (with no active controller) even in the presence of time-varying delays.

(2) A new stabilizing scheme is proposed to guarantee stability regardless of the linearity, time-dependence and passivity of the terminals and passivity of the communication. The scheme can also be used for conventional telerobotic systems.

(3) A telerobotic architecture is proposed that can support velocity, position, and viscoelastic domain tracking.

_Practical Contributions:_

Designing, implementing and analyzing the feasibility of an augmented therapeutic platform that (1) fuses the capabilities of conventional robotic therapy systems and the actions of a human therapist; (2) can be used to deliver therapeutic actions of a therapist over distances; and (3) allows to scale up the therapist’s efforts, so that he/she can rehabilitate patients having various biomechanical characteristics with no limit on the therapist’s capabilities.

The following notation is used throughout the chapter. Symbols $\mathbb{I}_n$ and $\mathbb{O}_n$ denote the $n \times n$ identity matrix and the $n \times n$ zero matrix, respectively. For a finite-dimensional object $a \in \mathbb{R}^{n \times n}$, $|a|$ denotes its Euclidean norm. The Laplace transform and the inverse Laplace transform are denoted by $\mathcal{L}(\cdot)$ and $\mathcal{L}^{-1}(\cdot)$, respectively. A rational transfer function $z(s) := q(s)/p(s)$ is called proper if $\deg p(s) \geq \deg q(s)$ (or, equivalently, its relative degree $r := \deg p(s) - \deg q(s) \geq 0$); it is called strictly proper if $\deg p(s) > \deg q(s)$ (or $r := \deg p(s) - \deg q(s) > 0$); furthermore, $z(s) := q(s)/p(s)$ is called bi-proper, if $\deg p(s) = \deg q(s)$ (equivalently, $r := \deg p(s) - \deg q(s) = 0$). A rational transfer matrix $Z(s) \in \mathbb{C}^{n \times n}$ is called proper (strictly proper, bi-proper) if every element of $Z(s)$ is a proper (strictly proper, bi-proper) transfer function. A rational transfer matrix $Z(s) \in \mathbb{C}^{n \times n}$ is said to be positive real if it: i) does not have poles in the open right-hand side of the complex plane, ii) is real for positive real
s, and iii) satisfies $Z(s) + Z^*(s) \geq 0$ for all $s \in C$ such that $Re s > 0$, where $Z^*(s)$ denotes the conjugate transpose of $Z(s)$ [16]. A rational transfer matrix $Z(s) \in \mathbb{C}^{n \times n}$ is said to be strictly positive real if $Z(s) \neq 0$ and there exists $\epsilon > 0$ such that $Z(s - \epsilon)$ is positive real. For a positive real transfer function (matrix), its relative degree is either 0 or 1.

2.2 The Proposed Telerobotic Rehabilitation System: Modeling and Control Design

The proposed telerobotic rehabilitation system considers the patient at the master device while the therapist interacts with the slave robot. The master device is described by

$$Z_m(s)V_p(s) = u_{cm}(s) + F_p(s),$$

(2.1)

where $s$ is the Laplace operator, $V_p(s) \in \mathbb{C}^n$ is the velocity of the patient’s hand, $Z_m(s) \in \mathbb{C}^{n \times n}$ is a strictly positive real transfer matrix of the master device, $F_p(s) \in \mathbb{C}^n$ is the force applied by the patient, and $u_{cm}(s) \in \mathbb{C}^n$ is the master control effort. The slave device is described as

$$Z_s(s)V_{th}(s) = u_{cs}(s) - F_{th}(s),$$

(2.2)

where $V_{th}(s) \in \mathbb{C}^n$ is the velocity of the therapist’s hand (equivalently, the velocity of the slave), $Z_s(s) \in \mathbb{C}^{n \times n}$ is a strictly positive real transfer matrix of the slave manipulator, $F_{th}(s) \in \mathbb{C}^n$ are the forces applied by the therapist, and $u_{cs}(s) \in \mathbb{C}^n$ is the control effort.

Remark 2.2. The linear models (2.1) and (2.2) have been used in the literature (e.g., [17][18]) and can be derived considering two local feedback linearization controllers to compensate for nonlinearities of the robots. In this work, we use (2.1) and (2.2) and focus on uncertain nonlinear behavior of the terminals.

A general form of the teleoperation architecture used in this work is defined below which is a modified version of the conventional Extended Lawrence Four-Channel (ELFC) teleoperation [18]. Note that the architecture below uses just two communication channels while providing
some flexibility through the use of force rejection gain $\zeta$ (discussed later).

\begin{equation}
 u_{cm}(s) = \hat{Z}_m(s)V_p(s) - \alpha \hat{F}_{th}(s),
\end{equation}

\begin{equation}
 u_{cs}(s) = \beta Z_s(s)P(s)\hat{V}_p(s) + \zeta F_{th}(s)
 + (1 - \zeta) \eta(s) \left( \beta P(s)\hat{V}_p(s) - V_{th}(s) \right).
\end{equation}

In (2.3), (2.4), $\hat{F}_{th}(s)$ and $\hat{V}_p(s)$ are the therapist’s forces available at the master (patient) side (transmitted through the first channel) and the patient velocity available at the slave (therapist) side (transmitted through the second channel), respectively; $\hat{Z}_m(s) \in \mathbb{C}^{n \times n}$ is a positive real transfer matrix used for compensation of the master robot impedance. It should be noted that potential uncertainty in $\hat{Z}_m(s)$ and the corresponding effect are discussed later in this section. The relevant notes are given at the end of Section 2.2. To reduce uncertainty, our team is in the process of developing a sensorized handle for the robot which can directly measure velocity and acceleration profiles, instead of calculating them based on the measurements provided by the encoders. In addition, $\eta(s) \in \mathbb{C}^{n \times n}$ is a transfer matrix that corresponds to the velocity control gain, and $P(s) \in \mathbb{C}^{n \times n}$ is a low-pass filter (explained later). $\alpha$ and $\beta > 0$ represent the force and the velocity scaling factors, respectively; and $\zeta \in \{0, 1\}$ is the force rejection gain that determines the type of telerobotic architecture. More precisely, in this work we propose two special cases of the slave control signal (2.4) that correspond to $\zeta = 1$ and $\zeta = 0$, as

\begin{equation}
 u_{cs}(s) = \beta Z_s(s)P(s)\hat{V}_p(s) + F_{th}(s) \quad \text{for } \zeta = 1,
\end{equation}

\begin{equation}
 u_{cs}(s) = \beta Z_s(s)P(s)\hat{V}_p(s) + \eta(s) \left( \beta P(s)\hat{V}_p(s) - V_{th}(s) \right) \quad \text{for } \zeta = 0.
\end{equation}

The control signal (2.5) that corresponds to $\zeta = 1$ is a transparency-oriented control law. Considering $\zeta = 1$ results in local cancellation of the force at the therapist's side. This force cancellation is similar to ELFC architecture [17], [18]. It will be shown that the control signal (2.5) allows for perfect transparency of the system using two communication channels. Implementation of (2.5), however, requires information about the therapist’s forces $F_{th}(s)$ which can be obtained by installing force sensor(s). On the other hand, control signal (2.6) that corresponds to $\zeta = 0$ is a cost-oriented control law (proposed in this chapter) which does not require
the force sensor (that is an expensive component). In fact, considering $\zeta = 0$, the effect of force at the slave side will be alleviated, instead of directly canceling the force. However, it may require higher control effort which should be monitored. It will be shown that considering $\zeta = 0$ and by proper tuning the velocity feedback matrix $\eta(s)$ the transparency can converge to ideal transparency and the resulting patient-therapist interconnection will converge to the case of $\zeta = 1$. A detailed discussion about parameter tuning for the case of $\zeta = 0$ will be given in Section 2.7 where practical considerations (such as cost) are discussed.

In this work, we address the situation where the communication is subject to delays which, in particular, can be time-varying, and discontinuous. The communication processes are described as follows,

$$\hat{v}_p(t) := v_p(t - \tau_f(t)) + \sigma_f(t),$$  
(2.7)

$$\hat{f}_{th}(t) := f_{th}(t - \tau_b(t)) + \sigma_b(t),$$  
(2.8)

where $v_p(\cdot)$ and $f_{th}(\cdot)$ are time-domain signals that describes the patient’s velocity and the therapist’s force, respectively; in other terms, $v_p(t) := \mathcal{L}^{-1}[V_p(s)], f_{th}(t) := \mathcal{L}^{-1}[F_{th}(s)]$. Also, $\tau_f(\cdot), \tau_b(\cdot)$ are the communication delays in the forward (master to slave) and the backward directions, respectively. $\sigma_f(t), \sigma_b(t) \in \mathbb{R}^{n \times 1}$ are the errors introduced during the communication process in the forward and backward channels, respectively. The errors $\sigma_f(t), \sigma_b(t)$ are assumed to be Lebesgue measurable and uniformly essentially bounded, i.e.,

$$\sup_{t \geq 0} |\sigma_f(t)| \leq \sigma_f^*, \quad \sup_{t \geq 0} |\sigma_b(t)| \leq \sigma_b^*,$$

for some $\sigma_f^*, \sigma_b^* \geq 0$. The assumptions imposed on the delays $\tau_f(t), \tau_b(t)$ in our work are described as follows.

**Assumption 2.1.** [19] [20] The communication delays $\tau_f, \tau_b : \mathbb{R} \rightarrow \mathbb{R}_+$ are Lebesgue measurable functions with the following properties:

i) there exist $\tau_* > 0$ and a piecewise continuous function $\tau^* : \mathbb{R} \rightarrow \mathbb{R}_+$ satisfying $\tau^*(t_2) - \tau^*(t_1) \leq t_2 - t_1$, such that the inequalities $\tau_* \leq \min \{ \tau_f(t), \tau_b(t) \} \leq \max \{ \tau_f(t), \tau_b(t) \} \leq \tau^*(t)$ hold for all $t \geq 0$;

ii) $t - \max \{ \tau_f(t), \tau_b(t) \} \rightarrow +\infty$ as $t \rightarrow +\infty$. 

**Remark 2.3.** Assumption [1] imposes very mild constraints on the communication process.
The constraints can always be satisfied in any real-life network unless the communication is completely lost on a semi-infinite time interval. The fulfillment of this assumption does not depend on the characteristics of the channel, such as bandwidth and information loss percentage (see, [20], [21]). One potential issue which may arise in the presence of discontinuous delays is that \( \hat{v}_p(t) \) which is reference velocity for the slave device may become discontinuous. To avoid this situation, a filter \( P(s) \in \mathcal{C}^{n \times n} \) is introduced in (2.4) to smooth out the reference trajectory for \( v_{th}(t) \).

One specific case allowed by Assumption 1 is that of an ideal communication channel, *i.e.*, \( \tau_f(t) \equiv \tau_b(t) \equiv 0, \quad \sigma_f(t) \equiv \sigma_f(t) \equiv 0, \) (2.9)

which, in particular, implies

\[
\hat{F}_{th}(s) \equiv F_{th}(s), \quad \hat{V}_p(s) \equiv V_p(s).
\]

In this case, ideal transparency can be achieved by an appropriate choice of control parameters in (2.3), (2.4). The term “ideal” refers to the situation where the dynamics of master and slave are eliminated so that the patient experiences undistorted interaction with the therapist (only subject to scaling factors \( \alpha > 0 \) and \( \beta > 0 \)). The ideal transparency is characterized as

\[
F_p = \alpha \cdot F_{th}, \quad V_{th} = \beta \cdot V_p.
\]

Considering definition of hybrid matrix \( H(s) \) [22] as:

\[
\begin{bmatrix}
F_p(s) \\
-V_{th}(s)
\end{bmatrix} = H(s) \begin{bmatrix}
V_p(s) \\
F_{th}(s)
\end{bmatrix},
\]

ideal transparency corresponds to the following formula [23]:

\[
H(s) = H_{ideal} := \begin{bmatrix}
0_n & \alpha \cdot I_n \\
-\beta \cdot I_n & 0_n
\end{bmatrix}.
\]
Under the assumption in (2.10), the ideal transparency can be achieved in system (2.1)-(2.4) by choosing \( \hat{Z}_m(s) \equiv Z_m(s) \) in (2.3) and \( \zeta = 1, P(s) = I \) in (2.4). This method is a modified version of the one proposed in [24]. In the 1-DOF (degree-of-freedom) case, it corresponds to the following choice of the parameters in the extended Lawrence architecture: \( c_1 = Z_s, c_2 = 1, c_3 = c_4 = c_6 = 0, c_5 = -1 \). However, we will consider below a situation where the master’s dynamics (2.1) cannot be fully compensated due to uncertainties \( \hat{Z}_m(s) \neq Z_m(s) \). To address this case, let us denote \( \tilde{Z}_m(s) := Z_m(s) - \hat{Z}_m(s) \); the relationship (2.11) between \( F_p \) and \( F_{th}(s) \) then becomes

\[
\tilde{Z}_m(s) \cdot V_p(s) = F_p(s) - \alpha \cdot F_{th}(s).
\]

It is assumed that \( \hat{Z}_m(s) \) is chosen such that \( \tilde{Z}_m(s) \) is positive real (which is also valid for \( \hat{Z}_m(s) \equiv Z_m(s) \)).

### 2.3 The Patient and Therapist Models

To conduct stability analysis of the tele-rehabilitation system, dynamics of the patient and the therapist are modeled as follows. Since the patient is at the master side and takes force as input and provides motion as output, admittance model can better represent patient-robot interaction. The patient’s velocity is decomposed into “active” and “reactive” components as

\[
v_p(t) := v_p^a(t) - \mathcal{L}^{-1} \left[ Z_p(s)^{-1} F_p(s) \right],
\]

where \( Z_p(s) \in \mathbb{C}^{n \times n} \) is a positive real transfer matrix that represents the patient’s hand impedance ( \( \mathcal{L}^{-1} \left[ Z_p(s)^{-1} F_p(s) \right] \) describes the reactive component). Also, \( v_p^a(t) \in \mathbb{C}^n \) are the active components voluntary generated by the patient’s muscles through applying voluntary forces \( f_p^a(t) \in \mathbb{C}^n \).

At the therapist side, the impedance model that describes the therapist’s forces is given by

\[
f_{th}(t) := f_{th}^a(t) + \mathcal{L}^{-1} \left[ Z_{th}(s) V_{th}(s) \right],
\]

where \( Z_{th}(s) \in \mathbb{C}^{n \times n} \) is a positive real transfer matrix of the reactive impedance of the thera-
pist’s hand, and $f_{th}^a(t) \in \mathbb{C}^n$ are the voluntary generated active therapeutic forces.

Remark 2.4. The active forces voluntary generated by the therapist $f_{th}^a(t)$ and the active velocity components on the patient’s side $v^a_{\rho}(t)$ are not independent on the movement of the master/slave devices; they are also subjected to nonlinear non-autonomous mutual adaptations, and can also include remaining nonlinear terms of the corresponding user’s hand dynamics. If the purpose of the therapy is to create a resistance to the patient’s movement, the therapist generates resistive forces considering the represented patient’s movement. Mathematically, this therapeutic action can be interpreted as actions of a strictly passive system, where the therapist actively dissipates the kinetic energy generated by the patient. If the purpose of the therapy is to provide assistance in executing a task, the therapist voluntary generates assistive forces that result in increasing the kinetic energy. In the latter case, the therapist behaves as a non-passive system that generates energy. Dissipation of this non-passive energy is generally not acceptable as this would defeat the purpose of the assistive therapy. It should be also noted that the hand dynamics of the therapist and patient can contain nonlinear components due to mutual interaction during the bilateral teleoperated therapy that allows the two users to kinesthetically interact. Consequently, the dynamic models of the terminals should not require any assumption on the linearity, passivity and time-dependency.

Remark 2.5. The voluntary actions of the therapist and the patient may be very complex and, in particular, may depend on the current and past trajectories of the tele-rehabilitation system as well as the therapist’s/patient’s intentions and potential mutual adaptation. To reflect this complexity, we use a very general model of the voluntary actions of the therapist and the patient dynamics which is represented by a system of unknown nonlinear non-autonomous functional-differential equations (FDEs) as explained in the rest of this section.

The notation below is borrowed from [25]. Given functions $x: \mathbb{R} \to \mathbb{R}^n$ and $t_d: \mathbb{R} \to \mathbb{R}_+$, then $x_d(t)$ denotes the restriction of $x(\cdot)$ on the interval $[t - t_d(t), t]$, i.e., $x_d(t) := \{x(\tau) : \tau \in [t - t_d(t), t]\}.$

The active component $f_{th}^a(t) := \mathcal{L}^{-1} \left[ F_{th}^a(s) \right]$ of the therapist’s forces is represented in the
time-domain as an output of the following system,

\[ \dot{x}_{th}^a = F_{th}(x_{thd}^a, v_{trd}, w^{th}), \]
\[ f_{th}^a = G_{th}(x_{thd}^a, v_{trd}, w^{th}), \]

where \( x_{thd}^a \) is the state of the system, \( v_{trd}^r := \mathcal{L}^{-1} \left[ \beta \cdot P(s) \cdot \dot{V}_p(s) \right] \) is the signal that represents (in the time domain) the information regarding the (scaled and filtered) velocity of the patient’s hand available to the therapist, and \( w^{th}(\cdot) \) is an arbitrary locally essentially bounded external signal that reflects the therapist’s intention.

Similar to the above, the active component \( v_{ap}^a(t) := \mathcal{L}^{-1} \left[ V_p^a(s) \right] \) of the patient’s action is represented in the time-domain as an output of the following system,

\[ \dot{x}_{ap}^a = F_p(x_{apd}^a, f_{ap}^r, w^p), \]
\[ v_{ap}^a = G_p(x_{apd}^a, f_{ap}^r, w^p), \]

where \( x_{apd}^a \) is the state of the system, \( f_{ap}^r := \mathcal{L}^{-1} \left[ \alpha \cdot \hat{F}_{th}(s) \right] \) is the signal that represents (in the time domain) the information regarding the scaled force of the therapist’s hand available to the patient, and \( w^p(\cdot) \) is an arbitrary locally essentially bounded external signal that reflects the patient’s intention.

Note that \( F_{th}(\cdot), G_{th}(\cdot), F_p(\cdot), G_p(\cdot) \) are assumed to be unknown locally Lipschitz functionals of their arguments. The assumption imposed on (2.17) and (2.18) is the weak input-to-output stability, explained in Appendix I (Section 2.9), [20]. The exact form of the assumption for (2.17) and (2.18) is given below:

**Assumption 2.2.** The model (2.17) that describes the voluntary actions of the therapist is weakly input-to-output stable (WIOS) with linear IOS gains \( \gamma_{th}^r \geq 0, \gamma_{th}^w \geq 0 \). Specifically, there exist \( \beta^{th} \in \mathcal{K}_\infty \) such that for any initial condition \( x_{thd}^a(t_0), t_0 \in \mathbb{R}_+, \) and any uniformly essentially bounded inputs \( v_{trd}^r(t), w^{th}(t) \), the solution \( x_{thd}^a(t) \) of (2.17) is well-defined for all \( t \in \mathbb{R}_+ \) and the following two properties hold:
2.3. The Patient and Therapist Models

i) uniform boundedness:

\[
\sup_{t \geq t_0} |f_{th}^a(t)| \leq \beta^p \left( |x_{pd}^a(t_0)| \right)
\]

\[
+ \gamma_p^v \cdot \sup_{t \geq t_0} |v_{th}^d(\tau)| + \gamma_p^w \cdot \sup_{t \geq t_0} |w_{th}^d(t)|;
\]  

\[\text{(2.19)}\]

ii) convergence:

\[
\limsup_{t \to +\infty} |f_{th}^a(t)| \leq \gamma_p^v \cdot \limsup_{t \to +\infty} |v_{th}^d(\tau)|
\]

\[
+ \gamma_p^w \cdot \limsup_{t \to +\infty} |w_{th}^d(\tau)|. \]

\[\text{(2.20)}\]

Assumption 2.3. The model \(2.18\) that describes the voluntary actions of the patient is WIOS with linear IOS gains \(\gamma^v_p \geq 0, \gamma^w_p \geq 0\). Specifically, there exist \(\beta^p \in \mathcal{H}_\infty\) such that for any initial condition \(x_{pd}^a(t_0), t_0 \in \mathbb{R}_+,\) and any uniformly essentially bounded inputs \(f_{th}^d(t), w_p(t)\), the solution \(x_{pd}^a(t)\) of \(2.18\) is well-defined for all \(t \in \mathbb{R}_+\) and the following hold:

i) uniform boundedness:

\[
\sup_{t \geq t_0} |v_{p}^a(t)| \leq \beta^p \left( |x_{pd}^a(t_0)| \right)
\]

\[
+ \gamma_p^v \cdot \sup_{t \geq t_0} |f_{th}^d(\tau)| + \gamma_p^w \cdot \sup_{t \geq t_0} |w_p(\tau)|;
\]  

\[\text{(2.21)}\]

ii) convergence:

\[
\limsup_{t \to +\infty} |v_{p}^a(t)| \leq \gamma_p^v \cdot \limsup_{t \to +\infty} |f_{th}^d(\tau)| + \gamma_p^w \cdot \limsup_{t \to +\infty} |w_p(\tau)|. \]

\[\text{(2.22)}\]

Remark 2.6. The exact form of the functionals \(F_{th}(\cdot), G_{th}(\cdot), F_{p}(\cdot), G_{p}(\cdot)\) in \(2.17\) and \(2.18\) is assumed to be unknown and is not used in the subsequent development. The only information about \(2.17\) and \(2.18\) that is used to develop the stability analysis (in Section 2.4) is the IOS gains \(\gamma^v_{th}\) and \(\gamma^v_p\). Moreover, in the development of the stabilizing scheme (presented in Section 2.5) for the tele-rehabilitation system, the exact value of \(\gamma^v_{th}\) and \(\gamma^v_p\) is also assumed unknown; thus, the only information about \(2.17\) and \(2.18\) that is used in Section 2.5 is the fact that the models \(2.17\) and \(2.18\) are WIOS.

Remark 2.7. The simplified intuitive implication of Assumption 2 and 3 is that both the therapist’s and the patient’s dynamics map finite inputs (the slave velocity for the therapist and the master force for the patient) to finite responses (bounded therapeutic forces at the therapist’s side and bounded patient velocity at the patient’s side). This is a realistic assumption.
2.4 Stability Analysis

Although the tele-rehabilitation system described above has a negative feedback interconnection structure, the nonlinearity, non-passivity, and non-autonomous behavior of the human voluntary dynamics \( (2.17) \) and \( (2.18) \) as well as the presence of networked induced constraints, such as time-varying delays and information losses, make it challenging to analyze and guarantee the stability of the system. In this section, we present a new approach to the stability analysis of the proposed tele-rehabilitation system based on the small-gain theorem.

To formulate the nonlinear small-gain stability conditions for the proposed tele-rehabilitation system, let us start by recalling the notion of \( \mathcal{L}_1 \)-gain (or peak gain) of a MIMO linear system. Consider a MIMO linear system with a proper transfer matrix \( G(s) \in \mathbb{C}^{n \times n} \). The \( \mathcal{L}_1 \)-gain is defined according to the formula (see, for example, [26, Section 5.3.3]):

\[
\|G(s)\|_1 := \max_{i=1, \ldots, n} \int_0^{+\infty} \sum_{j=1}^n |g_{ij}(\tau)| d\tau,
\]

where \( g(t) := [g_{ij}(t)]_{i,j=1,\ldots,n} \in \mathbb{R}^{n \times n} \) is impulse response matrix corresponding to \( G(s) \), i.e., \( g(t) := \mathcal{L}^{-1}(G(s)) \). For a stable linear system, its peak gain is well-defined if the transfer matrix is proper; in this case, the peak gain of a system is equal to its IOS gain [27]. The latter fact allows for the application of some general nonlinear IOS small-gain theorems to derive stability conditions for the proposed tele-rehabilitation system.

Let us first consider \( \zeta = 1 \). The following result is valid.

**Theorem 2.1.** Consider the tele-rehabilitation system described by \( (2.1), (2.2), (2.3), (2.4), (2.5), (2.7), (2.8), (2.15), (2.16), (2.17), \) and \( (2.18) \). Suppose Assumptions 1, 2, 3 hold. Suppose also that \( Z_{th}(s)P(s), (Z_p(s) + \tilde{Z}_m(s))^{-1}, \) and \( P(s) \) are stable and proper transfer matrices. If

\[
\left( \|Z_{th}(s)P(s)\|_1 + y_{th}^\nu \|P(s)\|_1 \right) \cdot \left( \|(Z_p(s) + \tilde{Z}_m(s))^{-1}\|_1 + y_p^\nu \|Q(s)\|_1 \right) < 1 / (\alpha \cdot \beta), \quad \text{where} \ Q(s) = Z_p(s)(Z_p(s) + \tilde{Z}_m(s))^{-1},
\]

then the trajectories of the tele-rehabilitation system are uniformly bounded and convergent.

**Proof of Theorem 1** Substituting \( (2.3), (2.15) \) into \( (2.1) \), the following closed-loop master-
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Patient dynamics are obtained

\[ V_p(s) = (Z_p(s) + \tilde{Z}_m(s))^{-1} \cdot [Z_p(s)V_p^a(s) - \alpha \cdot \hat{F}_{th}(s)] . \] (2.25)

On the other hand, substituting (2.5), (2.16) into (2.2), the closed-loop slave-therapist dynamics for \( \zeta = 1 \) are obtained as:

\[ F_{th}(s) = \beta \cdot Z_{th}(s) \cdot P(s) \cdot \hat{V}_p(s) + F_{th}^a(s) . \] (2.26)

Consider the interconnection of (2.25), (2.26) with the system (2.17) and (2.18) that describes the active component of the therapist’s dynamics. Taking into account Assumption 2 and also the fact that the \( \mathcal{L}_1 \)-gain of a stable proper transfer function is the IOS gain of the corresponding linear system, one can verify that (2.24) is essentially a small-gain stability condition for system (2.25), (2.26), (2.17), (2.18) with communication channels (2.7), (2.8). Applying Theorem 5 from Appendix I (Section 2.9), with \( \delta_1 = \delta_2 = 0, \sigma_1 := \sigma_f, \sigma_2 := \sigma_b, w_1 := f_p^a, \) and \( w_2 := \omega^h \), we can conclude that the trajectories of the system are uniformly bounded and convergent. This completes the proof. •

Remark 2.8. The assumption that both \( Z_{th}(s) \) and \( (Z_p(s) + \tilde{Z}_m(s))^{-1} \) are proper transfer matrices is perfectly reasonable considering the experimental results reported in [28]. It was experimentally found in [28] that the frequency response of the human hand (considering force as input and position as output) has a slope of -20 dB/decade at high frequencies. Accordingly, in [28] two different models are proposed for the human hand interacting with a teleoperator system. Both models have relative degree zero when force is the input and velocity is the output. Therefore, using any of the two models given in [28], both \( Z_{th}(s) \) and \( Z_p^{-1}(s) \) are bi-proper (their relative degrees are equal to zero). The fact that \( (Z_p(s) + \tilde{Z}_m(s))^{-1} \) is proper now follows from the assumption that \( \tilde{Z}_m(s) \) is positive real. This justifies the corresponding assumptions of Theorem 1. •

Remark 2.9. One interesting aspect of the proposed stability analysis approach can be clarified by considering the case where \( \alpha = \beta = 1, \tilde{Z}_m(s) = 0, P(s) = I, \) and the communication channel is ideal, i.e., (2.10) holds. As explained in Section 2.2, this choice of parameters results in a perfectly transparent teleoperator system. On the other hand, in this case the small-gain
stability condition (2.24) becomes
\[
\left( \|Z_{th}(s)\| + \gamma_{th}^{d} \right) \cdot \left( \|Z_{p}^{-1}(s)\| + \gamma_{p}^{d} \right) < 1.
\] (2.27)

We can therefore, conclude that fulfilment of the condition in (2.27) implies that the telerobotic system under consideration is both perfectly transparent and robustly stable (i.e., stable with nonzero stability margin). This represents a drastic difference from the conventional analysis, where it was demonstrated that stability and transparency are conflicting goals; more precisely, a perfectly transparent system has zero stability margin [29]. This can be attributed to the different assumptions imposed on the dynamic behavior of the human operator (patient) and environment (therapist) within our framework in comparison with the conventional one; this also reflects the potential advantages of the proposed approach.

In order to formulate a result similar to Theorem 1 for the case \(\zeta = 0\), let us denote
\[
Z_{1}(s) := Z_{th}(s)[Z_{th}(s) + Z_{v}(s) + \eta(s)]^{-1}[Z_{v}(s) + \eta(s)],
\] (2.28)
\[
Z_{2}(s) := I - Z_{th}(s)[Z_{th}(s) + Z_{v}(s) + \eta(s)]^{-1}.
\] (2.29)

The following result is valid.

**Theorem 2.2.** Consider the tele-rehabilitation system described by (2.1), (2.2), (2.3), (2.6), (2.7), (2.8), (2.15), (2.16), (2.17) and (2.18). Suppose Assumptions 1, 2 and 3 hold. Suppose also that \(Z_{1}(s)P(s), Z_{2}(s), (Z_{p}(s) + \tilde{Z}_{m}(s))^{-1}\), and \(P(s)\) are stable and proper transfer matrices. If
\[
\left( \|Z_{1}(s)P(s)\| + \gamma_{th}^{d}\|Z_{2}(s)\| \right) \cdot \left( \|P(s)\| + \|Z_{p}(s) + \tilde{Z}_{m}(s)\|^{-1} + \gamma_{p}^{d}\|Q(s)\| \right) < 1/(\alpha \cdot \beta),
\] (2.30)

then the trajectories of the tele-rehabilitation system are uniformly bounded and convergent.

**Proof of Theorem 2** follows along line of reasoning as the proof of Theorem 1 with the difference that for \(\zeta = 0\), the closed-loop slave-therapist dynamics (2.2), (2.6), (2.16) have the form of
\[
F_{th}(s) = \beta \cdot Z_{1}(s) \cdot P(s) \cdot \dot{Y}_{\hat{p}}(s) + Z_{2}(s) \cdot F_{th}^{a}(s).
\] (2.31)
It is straightforward to verify that (2.30) is the small-gain stability condition for the system (2.25), (2.31), (2.17), (2.18) with communication system (2.7), (2.8). Applying Theorem 5 from Appendix I (Section 2.9), with \( \delta_1 = \delta_2 = 0, \sigma_1 := \sigma_f, \sigma_2 := \sigma_p, w_1 := f^a_p, \) and \( w_2 := w^{th}, \) the statement of Theorem 2 follows.

**Remark 2.10.** The stability conditions (2.24) and (2.30) provide a new mathematical tool which shows how a telerobotic system can remain stable and transparent when the communication delay is not zero and is time varying (without any consideration of the linearity and passivity of the terminals). The developed small-gain stability condition is the basis for proposing a new stabilizer in the next section. The same stability calculation will be performed while considering the proposed controller in the loop of teleoperation to analyze the effect of the controller on the stability condition of the system.

### 2.5 Stabilizing Scheme for The Proposed Tele-Rehabilitation System

Theorems 1 and 2 present conditions for stability of the tele-rehabilitation system in the presence of communication constraints. However, the stability should be guaranteed even if the given stability conditions do not hold. Also, the proposed stability conditions (2.24), (2.30) depend on the gain \( \gamma_{th}^p \) and \( \gamma_p^p \) that characterize the therapist’s and the patient’s dynamics. In practice, these gains may not be exactly known beforehand. The natural question, therefore, is how to guarantee stability of the overall tele-rehabilitation system and relax the calculated stability conditions (2.24), (2.30). Our solution is described as follows. First, consider a known constant \( \gamma_p > 0 \) such that

\[
\left( \left\| (Z_p(s) + \tilde{Z}_m(s))^{-1} \right\|_1 + \gamma_p^p \| Q(s) \|_1 \right) \leq \gamma_p.
\]  

The inequality given in (2.32) essentially implies that there exists a known upper bound for the peak gain (IOS gain) of the patient’s side biomechanical admittance; equivalently, there exists a known lower bound for the peak gain of the patient’s “side” impedance. For the case of \( \tilde{Z}_m(s) \equiv 0, \) the inequality (2.32) is equivalent to find an upper bound for the patient’s “hand”
admittance \( \left( \| Z_p^{-1}(s) \|_1 + \gamma_p' \right) \).

The above given upper bound on the IOS gain of the patient’s side admittance can be estimated using and **identification procedure** (prior to the operation). During the procedure force perturbations are applied to the patient’s hand and corresponding motions are logged to find the mentioned bound on the IOS gain of the patient’s side dynamics. An example of this procedure is explained later in this chapter. Suppose (2.32) holds; picking a sufficiently small \( \varepsilon_0 > 0 \), denote

\[
\gamma_{th} := (\alpha \cdot \beta \cdot \gamma_p + \varepsilon_0)^{-1}.
\]

Furthermore, denote

\[
\chi(t) := \gamma_{th} \cdot \sup_{\tau \in [t-T, t]} |\dot{\gamma}_p(\tau)| + \delta_{th},
\]

where \( T > 0 \) and \( \delta_{th} \geq 0 \) are arbitrarily chosen parameters. Essentially, \( \chi(t) \) represents an upper bound for the therapist’s force that is admissible in terms of the small-gain stability condition proposed in the previous section, where \( T > 0 \) is the time horizon for the input and \( \delta_{th} \geq 0 \) is an offset. To guarantee overall stability, the force signal (sent to the patient’s side) should be modified at each \( t \) by the proposed small-gain stabilizer, defined as follows

\[
f_{th}^*(t) := \begin{cases} 
    f_{th}(t) & \text{if } |f_{th}(t)| \leq \chi(t), \\
    \frac{f_{th}(t)}{|f_{th}(t)|} \cdot \chi(t) & \text{otherwise}.
\end{cases}
\]

Consequently, the force reflected to the patient’s side is

\[
\hat{f}_{th}(t) := f_{th}^* (t - \tau_b(t)).
\]

**Remark 2.11.** The synthesized Small-Gain Controller (SGC), defined in (2.35) and (2.36), is implemented on the therapist’s side processor and is designed to guarantee stability (in the context of the small-gain theorem) regardless of any change in the dynamical behavior of the therapist. The proposed SGC modifies the therapeutic forces based on the quantified IOS gain of the patient’s upper-limb biomechanical impedance (\( \gamma_p \)). Consequently, the SGC allows higher intensity of therapy to be delivered for patients having heavy rigid upper-limbs. In fact, the controller customizes the therapeutic forces for each patient. It prevents the therapist providing
“too much” assistance for a patient with light-weight soft limbs. If the proposed controller observes that the defined small-gain stability condition is not violated during rehabilitation, it will not change the transmitted therapy (the transparency will be unaffected), even if the communication is delayed. If the developed small-gain condition is violated, the controller modifies the therapeutic forces and transmitted therapy to stabilize the system based on the identified IOS gain of the patient’s hand.

In order to show how the proposed technique can guarantee system stability, let us first consider the case $\zeta = 1$. The following result is valid.

**Theorem 2.3.** Consider the tele-rehabilitation system described by (2.1), (2.2), (2.3), (2.5), (2.7), (2.8), (2.15), (2.16), (2.17), and (2.18) with the stabilizing algorithm (2.34), (2.35), (2.36), where $\gamma_{th} > 0$ is calculated based on (2.33). Suppose Assumptions 1, 2, and 3 hold. Suppose also that $Z_{th}(s)P(s)$ and $P(s)$ are stable and proper transfer matrices. Then the trajectories of the tele-rehabilitation system are uniformly bounded and convergent.

**Proof of Theorem 3** Substituting (2.5), (2.16) into (2.2), the closed-loop slave-therapist dynamics for $\zeta = 1$ are described by equations (2.17), (2.18) and (2.26). This interconnection is WIOS as a cascade/parallel interconnection of WIOS subsystems. Let this system be augmented with the new output $f_{th}^*$ defined by (2.35). The augmented slave-therapist interconnection can be represented as a system of FDEs of the form

$$
\begin{align*}
\dot{x}_{st} &= F_{st}(x_{std}, \hat{v}_{pd}, w^{th}) \\
f_{th}^* &= H_{st}(x_{std}, \hat{v}_{pd}, w^{th}),
\end{align*}
$$

(2.37)

where $x_{std}$ is a combination of states of the subsystem (2.17) and those of the minimal realization of (2.26). By construction,

$$
|f_{th}^*(t)| \leq \gamma_{th} \cdot |\hat{v}_{pd}(t)| + \delta_{th}
$$

(2.38)

holds for all $t \geq 0$. Picking an arbitrary $\beta^y \in \mathcal{K}_\infty$, (2.38) then implies

$$
\sup_{t \geq 0} |f_{th}^*(t)| \leq \beta^y \left( |x_{std}(0)| \right) + \gamma_{th} \cdot \sup_{t \geq 0} |\hat{v}_{pd}(t)| + \delta_{th},
$$

(2.39)

i.e., the system (2.37) has the uniform boundedness property (Definition 1 in Appendix I (
Section 2.9). On the other hand, (2.38) also implies that

$$\limsup_{t \to +\infty} |f^*_h(t)| \leq \limsup_{t \to +\infty} \gamma_{th} |\dot{\psi}_{pa}(t)| + \delta_h.$$  

(2.40)

Thus, the system (2.37) is WIOS (Definition 1 in Appendix I) with linear gain $\gamma_{th}$ and offset $\delta_{th}$.

The overall tele-rehabilitation system can now be represented as a feedback interconnection of (2.37) and (2.25) implemented over the communication channels (2.7), (2.36). The small-gain stability condition for this feedback interconnection is

$$\alpha \cdot \beta \cdot (\|Z_p(s) + \tilde{Z}_m(s)\|^{-1} + \gamma_{th} \|Q(s)\|) \cdot \gamma_{th} < 1,$$

(2.41)

which is guaranteed to be satisfied due to (2.32), (2.33). Application of the small-gain result of Theorem 5 in Appendix I (Section 2.9) with $\delta_1 = 0, \delta_2 = \delta_{th}, \sigma_1 := \sigma_f, \sigma_2 := \sigma_b, w_1 := f^*_p$, and $w_2 := 0$ concludes the proof.

A result analogous to Theorem 3 for the case $\zeta = 0$ can be formulated as follows.

**Theorem 2.4.** Consider the tele-rehabilitation system described by (2.1), (2.2), (2.3), (2.6), (2.7), (2.8), (2.15), (2.16), (2.17), (2.18) with the stabilizing algorithm (2.34), (2.35), (2.36), where $\gamma_{th} > 0$ is chosen such that (2.33) holds. Suppose Assumptions 1, 2, and 3 hold. Suppose also that $Z_1(s)P(s), Z_2(s)$, and $P(s)$ are stable and proper transfer matrices. Then the trajectories of the system are uniformly bounded and convergent.

**Proof of Theorem 4** is analogous to the proof of Theorem 3 with the only difference being that in the description of the closed-loop slave-therapist dynamics for $\zeta = 0$, equation (2.31) should be used in place of (2.26). The rest of the arguments are the same as those used in the proof of Theorem 3.

It can be concluded that the proposed force reflection technique (2.35), designed for the proposed tele-rehabilitation system is capable of ensuring system stability regardless of any non-passivity, and nonlinearity of the therapist’s and patient’s dynamics and existing communication delays in the system.

**Remark 2.12.** It should be noted that using any type of controller for haptic systems, transparency modulation is inevitable for guaranteeing stability. An example can be the definition of $Z$-width developed in the literature for linear haptic rendering systems [30]. One specific fea-
ture of the proposed SGC is that it tries to use the available resources in the system to reduce the frequency and intensity of transparency modulation. For this purpose, the biomechanical characteristics of the patient’s hand in the context of small-gain theorem is utilized. If the dynamics of the patient’s hand is capable of keeping the stability margin positive, the controller will not change the reflected forces (and as a result the felt impedance). However, if the stability is questionable, the controller modifies the reflected forces since patient safety is the first priority. Consequently, SGC gives complete authority to the therapist to tune the therapy, “as long as the stability margin remains positive”. However, it puts a limit on the impedance transmitted to the patient’s side. This limit is based on the capabilities of the patient’s hand in absorbing therapeutic forces. As a result, in this chapter, the definition of “too much assistance” corresponds to the situation that the developed stability condition is not satisfied and this situation is diagnosed by SCG, as a fault in the bilateral interaction. The proposed tele-rehabilitation architecture provides the therapist with an auditory cue (a beeping sound) which shows that the extent of therapy is going to violate the stability condition, so the controller is going to be activated. This helps the therapist to realize how much assistance he/she can apply.

2.6 Simulations and Experimental Results

Pilot results are given in this section.

2.6.1 Simulation A: Assistive and Resistive Therapy

In Simulation A, we investigate stability and transparency of the tele-rehabilitation system (without including the controller) where the therapist acts in both resistive and assistive modes. It is assumed that $\tilde{Z}_m(s) = 0$. The voluntary actions of the therapist is simulated by $K_{th}(s)$. This transfer function is called the “therapist’s gain”. In simulation A, the impedance of the patient’s hand is $Z_p(s) = 110 + 70s^{-1}$, and the one for the therapist’s hand is assumed to be negligible. It should be noted that this assumption has not been imposed by the proposed theoretical framework. This is assumed here only to allow for conducting a particular analysis of the passive and non-passive behavior of the therapist in this simulation. The simulated therapist’s gain is $K_{th}(s) = 90 + 50s^{-1}$ for the resistive phase (phase 1) and $K_{th}(s) = -90 -$.
50\text{ s}^{-1}$ for the assistive phase (phase 4). The scaling factors are $\alpha = \beta = 1$. The simulated communication delay is a Gaussian noise with the mean value of 0.2 sec in each direction.

Simulation A consists of four phases:

Phase 1) The patient generates external forces as $f_p^a(t) = 100(\sin t)$ N. The therapist acts in the resistive mode.

Phase 2) The patient continues to generate active forces ($f_p^a(t) = 100(\sin t)$ N), while the therapist releases the slave, so that no assistive/resistive forces are generated.

Phase 3) The magnitude of $f_p^a(t)$ is decreased by a factor of three, $f_p^a(t) = \frac{100}{3}\sin t$ N to simulate a stroke. No assistive/resistive forces are generated.

Phase 4) The patient continues to generate $f_p^a(t) = \frac{100}{3}\sin t$ N. The therapist acts in the assistive mode.

Theoretically, it can be checked that during all four phases, the system satisfies the assumptions of Theorem 1 and stability condition (2.24). As a result, it is expected that the system behaves in a stable manner regardless of the non-passive behavior of the therapy terminal and existence of the delay. The results are shown in Fig. 2.2 and confirm the stability of the system during all four phases. As expected, during resistive therapy (Phase 1) the therapist dissipates
energy and the amplitude of velocity is reduced, while during assistive therapy (Phase 4), the therapist generates energy, thus acting as an active (non-passive) system. The overall tele-rehabilitation system remains stable and transparent (the force felt by the patient matches the therapeutic force) during all four phases.

2.6.2 Simulation B: The Proposed Small-Gain Controller

Simulations B illustrates the performance of the tele-rehabilitation system with the proposed SGC technique (2.34), (2.35) for assistive therapy. The communication delay is the same as in the previous simulation. Here, by “mild” assistance, we mean a situation where the impedance of the patient’s hand $Z_p(s)$ is larger (in the sense of its 1-norm) than the therapist’s gain $K_{th}(s)$. In this case, the small-gain stability condition is satisfied. By “strong” assistance, we mean the opposite situation. The therapy starts after $t = 40$ sec.

**Mild Assistance.** The patient’s hand impedance is $Z_p(s) = 110 + 40s^{-1}$ and the therapist’s transfer function is $K_{th}(s) = -60 - 10s^{-1}$. $\gamma_{th}$ is calculated based on the estimate of the patient’s hand impedance which is 20% lower than the actual impedance. The external force in this case is $f_p^a(t) = 30\sin(0.7t)$ N. The result is shown in Figs. 2.3a and 2.3b which show that the assistive therapy increases the magnitude of the patient’s movement, while the system remains stable. Since the small-gain condition is satisfied, the SGC does not alter the therapist’s assistive forces.

**Strong Assistance.** The patient’s hand impedance is $Z_p(s) = 80 + 10s^{-1}$ while the therapist’s transfer function is $K_{th}(s) = -150 - 20s^{-1}$. The external force is $f_p^a(t) = 30\sin(0.7t)$ N.
It can be checked that the small-gain condition is not satisfied in this case. Fig. 2.4 shows the divergent (unstable) system’s response when the SGC is off. In this case even assuming zero delay did not help the instability and the system remained divergent. Turning on the proposed SGC technique, the result is shown in Figs. 2.5a, 2.5b. Here, $\gamma_h$ is calculated based on the estimate of the patient’s hand impedance (20% lower than the actual impedance). Fig. 2.5a shows that the strong assistive therapy leads to significant increase in the magnitude of the movement and the system remains stable. The actions of the SGC can be seen in Fig. 2.5b. The controller modulates the magnitude of the therapist’s assistive forces to keep the overall system stable.

2.6.3 Simulation C: Transparency Modulation (Comparative Study)

Simulation C compares the behavior of the proposed Small-Gain Controller with the conventional state-of-the-art Time-domain Passivity-based Control (TDPC) technique for the proposed application. The focus of this simulation is on modification of system transparency (arising from the need to guarantee system stability) performed by SGC in comparison with that
of TDPC. For this purpose, the TDPC technique (initially formulated in [31]) is implemented. The technique for comparing the transparency of TDPC and SGC is based on the algorithm introduced in [32]. The simulation has been conducted in two parts. For the first part, the communication delay is considered to be ideally zero. The effect of time delay (which introduces phase-lag in the system) is separately analyzed in the second part. During both parts, each technique (TDPC and SGC) is simulated for handling ten different therapeutic environments which range from “very high power assistive therapy” to “very high power resistive therapy”, as explained below. The resistive environment is a positive viscous force field \( f_{th} = B_{th} \cdot v_{th} \) where \( B_{th} > 0 \) which has been used in the literature [33] to challenge the motor capability of patients and encourage them to provide higher motor activity for task performance. On the other hand, the power assistive environment is considered to be a negative viscous force field \( f_{th} = B_{th} \cdot v_{th} \) where \( B_{th} < 0 \) which amplifies the mechanical power of the patient. More details on this type of robotic assistive rehabilitation technique can be found in [34]. The goal of the utilized power assistive rehabilitation is to help patients using their own (reduced) mechanical power to perform tasks. The ten coefficient \( B_{th} \) which corresponds to the ten simulated therapeutic environments consists of \(-20N.s/m\) (very high assistance), \(-15N.s/m\) (high assistance), \(-10N.s/m\) (moderate assistance), \(-5N.s/m\) (mild assistance), \(-2N.s/m\) (very low assistance), \(+20N.s/m\) (very high resistance), \(+15N.s/m\) (high resistance), \(+10N.s/m\) (moderate resistance), \(+5N.s/m\) (mild resistance), \(+2N.s/m\) (very low resistance). Each of the above-mentioned therapeutic environments is simulated for 10 seconds. The reason for choosing these values is explained below.

In this simulation, the patient’s hand and rehabilitation robot are modeled by mass-damping dynamics. For the patient’s hand the mass and damping parameters are 1 Kg and 11 N.m/s, respectively; and those for the robot are 2 Kg and 3 N.m/s. The force generated by the patient is \( f_{p}^a(t) = 2(\sin(1t) + \sin(2t) + \sin(3t) + \sin(4t)) \). The identified IOS gain of the patient’s hand is 10.7 N.m/s. Considering a 0.7 N.m/s margin, the value used in the SGC for the IOS gain of the patient’s hand is 10 N.m/s. As a result, the cases of very low and mild assistive/resistive therapies are when the proposed stability condition for the patient-therapist interaction is satisfied since \( B_{th} < 10N.m/s \). The cases of moderate assistive/resistive therapies are when the stability condition is marginally satisfied (since \( B_{th} = 10N.m/s \)), and the cases of high and
very high assistive/resistive therapies are when the stability condition is not satisfied (since \( B_{th} > 10N.m/s \)).

During the second part of the simulation, the same rehabilitation environments and the parameters specified above have been used while the communication delay is considered from zero round-trip delay to 500\( ms \) round-trip delay. The step between the simulated communication delays is 25\( ms \). This means that in total 21 simulations have been conducted for each control technique (TDPC and SGC). In the first simulation, a zero communication delay is considered; in the second simulation, a 25 \( ms \) delay is considered; and in the 21\( st \) simulation, a 500 \( ms \) delay is considered. This allows us to analyze the trend of transparency modification delivered by the two control techniques when the communication delay changes from zero to high values. The reason for separately analyzing the effect of time delay is that phase lag can affect the therapeutic impedance felt by the patient. For example a phase lag of 180 degrees can totally convert the feeling of an assistive environment to a resistive one, and vice versa. As a result, we first compare the SGC and TDPC techniques under an ideal no-delay condition (part 1), then we gradually increase the communication delay up to 500 \( ms \) (part 2).

To analyze the effect of the two controllers on the transparency of the system (that correlates with the feel of assistance/resistance delivered to the patient) in comparison to the planned therapy, the transparency visualization technique proposed in [32] for general haptic systems is used. For this purpose, in [32] a transparency map is proposed which plots the parameters of the reflected impedance to the user’s hand (which is the extent of the delivered assistive/resistive therapy to the patient’s hand here), with respect to the parameters of the environmental impedance (which is the extent of the generated assistive/resistive therapy). To calculate the parameters, in [32], a conventional parameter identification scheme is utilized considering a Linear Time-Invariant (LTI) model for the reflected and environmental impedances. However, since both TDPC and SGC are nonlinear controllers which introduce time-varying damping and force modification into the system, we used a nonlinear energy-based identification scheme which calculates the average energy dissipation/generation felt by the patient (\( D_{reflect} \)) in comparison to the one generated by the therapeutic environment.
2.6. SIMULATIONS AND EXPERIMENTAL RESULTS

Figure 2.6: Graph of the transparency map of an ideal imaginary system (with infinite transparency width) that remains stable for infinite positive/negative loop gains.

\[ D_{\text{therapy}} = \frac{\int_{0}^{10} f_{th}(t)v_{th}(t)dt}{\int_{0}^{10} v_{th}(t)^2dt}; \quad D_{\text{reflect}} = \frac{\int_{0}^{10} f_{p}(t)v_{p}(t)dt}{\int_{0}^{10} v_{p}(t)^2dt}. \]  

(2.42)

Please note that for an LTI positive/negative viscous environment the outputs of the calculations given in (2.42) are equal to the amplitudes of the viscosity coefficient. Consequently, for the ten simulated therapeutic environments, since the therapy has an LTI model \( f_{th} = B_{th} \cdot v_{th} \) where \( B_{th} \in [-20, -15, -10, -5, -2, +2, +5, +10, +15, +20] \), the output of the calculation in (2.42) for the therapeutic environment \( D_{\text{therapy}} \) is equal to \( B_{th} \). This can be shown by replacing \( f_{th} \) of (2.42) with \( B_{th} \cdot v_{th} \). The end time for the simulation is \( t = 10\, \text{sec} \) which is used in the limits of the integrals in (2.42).

Now, consider an imaginary ideal interaction which remains stable and fully transparent for infinite positive and negative loop gains. The transparency map for that ideal interaction would be as the one drawn (not simulated) in Fig. 2.6, where the felt and the planned therapies would be identical for any arbitrary choice of the therapeutic environment. In the control theory and telerobotics literature, it is known that stable behavior cannot be expected for infinite loop gain with an arbitrary sign. Regarding the issue with the arbitrary sign, an example is the case of positive feedback loops which usually corresponds to a destabilizing behavior (in
Part 1 (Zero Communication Delay): As mentioned earlier, the first part of the results for Simulation C evaluates the transparency of the two controllers (SGC and TDPC) when the communication delay is set to zero. After simulating both controllers for all the ten rehabilitation environments, the transparency maps are developed as shown in Fig. 2.7. As can be seen in this figure, to guarantee stability, both techniques have modified the transparency map (compared to the map of the ideal system shown in Fig. 2.6). The proposed SGC controller, has opened a transparency width based on the identified IOS gain of the user’s hand (i.e. 10 N.m/s in this simulation). It allows both negative and positive viscous environments to be felt by the user if the amplitude of the therapeutic environment ($B_{th}$) is located within the mentioned width (which is from -10 N.s/m to +10 N.s/m). The controller saturates the reflected transparency if the amplitude of the environment’s coefficient goes beyond this width. In comparison to the TDPC technique, under the zero communication delay condition, the SGC technique allows higher negative viscosity to be felt by the user. However, SGC reduces the allowable range of positive viscosity to be reflected back to the patient’s hand, in comparison to TDPC.
To further compare the behavior of the two controllers, distributions of the resulting hand velocities of the patient are shown in Fig. 2.8. In this figure, the resulting velocities during the maximum resistance and the maximum assistance provided through the two controllers are compared. The distributions of velocities delivered through the SGC technique are denoted by SGC-A (for the maximum assistance) and SGC-R (for the maximum resistance). Similarly, the distributions of the velocities delivered through the TDPC technique are denoted by TDPC-A (for the maximum assistance) and TDPC-R (for the maximum resistance). For resistive therapy, lower velocities correspond to delivery of higher resistance (which is desirable for this type of therapy). For assistive therapy, higher velocities corresponds to delivery of higher assistance (which is desirable for this type of therapy). In order to statistically compare the distributions, the widely-used two-sample t-test statistical analysis was conducted for each of the four pairs of distributions shown in Fig. 2.8. The resulting p-values (output of t-test) were less than 0.001 for all four pairs shown in Fig. 2.8. This statistically validates the results. It implies that (a) (as expected) the velocities during resistive therapy for both SGC and TDPC techniques were (on average) lower than the velocities during assistive therapy and the difference was statistically significant; (b) the SGC controller resulted in higher velocities during assistive therapy in comparison to TDPC and the difference was statistically significant; (c) during resistive therapy, the TDPC technique resulted in lower velocities (compared to SGC) and the difference was again statistically significant. In summary, SGC performs better for negative viscosities while TDPC performs better for positive viscosities. This result is in agreement with the calculated transparency map shown in Fig. 2.7. As mentioned earlier, a communication delay can affect the transparency maps, as discussed in Part 2.

As the last evaluation of Part 1, to better clarify the behavior of the proposed SGC technique, the generated environmental force and the force felt by the patient (the modified force) are compared and the comparison is shown in Fig. 2.9 for moderate (\(|B_{th}| = 10N.s/m\)) and for very-high (\(|B_{th}| = 20N.s/m\)) resistance and assistance. As can be seen in this figure, during moderate therapy, the reflected force to the patient’s hand is equal to the one generated at the environment. However, when the intensity of the environment has gone beyond the transparency width of SGC, the controller reduces the amplitude of the reflected forces to guarantee stability.
**Part 2 (Non-zero Communication Delay):** In this part, the effect of a communication delay is analyzed while evaluating the transparency of the system using SGC and TDPC controllers. For this purpose the communication delay is increased from a zero round-trip delay up to $500\,\text{ms}$ in $25\,\text{ms}$ increments between every two consecutive simulations. The transparency visualization technique used in Part 1 of Simulation C is used here. The results can be seen in Fig. 2.10 for the SGC technique and in Fig. 2.11 for the TDPC technique. The figures are plotted in 3D space where (a) the generated therapeutic behavior $D_{\text{therapy}}$, (b) the therapeutic behavior felt by the patient $D_{\text{reflect}}$, and (c) the simulated delay are the three axes. As mentioned earlier, each of the two control techniques (TDPC and SGC) has been simulated for 21 communication delay values (ranging from 0 to $500\,\text{ms}$ in increments of $25\,\text{ms}$) and for 10 different therapeutic behavior $B_{\text{th}}$ (ranging from $-20\,\text{N.s/m}$ to $+20\,\text{N.s/m}$). As can be seen in Figs. 2.10 and 2.11, increasing the delay reduces the transparency width for both controllers. In other words, an increase in the communication delay has resulted in greater modification of transparency resulting from both the TDPC and SGC techniques in order to guarantee stability.
Figure 2.9: The force modification applied by the SGC technique for moderate (left) and very high (right) resistance (top) and assistance (bottom) therapies.

For example, comparing Fig. 2.10c and Fig. 2.7c, and also comparing Fig. 2.11c and Fig. 2.7b, it can be seen that the reflected transparency range is reduced by increasing the delay. Considering Figs. 2.10d and 2.11d, it can be seen that for high delay values, SGC shows higher transparency width in comparison to TDPC. However, for low values of delays, the TDPC shows higher transparency width for positive viscous environment while SGC shows higher transparency width for negative viscous environments.

2.6.4 Experiment A: (Time-varying Resistive/Assistive Therapy)

The goal of this set of experiments was to investigate the performance of the proposed controller when the therapist behaves in a non-autonomous (time-varying) passive and non-passive manners. Note that the proposed small-gain framework allows for having nonlinear time-varying non-passive behavior for the therapist and the patient. In this set of experiments, a human operator (which includes intrinsic nonlinear dynamics) plays the role of the patient, interacts with the haptic device (Phantom Omni from 3D Systems), and provides movement trajectories. Both assistive and resistive actions of the therapist are simulated in a time-varying manner to match with the main goal of this experiment. It is demonstrated that the proposed controller ensures system stability regardless of the time-varying behavior of the therapist. The
Figure 2.10: The 3D transparency map considering the effect of communication time delays for the SGC technique: (a) the 3D view, (b) the Delay-$D_{therapy}$ plane, (c) the $D_{reflect}$-$D_{therapy}$ plane, (d) the $D_{reflect}$-Delay plane.
Figure 2.11: The 3D transparency map considering the effect of communication time delays for the TDPC technique: (a) the 3D view, (b) the Delay-$D_{therapy}$ plane, (c) the $D_{reflect}$-$D_{therapy}$ plane, (d) the $D_{reflect}$-Delay plane.
Figure 2.12: Experiment A: (a) Varying therapeutic gain, (b) Passive and non-passive behavior of the therapist during the time-varying therapy, (c) Operator’s velocity trajectory during the time-varying therapy, d) The generated therapeutic force versus the modified force reflected to the operator’s hand.

plot of the chosen time-varying therapeutic gain used in this experiment is shown in Fig. 2.12a. As can be seen in this figure, the therapist gradually increases the level of resistance starting from $t = 10 \text{ sec}$ until $t = 25 \text{ sec}$. At $t = 25 \text{ sec}$, the therapist suddenly switches to assistive therapy and starts to gradually increase the level of assistance. The maximum assistive gain is achieved at $t = 38 \text{ sec}$ with its value equal to $20 \text{ N} \cdot \text{sec}/\text{m}$. The controller parameters in this simulation are chosen as $\gamma_{th} = 5$, and $\delta_{th} = 0$. The time-varying time delays are $\tau_f(t) = \tau_b(t) = 0.1 + 0.01 \cdot \sin 30t \text{ sec}$. Fig. 2.12b presents a plot of the power produced by the therapist. It can be seen that during the period from $t = 10 \text{ sec}$ to $t = 25 \text{ sec}$, the therapist absorbs power thus behaving like a passive system, while after $t = 25 \text{ sec}$, the therapist starts injecting power into the system which results in non-passive behavior.

The results are shown in Fig. 2.12c and 2.12d, where Fig. 2.12c shows the velocity profile of the operator’s movement, and Fig. 2.12d shows the forces generated by the therapist as well as the ones reflected to the operator (patient) which are modified by the controller to ensure system stability. This experiment demonstrates that the amplitude of the patient’s motion decreases during the resistive phase and increases during the assistive phase in a safe and stable
manner as expected, while the therapist’s behavior is changing over time and represents both passive and non-passive actions. Also, the proposed controller modifies the reflected forces and preserves stability in both time-varying resistive and assistive modes (in the presence of varying communication delays).

2.7 Full System Implementation

In this section, the full system implementation is addressed where two humans interact through the proposed tele-rehabilitation system (in the roles of therapist and patient) and the parameters are tuned based on practical requirements. The implemented system shown in Fig. 2.13 consists of:

- **Master haptic device at the patient side**

  This is a 2-DOF planar upper-limb rehabilitation robot from Quanser Inc. that moves in the horizontal (X-Y) plane allowing for arm flexion-extension movements. The robot measures the patient’s movements and applies the received forces from the therapist on the patient’s arm.

- **Slave haptic device at the therapist side**

  This is a 6-DOF Quanser $HD^2$ haptic device locked by software to have a fixed orientation. The vertical $Z_{axis}$ direction is used as an additional supervisory input from the therapist (explained later). So, the implemented system is a 2-DOF telerobotic interconnection in the X-Y plane. The role of the slave robot is to provide the therapist with motion trajectories generated by the patient and estimates the corresponding interaction forces provided by the therapist in response. Both haptic devices are run in Matlab/Simulink using the QUARC 2.2 real-time environment [35].

- **Shared monitored virtual-reality environment**

  The virtual-reality environment is monitored for the patient using a head-mounted display (to provide the patient with visual cueing about the required task and tell him/her when and where to move) and for the therapist using a computer monitor. In Fig. 2.13 the orange circle represents the patient’s position, the yellow circle is the therapist’s position, and the green square is
Figure 2.13: Implemented System: Left) Patient-side robot and Head-mounted display, Middle) Virtual Environment, Right) Therapist-side Robot

the target to be tracked by the patient. The purple squares are all possible locations of the target during rehabilitation. During the experiments, the patient attempts to track the target, while the therapist provides assistive/resistive/coordinative forces through the implemented system. For resistive therapy, the therapist pushes the yellow circle against the direction of the patient’s movement or follows it with a position lag. This will result in generating resistive forces which will be reflected to the patient’s hand. For assistive therapy, the therapist pushes the yellow circle while leading/coordinating the orange circle. The target switches its location in a randomized manner after a specific amount of time (which is set to 5 sec here considering the size of the workspace). The target switching scenario could be based on tracking accuracy threshold. Having a therapist in the loop allows him/her to provide inputs by pushing a foot pedal to switch the target location and tune the needed difficulty. The time-out scenario is chosen here. In a clinical environment, if the time-out scenario is chosen, it should be based on the capabilities of the patient in producing motions.

2.7.1 Control Parameters Tuning

In order to implement the proposed tele-rehabilitation architecture, $\zeta$ and $\eta$ should be tuned (which are needed for implementation of (2.4)). For the results given in this section, the following choice of parameters is considered.

\[
\zeta = 0, \quad \text{and} \quad \eta(s) = -Z_s(s) + \frac{(K_s + \theta_v s)}{(as + b)}.
\]
The choice given in (2.43) generates a viscoelastic coupling between the therapist and the patient without the need of a force sensor (as mentioned in Section II). The therapist can provide resistive/assistive forces through this viscoelastic coupling. In (2.43), $K_s \geq 0$, and $\theta_v \geq 0$ are the stiffness and viscosity coefficients of the viscoelastic coupling, and $(as + b)$ is the characteristic equation of a filter $(a, b \geq 0)$. These parameters can be tuned to achieve various desirable compliances. Note that the designed viscoelastic coupling is an inclusive case and it can be easily switched to position-tracking tele-rehabilitation or velocity-tracking tele-rehabilitation by changing the tuning factors $(a, b, K_s, \theta_v)$. In Appendix II (Section 2.10), details concerning the assignment of parameters in (2.43) and how these parameters can be tuned to address different practical requirements and specific needs are provided. In the experimental results reported in this section, we have used $a = 1$, $b = 0.001$, $K_s = 50$ N/m and $\theta_v = 10$ N·sec/m. In addition to the above, in order to implement the proposed SGC technique, an estimate of the lower bound for the IOS gain of the patient’s hand impedance is also needed. The identification procedure is presented later in this section.

2.7.2 Experimental Results For the Implemented System

In this subsection, we discuss some results of experimental studies performed using the implemented system.

**Experimental Results (Part A): Passivity Analysis of the Implemented Resistive/Assistive Therapy:** In the first set of the experiments (Part A), the communication delay was considered to be zero. In this part, the goal is to test the system performance and passivity for mild assistive and resistive therapy. For this goal, the second user (who plays the role of the therapist) delivers mild assistive/resistive therapeutic forces using the implemented telerobotic medium. Also the first user (playing the role of the patient) uses the master device while providing a high muscular tone. As a result, the proposed stability condition is expected to be satisfied so the system should remain stable, based on the developed theory and without using any controller. The functionality of the proposed controller for the situation when the stability condition is not satisfied is explained in Part C of this section. There are three phases in Part A. First, the patient tries to track the moving target resulting in a star-shaped 2D path, while
Figure 2.14: Experimental Results (Part A): (a) Resulting motions in 2D plane during: no-force (normal) phase, resisted phase and assisted phase; (b) Mean velocity during assistive/resistive therapy compared to no-force phase; (c) The therapeutic energy during assistive and resistive therapy.

the therapist applies “no force”. The resulting 2D path is shown by the solid red line in Fig. 2.14a (this phase is also called normal phase). The second phase (resistive therapy) starts at \( t = 150 \text{ sec} \). As a result, the magnitude of the movement should decrease as validated in Fig. 2.14a by the solid black line. During the second phase, the mean velocity of the movement is also decreased, compared to the first phase, as shown in Fig. 2.14b. During the second phase, the therapeutic behavior damps out the energy provided by the patient, as validated in Fig. 2.14c. The assistive therapy (the third phase) is started at \( t = 230 \text{ sec} \), which should result in a higher mean velocity and a larger movement magnitude as validated in Fig. 2.14a and 2.14b. During the assistive therapy, the therapist behaves as a non-passive subsystem and injects energy into the interconnection, as shown in Fig. 2.14c, while the system still performs in a stable manner, as validated in Fig. 2.14a. This is in complete agreement with the proposed stability condition which holds under the conditions of this experiment.
Experimental Results (Part B): IOS Gain Identification: As mentioned in Section 2.5, to implement the proposed SGC technique, first we need to have an estimate of the lower bound for the IOS gain of the patient’s side impedance. Consequently, in this part (Part B), an identification procedure is presented to find this value that will be used in Part C to implement the SGC technique. For this purpose, a sinusoidal signal with amplitude equal to 5N and a varying frequency from $0.2 \, \text{Hz} - 2 \, \text{Hz}$ is applied to the operator’s hand in both $X$ and $Y$ directions (when the operator is asked to keep the hand in a relaxed configuration). The hand velocity is measured; then a supremum for the hand velocity is found considering 5 second buffering (as shown, for the $X$ direction, Fig. 2.15a). With a constant-amplitude stimulation force and the recorded supremum of the hand velocity in 2DOF, an estimate for the IOS gain of the operator’s hand is obtained for the $X$ and $Y$ directions. The result for the $X$ direction is shown in Fig. 2.15b. From the results of this experiment, a conservative lower bound value for $\gamma_h$ is $35 \, \text{N} \cdot \text{sec/m}$. This value is used in the proposed SGC technique to stabilize the system in Part C, in the presence of varying communication delays.

Experimental Results (Part C): Stabilizing Control Implementation and Performance in Presence of Communication Delays: In this part, the delay is $\tau_f(t) = \tau_b(t) = 75 + 25 \cdot \sin(6t) \, \text{msec}$. In contrast to Part A, the operator (who plays the role of the patient) does not provide a high muscular tone while the therapist provides strong assistance. So it is expected that the stability condition is not satisfied and without the controller the system is unstable. Also, it is expected that by applying the SGC technique, the system remains stable while the therapist is capable of delivering assistive therapy. To show these, first, the haptic feedback is turned off so the therapist is not in the loop while the patient provides some movements.
After $t = 40\text{sec}$, the bilateral teleoperation system including the proposed SGC technique is turned on, while the therapist tries to assist the movement. The profile of the movement in the $X$ direction is given in Fig. 2.16a. Also, the 2D path of the movements is given in Fig. 2.16b. As can be seen, the movement is larger and the velocity amplitude is increased after $t = 40\text{sec}$, which shows that the assistance has been delivered through the proposed controller. At $t = 70\text{sec}$ the stabilizing controller is turned off. As expected, it results in interaction instability. This can be observed in Fig. 2.16 as the high-frequency uncoordinated movements. This validates the functionality of the proposed SGC technique in guaranteeing stability while allowing for delivering assistance when no assumption is made on the passivity and linearity of the terminals.

### 2.8 Conclusions

In this chapter, we have addressed the design, feasibility, safety and control synthesis for a new telerobotic architecture which is developed to allow for haptics-enabled bilateral teleoperated rehabilitation. The proposed architecture makes it possible to fuse the advantages of (local/remote) skilled human therapists and powerful sensorized robotic rehabilitation systems. Patient-robot interaction stability was studied in the context of the small-gain theorem. The major goal of the proposed new stability framework was to analyze and guarantee interconnection stability while putting no constraint on the passivity, time-dependency and linearity of the terminals and the network. The designed controller utilizes available resources to reduce trans-
2.9 Appendix I: The notion of weak input-to-output stability and the IOS small gain theorem

Here, some stability notions regarding the small-gain theorem used throughout this chapter are explained. The following notation is borrowed from [25]. Given functions \( x: \mathbb{R} \to \mathbb{R}^n \) and \( t_d: \mathbb{R} \to \mathbb{R}^+ \), then \( x_d(t) \) denotes the restriction of \( x(\cdot) \) on the interval \([t - t_d(t), t]\), i.e., \( x_d(t) := \{ x(\tau), \tau \in [t - t_d(t), t] \} \). Also, \( |x_d(t)| := \sup_{\tau \in [t - t_d(t), t]} |x(\tau)| \). Consider a system of functional differential equations (FDEs) of the form

\[
\begin{align*}
\dot{x} &= F(x_d, u_1^d, \ldots, u_l^d), \\
y &= H(x_d, u_1^d, \ldots, u_l^d),
\end{align*}
\]  

(2.44)

where \( x_d \) is a state, \( x_d(t) := \{ x(\tau), \tau \in [t - t_d(t), t] \} \), \( x \in \mathbb{R}^n \), \( u_i \in \mathbb{R}^{m_i} \), \( i = 1, \ldots, l \), are the inputs, \( u_i^d(t) := \{ u_i^d(\tau), \tau \in [t - t_d(t), t] \} \), and \( y \in \mathbb{R}^p \) is an output. It is assumed that both \( F \) and \( H \) are Lipschitz continuous operators, and the function \( t_d: \mathbb{R} \to \mathbb{R}^+ \) satisfies \( t_d(t_2) - t_d(t_1) \leq t_2 - t_1 \) for each \( t_1 \leq t_2 \in \mathbb{R} \), and \( \lim_{t \to +\infty} t - t_d(t) = +\infty \). In the special case where \( t_d(t) \equiv 0 \), we have \( x_d(t) = x(t), u_d(t) = u(t) \), and (2.44) becomes a system of ordinary differential equations with an output.

**Definition 2.1.** [20] The system (2.44) is said to be weakly input-to-output stable with linear IOS gains \( \gamma_i \geq 0 \), \( i = 1, \ldots, l \), and offset \( \delta \geq 0 \) if there exist \( \beta \in \mathcal{K}_\infty \) such that for any initial condition \( x_d(0) \) and any uniformly essentially bounded input \( u(\cdot): \mathbb{R}^+ \to \mathbb{R}^m \), the solution \( x(t) \) of (2.44) is well-defined for all \( t \in \mathbb{R}^+ \) and the following properties hold:

i) **uniform boundedness:**

\[
\sup_{t \geq 0} |y(t)| \leq \beta_w(|x_d(0)|) + \sum_{i=1}^{l} \gamma_i \cdot \sup_{t \geq 0} |u_i^d(\tau)| + \delta;
\]  

(2.45)

ii) **convergence:**
\[ \limsup_{t \to +\infty} |y(t)| \leq \sum_{i=1}^{l} y^i \cdot \limsup_{t \to +\infty} |u_d(\tau)| + \delta. \tag{2.46} \]

The following small-gain theorem is the main theoretical tool used in this chapter.

**Theorem 2.5.** Consider two systems of FDEs of the form

\[
\begin{align*}
\dot{x}_i &= F_i(x_{id}, u_d, w_i) \\
y_i &= H_i(x_{id}, u_d, w_i),
\end{align*} \tag{2.47}
\]

whose inputs and outputs are interconnected according to the following formulas: \( u_1(t) \equiv 0, \ u_2(t) \equiv 0 \) for \( t < 0 \), and

\[
\begin{align*}
u_2(t) &\equiv y^*_1(t - \tau_f(t)) + \sigma_2(t), \\
u_1(t) &\equiv y^*_2(t - \tau_b(t)) + \sigma_1(t)
\end{align*} \tag{2.48, 2.49}
\]

for \( t \geq 0 \), where \( y^*_i(t) \equiv 0 \) for \( t < 0 \) and \( y^*_i(t) \equiv y_i(t) \) for \( t \geq 0 \), \( i = 1, 2 \), \( w_1(\cdot), w_2(\cdot), \sigma_1(\cdot), \sigma_2(\cdot) \) are uniformly essentially bounded external inputs, \( \sigma_1(t) \equiv 0, \ \sigma_2(t) \equiv 0 \) for \( t < 0 \), and

\[
\begin{align*}
sup_{t \geq 0} |w_1(t)| &\leq w^*_1, \ \sup_{t \geq 0} |w_2(t)| \leq w^*_2, \ \sup_{t \geq 0} |\sigma_1(t)| \leq \sigma^*_1, \ \sup_{t \geq 0} |\sigma_2(t)| \leq \sigma^*_2, \ \limsup_{t \to +\infty} |w_1(t)| \leq \bar{w}^*_1, \\
\limsup_{t \to +\infty} |w_2(t)| &\leq \bar{w}^*_2, \ \limsup_{t \to +\infty} |\sigma_1(t)| \leq \bar{\sigma}^*_1, \ \limsup_{t \to +\infty} |\sigma_2(t)| \leq \bar{\sigma}^*_2, \ \sigma^*_1 \geq \bar{\sigma}^*_1 \geq 0, \ \sigma^*_2 \geq \bar{\sigma}^*_2 \geq 0\end{align*}
\]

\( \tau_f(\cdot), \ \tau_b(\cdot) \) are the time delay functions that satisfy Assumption \([1] \) of this chapter. Suppose both the systems in \((2.47)\) are WIOS with linear IOS gains \( \gamma^*_1, \gamma^*_2 \geq 0, \ \gamma^*_{12}, \gamma^*_{21} \geq 0, \) respectively, and offsets \( \delta_1 \geq 0, \ \delta_2 \geq 0, \) respectively. If the following small-gain condition holds

\[
\gamma^*_1 \cdot \gamma^*_{12} < 1, \tag{2.50}
\]

then the interconnected system is bounded and convergent; specifically, the trajectories of the closed-loop interconnected system are well-defined for all \( t \geq 0 \) and the following inequalities hold

\[
\begin{align*}
sup_{t \geq 0} |y_1(t)| &\leq \beta_1 (|x_{1d}(0)|) + \gamma^*_{12} \cdot \beta_1 (|x_{2d}(0)|) \\
&+ \gamma^*_{12} \cdot \gamma^*_2 \cdot w^*_2 + \gamma^*_1 \cdot w^*_1 + \gamma^*_1 \cdot \sigma^*_2 \\
&+ \gamma^*_2 \cdot \sigma^*_1 + \gamma^*_1 \cdot \delta_2 + \delta_1,
\end{align*}
\]

\[
\begin{align*}
sup_{t \geq 0} |y_2(t)| &\leq \beta_2 (|x_{2d}(0)|) + \gamma^*_{21} \cdot \beta_2 (|x_{1d}(0)|) \\
&+ \gamma^*_{21} \cdot \gamma^*_1 \cdot w^*_1 + \gamma^*_{12} \cdot w^*_2 + \gamma^*_2 \cdot \gamma^*_1 \cdot \sigma^*_1 + \gamma^*_{21} \cdot \sigma^*_2 \\
&+ \gamma^*_{21} \cdot \delta_1 + \delta_2.
\end{align*}
\]
2.10 Appendix II: Practical Requirements and Parameter Tuning

To implement the proposed tele-rehabilitation system, different aspects of its practical requirements were investigated. Particular attention was paid to choosing the parameters of the system to ensure its effectiveness and compatibility with the requirements. Based on consultation with specialists in the field of post-stroke rehabilitation, the following requirements were considered for parameter tuning:

**Requirement 1:** To provide a compliant/safe human-robot interaction and limit transmission of all unsmooth trajectories, it is proposed to consider a tunable viscoelastic constraint between the actions of the patient and those of the therapist.

**Requirement 2:** In addition to viscoelastic interaction, it is desirable that the therapist interacts with the patient in both position and velocity domains to assess/rehabilitate different aspects of the motor capabilities of the patient.

**Requirement 3:** During rehabilitation, therapists may wish to give more flexibility/freedom to the patient and allow for deviation from the trajectory. Also, therapists may choose an opposite scenario to provide strong hand-over-hand coordination and to minimize the allowed deviation.

**Requirement 4:** Delivering strong resistive or assistive therapies requires a relatively high level of physical power for the therapist. Therapists usually prefer to limit this amount to minimize their potential long-term musculoskeletal risks while delivering therapy on a daily basis. To address Requirements 3 and 4, an authority amplification feature is desirable.

**Requirement 5** The cost of the system can be reduced while ensuring acceptable performance by omitting the use of a force sensor in the system. This corresponds to setting ζ to...
2.10.1 Control Parameters Tuning

As mentioned in (2.43), to achieve the above-mentioned practical requirements, the following design is considered.

\[
\zeta = 0, \quad \text{and} \quad \eta(s) = -Z_s(s) + \frac{(K_s + \theta_v s)}{(as + b)}. \tag{2.51}
\]

In (2.51), \( K_s \geq 0 \), and \( \theta_v \geq 0 \) are tuning parameters of the viscoelastic impedance introduced to create compliant interaction between the therapist and the patient, and \((as + b)\) is the characteristic equation of a filter \((a, b \geq 0)\).

**Discussion I:** Here, we explain why the parameter assignment (2.51) addresses the above-mentioned requirements and how each parameter can be tuned based on a specific need. For this goal, first substitute (2.51) into the slave’s control signal (2.4). The resulting closed-loop slave subsystem has the form

\[
\frac{(K_s + \theta_v s)}{(as + b)} \left( V_{ih}(s) - \beta \cdot P(s) \cdot \dot{V}_p(s) \right) = -F_{ih}(s). \tag{2.52}
\]

Equation (2.52) describes the interaction between the therapist and the patient. Considering (2.52), the practical requirements are evaluated as follows:

- **Cost Reduction:**

Since the local force rejection gain \( \zeta \) is considered zero, the need for the force sensor is eliminated which can significantly reduce the cost. Although dropping the need for a force sensor is desirable, the motion tracking performance in the absence of the force sensor should be evaluated; and the force reflection algorithm should be also checked since a measure or estimate of the therapist’s force is still needed to be transferred to the patient’s side. This is explained below for three types of interactions (which correspond to different choices of parameters).

- **Velocity-Domain Tele-rehabilitation:**
To implement velocity-domain tele-rehabilitation, the following choice should be used in (2.52): $\theta_v = 0$, $a = 0$, and $b = 1$. In this case, the closed-loop slave subsystem is described by:

$$
\left( V_{th}(s) - \beta \cdot P(s) \cdot \hat{V}_p(s) \right) = -\frac{F_{th}(s)}{K_s}.
$$

(2.53)

Considering (2.53), it can be seen that a high value for the proposed $K_s$ (which corresponds to a strong constraint) can asymptotically eliminate the effect of the not-compensated force of the therapist and results in a high velocity tracking performance for the teleoperated system ($V_{th}(s) \rightarrow \beta \cdot P(s) \cdot \hat{V}_p(s)$) without using a force sensor and with no local force rejection control loop at the slave side. $P(s)$ and $\beta$ are the low-pass filter and velocity amplification gain introduced earlier. The formula (2.52) is also utilized to estimate the therapist’s force $F_{th}(s)$ which is transmitted to the patient’s side according to (2.3) to deliver therapy.

- **Position-Domain Tele-rehabilitation:**

Therapists often need to evaluate and challenge different parts of the patient’s hand workspace. To enable the tele-rehabilitation system for this common therapy, position tracking between the slave and master devices should be considered. This feature is called position-domain rehabilitation here. To achieve this, first consider $a$, $b$, non-zero while still keeping $\theta_v$ equal to zero, in (2.52). As a result we have:

$$
\left( V_{th}(s) - \beta \cdot P(s) \cdot \hat{V}_p(s) \right) \cdot \left( \frac{1}{as + b} \right) = -\frac{F_{th}(s)}{K_s}.
$$

(2.54)

Considering (2.54), $1/(as + b)$ acts as a low-pass filter which enables tracking in the position domain if $a \rightarrow 1$, $b \rightarrow 0$. The aforementioned choice of $a$ and $b$ makes the left side of (2.54) the position tracking error. Similar to the case of velocity-domain rehabilitation, increasing $K_s$ will asymptotically make the position tracking error equal to zero.

- **Compliant Visco-Elastic-Domain Tele-rehabilitation:**

As mentioned earlier, to provide safe and compliant interaction between the therapist and the patient, it is required to have compliant coupling. For this goal, consider $a$, $b$, and $\theta_v$ as nonzero values in (2.52). This allows for tuning the viscoelastic coupling between the therapist and the
patient. In this context, $K_s$ changes the elasticity and $\theta_v$ tunes the viscosity. By implementing the visco-elastic-domain tele-rehabilitation, the therapist’s force is calculated from

$$\left(\frac{K_s + \theta_v}{a+b}\right) \left(V_{th}(s) - \beta \cdot P(s) \cdot \dot{V}_p(s)\right) = -F_{th}(s), \quad \text{where} \quad a, b, K_s, \theta_v > 0.$$  \hspace{1cm} (2.55)

As a result, the system parameters can be tuned to achieve desirable compliances. The designed viscoelastic-domain is the most inclusive case and it can be easily switched to position-domain or velocity-domain tele-rehabilitation by changing the parameters $(a, b, K_s, \theta_v)$.

- **Therapist’s Authority Amplification**:

The proposed system allows the therapist to change $K_s$ in real-time by moving the vertical degree of freedom ($Z_{axis}$) of the slave robot as an input from the therapist. This allows the therapist to modify the authority of his/her actions and gradually change the type of therapy from rigid hand-over-hand coordination to free-motion and vice versa. In other words, this allows the therapist to change the characteristics of the viscoelastic constraint. To give an intuitive feel of the provided authority, a kinesthetic cueing force is applied to the therapist’s hand in the $Z_{axis}$ direction proportional to the amplification/reduction factor.
Bibliography


Chapter 3

A Passivity-based approach for Stable Patient-Robot Interaction in Haptics-enabled Rehabilitation Systems: Modulated Time-domain Passivity Control (M-TDPC)

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3.1 Introduction and Preliminaries

Based on the World Health Organization statistics and according to epidemiology studies, there are more than 15 million people who experience stroke each year [1], [2]. In addition, official numbers show that the population of senior adults are rapidly increasing and is expected to be more than double by 2050 compared to the numbers in 2013 [3]. This fact is called society
ageing, which directly increases the incidence of age-related conditions including post-stroke motor disabilities. The affected population require labour-intensive motor therapy services for extended periods which places a significant burden on therapists and healthcare systems. In many cases, the only offered service is limited and often delayed outpatient therapy. The situation is worse for patients in remote areas with limited access to sophisticated rehabilitation clinics [4]. One solution is to develop cloud-based technologies that provide efficient, optimal and affordable means of in-hospital and in-home rehabilitation to help patients regain their lost motor functions through utilizing Neural Plasticity (NP). NP is brain remodeling that happens in chemical (synaptic) and structural (non-synaptic) levels and can result in regaining lost motor functions and enhancement of standard sensorimotor performance metrics in post-stroke patients [5, 6]. In this context, Haptics-enabled Robotic Rehabilitation (HRR) has been demonstrated to accelerate NP and neural recovery [7–9].

There are two types of therapeutic procedures that can be delivered using HRR systems: (a) Assistive Therapy (AT), mostly administered in early stages of rehabilitation, and (b) Resistive Therapy (RT), mostly considered for later stages of therapy. During the AT, the haptic robot helps patients to perform task-based movements that need high power/force, large motion range and good targeting accuracy. AT is mostly applied in order to trigger and accelerate NP. During RT, the haptic robot resists the movements initiated by the patient [7, 9] with the goal of helping patients to develop and equalize musculoskeletal strength.
Conventional HRR systems are composed of three major components: (a) a powerful haptic robot that registers the patient’s impaired limb force/motion profiles and applies the assistive/resistive forces; (b) a game-like virtual reality (VR) software environment that provides visual cues and demonstrates the desired path of motion; and (c) a Programmable Virtual Therapist (PVT) algorithm that uses the measured patient’s force/motion data and determines the needed AT/RT to be delivered to the patient’s impaired limb \[7,9,10\]. A representative HRR system used in this chapter is shown in Fig. 3.1.

Research has shown that key to an effective therapy is to modify the type, duration and intensity of exercises, considering the state and progress of the patient’s motor recovery [11]. There are some adaptive techniques proposed in the literature to tune the parameters of the PVT [12, 13] based on some sensorimotor measurements. However, direct, intuitive and interactive contribution of a human therapist is bypassed using PVT-based HRR systems. This limits the ability of the human therapist in choosing the best position/force therapeutic trajectories and tasks for patient rehabilitation and motor assessment.

In order to deal with this issue, the authors have recently proposed and simulated a bilateral Haptics-enabled Telerobotic Rehabilitation (HTR) architecture [14, 15] that can fuse the advantages of conventional HRR systems and the skills of a human therapist in the loop and provide patients with an “augmented” therapeutic environment instead of virtual therapy. The concept is close to comparing the augmented reality over virtual reality, thus we proposed to call HTR an augmented therapy framework. A schematic of the implemented HTR system, including the proposed stabilizer (which will be explain later), is given in Fig. 3.2. By virtue of telerobotics-aided telepresence, HTR also enables remote/in-home assessment and therapy delivery for post-stroke patients. This directly responds to a need of patients in areas far from sophisticated rehabilitation centres and is helpful given the current trend in modern healthcare systems to embrace the possibilities offered by “telemedicine” (providing medical services and stroke cares over distance to enhance accessibility) [4], [16], [17].

Besides clear advantages to the use of HRR and HTR technologies for in-clinic and in-home assessment and rehabilitation, the safety of human-robot interactions (and specifically patient-robot interaction) could be a major concern [13], which should be considered, studied and guaranteed in an appropriate manner, while maximizing the system transparency and ef-
fectiveness. Realizing the aforementioned need is more challenging when high control efforts are needed for a patient during rehabilitation to deliver a prescribed therapy (especially when the system is used for in-home usages). To make it more clear, consider a patient who has unbalanced high tone of muscular system (this condition is a common side effect of stroke). In order to assist this patient in executing rehabilitation exercises (such as workspace stretching during object tracking), it is needed to apply high forces compare to a patient who does not have this symptom. In this case, the behavior of the rehabilitative system should be different for these two patients while the stability must be guaranteed for both. Also, as shown in the rest of this chapter, assistive forces generated by a remote human or a cloud-based software result in a nonpassive interconnection which can potentially challenge the stability. Consequently, proper stability analysis and development of new stabilization techniques which perform minimal transparency modification is a practical need. In this chapter, the mentioned concern is studied for haptics-enabled systems (specifically for HRR and HTR architectures). We study and guarantee patient-robot interaction safety using a novel passivity-based technique entitled Modulated Time Domain Passivity Control (M-TDPC), which can optimize the delivered transparency by utilizing the passivity characteristics of the user’s hand biomechanics, while guaranteeing stability. For this purpose first a new stability condition is developed, in the context of SPT. Then, the proposed M-TDPC approach is defined. The stability condition shows that under specific quantifiable conditions, it is possible to avoid applying damping into the interconnection, during the operation, while still guarantee the system stability regardless of nonpassivity of the communication and/or the environment.

The rest of this chapter is organized as follows. In Section 3.2 the motivation and an overview of the proposed M-TDPC technique are given. In Section 3.3 the mathematical modeling and transparency analysis are presented. In Section 3.4 the therapy passivity is analyzed. In Section 3.5 the proposed stability analysis for assistive and resistive therapies is introduced. In Section 3.6 the M-TDPC stabilizing scheme is explained. Simulations results are given in Section 3.7 and the experimental evaluations are presented in Section 3.8. Finally, the chapter is concluded in Section 3.9.
3.2 Motivation and Overview of M-TDPC Scheme

The propose M-TDPC technique answers how one can minimally adjust the intensity of the potentially nonpassive therapeutic interventions prescribed by the virtual/human therapist in an HRR/HTR system (in the context of SPT) to ensure patient safety and human-robot interaction stability. The proposed controller is a new member of the family of state-of-the-art TDPC controllers [19], [20], [21]. In this chapter, we will show how to utilize biomechanical characteristics of the user’s hand, in the context of SPT [22], to deliver patient-specific customized therapeutic forces that can guarantee the system stability and causes minimal disruptions to transparency.

Note that some of the stabilizers developed in the literature such as the wave variable approach are composed of two transformations: one before the communication channel and one after. If the delay in the system converges to zero, the two transformations cancel each other out to keep the transparency ideal. However, in this chapter, we need the controller to be functional even if the delay is zero since there is a second source of nonpassivity in the system under study (which can be due to assistive could-based virtual software or a human therapist in the loop or a combination of the two). This has been realized by the proposed M-TDPC approach, which can deal with both delay-induced and environment-induced nonpassivities separately and simultaneously.
The proposed M-TDPC approach is also motivated by ensuring human-robot interaction stability without imposing the pre-fixed conservative saturating force caps (such as those in [8], [23]). Using M-TDPC the haptic rehabilitation robot will be able to apply maximum forces considering the specific biomechanical capabilities of the patient’s limb in absorbing therapeutic energies. This promises to result in therapeutic interventions much closer to those prescribed.

The design framework is based on the core hypothesis that “when there is nonpassivity in haptics-enabled rehabilitation systems (HRR and HTR) caused by (a) the nonpassive behavior of a virtual/human therapist and/or (b) the delayed communication network, the closed-loop haptics-enabled system remains passive and stable if the quantifiable Excess of Passivity (EOP) of the nonlinear biomechanical impedance of the patient’s limb can compensate for the total Shortage of Passivity (SOP) caused by the aforementioned nonpassivities”. The hypothesis is validated in this chapter in the context of SPT.

This principle is then used to design the M-TDPC strategy that (a) identifies the EOP of the patient’s limb prior to the therapeutic task execution, (b) monitors the extent of nonpassivity of the administered therapy delivered through the communication network during the operation, (c) calculates in real-time the “minimum necessary” energy, to be damped by the proposed controller, and (d) injects a time-varying damping factor to compensate for the energy. The controller keeps the injected damping as small as possible, using the identified patient’s limb EOP, causes minimal alterations to the prescribed therapy and allows the nonpassive energy (i.e., therapeutic assistance) to optimally flow from the (virtual or actual) therapist to the patient.

The M-TDPC technique can not only be used for (a) HRR and HTR systems (to relax the limitation on the therapy intensity and passivity and deal with potential delays), but can also be used for (b) conventional haptic interactions (to deal with the delay-induced instabilities and enhance the system transparency).
3.3 System Modeling and Transparency Analysis

In order to model human-robot interaction to analyze the stability and implement appropriate stabilizing controller for high-intensity therapy, transparent two-channel bilateral model [24] is considered which is an extension of Lawrence’s four-channel architecture [25]. For both the HTR and HRR architectures, the patient is at the master robot to allow him/her to apply different motion trajectories. Also, for the HTR architecture, the human therapist is at the slave robot so that he/she can feel the patient’s motions and provide resistive/assistive forces in response in order to administer the desired therapy. For the case of HRR architecture, software-based therapy is provided by a virtual environment that generates therapeutic forces in response to the measured patient’s movements. The virtual-reality environment provides visual cues for the patient using a head-mounted display or a table-top screen.

3.3.1 Local Interaction Modeling

In this subsection, the models considered regarding (a) patient-robot interaction for both HTR and HRR architectures, (b) therapist-robot interaction for HTR architecture, and (c) virtual therapist for HRR architecture are presented.

- **Patient-robot Interaction**

A local feedback linearization algorithm [26] is considered for the master robot to compensate for nonlinear dynamics of the robot. As a result, the linearized model for the Patient-Robot (P-R) interaction are

\[ z_m(t) \ast v_p(t) = u_{cm}(t) + f_p(t) \]  \hspace{1cm} (3.1)

In (3.1), \( t \) is time, \( \ast \) is the convolution operator, \( z_m(t) \) is the impulse response of the linearized master robot dynamics, \( u_{cm}(t) \) is the control input for the master robot delivering needed therapy, \( v_p(t) \) is the patient’s hand velocity, and \( f_p(t) \) is the force applied by the patient to the master robot. The patient’s force can be decomposed into “voluntary”, i.e. \( f_p^*(t) \), and “reactive”, i.e. \( f_{react}(t) \), components as

\[ f_p(t) = f_p^*(t) - f_{react}(t), \text{ where } f_{react} = z_p(v_p, t) \]  \hspace{1cm} (3.2)
In (3.2), \( z_p(v_p,t) \) is the non-autonomous nonlinear impedance model considered for the mechanical reaction of the patient’s limb in response to the master robot movements. This relaxes the conventional assumption on linearity of the operator’s hand, which is not the case in practical situations. Also, \( f_p^*(t) \) is the voluntary component of force applied by the musculoskeletal system of the patient’s hand to generate motion and perform tasks. The other possible representation of the aforementioned patient’s force decomposition is admittance notation, given in

\[
v_p = \Omega_p(f_p^*(t) - f_p(t),t)
\]  

(3.3)

*Therapist-Robot Interaction*

This part focuses on the dynamical behavior of the in-the-loop human therapist for the HTR architecture. A general model is considered for the therapist’s behavior to cover a wide range of nonlinear, non-autonomous and nonpassive dynamical effects of the therapists, in realistic cases. Placing the human therapist at the slave side of the tele-rehabilitation system allows him/her to intuitively assist/resist patient’s trajectories based on his/her therapeutic skills. Same as the master side, a local feedback linearization algorithm is considered for the slave robot to compensate for the robot nonlinearities. The Therapist-Robot (T-R) interaction model is

\[
z_s(t) * v_{th}(t) = u_{cs}(t) + f_{th}(t),
\]  

(3.4)

where \( z_s(t) \) is the impulse response of the linearized slave robot’s dynamics, \( u_{cs}(t) \) is the control input for the slave robot, \( v_{th}(t) \) is the therapist’s hand velocity, and \( f_{th}(t) \) is the force, applied by the therapist to the slave robot in order to administer therapy. The therapist’s force model is

\[
f_{th}(t) = z_{th}(v_{th}(t),f_p^*(t),t)
\]  

(3.5)

In (3.5), \( z_{th} \) is the nonlinear non-autonomous reaction provided by the therapist to deliver a therapeutic response. In this chapter, \( z_{th} \) is called “therapeutic reaction dynamics” and is function of the delivered movement to the therapist by the slave robot \( v_{th} \), the exogenous force of the therapist \( f_{th}^* \), and time. \( f_{th}^* \) can be considered as an additive term. During a therapy session, the therapist tunes her/his reaction \( z_{th} \) to generate a desirable therapeutic response based on the
patient’s need. This behavior can result in either dissipating the energy provided for the therapist (when the therapist is performing a resistive therapy), or elevating the provided energy to perform faster/larger movements (when the therapist is performing an assistive therapy). That is why resistive therapy is passive in contrast to assistive therapy (more discussions are given later in this chapter).

- **Considered Modeling Assumptions**

As a result of the defined interaction models, the following assumptions are considered to analyze the stability of the system and design stabilizer for realistic conditions:

1. The therapist is allowed to behave as a nonpassive dynamical terminal for the interconnection. This enables him/her to inject energy into the interaction as is needed in assistive therapy.

2. The therapist can behave as a nonlinear non-autonomous system. This enables him/her to administer various types of therapy, tune the therapy intensity, and switch between different therapeutic regimes.

3. The reaction component of the patient’s hand $z_p(v_{th}, t)$ is considered to be a passive nonlinear non-autonomous mechanical system. This model is in agreement with the one introduced in [27]. Special case for $z_p(v_{th}, t)$ is the common passive mass-spring-damper model widely used in the literature to model the dynamical reaction of human upper-limb [28–31]. In this work no restriction is considered for linearity of $z_p(v_{th}, t)$ to analyze/guarantee the stability in a more realistic condition.

4. The communication network can be subject to time-varying delays (which is the conventional source of nonpassivity in haptics-enabled systems).

- **The Case of Virtual Therapist**

The virtual therapist model is in fact a subcategory of the above-given therapist-robot interaction dynamics where there is no slave robot. Instead of having a general nonlinear model for a human therapist $z_{th}$ we have a multiplicative linear model (defined below) that generates
therapeutic forces. Similar to the behavior of a human therapist, there are two major types of virtual therapy that can be programmed, namely, resistive and assistive therapies. For resistive virtual therapy in HRR systems, the therapist’s side model is

\[ f_{th}(t) = D_{th}(t) \cdot v_{th}(t) \quad \text{where} \quad v_{th}(t) = \dot{v}_{p}(t), \quad D_{th}(t) < 0 \] (3.6)

In (3.6), \( f_{th}(t) \) is the therapeutic force generated by the programmed virtual therapist in response to the measured patient’s hand movement \( \dot{v}_{p}(t) \); \( D_{th}(t) \) is the therapeutic intensity gain which is negative for the case of Resistive Therapy (RT), when the patient feels a viscous interaction resisting against her/his movement.

For the case of assistance, two different behaviors can be programmed, namely, Power Assistive Therapy (PAT) and Coordination Assistive Therapy (CAT). For PAT, we have

\[ f_{th}(t) = D_{th}(t) \cdot v_{th}(t) \quad \text{where} \quad v_{th}(t) = \dot{v}_{p}(t), \quad D_{th}(t) > 0 \] (3.7)

Positive values for \( D_{th}(t) \) lets the patient feel amplified power while providing movements and performing tasks. Using PAT, the system provides assistive forces in the same direction as that of the patient’s movements. As a result, the patient with reduced muscular power can perform tasks require higher power, larger workspace, and faster motions.

For the second type of assistance (CAT), the goal is to coordinate the patient’s movements towards the desirable path of therapy. This is useful when patients have coordination deficits due to stroke. CAT provides patients with a correct model of sensorimotor fusion during task performance. The therapist-side interaction model for CAT is

\[ f_{th}(t) = D_{th}(t) \cdot e_{th}(t), \quad D_{th} \geq 0 \]
\[ \text{where:} \quad e_{th}(t) = x_{\text{goal}}^*(t) - x_{th}(t), \]
\[ x_{th}(t) = \int_{0}^{t} v_{th}(\tau) \, d\tau, \]
\[ \text{and} \quad v_{th}(t) = \dot{v}_{p}(t). \] (3.8)

In (3.8), \( x_{\text{goal}}^* \) is the varying target position displayed to the patient, and the therapeutic intensity gain \( D_{th} \) is a corrective factor that makes the patient movement follow the target.
3.3.2 Transparency Analysis

In order to provide the patient with high-fidelity administered therapy and the therapist (for the case of HTR) with an accurate feel of the patient’s limb movement trajectories, a two-channel transparent teleoperation architecture, proposed by the authors in [24], is considered. The utilized architecture is a modification of the Lawrence’s four-channel scheme [25], which uses the minimum number of communication channels (two) while guaranteeing the system’s transparency. To implement the aforementioned architecture, the control signals $u_{cm}(t)$ is designed at the master side (for both HTR and HRR systems) as

$$u_{cm}(t) = c_1(t) \cdot v_p(t) + \hat{f}_{th}(t) \quad \text{where} \quad c_1(t) = z_m(t). \quad (3.9)$$

Also, the control signal $u_{cs}(t)$ is implemented at the slave side for the case of HTR system as

$$u_{cs}(t) = -f_{th}(t) + c_2(t) \cdot \hat{v}_p(t) \quad \text{where} \quad c_2(t) = z_s(t). \quad (3.10)$$

In (3.9) and (3.10), $\hat{f}_{th}(s)$ is the delayed received therapeutic force at the patient-side, sent through the first (slave to master) communication channel, and $\hat{v}_p(t)$ is the received patient’s hand velocity at the therapist-side, sent through the second (master to slave) communication channel. In order to enable the case of remote rehabilitation, the communication is considered subjected to time-varying delays defined by $\tau_1(t)$ for the first channel and by $\tau_2(t)$ for the second channel. Consequently, we have $\hat{f}_{th}(t) = f_{th}(t - \tau_1(t))$, and $\hat{v}_p(t) = v_p(t - \tau_2(t))$. The schematic of the designed transparent two-channel haptics-enabled architecture for the case of HTR is given in Fig. 3.3.

It should be noted that for conventional HRR systems, $\tau_1(t)$ and $\tau_2(t)$ might be zero. However, considering the recent tendency in the literature for implementing internet-based cloud rehabilitation systems [32] and to keep the generality of the technique, in this chapter, we have considered $\tau_1(t)$ and $\tau_2(t)$ to have non-zero values for both HRR and HTR systems. Combining the control signals defined in (3.9) and (3.10) with the dynamics of the master and slave robots given in (3.1) and (3.4), for the HTR architecture, the force-feedback transparency and
velocity tracking of the teleoperation system can be shown as

\[ f_p(t) = -\hat{f}_{th}(t), \quad (3.11) \]

\[ v_{th}(t) = \hat{v}_p(t). \quad (3.12) \]

For HRR systems, force-feedback transparency (3.11) can be achieved through similar calculations based on the defined \( u_{cm}(t) \) given in (3.9). In addition, velocity tracking (3.12) is set through software for HRR systems as there is no slave robot at the therapist’s side.

Consequently, the resulting dynamics for both HTR and HRR systems is a two-channel interconnection (shown in Fig. 3.4) between the admittance model of the patient’s dynamics \( \Sigma_3 \) and impedance model of the therapist’s reaction dynamics \( \Sigma_0 \), communication through the network. Note that the admittance \( \Sigma_3 \) has force as input and motion as output and is defined by (3.3) as \( \Omega_p \). Also, the impedance model \( \Sigma_0 \) has motion as input and force as output, and is defined by (3.5) for HTR, by (3.6) for HRR-RT, by (3.7) for HRR-PAT, and by (3.8) for HRR-CAT. As shown in Fig. 3.4, the sources of potential nonpassivity (therapist’s behavior and communication delays) can be bundled as the therapy terminal \( \Sigma_1 \). This enables us to analyze the HTR and HRR interconnections from the perspective of input-output energy exchange between \( \Sigma_1 \) and \( \Sigma_3 \). As a result, in the rest of this chapter, we will focus on the inclusive interconnection shown in Fig. 3.4 and will developed the stability condition and stabilizing scheme for this interconnection. Consequently, studying the interconnection shown in Fig. 3.4...
3.4 Passivity Evaluation for Assistive/Resistive Therapies

In order to resist a patient’s movements, the therapist needs to dissipate the energy provided by the patient. This results in giving the patient feel of moving in a viscous environment. Also, in order to assist movements of a disabled patient, the therapist needs to elevate the energy by injecting it into the interconnection to allow for having faster movements, higher workspaces and more accurate task executions.

Intuitively speaking, it can be said that energy dissipation during resistive therapy is passive, while energy elevation resulting from assistive therapy is nonpassive. To show this concept, in this section, we mathematically evaluate PAT, CAT and RT cases using the developed models for HRR presented in the previous section. The goal is to show differences between the nature of resistance and that of assistance by analyzing their energy characteristics. The main statement of this section is: resistive therapy is passive by its nature and assistive therapy is either nonpassive or potentially-nonpassive.
To show this, first, the mathematical definition of a passive system with input vector $u_{in}(t)$, output vector $y_{out}(t)$, and initial energy $\beta$ at $t = 0$ is [22]:

**Definition 1.** If there is a constant $\beta$ such that for all $t \geq 0$ we have

$$\int_{0}^{t} u_{in}(\tau)^{T} \cdot y_{out}(\tau) \, d\tau \geq \beta,$$

(3.13)

the system is passive. ●

First, consider the therapy terminal $\Sigma_1$ in Fig. 3.4. To focus on studying the passivity of therapies, the communication time delays ($\tau_1(t)$ and $\tau_2(t)$) are considered zero. Also, we assume that the system starts from a rest condition, so the initial energy $\beta$ is considered to be zero. Note that for $\Sigma_1$, we have $u_{in} = v_p$ and $y_{out} = f_p$. Consequently, considering (3.11), (3.12), and (3.13), the passivity of $\Sigma_1$ can be evaluated by determining the sign of

$$\int_{0}^{t} -f_{th}(\tau)^{T} \cdot v_{th}(\tau) \, d\tau.$$

(3.14)

Combining (3.14) and model (3.6), defined for PAT and RT, we have:

$$\int_{0}^{t} -f_{th}(\tau)^{T} \cdot v_{th}(\tau) \, d\tau =$$

$$\int_{0}^{t} -v_{th}(\tau)^{T} \cdot D_{th}(\tau)^{T} \cdot v_{th}(\tau) \, d\tau.$$

(3.15)

Considering (3.15) and assigning negative definite diagonal $D_{th}$ for resistive behaviors results in positive sign for the integral in (3.14). This means that, the resistive behavior of a therapist dissipates energy of the system and it is passive (considering the definition of passive systems (3.13)). Similar calculations can be performed for PAT where we have positive definite $D_{th}$. This results in having negative value for the integral in (3.14), which means that PAT injects energy into the system and is nonpassive.

For the case of CAT, we have

$$\int_{0}^{t} -f_{th}(\tau)^{T} \cdot v_{th}(\tau) \, d\tau =$$

$$\int_{0}^{t} -e_{th}(\tau)^{T} \cdot D_{th}(\tau)^{T} \cdot v_{th}(\tau) \, d\tau.$$

(3.16)

In this case, the sign of the passivity integral can not be defined and is directly related to the
sign of tracking error $e_{th}$ (which can be positive or negative in each time stamp) and the history of it. As a result, it is not possible to assign a definite sign for the passivity integral which means that the system can inject energy into the interconnection and challenge the stability of the system. Consequently, CAT is potentially nonpassive.

In summary, the natures of increasing the power during task performance or coordinating the patient during rehabilitation can render therapy terminal $\Sigma_1$ nonpassive and challenge the stability of the system, even if the communication delay is zero. In contrast, resistive therapy dissipates the interconnection energy as a passive component.

It should be noted that in the presence of the communication delays, there will be two sources of nonpassivity in the system. As mentioned earlier, in this chapter both possible sources of nonpassivity are bundled into the one-port therapy terminal $\Sigma_1$. In Section 3.5, a new framework will be proposed that allows for evaluating the stability condition of the system even if $\Sigma_1$ is nonpassive. Then in Section 3.6 the framework will be used to develop the proposed stabilizing scheme (M-TDPC).

It should be highlighted that since the analysis and stabilizing schemes proposed in this chapter account for any nonpassive behavior of $\Sigma_1$, not only they can be used for nonpassive rehabilitation systems, but also they can be used for conventional time-delayed telerobotic architectures and haptics systems to handle delay-induced instability.

### 3.5 Proposed Stability Analysis Framework Using EOP/SOP Definitions

Considering Fig. 3.4, in order to analyze the stability of the system and calculate the stability condition of the interconnection in the presence of nonpassive $\Sigma_1$, the following hypothesis is proposed and mathematically proven in this section:

**Hypothesis 1.** When there is a nonpassive therapy terminal ($\Sigma_1$) in a haptics-enabled rehabilitation system due to (a) nonpassive behavior of a therapist and/or (b) nonpassive communication network, the closed-loop system can still remain stable if the excess of passivity of the patient’s limb mechanical dynamics can compensate for the shortage of passivity of the therapy terminal $\Sigma_1$. •
The remainder of this section focuses on how this hypothesis can be mathematically proven. It should be noted that, there is an important difference between the conventional use of passivity theory and the way used in this chapter based on SPT, as discussed below.

**Remark 3.1.** In the conventional use of passivity theory \([22, 33]\), assuming passive operator and environment terminations for a haptics-enabled system, ensuring the communication passivity provides an interconnection of cascaded passive subsystems, which remains stable. This is called the Weak Passivity Theorem (WPT), which is widely used in the literature of conventional telerobotic systems \([21]\) to analyze and guarantee system stability \([34]\). The communication delay is considered to be the sole source of nonpassivity in this regard. However, for the case of assistive HTR and HRR systems, even if the communication channel is ideally passive, the passivity of the resulting cascaded interconnection \(\Sigma_2\) is not guaranteed because \(\Sigma_1\) is still nonpassive. •

**Remark 3.2.** Contrary to conventional haptics-enabled teleoperation systems, the nonpassive behavior caused by assistive therapy is exactly what is needed for therapeutic application, should not be interpreted as an unwanted, and should not be cancelled out by the control system. It is counterproductive to separately passify the nonpassive therapist since it defeats the very purpose of power assistance and coordination by damping all the needed therapeutic energy. Consequently, to preserve the patient-robot interconnection safety while still allowing the nonpassive therapy terminal \(\Sigma_1\) to inject energy, the passivity of the entire interconnection \(\Sigma_2\) should be analyzed (instead of passivity of isolated components considered in WPT-based approaches). This has correlations with the definition of the SPT given in \([22, 35]\) and utilized in this chapter to analyze and guarantee the entire system’s passivity. •

For this goal and to validate Hypothesis I, first the mathematical definitions of input-passive modeling, output-passive modeling, EOP and SOP for a system with input vector \(u_{in}(t)\), output vector \(y_{out}(t)\), and initial energy \(\beta\) at \(t = 0\) are taken from \([22, 36, 37]\), as given below. Note that the system is considered to be square which means that the number of inputs and outputs are equal.

**Definition II.** If there is a constant \(\beta\) such that for all \(t \geq 0\) we have

\[
\int_0^t u_{in}(\tau)^T \cdot y_{out}(\tau) d\tau \geq \beta + \delta \int_0^t u_{in}(\tau)^T \cdot u_{in}(\tau) d\tau,
\]

(3.17)
for $\delta \geq 0$, the system is Input Strictly Passive (ISP) with an excess of passivity (EOP) equal to $\delta$. Also, if we have $\delta < 0$, the system is Input Nonpassive (INP) with the Shortage of Passivity (SOP) of $\delta$. •

**Definition III.** If there is a constant $\beta$ such that for all $t \geq 0$ we have

$$
\int_0^t u_i(\tau)^T \cdot y_{out}(\tau) d\tau \geq \beta + \xi \cdot \int_0^t y_{out}(\tau)^T \cdot y_{out}(\tau) d\tau,
$$

(3.18)

for $\xi \geq 0$, the system is Output Strictly Passive (OSP) and the EOP is $\xi$. Also if we have $\xi < 0$, the system is Output Nonpassive (ONP) and the SOP is $\xi$. •

**Remark 3.3.** It has been shown that passive systems (including ISP and OSP) are asymptotically stable. In addition, an OSP systems is also $L_2$ stable with finite $L_2$ gain less than or equal to $1/\xi$, where $\xi$ is the EOP of the OSP model [26]. The mathematical description of $L_2$ stability for an OSP system is given below (where $\alpha_0 \geq 0$ is related to the initial energy and is zero in this chapter since the system is assumed to start from rest):

$$
\|y_o(t)\|_{L_2} \leq \frac{1}{\xi} \cdot \|u_i(t)\|_{L_2} + \alpha_0.
$$

(3.19)

Considering (3.19), $\xi$ defines an upper-bound on the energy of the system’s output, based on the input energy. •

In order to validate Hypothesis I, consider the entire system as the one-port network $\Sigma_2$ shown in Fig. 3.4. $\Sigma_2$ consists of a nonpassive therapy-terminal impedance $\Sigma_1$ and a passive patient’s reaction admittance $\Sigma_3$. The exogenous force $f_p^e(t)$ is the input for $\Sigma_2$ and the velocity of the patient’s hand $v_p(t)$ is the response to this input. Consequently, considering (3.13), to first guarantee the passivity of the entire interconnection, the following passivity condition should be held (assuming the initial energy at $t = 0$ is zero):

$$
\int_0^t f_p^e(\tau)^T \cdot v_p(\tau) d\tau \geq 0,
$$

(3.20)
Considering (3.20) and the force decomposition (3.2), we have
\[
\int_0^t f_p^* (\tau) \cdot v_p (\tau) d\tau = \int_0^t f_p (\tau) \cdot v_p (\tau) d\tau + \int_0^t f_{\text{react}} (\tau) \cdot v_p (\tau) d\tau.
\] (3.21)

As a result, the passivity condition for the entire system $\Sigma_2$ can be evaluated by the following passivity integral:
\[
\int_0^t f_p (\tau) \cdot v_p (\tau) d\tau + \int_0^t f_{\text{react}} (\tau) \cdot v_p (\tau) d\tau \geq 0.
\] (3.22)

It can be seen from Fig. 3.4 that $\int_0^t f_{\text{react}} (\tau) \cdot v_p (\tau) d\tau$ is the passivity integral of the patient’s hand reaction dynamics $\Sigma_3$ and $\int_0^t f_p (\tau) \cdot v_p (\tau) d\tau$ is the passivity integral of the therapy terminal $\Sigma_1$. Consequently, considering the passivity condition (3.22), if the therapy terminal $\Sigma_1$ behaves as a nonpassive system, the entire system $\Sigma_2$ can still remain passive if the energy of patient hand’s reaction dynamics, i.e. $\int_0^t f_{\text{react}} (\tau) \cdot v_p (\tau) d\tau$, can compensate for the energy injected by the therapy terminal.

Considering the passivity condition (3.22) and the definition of $L_2$ stability given in Remark 3.3 when initial energy at $t = 0$ is zero, we have

the entire system $\Sigma_2$ is $L_2$ stable if $\exists \xi_r > 0$ s.t.
\[
\int_0^t f_p (\tau) \cdot v_p (\tau) d\tau + \int_0^t f_{\text{react}} (\tau) \cdot v_p (\tau) d\tau \geq \xi_r \cdot \int_0^t v_p (\tau) \cdot v_p (\tau) d\tau.
\] (3.23)

Consequently, if (3.23) is satisfied and the input energy provided to the entire system through $f_p^*$ is bounded, the output energy of the entire system will remain bounded and the system $\Sigma_2$ will remain $L_2$ stable.

Let us consider an INP model for the therapy terminal impedance $\Sigma_1$ with shortage of passivity of $\hat{\delta}_h \leq 0$ as
\[
\int_0^t f_p (\tau) \cdot v_p (\tau) d\tau \geq \hat{\delta}_h \cdot \int_0^t v_p (\tau) \cdot v_p (\tau) d\tau,
\] s.t. $\hat{\delta}_h \leq 0$.
(3.24)
and an OSP model for the patient reaction admittance $\Sigma_3$ with excess of passivity $\xi_p \geq 0$ as

\[
\int_0^t f_{\text{react}}(\tau) \cdot v_p(\tau) \, d\tau \geq \xi_p \cdot \int_0^t v_p(\tau)^T \cdot v_p(\tau) \, d\tau,
\]

\[\text{s.t. } \xi_p \geq 0. \tag{3.25}\]

Combining (3.23), (3.24), and (3.25) the following will result:

the entire interconnection $\Sigma_2$ is $L_2$ stable if

\[
(\xi_p + \hat{\delta}_h - \xi_r) \cdot \int_0^t v_p(\tau)^T \cdot v_p(\tau) \, d\tau \geq 0
\]

Considering (3.26) and a small positive arbitrary value $\xi_r$, the novel $L_2$ stability condition of the entire system $\Sigma_2$ is

\[
\xi_p + \hat{\delta}_h - \xi_r \geq 0 \tag{3.27}
\]

This validates Hypothesis I that is a new analysis of stability for haptics-enabled systems. It should be noted that in (3.27), $\xi_r$ is a tunable factor that defines a flexible stability margin for the system. Higher values for $\xi_r$ provide a more conservative stability condition for the system which can be used if uncertainty in the system dynamics is considerable.

As a result, the entire system $\Sigma_2$ will remain $L_2$ stable with the stability margin $\xi_r$, if the EOP of the reaction dynamics of the patient’s hand $\Sigma_3$ can compensate for the SOP of the therapy terminal $\Sigma_1$. This result is in strong agreement with that reported in [27] which highlights the effect of linear damping of an operator’s arm on the stability margin of a teleoperated system.

Based on (3.27), the minimum required value for the EOP of the patient’s limb is $\xi_p > |\xi_r| + |\hat{\delta}_h|$. If the above-mentioned condition is not satisfied, damping should be added to compensate only for the extra energy not dissipated by the EOP of the patient’s limb. In the next section, the M-TDPC approach is proposed to stabilize the system, when the stability condition (3.27) is not met due to insufficient EOP. The approach, customizes the delivered therapeutic energy to achieve the performance goals.

**Remark 3.4.** Note that the EOP of a person’s hand is the capabilities of his/her limb in absorbing the interactive energies, and is linked to the biomechanical characteristics of the corresponding limb. As a result, if a patient has a rigid or spastic hand with high muscular
activity tone (a common symptom of stroke), he/she has a higher EOP compared to a patient with softer limbs. •

3.6 Proposed Stabilizing Control Design: M-TDPC Scheme

In this section, the proposed control scheme is presented, which is capable of guaranteeing stability of the system when the stability condition (3.27) is not satisfied. The controller is a new member of the TDPC approach family and is named M-TDPC. The goal is to utilize the biomechanics of the patient’s hand to enhance transparency while allowing the nonpassive assistive energy to flow and ensuring passivity and stability of the entire system. The philosophy of the proposed M-TDPC controller is to provide the minimum necessary damping injection, taking advantage of our knowledge about the EOP of the patient’s hand, and is capable of eliminating just the extra energy while letting the therapist provide assistance to the patient. The proposed controller has two major components: (a) a Passivity Differential (PD) calculator, (b) a stabilizing core. The roles of the mentioned components are as follows.

3.6.1 Passivity Differential (PD) Calculator

This component of the controller is responsible to find the minimum amount of energy that results in deviation from stability condition (3.27) and needs to be dampened out. As a result, the PD calculator takes into account the EOP of the patient’s limb and the SOP of the delivered therapy to calculate the minimum amount of energy to be dampened out that guarantees stability in the context of SPT. Considering (3.26) and (3.27), let us define

\[
E_p(t) := (\xi_p - \xi_r) \cdot \int_0^t v_p(\tau)^T \cdot v_p(\tau) d\tau,
\]

\[
E_{th}(t) := \int_0^t f_p(\tau)^T \cdot v_p(\tau) d\tau,
\]

(3.28)

Based on (3.28), the PD can be calculated as

\[
PD(t) := E_p(t) + E_{th}(t).
\]

(3.29)
3.6. PROPOSED STABILIZING CONTROL DESIGN: M-TDPC SCHEME

PD represents the difference between the energy that can be damp out by the user’s limb, i.e. \( E_p(t) \), and the energy delivered by the therapist through the communication network, i.e. \( E_{th}(t) \). Based on the definition of PD given in (3.29), the Lack of Passivity (LOP) is defined as

\[
LOP(t) = \begin{cases} 
0 & \text{if } PD \geq 0 \\
PD & \text{if } PD < 0 
\end{cases} 
\]  (3.30)

Considering (3.30), if the passivity of the patient’s limb \( E_p \) can compensate for the nonpassivity of the therapy terminal \( |E_p| > |E_{th}| \), the \( LOP(t) \) is zero. This is because in this situation, there is no need to compensate for any energy, even if the therapy terminal (combination of environment and communication) is nonpassive \( E_{th} \leq 0 \). In addition to the above, \( LOP(t) \) remains zero if the therapy terminal is passive \( E_{th} > 0 \). However, if \( E_p + E_{th} \leq 0 \), which means that the EOP of the patient’s limb is not capable of providing enough dissipation to compensate for the nonpassivity of the therapy terminal, the \( LOP(t) \) will be equal to the differences between \( |E_p| \) and \( |E_{th}| \) and will have a negative sign. This defines the minimum energy required to be dampened out by the controller to keep the entire interconnection stable.

**Remark 3.5.** Considering (3.30), to calculate \( PD(t) \) and \( LOP(t) \), we need to have access to \( E_p \) and \( E_{th} \). Based on the definitions given in (3.28), \( E_{th} \) is accessible in real-time since both \( v_p \) and \( f_p \) are measurable. However, this is not the case for \( E_p \). In fact, \( E_p \) is a property of the dynamics of the patient’s limb and is a function of \( \xi_p \), which is directly related to \( f_{react} \) as can be seen in (3.25). \( f_{react} \) is not directly accessible in real-time since (3.2) is an undetermined equation. As a result, the question is: “how to identify the excess of passivity of the patient’s hand in order to calculate \( PD(t) \)?” In order to deal with this issue, we have proposed an identification technique for \( \xi_p \), as given in the next subsection.

**EOP Identifier for the Patient’s Hand :**

As mentioned, there is no direct way to quantify the EOP of the reaction dynamics of the patient’s limb, i.e., \( \xi_p \), and passivity integral \( \int_0^t f_{react}(\tau)^T \cdot v_p(\tau) d\tau \), during task performance, when the operator is applying \( f_p^* \). The aforementioned issue arises since the only measurable component of the force decomposition (3.2) is \( f_p \). Consequently, \( f_{react}(t) \) is not accessible when the exogenous force \( f_p^*(t) \) in (3.2) is not zero. As a result, during rehabilitation tasks,
Since patient is applying $f_p^*$, it is not possible to calculate $\xi_p$. In this part, an identification scheme is proposed to estimate the EOP for the reaction dynamics of the patient’s limb that can be used in the proposed PD calculator (3.29).

For this purpose, an off-line identification scheme is used before the start of the therapy. This allows us to estimate $\xi_p$ for each patient in order to customize the allowed therapeutic energy for him/her during the therapy. As a result, the proposed technique will be able to distinguish between a patient with rigid limbs versus a one who has compliment limbs. To achieve the above-mentioned goal, during the identification phase (before the start of therapy), the patient is asked to hold the robotic handle in a “relaxed” condition and let the robot perturb her/his hand. The definition of the relaxed condition and why this condition is considered will be detailed later in Remarks 3.7 and 3.8. The robot provides movements of different frequencies/trajectories while recording motion and force information.

Since during identification procedure the patient is not asked to track any trajectory, he/she does not apply exogenous forces: $f_p^* = 0$. Consequently, during the identification procedure, $\int_0^T f_{\text{react}}(\tau) \cdot v_p(\tau) d\tau = \int_0^T f_p(\tau) \cdot v_p(\tau) d\tau$, while both $f_p(t)$ and $v_p(t)$ are measured. As a result, based on (3.25) and using the collected data from the identification phase, the estimated EOP for the patient’s limb in the relaxed condition can be calculated as

$$\xi_{p - \text{relax}} = \frac{\int_0^{T_e} f_{\text{react}}(\tau) \cdot v_p(\tau) d\tau}{\int_0^{T_e} v_p(\tau) \cdot v_p(\tau) d\tau}$$

(3.31)

In (3.31), $\xi_{p - \text{relax}}$ is the estimated EOP for the patient’s limb in the relaxed condition and $T_e$ is the duration of identification procedure. Then during the rehabilitation phase, $\xi_{p - \text{relax}}$ is used in (3.28), (3.29) and (3.30) to calculate $PD(t)$ and $LOP(t)$. For this purpose, after estimating $\xi_{p - \text{relax}}$ for each patient, $PD(t)$ and $LOP(t)$ are calculated as

$$LOP(t) = \begin{cases} 
0 & \text{if } PD \geq 0 \\
PD & \text{if } \tilde{PD} < 0
\end{cases}$$

(3.32)
3.6. Proposed Stabilizing Control Design: M-TDPC Scheme

Figure 3.5: The 2D trajectories used for perturbation during the EOP identification procedure.

where \( PD(t) := E_{p-relax}(t) + E_{th}(t), \)

\[
E_{p-relax}(t) := (\xi_{p-relax} - \xi_r) \cdot \int_0^t v_p(\tau)^T \cdot v_p(\tau) \, d\tau
\] (3.33)

In (3.33), \( v_p(t) \) is the real-time measurement of the patient’s hand velocity during the rehabilitation phase and \( \xi_{p-relax} \) is the EOP of the patient’s limb in the relaxed condition and as identified during the identification phase.

**Remark 3.6.** In this work, two degrees of freedom (DOF) horizontal Cartesian perturbation is considered for the identification phase. The user’s limb is perturbed for 60 seconds, using a stimulation trajectory that is a summation of ten sinusoidal, in the range \( 0 - 3Hz \) (to cover rehabilitation requirements) with a maximum amplitude of \( 1.5 \) cm. The perturbation signal is shown in Fig 3.5.

**Remark 3.7.** The reason that the relaxed condition of the limb is considered in the identification procedure for the EOP is that the patient may vary the properties of his/her grasp during the rehabilitation phase. As a result, he/she may provide a rigid grasp at some time episodes while providing a loose grasp at some others. We need to make sure that the system performs appropriately in any condition. Consequently, we have considered the minimum EOP that can be delivered by the operator to find the minimum energy that can be observed by the patient’s limb. The minimum \( \xi_p \) happens in the relaxed condition, when the patient grasp the robotic handle in a relaxed manner. For consistency and to make sure that the patient remains in the relaxed condition, during the identification phase, a sensorized handle is constructed and connected to the end-effector of the rehabilitation robot as shown in Fig. 3.6. The relaxed condition is defined as when the grasp pressure is at a very low value (between 2% – 5% of the
user’s maximum achievable grasp pressure). The mentioned range is monitored to the patient (using a head-mounted display) and the patient is asked to keep the grasp pressure within the monitored range regardless of the motion of the robot, during the identification phase.

Remark 3.8. To illustrate the effect of grasp pressure on $\xi_p$, we have calculated the EOP for a healthy participant under an ethics approval from the University of Alberta Research Ethics Board (Study ID: Pro00033955). We have tested $\xi_p$ in two conditions: (a) relaxed condition defined above to calculate $\xi_{p-relax}$, and (b) rigid grasp condition (when the participant is asked to keep the pressure between 75% – 85% of the maximum pressure during identification) to calculate $\xi_{p-rigid}$. It is observed that increasing the grasp pressure increases the EOP of the hand to more than 400% of that in the relaxed condition (from 5.56 N.s/m for $\xi_{p-relax}$ to 25.06 N.s/m for $\xi_{p-rigid}$). In summary, $\xi_{p-relax}$ is the lower-bound for the possible EOP delivered by the patient during rehabilitation and can define the minimum energy that can be observed by the user during task execution. That is why it is considered in (3.33) to ensure stability for all possible grasp conditions.

3.6.2 Stabilizing core

The second component of the controller is responsible to compensate for the calculated the nonpassive energy which cannot be absorbed by the EOP of the patient’s limb.

In the literature, compensating for energy is done in TDPC approach [19], [20], [21], [38]. We will use the similar concept to meet the stability condition (3.22). This enables customizing
the therapeutic energy based on the biomechanical capabilities of the patient’s limb (specifically EOP of the limb). Consequently, for a patient with high EOP value of his/her limb that can absorb more therapeutic energy, the proposed controller allows more assistive energy to be delivered compared to a patient with low EOP value.

Such as all TDPC approaches (e.g., [38]) compensating for energy is done through injecting time-varying damping $\alpha(t)$ into the system, considering the derivative of the energy. The aforementioned derivative is $\frac{d}{dt}PD(t)$ in this work and is defined by $P_L(t)$ as

$$P_L(t) = \frac{d}{dt}PD(t).$$

Considering the time stamp $n$ for the current sample of signals, the proposed M-TDPC is formulated as

$$f_{th-mod}(n) = \hat{f}_{th}(n) + \alpha(n) \cdot v_p(n)$$

where $\alpha(n) = \begin{cases} 
\frac{-LOP_{obs}(n)}{\Delta T(v_p(n)^T \cdot v_p(n))} & \text{if } LOP_{obs}(n) \leq 0 \\
0 & \text{if } LOP_{obs}(n) \geq 0,
\end{cases}$

and $LOP_{obs}(n) = LOP_{obs}(n-1) + [P_L(n) + 
\alpha(n-1)v_p(n-1)^T \cdot v_p(n-1)]\Delta T.$

In (3.35), (3.36) and (3.37), $\Delta T$ is the sampling period, $\alpha$ is the designed time-varying damping implemented on the patient’s side, $f_{th-mod}$ is the modified force to be reflect to the patient’s hand, $LOP_{obs}$ is the output of the energy observer (3.37). The details regarding the stabilizing behavior of the controller is given in Appendix I (Section 3.10).

Up to this point, we have the stabilizer which is developed based on the new definition of system passivity which considers the effect of the biomechanical features of the operator’s hand and allow for delivering customized nonpassive energy. In the next step a new way of further enhancing the performance of the stabilizer is proposed.

### 3.6.3 Performance Enhancement

One of the challenges of TDPC-based techniques is potential lagged diagnosis of nonpassivity, which may ultimately result in sudden change and large control forces. In fact, when an
interconnection remains passive for a relatively long period of time, the passive energy will be accumulated in the energy reservoir of the observer. Consequently, if at some point the behavior of the interconnection changes to a nonpassive one, it may take some time for the energy observer to recognize the nonpassivity. When the nonpassivity is observed, the controller will try to compensate as quickly as possible, which can result in the mentioned behavior of the control signal. This behavior could be oscillations or sudden increase of the force input. This has been studied in the literature. For the case of rehabilitation, this situation should be analyzed and addressed exclusively as the therapist may frequently switch from resistive to assistive therapy, and vice versa.

In the literature, to deal with the aforementioned issue, the Power-domain TDPC (PTDPC) has been developed [39, 40]. The PTDPC observes the power instead of energy. Once the technique observes a negative power packet, which may challenge the passivity, it provides damping to cancel out the packet. Although this technique distributes the damping on a larger period of time, makes the control signal smoother compared to energy-domain TDPC, and resolves the issue of energy accumulation in the observer’s reservoir, it may degrade the performance [40] since it does not allow any negative power packet to flow and does not consider any part of the history of the system’s energy.

**Remark 3.9.** It should be noted that the proposed M-TDPC approach given in (3.35), (3.36), (3.37) works in the energy domain. It is possible to develop the power-domain version of the M-TDPC approach (as explained in the remaining of this section). However, if we develop the power-domain version of the proposed M-TDPC approach, when the therapist switches from passive behavior to nonpassive behavior, the power-domain version is more conservative than the energy-domain one (since it quickly starts dampening the energy of the system). However, when the behavior switches from nonpassive to passive, the energy-domain version is more conservative than the power-domain one (since it continues to dampening the energy for a period of time while the interconnection has already became passive). Consequently, both designs may have some advantages and disadvantages in the context of rehabilitation since the therapist may provide a mixed variation of resistive and assistive energies during therapy.

To address the raised concern, the corresponding design of the M-TDPC technique given in
(3.35)-(3.37) is enhanced using a new definition of energy function, entitled Windowed Energy (WE). The goal of the proposed enhancement is to consider a sliding weighted time window to calculate the energy, and provide damping if the energy of the considered window is nonpassive. The enhanced M-TDPC approach is given in (3.38)-(3.40), wherein the main difference from the original design is applying the concept of WE by adding $\Gamma_w$ in the observer’s formulation (3.40).

$$f_{ih-mod}(n) = \hat{f}_{ih}(n) + \alpha(n) \cdot v_p(n)$$  \hspace{1cm} (3.38)

where $\alpha(n) = \begin{cases} 
\frac{-LOP_{obs}(n)}{\Delta T(v_p(n)^T v_p(n))} & \text{if } LOP_{obs}(n) \leq 0 \\
0 & \text{if } LOP_{obs}(n) \geq 0, \end{cases}$  \hspace{1cm} (3.39)

$$LOP_{obs}(n) = \Gamma_w \cdot LOP_{obs}(n-1) + [P_L(n) + \Gamma_w \cdot \alpha(n-1)v_p(n-1)^T v_p(n-1)] \Delta T, \hspace{0.5cm} 0 \leq \Gamma_w \leq 1.$$  \hspace{1cm} (3.40)

Considering (3.40), if $\Gamma_w$ is equal to unity, the technique will convert to the energy-domain M-TDPC technique given in (3.35), (3.36), (3.37). If $\Gamma_w$ is equal to zero, the technique will convert to the power-domain version of the M-TDPC approach (which just accounts for power packets and not the history of the system energy). Considering an $\Gamma_w$ value between zero and unity acts as a forgetting factor for the dynamics of the observer and provides very small weights for the early power packets and higher weights for the recent packets. Tuning the $\Gamma_w$ value can change the effective width of the window (memory of the observer). In other words, for $0 < \Gamma_w < 1$, the M-TDPC approach acts quicker than the energy-domain version of it (to avoid energy accumulation issue) and slower than power-domain version. Consequently, by using $0 < \Gamma_w < 1$ (a) the behavior of the therapist in the very early periods of therapy will not change the decision on modifying therapeutic forces for later stages of procedure, (b) the controller does not eliminate all negative power packets and still considers a windowed history of the delivered therapeutic energy.

A schematic of the interaction including the stabilizer, PD calculator, and EOP estimator is shown in Fig. 3.7.
3.7 Simulation Results

In this section results of some numeric simulations are given to evaluate the performance of the stability analysis technique and the proposed controller. For this purpose two sets of simulations are presented, as follows.

3.7.1 Simulation I: Stability Analysis

In the first simulation, the derived stability condition (3.27) is evaluated. For this purpose PAT is simulated under communication delays. The SOP of the therapy is considered to be lower than the EOP of the operator for the first phase of the simulation (entitled mild assistance) and then it is considered to be higher than the EOP for the second phase (entitled strong assistance). No controller is applied to evaluate the proposed stability condition. It is expected that when the stability condition (3.27) is satisfied (the first phase) the entire system remains stable (though the therapy terminal is nonpassive due to the communication delay and the assistive behavior of the simulated therapist). Also, we expect that when the stability condition is not satisfied (the second phase) the entire system becomes unstable. The simulation parameters are given in Table 3.1, where the EOP of the patient’s hand and the SOP of the therapies, in both phases, have been calculated using the identification technique defined in the previous
3.7 Simulation Results

Table 3.1: The Simulation Parameters

<table>
<thead>
<tr>
<th>Master Robot Dynamics</th>
<th>$Z_m(s) = \frac{V_m(s)}{F_m(s)} = \frac{1}{2s + 2}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient’s hand Dynamics</td>
<td>$Z_p(s) = \frac{V_p(s)}{F_p(s)} = \frac{1}{s + 8}$</td>
</tr>
<tr>
<td>Therapist’s PAT Gain</td>
<td>First phase: $D_{th} = 4$, Second phase: $D_{th} = 16$</td>
</tr>
<tr>
<td>Communication Delay</td>
<td>$\tau_1(t) = \tau_2(t) = 80 + 10\sin(\frac{\pi}{4}t)$ ms</td>
</tr>
<tr>
<td>Exogenous Input</td>
<td>$f_p^e(t) = 2\left(\sin(0.5t) + \sin(t) - \sin(1.5t) - \sin(2t)\right)$</td>
</tr>
<tr>
<td>Sampling Time</td>
<td>$\Delta T = 0.01 s$</td>
</tr>
<tr>
<td>EOP of the Patient’s limb</td>
<td>$\xi_p = 8.05 N.s/m$</td>
</tr>
<tr>
<td>SOP of the delivered therapy</td>
<td>The first phase: $\delta_{th} = -3.92 N.s/m$ The second phase: $\delta_{th} = -15.67 N.s/m$</td>
</tr>
</tbody>
</table>

section. During both phases, the therapies start from $t = 30$. If the assistance is delivered the amplitude of velocity trajectories should become larger. For the first phase, the results of the velocity tracking and force tracking can be seen in Figs. 3.8a and 3.8b, respectively. As can be seen in Figs. 3.8a and 3.8b during mild assistance phase, since the stability condition (3.27) is satisfied, the entire system behaves in a stable manner. The velocity tracking and the force tracking results follow (3.11) and (3.12). In addition, the amplitude of the velocity trajectories are amplified due to the delivered assistive energy. The next step is to simulate the strong assistance phase when there is no controller. The corresponding velocity tracking result for the second phase is given in Fig. 3.8c. As can be seen in Fig. 3.8c during strong assistance, since the stability condition (3.27) is not satisfied and no controller is applied, the interconnection becomes unstable and the trajectories grow in an unbounded manner. This shows the necessity of having a stabilizer.

3.7.2 Simulation II: M-TDPC stabilizer

In this part, the performance of the propose M-TDPC is analyzed. For this purpose, in addition to the proposed controller, the original One-port TDPC is simulated (and named TDPC throughout the simulation). The One-port TDPC approach composed of an observer and a controller on the master side to compensate for nonpassivity of $\Sigma_1$. Both of the simulated controllers can be applied even when the communication delay is zero. In fact, this simulation
focuses on the effects of considering the EOP of the patient’s hand in the design of the TDPC-based stabilizers. The simulation conditions are the same for both controllers. For this goal, the total simulation time is considered to be 180s. In addition, for M-TDPC approach, $\Gamma_w$ and $\xi_r$ are considered to be 0.7 and 1.05, respectively. During the first 60 seconds no therapy is applied, then the resistive therapy is started considering $D_{th} = -16$, till $t = 120s$. Afterwards, the therapy is switched to strong assistance ($D_{th} = 16$). Other simulation parameters are similar to that of Simulation I. The corresponding results (velocity tracking, force tracking and energy modulation) for the cases of One-port TDPC and M-TDPC are given in Figs. 3.9 and 3.10 respectively. As can be seen in Fig. 3.9a using the TDPC approach, during the resistive phase ($60 < t < 120$), the amplitude of the velocity trajectories have been reduced in comparison to
3.7. Simulation Results

Figure 3.9: The simulation results for applying TDPC approach for resistive therapy ($60 < t < 120$) and assistive therapy ($120 < t < 180$), (a) Velocity tracking, (b) Force Modulation, and (c) Energy Modulation.

that of the no-therapy phase ($0 < t < 60$). This means that the resistive behavior is delivered, which is the goal of the therapy. Also, the TDPC technique is not considerably changing the reflected forces during resistive therapy (as in Fig. 3.9b). In Fig. 3.9c left part, the generated resistive energy at the therapist’s side is compared to the applied energy to the patient’s hand, during $60 < t < 120$. The slight difference between the energies is due to the communication delay. In other words, the TDPC approach has delivered most of the resistive energy.

However, in contrast to the resistive phase of the simulation, during the assistive phase ($120 < t < 180$), the therapy is not delivered using the One-port TDPC. This can be seen in
Figure 3.10: The simulation results for applying M-TDPC approach for resistive therapy \((60 < t < 120)\) and assistive therapy \((120 < t < 180)\), (a) Velocity tracking, (b) Force Modulation, and (c) Energy Modulation.

Fig. 3.9a, where the velocity trajectories have not become larger, in Fig. 3.9b, where the applied force is almost zero, and in Fig. 3.9c (the right figure), where the applied energy is flattened. This problem is due to the fact that the One-port TDPC approach assumed that the assistive energy is not desirable and should be dampened out.

Note that the overshoot at \(t = 120s\) is due to the energy accumulation in the observer reservoir that has been discussed in the previous section. This overshoot is excluded from the result analysis, in this simulation, but is exclusively studied in Simulation III.

Considering Fig. 3.10, during the resistive phase of the simulation \(60 < t < 120\) the be-
behavior of the propose M-TDPC approach is similar to that of the TDPC technique in Fig. 3.9. This means that the M-TDPC approach is also able to deliver resistance over communication delays, in a similar manner to one-port TDPC approach. However, using the proposed M-TDPC approach it is possible to deliver assistive energy, and simultaneously guaranteeing the interconnection stability. This fact can be seen during $120 < t < 180$ in Fig. 3.10a, where the amplitude of the velocity trajectory is considerably amplified, in Fig. 3.10b where the amplitude of the assistive force is not zero, and in Fig. 3.10c where the applied assistive energy to the patient’s hand is not flattened while the system is behaving in a stable manner. Considering Figs. 3.10b and 3.10c the force/energy modulation performed by the M-TDPC technique can be observed. In fact, the proposed controller has modified the applied energy to the patient’s hand (in comparison with the generated energy), based the capabilities of the patient’s limb in absorbing/dissipating the nonpassive therapeutic energy. As given in Table 3.1, the identified EOP of the simulated user is 8.05; considering $\xi_r = 1.05$ the proposed controller is able to guarantee the stability of the system while allowing the nonpassive energy to flow.

In Fig. 3.11, the distribution of the absolute value of the velocities during the no-therapy phase, the assistive therapy phase and the resistive therapy phase have been shown for the cases of M-TDPC approach (Case #1) and the simulated One-port TDPC approach (Case #2). Based on Fig. 3.11 using the M-TDPC approach, the resulting velocities during assistance is considerably higher than that of the no-therapy phase. However, this is not the case for the other approach.

In addition, the Force Reflection Ratio (FRR) is defined in Table 3.2. FRR is the ratio between the mean value of the modified forces over the mean value of the generated therapeutic forces. For resistive therapy, both M-TDPC and TDPC approaches were able to deliver most of the generated forces. The slight deviation from ideal 100% reflection is due to the behaviors of the controllers in dealing with the existing delays. Using the M-TDPC approach, for the case of assistive therapy, the FRR is 43.88% which interestingly is close to $(\xi_p - \xi_r)/\hat{h}_h$. It tells that the higher the EOP of the patient’s limb, the more assistive forces can be reflected to the patient’s hand through the M-TDPC approach. However, for the case of TDPC technique (during assistive phase) the FRR is small, which tells that the technique is not capable of delivering assistance and it cancels out the assistive forces.
3.7.3 Simulation III: The Effect of $\Gamma_w$

In this simulation, the effect of $\Gamma_w$ is analyzed. For this purpose the simulation condition is considered similar to Simulation II. The performance of the proposed M-TDPC approach is evaluated considering $\Gamma_w = 1$ and $\Gamma_w = 0.7$. The corresponding results are given in Fig. 3.12. As can be seen in Fig. 3.12a, when $\Gamma_w = 1$ the velocity trajectory has an overshoot of 296%. This is due to the fact that with $\Gamma_w = 1$ the width of the considered window of the energy reservoir in the observer is infinity. Consequently, the accumulated energy during the entire resistive phase ($60 < t < 120$) results in late detection of nonpassive therapy. As a result, the velocity trajectories suddenly increase when the task switches from a resistive one to an assistive one. This issue is resolved using the concept of WE by considering $\Gamma_w = 0.7$, as can be seen in Fig. 3.12b.
3.8 Experimental Evaluation

In this section, experimental results are provided to support the proposed M-TDPC approach for an implementation of the HTR system. The setup consists of the following:

(A) **Master robot at the patient’s side:** This is a 2-DOF planar upper-limb rehabilitation device from Quanser Inc. (Markham, ON, Canada) that moves in the horizontal (X-Y) plane allowing for arm flexion-extension. The robot is shown in Fig. 3.1 and Fig. 3.6. The handle of the robot was sensorized (Fig. 3.6) using two pressure sensors.

(B) **Slave robot:** This is a 6-DOF Quanser $H D^2$ haptic device locked in 4 degrees of freedom using software to provide a similar workspace to that of the master robot.

(C) **Virtual Environment (VE):** This is shown in Figs. 3.2 and 3.1. The VE was developed in C++ and communicates with the robots through the UDP protocol. A head-mounted display (shown in Fig. 3.1) is used at the patient’s side to represent the VE and provide visual cues.

3.8.1 Experimental Scenario and Results

In this experiment, the first operator, who played the role of the patient, tried to track the green target in the VE. The second operator, who played the role of the therapist, applied assistive forces during the first phase, and then resistive forces during the second phase, while the M-
TDPC controller was ON. The controller was turned off in the third phase. The communication delay was $\tau_1 = \tau_2 = 80 + 10 \sin(\frac{\pi}{4}t)$ ms. The EOP of the operator’s hand was identified as $\xi_{\text{p-relax}} = 5.56$. In addition, we have $\xi_r = 0.56$ and $\Gamma_w = 0.7$. The goal was to evaluate the behavior of the M-TDPC approach in addressing resistive and assistive environments.

In the VE, the target switched every 1 second between two locations along the vertical axis ($X$ direction). The first operator was asked to keep the effort as consistent as possible during both phases. The result of the tracking should be vertical trajectories. The switching time was considered small to challenge the operator, playing the role of the patient. The position tracking result is shown in Fig. 3.13. As can be seen, the amplitudes of the generated motion for the case of assistive therapy were increased in comparison to that of the resistive phase. For the resistive phase, the first operator was not able to reach the targets within the 1-second time window since the second operator was resisting him. The system became unstable once the controller was turned off. This resulted in uncoordinated motions in both the $X$ and $Y$ directions. The velocity tracking result is shown in Figs. 3.14a and 3.14b. As can be seen in Fig. 3.14a, the amplitude of the velocity trajectory during assistive phase was considerably higher than that of the resistive phase and the system was able to properly deliver both types of actions. It quickly became unstable once the controller was turned off. Fig. 3.14b shows
3.8. Experimental Evaluation

Figure 3.14: (a) Velocity trajectory, (b) Velocity distribution for 20 seconds of assistive and resistive therapies.

Figure 3.15: The modified therapeutic forces (solid blue line), versus the delivered forces (solid red line)

the distribution of the absolute values of the velocity trajectories for 20 seconds of assistive therapy versus resistive therapy. The mean value for the assistive phase was $0.2095 \text{ m/s}$ and for the resistive phase was $0.043 \text{ m/s}$. Using statistical analysis (two-sample t-test) a $p$-value of $0.00014$ was obtained which means that the difference between the two mean values was statistically significant.

To analyze the behavior of the controller, the modified and received therapeutic forces were monitored, as well. Note that force saturation of $30N$ was also used. The result can be seen in Fig. 3.15. As can be seen, during the assistive therapy, the controller was capable of detecting the nonpassive nature of the therapy; as a result, it modified the therapeutic forces (based on the identified $\xi_{p\rightarrow \text{relax}}$) before reflecting them to the hand of the operator. Although the nature
of the therapy was assistive (in the first phase), the controller allowed for assistive forces to be
delivered in a modified manner (which was compatible with the biomechanical capabilities of
the user’s limb), while preserving stability. Note that if the operator had a higher \( \xi_p - \text{relax} \) or
if the therapist had applied milder assistive forces, the required force modification would be
less. Here, the second operator tried to apply high assistive forces to highlight the behavior
of the controller. During the resistive therapy, since the nature of the therapy was passive, the
controller did not considerably modify the forces (as expected). The slight modification during
resistance was due to the existence of the communication delay. During the third phase, when
the controller was turned off, the system became unstable. This can be seen as high-frequency
uncoordinated high-amplitude oscillations. In summary, the experimental results support the
effectiveness of the developed theory and functionality of the proposed stabilizer.

3.9 Conclusion

In this chapter, the stability of haptics-enabled robotic/ telerobotic rehabilitation systems was
mathematically analyzed in the context of strong passivity theory to ensure safe patient-robot
interaction. The proposed controller named M-TDPC which is a new member of the family of
state-of-the-art TDPC controllers. The focus was to take advantage of the quantifiable EOP of
the user’s hand to guarantee interconnection stability. The proposed M-TDPC stabilizer allows
the therapist to deliver nonpassive assistance over a delayed communication channel, based on
the biomechanical capabilities of the patient’s hand. The results in this chapter can be extended
for any general haptics-enabled robotic/telerobotic systems to also deal with delay-induced
instability. The proposed M-TDPC controller increases the transparency of haptics-enabled
systems since it does not require the modification of reflected forces if the EOP of the user’s
limb can compensate for the non-passivity in the system. In addition, based on the strong
passivity theorem, the proposed stability analysis technique shows that under some specific
conditions, the system can still remain stable without modifying the transparency, even if the
communication system is exposed to variable time-delays. It should be noted that there is no
assumption about the linearity and time-invariance of the therapist and the patient models. A
simulation study and an experimental evaluation were conducted to validate the theory.
3.10 Appendix I: Stability Proof

To show how the proposed controller guarantees stability of the system, considering (3.33) and (3.34), we have:

\[ P_L(t) = (\xi_{p-relax} - \xi_{r}) v_p(t)^T v_p(t) + f_p(t)^T v_p(t) \]  

(3.41)

and

\[ \sum_{k=0}^{n} P_L(k) = \sum_{k=0}^{n} (\xi_{p-relax} - \xi_{r}) v_p(k)^T v_p(k) + \sum_{k=0}^{n} f_p(k)^T v_p(k). \]  

(3.42)

Let us define \( W(n) = \frac{1}{\Delta T} LOP_{obs}(n). \) Considering (3.37), we have:

\[ W(n) = \sum_{k=0}^{n} P_L(k) + \sum_{k=0}^{n-1} \alpha(k) v_p(k)^T v_p(k). \]  

(3.43)

Now consider the passivity condition (3.22); in the presence of the controller (variable damping), the condition can be rewritten as

\[ \Psi \geq 0 \text{ where } \Psi = \sum_{k=0}^{n} f_p(k)^T v_p(k) + \sum_{k=0}^{n} f_{react}(k)^T v_p(k) + \sum_{k=0}^{n} \alpha(k) v_p(k)^T v_p(k). \]  

(3.44)

For \( \Psi \) we have:

\[ \Psi = \sum_{k=0}^{n} f_p(k)^T v_p(k) + \sum_{k=0}^{n} f_{react}(k)^T v_p(k) + \left( \sum_{k=0}^{n-1} \alpha(k) v_p(k)^T v_p(k) \right) + \alpha(n) v_p(n)^T v_p(n). \]  

(3.45)

Considering the definition of EOP, we have \( \Psi > \hat{\Psi} \) where

\[ \hat{\Psi} = \sum_{k=0}^{n} f_p(k)^T v_p(k) + \sum_{k=0}^{n} (\xi_{p-relax} - \xi_{r}) v_p(k)^T v_p(k) \]

\[ + \left( \sum_{k=0}^{n-1} \alpha(k) v_p(k)^T v_p(k) \right) + \alpha(n) v_p(n)^T v_p(n). \]  

(3.46)

Combining (3.42), (3.43) and (3.46), we get:

\[ \Psi > \hat{\Psi} \text{ where } \hat{\Psi} = W(n) + \alpha(n) v_p(n)^T v_p(n). \]  

(3.47)

Considering (3.47) and the definition of \( W(n) \), we have:

\[ \Psi > \hat{\Psi} \text{ where } \hat{\Psi} = \frac{1}{\Delta T} LOP_{obs}(n) + \alpha(n) v_p(n)^T v_p(n). \]  

(3.48)
Combining the design of the stabilizer given in (3.36), and the relation (3.48), the stability condition (3.44) is validated.
Bibliography


Chapter 4

A Grasp-based Passivity Signature for Haptics-enabled Human-Robot Interaction: Application to Design of a New Safety Mechanism for Robotic Rehabilitation

The material presented in this chapter has been accepted for publication in the International Journal of Robotics Research, 2016.

4.1 Introduction

4.1.1 Motivation

Telerobotic and haptic systems have attracted a great deal of interest in the context of medical robotics during the last two decades. Accordingly, in the literature, two major categories

for haptics-enabled and telerobotic medical systems have been developed, namely: Robotics-assisted Minimally Invasive Surgical (RAMIS) systems [1], [2], [3], [4], and Haptics-enabled Robotic Rehabilitation systems (HRR) [5], [6], [7], [8], [9].

One of the major research questions about the use of haptic technology in medicine is “how to optimize the haptic system fidelity (transparency) while guaranteeing safety and stability of physical human-robot interaction”. An ideally transparent haptic system is capable of providing the user (at the master side) with the kinesthetic feel of force equal to that measured/calculated at the actual/virtual environment side. The case of an actual environment is for telerobotics systems and the case of a virtual environment is for virtual-reality based haptic rendering systems. However, there is a trade-off between stability and ideal transparency in haptic systems.

For RAMIS systems, although the contribution of haptic feedback during surgery is not negligible, this feedback is turned off in most of the currently-available commercial systems [10], [11]. One of the main reasons for the above-mentioned exclusion is to relax the safety/stability concern by avoiding the closed-loop system which would exist if haptic feedback is included. There are also other reasons for excluding this feedback in RAMIS systems, such as cost and concerns about bio-compatibility and size of sensors [11], [12]. The lack of haptic feedback in commercial systems has nevertheless been successful since without haptic feedback, it is still possible to perform the main goal of RAMIS systems which is accurately translating the “motions” of a surgeon’s hand inside a patient’s body.

In contrast to surgical applications, haptic feedback and kinesthetic interaction are essential key features of robotic rehabilitation systems and cannot be excluded [5], [6], [7], [8], [9]. This forms the main motivation of this chapter which is guaranteeing stability and safety of human-robot interaction during haptic upper-limb motor rehabilitation while preserving system transparency. The results of this study can be used for any haptic/telerobotic system.

In fact, the safety of human-robot interaction in haptics-enabled rehabilitation systems could be a major concern [13], [14], [15], [16]. Most post-stroke rehabilitation robots are designed to generate powerful force fields in order to deliver sufficient energy for the required motor therapy while working in contact with post-stroke patients. Consequently, instability in the robots can cause serious injuries including bone, joint, and soft tissue damage [13], [17].
As a result, patient-robot interaction safety should be explicitly studied and guaranteed. This is an active line of research since conservative solutions can degrade the performance of robotics-assisted therapeutic systems [13], [14]. In most HRR systems, predefined conservative force caps have been utilized as a safety mechanism [8], [18]. This can jeopardize system transparency especially when there may be no stability concern (as explained later in this chapter).

Based on the above, the authors believe that the kinesthetic biomechanical capabilities of the human upper limb should be studied not only for motor assessment purposes but also to develop optimal stabilizers which can guarantee patient-robot interaction safety while minimizing transparency distortion and maximizing the allowable intensity of the therapeutic impedance.

### 4.1.2 Background

HRR systems have been developed to accelerate Neural Plasticity (NP) in the brain through facilitating therapeutic physical interaction of a patient with actual/virtual objects [7], [8], [9]. NP involving brain remodeling in synaptic and non-synaptic manners helps patients to regain some of their lost motor functions [19], [20]. The effectiveness of HRR systems in accelerating NP have been investigated in several studies [7], [8], [9]. Conventional HRR systems are composed of (a) a powerful haptics-enabled robot, (b) a virtual-reality interface, and (c) a Programmable Virtual Therapist (PVT) software which is responsible for tuning the therapeutic forces and the intensity of kinesthetic interaction [7], [9].

Through the use of PVT software incorporated in HRR systems, assistive and coordinative therapies are usually prescribed in early stages of rehabilitation to accelerate NP. Also, resistive therapy is mostly prescribed in later stages to equalized and strengthen muscular tone [7], [9].

In addition to HRR systems, taking advantage of recent developments in the field of communication and cloud-based computerized systems, there is a tendency towards developing remote cloud-based medical applications and rehabilitation systems [21], [22], [23]. An example is the recently-developed Haptics-enabled Telerobotic Rehabilitation (HTR) system, proposed by the authors in [24], [25], [26], [27], which can deliver supervised haptic therapy to remote areas, replace PVT software of HRR systems by keeping a human therapist in the loop, and augment capabilities of human therapists using robotic technology.

It should be noted that the other major safety challenge which is highlighted for cloud-
based HRR and HTR systems is the destabilizing effect of variable communication time delays and non-passive interaction.

Stability concerns in conventional telerobotic systems have been studied in the literature [28], [29], [30]. In this regard, several techniques have been developed to guarantee stability of delayed haptic systems [31], [32], [33], [34], [28]. However, most of these techniques (a) assume that the terminals are passive and the only source of instability is the time delay; (b) try to guarantee stability for a wide range of users regardless of the corresponding biomechanical capabilities; and (c) are specifically developed for communication-induced instabilities.

### 4.1.3 Contributions of This Chapter

Although, conventional stabilizers have shown good performance in guaranteeing stability of conventional delayed haptic systems, further developments are essential when dealing with nonpassive rehabilitation systems. The reason is that having a disabled patient as the user not only requires further consideration, but also no assumption can be made regarding the capability of the user in dealing with unstable situations. In addition, transparency manipulation needs to be minimized since force-feedback is the key factor for HRR and HTR systems. However, the quality of force feedback would be affected by using conservative force limits and/or by implementing a stabilizers that trade-off transparency in order to guarantee stability for a wide range of users (having different biomechanics).

Recently, the authors have shown that it is possible to enhance system transparency and guarantee stability through incorporating some quantitative information of the user’s hand biomechanics into the design of the stabilizers [24], [25], [26]. However, in the aforementioned work, a constant lower-bound is considered for the capability of the user’s hand in absorbing interactive force and energy.

In this chapter, we have relaxed the above-mentioned assumption by proposing a novel Grasp-based Passivity Signature (GPS) map which takes into account the variable energy absorbability of the user’s hand during the operation. The presented work has two major contributions:

- Developing the GPS map which correlates the grasp condition and geometry of haptic interaction with the capability of the user’s upper limb in absorbing physical interaction
• Proposing a new safety mechanism which incorporates the proposed GPS map to perform minimum manipulation of transparency while guaranteeing stability, in the context of Strong Passivity Theorem (SPT) \cite{35}, \cite{36}.

For this purpose, in the first part of this work, a user study was conducted with 11 human subjects to study nonlinear biomechanics of both their left and right hands. The study was conducted separately for the users’ arms and wrists. Consequently, two haptic systems were utilized: (a) an upper-limb rehabilitation robot (from Quanser Inc., Markham, ON, Canada) for studying arm biomechanics; and (b) an \( HD^2 \) haptic device (from Quanser Inc.) for the wrist. The participants were asked to tune their grasp pressure to levels shown by a monitor, while the robot perturbed their limb. Force and motion data were captured and analyzed and the quantitative Excess of Passivity (EOP) was calculated for different directions of motion. Then, the correlation between the calculated EOP (in different geometries of motion) and the amount of grasp pressure was identified and statistically evaluated. The result of this study provides a user-specific GPS map which represents the biomechanical capability of the human upper limb in absorbing interaction energy under variable grasp conditions and in different directions of motion.

In the second part of this work, the identified GPS map was utilized in the design of a
new controller, called GPS-map Stabilizer. The proposed technique utilizes the identified user-specific GPS map in a nonlinear Force Reflection Gate (FRG) function, defined to guarantee the interaction safety in the context of SPT. The proposed FRG function can be explained as a nonlinear gain that converges to zero when the user provides minimal to no energy absorption and converges to unity when the user provides enough energy absorption. In the latter case, even if the communication is delayed and the therapy is non-passive (e.g., assistive therapy), the transparency will not be affected by the stabilizer.

It should be noted that the controller can be used not only for HRR/HTR systems but also for conventional haptic and haptic teleoperation systems. Experimental validations are reported to support the proposed technique. The setup is shown Fig. 4.1.

The rest of this chapter is organized as follows. In Section 4.2, the required preliminaries are presented. In Section 4.3, the GPS map is introduced. In Section 4.4, the design of the proposed FRG function is given. In Section 4.5, experimental evaluations are presented. Finally, concluding remarks are given in Section 4.6.

4.2 Preliminaries and Mathematical Modeling

The preliminaries given in this section are mostly taken from the authors’ previous work [24]. In order to analyze the passivity of the user’s hand and develop the stabilizing controller, a transparent two-channel bilateral architecture was previously proposed by the authors [37] and used for both HRR and HTR systems [24], [25], [26], [27]. The architecture is an extended version of Lawrence’s four-channel model [38]. Using this architecture, it is shown that only two communication channels are needed to allow the patient to feel the delayed therapeutic forces and the human/virtual therapist to feel the patient’s delayed hand motion. The details of the utilized telerobotic architecture are in [24]. Using the above-mentioned two-channel telerobotic system, transparency is achieved as follows:

\[ f_p(t) = -\hat{f}_{th}(t), \]  
\[ v_{th}(t) = \hat{v}_p(t). \]
In (4.1), (4.2), \( f_p(t) \) is the force applied by the patient to the master robot, \( \hat{f}_{th}(s) \) is the delayed therapeutic force received at the patient’s side, sent through the first communication channel (slave to master), \( \hat{v}_p(t) \) is the patient’s delayed hand velocity, received at the therapist’s side, sent through the second communication channel (master to slave). In addition, \( v_{th} \) is the therapist-side velocity. Note that for HRR systems \( v_{th} \) is the velocity of the virtual object in the virtual reality environment while for HTR systems \( v_{th} \) is the velocity of the human therapist. For HRR systems, \( \hat{f}_{th}(s) \) is the delayed force generated by the PVT software to deliver assistive/resistive/coordinative therapeutic forces. For HTR systems, \( \hat{f}_{th}(s) \) is the delayed force applied by the human therapist on the slave robot.

### 4.2.1 Patient’s Force Decomposition

The patient’s force can be decomposed into an active component \( f_p^*(t) \) (which generates movement), and an impeding reactive component \( f_{react}(t) \) (which behaves similar to resistive impedance in linear models), as shown below:

\[
f_p(t) = f_p^*(t) - f_{react}(t), \text{ where } f_{react} = z_p(v_p,t)
\]  

(4.3)

In (4.3), \( z_p(v_p,t) \) is the non-autonomous nonlinear impedance function which models the mechanical resistance of the patient’s limb. This function relaxes the conventional linearity assumption for the operator’s hand dynamics (such as in [39] for a healthy human, and in [40] for post-stroke patients). \( f_p^*(t) \) is the active component of the force applied by the patient’s hand while performing the tasks. \( f_p^*(t) \) is composed of (a) residual voluntary (functional) active forces, denoted by \( f_{p-v}^*(t) \), and (b) abnormal and involuntary active forces such as abnormal patterns of activation and involuntary reflexes, denoted by \( f_{p-i}^*(t) \). Consequently, \( f_{p-v}^*(t) \) and \( f_{p-i}^*(t) \) result in (a) voluntary, and (b) uncoordinated and involuntary patterns of motion, respectively ([41–44]). The force decomposition can be modeled using the notation of an admittance function \( \Omega_p(\cdot) \) as

\[
v_p = \Omega_p(f_p^*(t) - f_p(t),t)
\]  

(4.4)
4.2.2 Characteristics of the Components of the Interaction

The components of the system have the following characteristics [24].

1. The therapist is considered to be a non-passive nonlinear non-autonomous dynamical terminal for the interconnection. This enables the therapist (virtual/human) to inject energy into the system during assistive and coordinative therapies. The model remains valid during time-varying nonlinear complex therapies.

2. The second norm of the active component of the patient’s hand $f_p^*$ is considered to be bounded. This means that the patient can generate positive or negative (voluntary and involuntary) time-varying forces that result in movement; however, the patient does not generate unbounded (in terms of the second norm) forces. This is a realistic assumption.

3. The reaction component of the patient’s hand $z_p(v_p, t)$ is initially considered as a passive nonlinear non-autonomous biomechanical terminal which absorbs therapeutic energies. This model includes (but is not limited to) the commonly-used passive linear mass-spring-damper models introduced in the literature for the dynamical reaction of a healthy human upper-limb [39], [45], [46] and post-stroke patients [40, 47, 48]. In Section 4.1, it is shown that the assumption of passivity on $z_p$ can be relaxed in the proposed framework. This helps to ensure the generality of the technique.

4. The communication network can be subjected to time-varying delays which is the case for cloud-based HRR and HTR systems and is the conventional source of non-passivity in haptic systems.

The above mentioned considerations are valid for most of the conventional applications of haptic and telerobotic systems including HRR and HTR architectures.

**Remark 4.1.** It should be noted that the three common symptoms after stroke are motor weakness, increased joint and muscle resistance to movement (i.e., hypertonia), and increased involuntary reflex activities (47, 49, 50). The weakness in generating motor commands, will result in reduced ability to move the limbs for performing tasks (e.g., position and/or velocity tracking). Considering (4.3), this corresponds to a reduced capability in generating $f_{p-v}(t)$. 

Hypertonia results in increasing the viscosity and stiffness of the muscles. Clinicians usually apply movements to the joints to feel the resistance and objectively evaluate hypertonia. As mentioned above, this has been modeled in the literature using linear viscoelastic dynamics, e.g., [40, 47, 48]. An increase in viscoelastic parameters due to hypertonia increases the magnitude in terms of nonlinear norms of $z_p$ in (4.3). In addition, the involuntary and abnormal post-stroke muscle activities (such as involuntary reflexive activities and abnormal muscle synergy) result in involuntary forces $f^*_p(t)$ in (4.3) and subsequently abnormal involuntary patterns of movement (41–44).

**Remark 4.2.** It should be noted that in this chapter, we *initially* assume the passivity characteristic for the resistive component of the hand dynamics (i.e. $z_p$). This assumption does not restrict other hand activities such as voluntary and involuntary behavior of the user’s hand. In this chapter, the only requirement for the active component $f^*_p$ is that the patient should not generate unbounded (in terms of the second norm) active forces, which is realistic. The assumption of passivity on $z_p$ is in agreement with existing linear and passive viscoelastic models which have been used in the literature for modeling limb impedance in post-stroke patients (40, 47, 48), where increased stiffness and viscosities have been correlated to post-stroke hypertonic symptoms. However, a specifically-designed clinical study is yet to be conducted to provide more details on the passivity characteristics of the impeding component $z_p$ for the upper-limbs (the focus of this chapter) of post-stroke patients. Consequently, in order to preserve the generality of the proposed technique and since further investigation may report some non-passive behavior for neurologically-damaged patients (such as the one suggested in [51] for the lower-limb), in Section 4.1 we will show that the assumption of passivity can be relaxed for the proposed framework.

### 4.2.3 Closed-loop system

Utilizing the architecture introduced in the above and detailed in [24], the resulting interconnection for both HTR and HRR is a two-channel closed-loop haptic system which is shown in Fig. 4.2. The resulting system is an interconnection between (a) the admittance model of the patient’s reaction dynamics $\Sigma_3$; (b) the impedance model of the therapist’s behavior $\Sigma_0$; and (c) the communication network. Combination of $\Sigma_0$ and the communication network is called
Figure 4.2: The overall schematic of the resulting interconnection. The subsystem $\Sigma_1$ is called the “therapy terminal” which consists of the communication and any behavior of the therapist. $\Sigma_2$ is the entire interaction which gets $f_p^*$ as the input and provides $v_p$ as the output. $\Sigma_3$ is the admittance model of the patient’s limb mechanical reaction.

“therapy terminal”, denoted by $\Sigma_1$. Consequently, the resulting system can be summarized as the interconnection of $\Sigma_1$ and $\Sigma_3$. This enables us to analyze the interaction stability from the perspective of input-output energy exchange between $\Sigma_1$ and $\Sigma_3$. Note that $\Sigma_1$ includes both sources of non-passivity which can destabilize the system (i.e., the delayed communication network and the non-passive therapeutic behaviors). The proposed controller estimates the extent of energy absorption by $\Sigma_3$ (using GPS map) and compares it to the energy generated by $\Sigma_1$ to tune force reflection parameters and stabilize the system.

### 4.2.4 Passivity Definition and EOP-based Stability Condition

When a (virtual/human) therapist provides resistive therapy, they essentially dissipate the energy of the patient’s movements. In this case, if the communication is not subject to delays, the situation results in a passive interconnection. However, when the therapist provides assistive/coordinative forces or if the communication network is delayed (which is the case for cloud-based HRR/HTR), the interconnection will be non-passive and can jeopardize the stability of patient-robot interaction [52], [24], [53]. In practice, therapists provide mixed therapies in various time episodes. Also the communication can be delayed. As a result, analyzing the stability in the context of the passivity theorem can allow us to diagnose potential instabilities
and provide stabilizing actions through the controller. In this regard, to minimize the transparency distortion and manipulation (commonly used to guarantee stability), we propose to identify the capability of the user’s hand reaction dynamics in absorbing energies. Since we do not assume linearity for the limb’s dynamics, the passivity is studied in the context of nonlinear control theory and the following definitions are given.

**Definition I.** For a system with input vector \( u_{in}(t) \), output vector \( y_{out}(t) \), and initial energy \( \beta \) at \( t = 0 \), if there exists a constant \( \beta \) such that for all \( t \geq 0 \) we have

\[
\int_{0}^{t} u_{in}(\tau)^{T} \cdot y_{out}(\tau) \, d\tau \geq \beta,
\]

the system is passive [35], [54], [55], [56]. •

**Definition II.** For the system mentioned above, if there is a constant \( \beta \) such that for all \( t \geq 0 \) we have

\[
\int_{0}^{t} u_{in}(\tau)^{T} \cdot y_{out}(\tau) \, d\tau \geq \beta + \delta \cdot \int_{0}^{t} u_{in}(\tau)^{T} \cdot u_{in}(\tau) \, d\tau,
\]

for \( \delta \geq 0 \), the system is Input Strictly Passive (ISP) with an excess of passivity (EOP) equal to \( \delta \). Also, if we have \( \delta < 0 \), the system is Input Non-Passive (INP) with the Shortage of Passivity (SOP) of \( \delta \) [35], [54], [55], [56]. •

**Definition III.** For the system mentioned above, if there is a constant \( \beta \) such that for all \( t \geq 0 \) we have

\[
\int_{0}^{t} u_{in}(\tau)^{T} \cdot y_{out}(\tau) \, d\tau \geq \beta + \xi \cdot \int_{0}^{t} y_{out}(\tau)^{T} \cdot y_{out}(\tau) \, d\tau,
\]

for \( \xi \geq 0 \), the system is Output Strictly Passive (OSP) and the EOP is \( \xi \). If \( \xi < 0 \), the system is Output Non-Passive (ONP) and the SOP is \( \xi \) [35], [54], [55], [56]. •

**Remark 4.3.** It has been shown that all passive systems are asymptotically stable. In addition, an OSP systems is also \( L_{2} \) stable with a finite \( L_{2} \) gain less than or equal to \( 1/\xi \), where \( \xi \) is the EOP of the OSP model [56]. •

**Remark 4.4.** In [24], the authors have shown that when there is a nonpassive therapy terminal (\( \Sigma_{1} \)) in a haptic rehabilitation system (due to a non-passive therapist and/or a non-passive communication network), the closed-loop system \( \Sigma_{2} \) can still remain stable if the energy absorbed by the impeding component of the patient’s limb (i.e. \( \int_{0}^{t} f_{\text{react}}(\tau)^{T} \cdot v_{p}(\tau) \, d\tau \)) can compensate for the energy injected by the therapy terminal \( \Sigma_{1} \), (i.e. \( \int_{0}^{t} f_{p}(\tau)^{T} \cdot v_{p}(\tau) \, d\tau \)). This
Remark 4.4 can be summarized in the following condition.

\[
\text{The entire interconnection } \Sigma_2 \text{ remains passive if }
\int_0^t f_p(\tau)^T \cdot v_p(\tau) \, d\tau + \int_0^t f_{\text{react}}(\tau)^T \cdot v_p(\tau) \, d\tau \geq 0.
\] (4.8)

This is equivalent to

\[
\xi_p + \hat{\delta}_{th} \geq 0,
\] (4.9)

where, \(\xi_p\) is the EOP of the patient’s hand biomechanics and \(\hat{\delta}_{th}\) is the SOP of \(\Sigma_1\). Details can be found in [24].

Remark 4.5. The EOP of a human upper limb is the quantitative capability of the corresponding biomechanics in absorbing kinesthetic energy. The more rigid the impeding component of a human upper limb is, the higher the EOP that might be expected. As a result, if a patient has a rigid hand with hypertonia, his/her upper limb might be expected to demonstrate a higher EOP. In the literature higher viscoelasticity has been reported for post-stroke patients with hypertonia. High viscoelasticity can mathematically result in high EOP. Clinical analysis is still needed to evaluate this point, as other post-stroke symptoms may affect the result. It should be noted that as discussed in Section 4.1, the assumption on passivity (which results in positive EOP) can be relaxed in the context of the proposed framework.

If the mentioned passivity condition (4.8) is not satisfied, some sort of energy manipulation technique should be implemented to compensate for parts of the energy which cannot be absorbed by the EOP of the user’s hand. There is no need to compensate for all non-passive therapeutic energies. Consequently, knowledge of the EOP of a user’s hand and the corresponding variation and geometry can result in a new stability paradigm which takes into account variable biomechanical capabilities of the user’s upper limb in absorbing interaction energies to stabilize the system while performing minimal transparency manipulation.

In this chapter, the extent of grasp pressure and the geometry of haptic interaction are correlated with the change in EOP, through the definition of GPS map. This allows us to account for variable grasp-based and geometry-based changes in the capability of the user’s upper-limb
in absorbing interactive energies, during haptic task execution. The quantified GPS map is then utilized in the design of a new controller (called GPS-map Stabilizer) which modifies the delivered therapeutic energy considering the aforementioned changes in EOP.

### 4.3 GPS map Identification and User Study

In this section, the proposed GPS map is introduced and statistically analyzed. For this purpose, the experimental setup shown in Fig. 4.3 is utilized. For the case of arm interaction, the Quanser upper-limb rehabilitation robot is used to provide 2D planar arm motions composed of elbow flexion-extension, shoulder protraction-retraction and internal-external rotation. In addition, for the case of wrist interaction, the Quanser HD² robot is utilized to apply 2D angular wrist movements composed of wrist abduction-adduction and pronation-supination.

#### 4.3.1 Demographic Data

In order to develop and analyze the proposed GPS map, 11 healthy human subjects (with no known history of neuromuscular disorders) were recruited for both the arm and the wrist experiments. Some of the subjects participated in both experiments and some did not. As explained later in this chapter, to make each GPS map, two experiments need to be conducted (considering two grasping conditions). In total, the participants participated in 80 experiments which resulted in identifying 40 GPS maps. Table 4.1 shows the participation chart. Note that each item in Table 4.1 contains two experiments. The study was conducted at the University
Table 4.1: Participation Chart for the 40 Calculated GPS maps

<table>
<thead>
<tr>
<th>ID</th>
<th>Right Wrist Experiment</th>
<th>Left Wrist Experiment</th>
<th>Right Arm Experiment</th>
<th>Left Arm Experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>P0</td>
<td>✓</td>
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</tbody>
</table>

of Alberta, Canada, under an ethics approval from the corresponding Research Ethics Board. The details of the experiments were explained to the participants prior to the experiment and they were given time to become familiar with the robotic system. For the arm experiment, the participants (6 males, 5 females) were aged between 25 and 30 (mean value: 27.63, standard deviation: 1.36). For the wrist experiment, the participants (8 males, 3 females) were aged between 26 and 40 (mean value: 28.63, standard deviation: 3.93).

4.3.2 GPS map Identification Protocol

To find the user-specific GPS maps, sinusoidal linear and angular motions were applied to participants’ arms and wrists, while force and velocity data were logged. The identifying motion profile was composed of 10 sinusoids with frequencies range from 0 to 2 Hz. It should be noted that 2 Hz is usually considered in the literature as the upper-limit of the frequency range of motion during normal daily activities [57, 58]. One of the factors which was studied in this chapter is the geometry of GPS maps. To account for the geometry,
the identifying motion profile was designed in a way that specifically engages different degrees of interaction separately. Consequently, 8 directions of stimulation were considered: \( \theta = 0, \pi/4, \pi/2, 3\pi/4, \pi, 5\pi/4, 3\pi/2, 7\pi/4 \), where \( \theta \) is the angle of stimulation. The stimulating signal stayed in each of the mentioned 8 phases for 10 seconds and then switched to the next phase. Consequently, the total identification time for one trial was 80 seconds.

For each hand of a participant (right and left) and each limb (wrist and arm), the above-mentioned protocol was conducted two times considering the two different grasp requirements described below. The two aforementioned sets of experiments are denoted as (a) Relaxed Grasp (RG) and Stiff Grasp (SG) tests. The RG test corresponds to the participant keeping the grasp pressure less than 5% of his/her maximum grasp pressure while the robot is stimulating the limb by applying the motion perturbations. The SG test corresponds to the participant keeping the grasp pressure close to 80% of their maximum grasp during perturbations.

The grasp pressure for each participant was measured using the sensorized robotic handles. The measurement system composed of two FSR-406 (Interlink Electronics) pressure sensors for each robot. Using a head-mounted display, the two levels of grasp pressure (for SG and RG tests) were shown to the participants. Participants were asked to keep the grasp pressure close to the levels shown. Since the experiment was designed such that the participants were not asked to track any trajectory during the identification procedure, they did not apply exogenous kinesthetic forces which means that \( f_p^\ast \rightarrow 0 \). Consequently, during the identification procedure we have \( \int_0^t f_{\text{react}}(\tau)^T \cdot v_p(\tau)\,d\tau = \int_0^t f_p(\tau)^T \cdot v_p(\tau)\,d\tau \), where both \( f_p(t) \) and \( v_p(t) \) are accessible.

The aforementioned two sets of experiments (SG and RG) were conducted for both the wrist and the arm, and for the left and right hands. As a result, each participant was invited to participate in 8 trials. Out of these 8 trials, four were for the right hand and four for the left hand. Also, out of the mentioned four experiments, two sets (SG and RG) were for the wrist and the other two for the arm. Most of the participants agreed to participate in all 8 trials. In total, 80 experiments were conducted as summarized in Table 4.1. The results are given in the next subsection. The goal was to identify the GPS map (a) for both the wrist and the arm since it was likely that the GPS map of the wrist and the arm would behave differently in response to the change in the grasp condition; and (b) for both left and right limbs to have a
4.3. GPS map Identification and User Study

statistically-rich data set.

Remark 4.6. The study developed in this section addresses the following questions: (a) Is there a statistically significant change in the EOP of the human upper-limb (wrist and arm) under different grasp conditions (realized by the RG and SG tests)? (b) Is the EOP of the human upper-limb (wrist and arm) geometry-specific? As shown later in this chapter, the answers to both questions are affirmative and that is why the identified result is denoted as GPS map for EOP of the human upper-limb. •

Using the collected force and velocity data from each of the 8 identification trials and using the definition of EOP given earlier, the EOP for the participant’s limb in the $i^{th}$ direction of stimulation (which corresponds to the $i^{th}$ item of $\theta$), is calculated as

$$\xi_{p-i} = \frac{\int_{T_{s_i}}^{T_{e_i}} f_{react}(\tau)^T \cdot v_p(\tau) \, d\tau}{\int_{T_{s_i}}^{T_{e_i}} v_p(\tau)^T \cdot v_p(\tau) \, d\tau}. \tag{4.10}$$

In (4.10), $\xi_{p-i}$ is the estimated EOP of the participant’s limb calculated for the $i^{th}$ direction of stimulation, $T_{s_i}$ is the starting time for stimulating the $i^{th}$ direction, and $T_{e_i}$ is the stop time. The results are given in the following subsection.

4.3.3 GPS map Identification Results

The results of the proposed GPS map identification protocol are given below. Eight phases of the identification procedure are shown in Fig. 4.4 for Participant #2, considering the RG test conducted on the right arm. As can be seen in Fig. 4.4 (a) and (b), force and velocity profiles are collected during 8 phases. Based on the collected data and (4.10), the EOP of the participant’s arm is calculated as given in Fig. 4.4(c). As can be seen in Fig. 4.4(c), changing the direction of the stimulation considerably changes the EOP of the participant’s hand. In this case, the maximum EOP is 3 times larger than the minimum EOP. Afterwards, the result is transformed to the radarplot of EOP shown in Fig. 4.4(d). The same procedure is also conducted for the SG test to finally make the complete radarplot (which is the GPS map). Consequently, each map includes the geometry of EOP for both the SG and RG tests and represents their graphical summary (which defines the EOP value considering different
directions of interaction and levels of grasp pressure). With the 80 experiments that were conducted, 40 GPS maps were made. Figs. 4.5 and 4.6 shows 15 GPS maps out of the total 40.

Considering the plotted GPS maps in Figs. 4.5 and 4.6, increasing the grasp pressure results in enlarging the area of EOP in the map. As a result, when a user applies higher grasp pressure, higher energy can be absorbed by their limb. In addition, the EOPs were different in various directions of interaction. The pattern of grasp-based increase and the shape of the EOP area are specific for each participant and each limb. That is why the factor is termed “signature”. This information is utilized in the next section to design the GPS-map Stabilizer.

**Remark 4.7.** The GPS map of a user’s hand can also be potentially used as a graphical representation which has encapsulated information about the user’s biomechanical capabilities, and can be studied from the point of view of symmetry, shape and grasp-based size variations. This could be a tool for monitoring progress in strengthening and equalizing muscular functionality, which is critical to assess progress during rehabilitation procedures.
Figure 4.5: The Calculated GPS maps for 15 items. Note that the blue line corresponds to the SG test and the red line corresponds to the RG test. For the wrist GPS maps, the 1st direction is Pronation-Supination and the 2nd direction is Abduction-Adduction. (a) Participant #18: Right Wrist Experiment, (b) Participant #18: Left Wrist Experiment, (c) Participant #16: Right Wrist Experiment, (d) Participant #16: Left Wrist Experiment, (e) Participant #2: Right Wrist Experiment, (f) Participant #2: Left Wrist Experiment, (g) Participant #0: Right Wrist Experiment, (h) Participant #0: Left Wrist Experiment,

**Remark 4.8.** The order of directions for stimulating the user’s biomechanics can be interpreted by comparing Figs. 4.4(c) and 4.4(d). In fact in the conducted experiment, during the first phase \((0 < t \leq 10)\) the stimulation angle \(\theta\) was 0; for the second phase \((10 < t \leq 20)\), we had \(\theta = \pi/4\); for the third phase \((20 < t \leq 30)\), we had \(\theta = \pi/2\); for the fourth phase
Figure 4.6: The Calculated GPS maps for 15 items. Note that the blue line corresponds to the SG test and the red line corresponds to the RG test. For the wrist GPS maps, the 1st direction is Pronation-Supination and the 2nd direction is Abduction-Adduction. (a) Participant #17: Right Arm Experiment, (b) Participant #16: Right Arm Experiment, (c) Participant #7: Right Arm Experiment, (d) Participant #5: Right Arm Experiment, (e) Participant #2: Right Arm Experiment, (f) Participant #0: Right Arm Experiment, (g) Participant #0: Left Arm Experiment,

\( 30 < t \leq 40 \), we had \( \theta = 3\pi/4 \); for the fifth phase \( 40 < t \leq 50 \), we had \( \theta = \pi \); for the sixth phase \( 50 < t \leq 60 \), we had \( \theta = 5\pi/4 \); for the seventh phase \( 60 < t \leq 70 \), we had \( \theta = 3\pi/2 \) and for eighth phase \( 70 < t \leq 80 \), we had \( \theta = 7\pi/4 \). Any different order (such as a ran-
dom one) could be considered for generating GPS maps. The order does not change the entire framework that is proposed in this chapter. It should be noted that based on our observations we have not seen correlations between the order, in which the biomechanics of the users were stimulated, and the GPS maps. However, further analysis is needed to scientifically evaluate this point. This forms part of our future study.

Remark 4.9. Considering Fig. 4.4(c), during each phase the identified EOP converges to the corresponding value in less than 5 seconds. This tells us that we may be able to reduce the identification phase to half of what has been tested. In addition, a good suggestion can be to give the user resting episodes between every two consecutive phases and evaluate different directions of stimulation with a break in between. This can help to avoid potential fatigue specifically when we ask the user to hold a high grip value.

4.3.4 GPS map: Statistical Analysis

This part of the chapter focuses on statistical evaluation of the 40 identified GPS maps to analyze them in a more accurate manner. The goal is to illustrate that the correlation between the EOP and (a) grasping condition and (b) geometry of interaction are statistically significant. For this purpose, the following two-step analysis is conducted.

Step #1: The Effect of the Grasping Condition on GPS maps: First, the areas of both radarplots in the GPS maps are calculated. The area for the RG test is denoted by $A_{RG}$ and the area for the SG test is denoted by $A_{SG}$. The average increase in EOP was calculated for each GPS map as

$$\beta = \sqrt{\frac{A_{SG}}{A_{RG}}} - 1. \quad (4.11)$$

Note that $\beta = 0$ is equivalent to having zero average increase. In total, forty $\beta$ values were calculated and the corresponding distributions were developed and analyzed. Note that out of the 40 values, 22 items correspond to the wrist experiments and 18 items correspond to the arm experiments. The results are shown in Fig. 4.7. As can be seen in Fig. 4.7, increasing the grasp pressure has increased the EOP of all the GPS maps for both the arm and the Wrist. For the case of the arm, the mean value for the increases was 0.82 (that is equivalent to 82% increase in EOP). For this case, the standard deviation was 0.29 (i.e. 29%). For the case of the wrist,
the mean value for the increases was 3.7 (that is equivalent to 370% increase in EOP). For this case, the standard deviation is 2.26.

**Remark 4.10.** In order to statistically analyze the significance of the results obtained, we have conducted standard one-sample *t*-test evaluations on the distributions shown in Fig. 4.7. A similar approach has also been used for analyzing other results of the chapter. The statistical *t*-test evaluation returns a test decision for the null hypothesis that the study data comes from a normal distribution with mean value of zero and unknown variance. The output of the conducted t-test is a *p*-value which is a probability. Small values for *p* (usually < 0.05) correspond to statistically significant evidence to reject the null hypothesis ([59] [60]). In this chapter, in order to show that the observed positive increases in the area of the calculated GPS maps (resulting from increases in grasp pressure) is statistically significant, we should reject the null hypothesis that the observed changes in the area of the maps comes from a distribution with zero mean increase. A similar approach has also been used for analyzing the effect of geometry on GPS map, in this chapter.

Considering the definitions given in Remark 4.10, the results of the statistical analyses, that is conducted on the distributions shown in Fig. 4.7 (against β = 0), are given in Table 4.2. The results (in Table 4.2) indicate that the positive average increase in EOP of the participants’ arms and wrist (due to increase in grasp pressure) is statistically significant.

**Remark 4.11.** Based on the results shown in Table 4.2 it can be concluded that the increase in grasp pressure considerably increases the EOP of the user’s arm and wrist. This was the first hypothesis of the chapter which is validated by the above results. The grasp-dependent increase in EOP is statistically significant (*p*-value<0.001) and the average increase is higher for the case of the wrist (i.e., 370%) in comparison to the arm (i.e., 82%). More information about the results of this statistical analysis (including the t-statistic and degrees of freedom can be found in Table 4.2). To highlight the importance of the results, it should be noted that an α% increase in EOP can be transformed to an α% increase in the allowable amplitude of the force to be reflected to the user’s hand which directly results in improvement in the system transparency.

**Step #2: The Effect of Geometry on GPS maps:** In the second step, the geometry of GPS maps was separately analyzed for the SG and RG tests and for the cases of the wrist and arm,
4.3. GPS map Identification and User Study

Figure 4.7: Distributions for grasp-based increase in EOP: (a) Arm, (b) Wrist. In the distributions shown, a sample $\beta$ value equal to 1 is equivalent to 100% increase in EOP due to increase in grasp pressure.

Table 4.2: Summary of the Statistical Evaluation for the Distributions Given in Fig. 4.7. $\beta = 0$ is the value that the t-test is being compared against.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>SD</th>
<th>t-test result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arm</td>
<td>0.82</td>
<td>0.38</td>
<td>1.40</td>
<td>0.29</td>
<td>[t(17)= 11.81, p-value&lt;0.001]</td>
</tr>
<tr>
<td>Wrist</td>
<td>3.70</td>
<td>1.09</td>
<td>9.60</td>
<td>2.26</td>
<td>[t(21)= 7.65, p-value&lt;0.001]</td>
</tr>
</tbody>
</table>

using the following metric:

$$\gamma = \frac{\text{Max}_{EOP}}{\text{Min}_{EOP}} - 1. \quad (4.12)$$

In (4.12), $\text{Max}_{EOP}$ is the maximum value of the eight EOP values achieved by perturbing the corresponding limb in eight different directions of interaction (i.e., $\theta = 0, \pi/4, \pi/2, 3\pi/4, \pi, 5\pi/4, 3\pi/2, 7\pi/4$). Also, $\text{Min}_{EOP}$ is the corresponding minimum value. Consequently, in this step, we evaluate the deviation of the GPS map geometries from a circle with a radius equal to $\text{Min}_{EOP}$. In other words, we have evaluated the anisotropy of the proposed GPS map using $\gamma$. The above-mentioned circle is denoted by “EOP circle” in this chapter. In order to evaluate this anisotropy, the distributions of the $\gamma$ values are analyzed. As a result, four statistical distributions have been calculated namely: (a) SG-Arm, (b) RG-Arm, (c) SG-Wrist and (d) RG-Wrist. Note that the SG-Wrist and RG-Wrist distributions include 22 items and the other
two distributions include 18 items. It should be mentioned that $\gamma = 0$ is equivalent to having no geometry-based differences between the calculated EOP values. Also, the higher the $\gamma$ value, the more deviation from the EOP circle. Consequently, $\gamma = 1$ means that in one direction the EOP is two times larger than $Min_{EOP}$ that results in having two times more capability in absorbing interaction energies. The distributions are shown in Fig. 4.8. The outcomes of the statistical test conducted on the results given in Fig. 4.8 (against $\gamma = 0$) are given in Table 4.3.

**Remark 4.12.** From the results shown in Fig. 4.8 and Table 4.3, it can be concluded that the geometry of stimulation plays an important role in the capabilities of the human hand in absorbing interaction energies. This was our second hypothesis which has been validated using the results given above. In some cases, the EOP can be even more than three times in some directions compared to the minimum EOP.

Considering Remarks 4.11 and 4.12, we have shown that the EOP of the user’s hand can be significantly changed by (a) increasing the grasp pressure, and (b) changing the direction
4.3. GPS map Identification and User Study

Table 4.3: Summary of the Statistical Evaluation for the Distributions of $\gamma$ given in Fig. 4.8. $\gamma = 0$ is the value that the t-test is being compared against.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>SD</th>
<th>t-test result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arm-SG</td>
<td>2.53</td>
<td>1.21</td>
<td>7.13</td>
<td>1.3</td>
<td>$[t(17)= 8.16, $p$-value&lt;0.001]$</td>
</tr>
<tr>
<td>Arm-RG</td>
<td>2.7</td>
<td>0.94</td>
<td>5.7</td>
<td>1.05</td>
<td>$[t(17)= 10.89, $p$-value&lt;0.001]$</td>
</tr>
<tr>
<td>Wrist-SG</td>
<td>1.5</td>
<td>0.89</td>
<td>2.3</td>
<td>0.4</td>
<td>$[t(21)= 17.34, $p$-value&lt;0.001]$</td>
</tr>
<tr>
<td>Wrist-RG</td>
<td>0.87</td>
<td>0.34</td>
<td>1.85</td>
<td>0.42</td>
<td>$[t(21)= 9.45, $p$-value&lt;0.001]$</td>
</tr>
</tbody>
</table>

of interaction. Consequently, during haptics-enabled task execution, taking advantage of measurable direction of interactive forces and grasp pressure plus the pre-identified GPS map, it is possible to interpolate the expected EOP of the user’s hand. This information corresponds to the capability of absorbing interaction energy and can be used to significantly enhance the system transparency while guaranteeing stability. This is accomplished in the next section utilizing the proposed controller, called the GPS map-Stabilizer. If the user provides enough EOP, the controller will not undermine the system transparency for preserving stability.

4.3.5 Case Study: Pattern of Growth in GPS map

In this part of the chapter, a case study is presented which focuses on the growth pattern of the introduced GPS maps. The question which is investigated here is “how to interpolate the EOP value using the proposed GPS maps based on real-time measurement of grasp pressure?” There are several ways for interpolating the EOP values, in practice. The most straightforward simple technique is to enrich the GPS map by considering more values for the grasp pressure (called “fractions” in this chapter) other than the two values used here (i.e. 5% and 80% of the maximum pressure). An example is a 5-point fractioning technique which is equivalent to conducting the identification procedure for 5%, 20%, 40%, 60%, and 80% of the maximum grasp pressure. The higher the number of fractions, the more accurate is the interpolation of EOP value. Consequently, this technique suggests that the identification procedure could be
repeated for more values of grasp pressure to find a more accurate GPS map. Although, this technique is straightforward, in this section we investigate the possibility of developing a quick interpolation. For this purpose, we have conducted a new set of experiments for 8 participants \((P_0, P_1, P_2, P_4, P_5, P_{18}, P_{19}, P_{20})\), and for both left and right wrists.

The new set of experiments examines the EOP of the participants’ wrists considering the 5-point fractioning technique for their grasp pressure. As a result, we identified the EOP of the participants’ wrists for 5%, 20%, 40%, 60%, and 80% of their maximum grasp pressures. For each participant, we individually normalized the calculated EOP using the maximum EOP observed during the 5 stages of the mentioned fractioning. The result of this case study consists of 32 graphs of normalized EOP versus pressure percentage. Each graph contains 5 values of EOP which corresponds to 5%, 20%, 40%, 60%, and 80% of a participant’s maximum grasp pressures. The 32 results were obtained by conducting the identification procedure for both right and left wrists of the 8 participants and for both major directions of motion (Supination-Pronation and Abduction-Adduction). Twelve sample graphs are shown in Fig. 4.9. An interesting phenomenon was observed for all the aforementioned 32 results including the ones which are shown in Fig. 4.9. The observation is discussed in the following remark.

**Remark 4.13.** All 32 results support the fact that the growth pattern of EOP can be modelled using a “**Two-Segment Piecewise Linear (TSPL)**” model. The aforementioned model includes a sharp growth for the first 20% increase in the grasp pressure, and a second linear growth, with a smaller slope, for the next 60% increase in the grasp pressure. The TSPL model is shown by black dashed lines in the graphs of Fig. 4.9. This pattern can be used to generate the TSPL model by only employing a **3-point fractioning technique** using grasp percentages of 5%, 20% and 80%.

Although the cause of the two-segment piecewise behavior is not the focus of this chapter, the authors believe that one possible explanation could be the existence of a dual-stage behavior for the EOP growth pattern. The behavior suggests that increasing the grasp pressure

(A) results in an increase in the antagonistic muscle tone which gradually increases the EOP;

(B) results in a sharp increase due to a sudden forming of a stiff linkage between the high-impedance parts of the hand (located in upper part) and the wrist (which interacts with the robotic handle). This is called locking mechanism in this chapter.
Figure 4.9: The Calculated EOP percentage versus the grasp pressure percentage. The grasp pressure is normalized using the maximum pressure, and the EOP is normalized by the maximum EOP observed. Each graph is made using 5 values. The dashed red line is the conservative interpolation which avoids over estimation of EOP. These figures show 12 results out of the total 32. (a) Participant #0: Left Wrist Pronation-Supination, (b) Participant #0: Left Wrist Abduction-Adduction, (c) Participant #20: Right Wrist Pronation-Supination, (d) Participant #20: Right Wrist Abduction-Adduction, (e) Participant #5: Right Wrist Pronation-Supination, (f) Participant #5: Right Wrist Abduction-Adduction, (g) Participant #4: Left Wrist Pronation-Supination, (h) Participant #4: Left Wrist Abduction-Adduction, (i) Participant #1: Left Wrist Pronation-Supination, (j) Participant #1: Left Wrist Abduction-Adduction, (k) Participant #2: Left Wrist Pronation-Supination, (l) Participant #2: Left Wrist Abduction-Adduction.
Consequently, the dual-stage behavior suggests that the EOP increase which corresponds to the first 20% grasp pressure is affected by both of the above-mentioned points while an increase in EOP beyond 20% is affected mainly by case A (since the linkage is formed by the first 20% of the grasp pressure). More investigations might be needed to better explain the reason.

Here we study a fast interpolation technique using only a 2-point fractioning technique as a simple conservative alternative approach to the TSPL technique. The suggested simplified fast scheme is called the Quick Interpolation Technique (QIT) in this chapter, which considers only the minimum (5%) and maximum (80%) grasp percentages, without using the EOP value for the 20% grasp percentage.

As mentioned, the TSPL model can be used for accurate interpolating the EOP. However, the QIT utilizes a monotonic linear growth for interpolating the EOP value, in a simple but conservative manner. The QIT model is shown by the red dashed lines in Fig. 4.9. In fact, (a) it represents a linear monotonic behavior to interpolate EOP; (b) it is simpler to implement (compared to the TSPL model) since it only requires two EOP values; (c) it avoids over estimation of the EOP; and (d) it provides a positive confidence margin for the EOP estimation. For some of the results (such as in Fig. 4.9g and 4.9k), the QIT model is very close to the TSPL model and for some others, it provides a higher confidence margin (such as in Fig. 4.9d).

It should be highlighted that “based on our observations for all 32 results of this case study, the QIT model avoids over estimation of the EOP and can be used for estimating the EOP while providing a confidence margin.” To statistically evaluate the significance and the correctness of the above point, a new statistical analysis was conducted as discussed below.

First, for each user, a polygon shape is constructed using the 5 calculated values of the EOP. The polygons are formed in a plane which has the EOP percentage as the vertical axis and the grasp pressure percentage on the horizontal axis. As a result, on the vertical axis, 0% corresponds to 0 value for EOP and 100% corresponds to maximum observed EOP value for that user. In addition, on the horizontal axis, 0% means 0 grasp pressure and 100% means maximum observed grasp pressure for the user. After making the polygon shapes, we define and calculate a new factor called the “Signed Area (SA)”. The magnitude of this factor is the area of the polygon shape normalized by the area of a reference polygon which has 0%, 100%, 100%, 100% values on the vertical axis for grasp percentages of 5% 20%, 40%, 60%
and 80%, respectively. The area of this reference polygon is 3000. The sign of the SA factor is based on the locations of the 5 EOP values with respect to the QIT model. If the EOP values are higher than their QIT-based estimations, the sign is positive. So, the positive sign means that all of the 5 EOP values are higher than those from the QIT model and no over-estimation has occurred. This has been carried out for all 32 results.

In the next step, the statistical distributions of the calculated SAs are created and analyzed using the standard t-test technique. The distribution of SAs is shown in Fig. 4.10. The results of the statistical test conducted on the distribution given in Fig. 4.10 (against $SA = 0$) are given in Table 4.4. As can be seen in Table 4.4, having a minimum value equal to 0.065 (which has a positive sign) means that no over-estimation has occurred (since no negative SA has been observed). The statistical analysis given in Table 4.4 shows that the calculated positive average value for SA is statistically significant. This validates the effectiveness of the QIT model as a fast technique, calculated by using only two grasp conditions, and can conservatively interpolate the EOP while providing a positive confidence margin (i.e., the amplitude of SA).

**Remark 4.14.** As can be seen in Fig. 4.9 the accuracy of the TSPL technique (which includes the EOP value at grasp percentage of 20%) is considerably higher than the QIT model. The reason is the the QIT model does not use any information about the sharp increase in the growth pattern of EOP that occurs during the first 20% increase in grasp pressure. The goal of the study, reported in this part, was only to show that the value of EOP is higher than the one which can be estimated by a monotonic linear growth (QIT model). In other words, the
Table 4.4: Summary of the Statistical Evaluation for the Distribution of SA given in Fig. 4.10.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>SD</th>
<th>t-test result</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA</td>
<td>0.25</td>
<td>0.065</td>
<td>0.5</td>
<td>0.1</td>
<td>[t(31) = 14.2, p-value &lt; 0.001]</td>
</tr>
</tbody>
</table>

QIT model can provide a conservative estimate of the EOP and avoid over estimation of this value. This has been statistically validated by analyzing the calculated SA values that are indicators of the distance between the QIT model and the TSPL model. It should be added that a statistical curve fitting might be conducted over a population of users to find an average pattern of increase. Although, this can be an interesting investigation, it was not the goal of the reported result. The reason is that an average pattern can lead to considerable over estimation of the EOP value when we only use the relaxed and the stiff grasp conditions. Excessive over estimation of the EOP value is not desirable from the stability point of view for human-robot interaction (as will be clarified in the next section). In summary, in order to estimate the EOP value for an individual for use in the design of the controller, we can either (a) use the three-point/five-point-fractioning technique and generate the TSPL model (which includes the 20% grasp pressure), or (b) use the conservative value suggested by the QIT model that only needs two grasp conditions and does not result in excessive over estimation of the EOP, as supported by the results shown in Table 4.4.

4.4 Proposed Control Design: GPS-map Stabilizer

Based on the results shown in the previous section, using real-time measurement of the grasp pressure in addition to the geometry of the received forces at the user’s side, it is possible to estimate the EOP of the user’s hand through the proposed user-specific GPS map. In this section, the proposed stabilizing scheme is presented which uses the estimated EOP to guarantee stability and enhance transparency. The controller is implemented at the patient’s side and is called the GPS-map Stabilizer. The main action of the controller is to use the estimated EOP of the user’s hand in a Force Reflection Gate (FRG) function which changes the loop gain of the system. The FRG function is a time-varying nonlinear force feedback gain which modifies the
4.4. Proposed Control Design: GPS-map Stabilizer

Figure 4.11: Schematic of the closed-loop interconnection applying the proposed GPS-Stabilizer.

reflected forces to ensure that the stability condition remains satisfied so the system remains stable and the interaction remains safe. Consequently, if a user represents a low EOP when the delivered therapy is nonpassive (such as assistive therapy), the controller makes the force reflection gate tight to ensure that the amount of delivered nonpassive energy can be absorbed by the user’s limb biomechanics to guarantee interaction safety. However, when the user provides higher EOP (which corresponds to the higher capability in absorbing nonpassive energy), the controller opens the gate and allows the forces to be reflected and felt more by the user.

After applying the proposed controller, the original close-loop interconnection shown in Fig. 4.2 is transformed to the one given in Fig. 4.11. As can be seen in Fig. 4.11, the controller uses prior knowledge about the GPS map in addition to the real-time measurement of the grasp pressure and the geometry of interaction to calculate the FRG function and tune the loop gain. The proposed controller does not involve a classical additive damping loop; instead, it modifies the amplitude of the reflected forces to guarantee stability while preserving
the direction of kinesthetic interaction. This feature is important from a practical consideration and is helpful for enhancing transparency.

Given the estimated EOP of the user’s hand $\xi_p(t)$, the functionality of the stabilizer is explained below. Considering the stability condition of the original system (4.8), applying the controller, the new stability condition is as follows:

$$\int_0^t f_{\text{react}}(\tau)^T \cdot v_p(\tau) + f_{p-\text{mod}}(\tau)^T \cdot v_p(\tau) d\tau \geq 0.$$  \hspace{1cm} (4.13)

In (4.13), $f_{p-\text{mod}}$ is the output of the controller which is the modified force to be reflected. The above stability condition can also be rewritten in a short version as

$$E_p(t) \geq -E_{\text{th}-\text{mod}}(t).$$  \hspace{1cm} (4.14)

In (4.14), $E_p$ is the energy that can be absorbed by the biomechanics of the patient’s hand and is equal to $\int_0^t f_{\text{react}}(\tau)^T \cdot v_p(\tau) d\tau$, while $E_{\text{th}-\text{mod}}$ is the therapeutic energy received at the patient’s side after modification by the nonlinear FRG function. Consequently, we have $E_{\text{th}-\text{mod}}(t) = \int_0^t f_{p-\text{mod}}(\tau)^T \cdot v_p(\tau) d\tau$. Note that the delivered energy before modification is $E_{\text{th}}(t) = \int_0^t f_p(\tau)^T \cdot v_p(\tau) d\tau$.

It should be noted that during task execution, $E_{\text{th}}(t)$ is measurable; however it is not possible to measure $E_p(t)$ since $f_{\text{react}}$ is not accessible when the user performs a task. To design the FRG function, first, assume that $E_p(t)$ is also accessible in real-time. This assumption is relaxed later in this section. Based on the stability conditions (4.13) and (4.14), one possible initial design for the FRG function which may guarantee system stability is $f_{p-\text{mod}}(t) = \alpha \cdot FRG(f_p, v_p, f_{\text{react}})$ where

$$FRG(f_p, v_p, f_{\text{react}}) := \begin{cases} f_p(t) & \text{if } f_p(t)^T \cdot v_p(t) \geq 0, \\ \Psi(t) & \text{otherwise}. \end{cases} \hspace{1cm} (4.15)$$
In (4.15), we have

\[
\Psi(t) = \begin{cases} 
  f_p(t) & \text{if } |f_{\text{react}}(t)\cdot v_p(t)| \geq |f_p(t)\cdot v_p(t)|, \\
  \|f_{\text{react}}\|_2 \cdot \frac{f_p(t)}{\|f_p(t)\|_2} & \text{otherwise.}
\end{cases}
\] (4.16)

In (4.15), \(\alpha\) is a positive confidence design factor \((0 \leq \alpha \leq 1)\). \(\alpha = 1\) defines the maximum gain of the system which can still satisfy the stability condition of the system. \(\|\cdot\|\) represents the 2-norm of a vector.

Through the use of the proposed controller, when the FRG function observes (a) a dissipative power packet \(f_p(t)^T \cdot v_p(t) \geq 0\), or (b) a nonpassive packet which can be absorbed by the user’s hand \(|f_{\text{react}}(t)^T \cdot v_p(t)| \geq |f_p(t)^T \cdot v_p(t)|\), it does not change the loop gain and allows the power packet to flow. In addition, when the controller observes a non-dissipative power packet, \(f_p(t)^T \cdot v_p(t) < 0\), which cannot be absorbed by the user’s hand \(|f_{\text{react}}(t)^T \cdot v_p(t)| < |f_p(t)^T \cdot v_p(t)|\), the proposed FRG function lowers the loop gain to guarantee system stability.

As mentioned before, the controller given by (4.15) assumes that the energy which can be absorbed by the patient’s hand (i.e., \(E_p(t)\)) and the impeding component of the user’s hand dynamics \(f_{\text{react}}\) are accessible measurements. However, in practice, when the user utilizes the robot to perform a task, \(f_{\text{react}}(t)\) is neither measurable nor accessible. Consequently, it is not possible to directly calculate the energy that can be absorbed by the patient’s hand \(E_p(t)\) and the corresponding power packets. This issue is addressed by the proposed GPS map which provides an estimate of the energy that can be absorbed by the user’s hand. Consequently, instead of using \(E_p(t)\) and \(f_{\text{react}}\) in (4.16) to calculate \(\Psi(t)\), the estimated EOP value provided by the GPS map is utilized and the design of the controller is modified as explained below.

First, regarding the passivity condition of the user’s hand and considering (4.7), it can be shown that when the EOP is changing, we have

\[
\int_0^t f_{\text{react}}(\tau)^T v_p(\tau) d\tau \geq \int_0^t \xi_p(\tau)v_p(\tau)^T v_p(\tau) d\tau \\
\geq \xi_{p-\text{min}} \int_0^t v_p(\tau)^T v_p(\tau) d\tau.
\] (4.17)

In (4.17), \(\xi_p(t)\) is the varying EOP of the user’s hand which can be estimated using the corresponding GPS map. Also, \(\xi_{p-\text{min}}\) is the minimum value of \(\xi_p(t)\). Consequently, considering
(4.17) and (4.14), the following new stability condition can be obtained:

\[ \dot{E}_p(t) \geq -E_{th-mod}(t) \]  (4.18)

where \( \dot{E}_p(t) = \int_0^t \xi_p(\tau) v_p(\tau)^T v_p(\tau) d\tau \).

The expanded version of the above stability condition is

\[ \int_0^t \xi_p(\tau) v_p(\tau)^T v_p(\tau) + f_{p-mod}(\tau) \cdot v_p(\tau) d\tau \geq 0 \]  (4.19)

Using the Cauchy-Bunyakovsky-Schwarz inequality and based on (4.19), the GPS-map Stabilizer that guarantees system stability can be designed as

\[ f_{p-mod}(t) = \alpha \cdot FRG(f_p, v_p, \xi_p \cdot v_p) \]

where

\[ FRG(f_p, v_p, \xi_p \cdot v_p) := \begin{cases} f_p(t) & \text{if } f_p(t)^T \cdot v_p(t) \geq 0, \\ \Psi(t) & \text{otherwise.} \end{cases} \]  (4.20)

In (4.20), we have

\[ \Psi(t) = \begin{cases} f_p(t) & \text{if } \|\xi_p(t)v_p(t)^T v_p(t)\| \geq \|f_p(t)^T \cdot v_p(t)\|, \\ \frac{\|f_p(t)\|}{\|f_p(t)\|} & \text{otherwise.} \end{cases} \]  (4.21)

In fact, (4.20) and (4.21) define the proposed GPS-map Stabilizer. The technique utilizes the user-specific GPS map to calculate \( \xi_p(t) \) and finally tune the loop gain through the proposed nonlinear \( FRG(\cdot) \) function, in order to guarantee that the stability condition (4.19) is satisfied.

Using the proposed GPS-map Stabilizer, the force reflection gate will be tuned in a real-time and the user-specific manner based on the corresponding biomechanical capabilities of the user’s hand in absorbing interactive energy. As a result, if a user represents a high EOP (considering the direction of interaction and the grasp pressure), the controller may completely open the force reflection gate and allow the non-passive energy to flow since it can be absorbed by the user’s hand biomechanics and will not result in unsafe instability. Consequently, even if the interconnection includes a non-passive communication network and/or non-passive environment, the controller only compensates for a part of non-passive energy which cannot be
absorbed by the user’s hand at each time instant. The proposed GPS-map Stabilizer takes into account the intensity of grasp pressure and the geometry of interaction together with the user-specific GPS map to find the amount of energy to be compensated for. If the calculated EOP of the user’s hand is high-enough, the controller can guarantee a perfectly transparent and stable system regardless of existence of nonpassivity sources.

The proposed GPS-map Stabilizer can be used for any haptic system, including HRR and HTR, to guarantee stability while enhancing transparency. It relaxes the conventional passivity assumption on the behavior of the environment (such as the one made in [28, 61]). The major differences between the proposed GPS-map Stabilizer and conventional state-of-the-art time-domain passivity controllers, designed for haptic systems [62], are that the proposed technique (a) takes into account the variable EOP of the user’s biomechanics (considering the amount of grasp pressure and the geometry of interaction) in order to take advantage of the existing EOP resources during interaction; and (b) preserves the direction of force feedback in the Cartesian domain which is important from a practical point of view.

4.4.1 Case Study: Non-passivity of Hand and The GPS-map Stabilizer

In this part, we discuss how the proposed framework can be extended to relax the passivity assumption on the impeding part of the patient’s hand. Relaxing the non-passivity assumption for the proposed framework requires some extensions in the design of both the GPS-map visualization technique and the proposed stabilizer. The discussion is divided in two parts:

Part A: Exponential GPS map (E-GPS map)

Considering the definition given in (4.7), the extent of passivity can be either non-negative ($\xi \geq 0$) which is denoted as EOP, or negative which is denoted as SOP in Section 2.4. As a result, by conducting the identification calculation given in (4.10), if the outcome (i.e., $\xi_{p-i}$) is non-negative, then we call it EOP. However, if the patient shows a non-passive behavior in some directions of interaction, we will have negative $\xi_{p-i}$ values which is called SOP. The current design of the proposed radar plot of the GPS-map (explained in Section 3.3 and shown in Fig. 4.4(d) for Participant #2) is based on a non-negative radius value (which shows $\xi_{p-i}$) and a phase value (which shows the direction of interaction). As a result, negative values for
the radius (which correspond to SOP) are not supported by the design of the radar plot shown in Section 3.3.

There are different ways to address this. One is to add a third axis to the visualization of the GPS map which can visualize the negative values. The other technique, explained here is to use a nonlinear one-to-one mapping function which maps the \((-\infty, +\infty)\) window of the extent of passivity to \((0, +\infty)\) window of the transformed one. Here we suggest an exponential mapping. The result is denoted as Exponential GPS map (E-GPS map) which uses the following calculation for \(E_{\xi_{\text{p}}-i}\) as the radius of its 2D radar plot:

\[
E_{\xi_{\text{p}}-i} = e^{\xi_{\text{p}}-i}. 
\]

In (4.22), \(\xi_{\text{p}}-i\) is the extent of passivity. This value is EOP when it has the positive sign and is SOP when it has the negative sign. \(\xi_{\text{p}}-i\) is calculated using (4.10) for the \(i^{th}\) direction of stimulation. In addition, \(E_{\xi_{\text{p}}-i}\) is the radius of the radar plot for the E-GPS map. As a result, \(E_{\xi_{\text{p}}-i}\) can represent both passive and non-passive limb activities. If a patient shows non-passive limb dynamics in some directions, the E-GPS value in those directions will be inside the unit circle; and if he/she shows passive limb dynamics, the corresponding value in the E-GPS map will be outside of the unit circle. As a result, the unit circle represents the border of passivity in the E-GPS map, proposed to visualize both passive and non-passive behavior of a user.

Part B: E-GPS-map Stabilizer

In the next step, we need to relax the passivity assumption for the proposed controller. For this purpose, using the same mathematical approach, as used for (4.20) and (4.21), the design of the FRG function is extended as given in (4.23) and (4.24).

\[
FRG(f_p, \psi_p, \xi_{\text{p}}) := \begin{cases} f_p(t) & \text{if } f_p(t)^T \cdot \psi_p(t) + \xi_{\text{p}}(t)\psi_p(t)^T \psi_p(t) \geq 0, \\ \Psi(t) & \text{otherwise.} \end{cases} 
\]
In (4.23), we have \( \Psi(t) = \mu(t) \cdot \frac{f_p(t)}{||f_p(t)||_2} \), where:

\[
\mu(t) = \begin{cases} 
||\xi_p(t)v_p(t)||_2 & \text{if } \xi_p(t)v_p(t)^Tv_p(t) \geq 0, \\
||\xi_p(t)v_p(t)||_2 & \text{if } f_p(t)^Tv_p(t) \geq 0, \\
0 & \text{otherwise.}
\end{cases}
\] (4.24)

Considering (4.23) and (4.24), if the patient has a passive limb impedance \( (\xi_p \geq 0) \) the designed FRG function behaves as the one designed in (4.20) and (4.21). However, the new design covers the case of non-passivity in the patient’s hand \( (\xi_p < 0) \), as well. The extended stabilizer is denoted as E-GPS-map Stabilizer which utilizes the E-GPS map to observe the extent of passivity at the patient’s side. For this purpose, it uses the natural logarithm operator to calculate \( \xi_p \) from the E-GPS map of the patient’s hand.

This stabilizer observes the passivity characteristics of the patient’s hand biomechanics besides those for the reflected therapeutic forces. If the observed non-passivities in the system (which can either be from the therapy terminal or the patient terminal) can be absorbed by the existing passivity resources in the interconnection, the stabilizer does not change the transparency. If the above-mentioned condition is not observed by the controller, the stabilizer tunes the force reflection gate as needed to guarantee the stability of the system according to the stability condition given in (4.19).

### 4.5 Experimental Evaluation of GPS-map Stabilizer

In this section, the proposed GPS-map Stabilizer is implemented and the corresponding performance is experimentally evaluated. For this purpose, the table-top upper-limb robotic rehabilitation device from Quanser Inc. was utilized. The robotic handle was sensorized using two Interlink pressure sensors which registered the grasp pressure of the user. The experimental setup is shown in Fig. 4.1. The sensors were connected to a PCIe-6320 data acquisition card from National Instruments to read the pressure values. The Real-time Quarc library (from Quanser Inc.) in Matlab/Simulink was used to run the system. The sampling period for running the setup was 1ms and for data logging was 10ms. To account for possible time-varying
communication delays (which exist in the case of cloud-based rehabilitation), a variable round trip delay of $\tau(t) = 100 + 20\sin(2\pi t) \text{ ms}$ was considered as shown in Fig. 4.12.

In order to evaluate the performance of the stabilizer, the experiment was performed for both a resistive environment (which is a passive viscous force field) and a power-assistive environment (which is a non-passive negatively viscous force field). During the first phase, the power-assistive force field was generated in Matlab/Simulink with an assistive gain of $20 N.s/m$. During the second phase of the experiment, a resistive viscous force field was generated having a viscous gain of $-20 N.s/m$. It should be noted that while a resistive environment is a passive component of the system, because of the existence of the communication delays, it can realize a non-passive interconnection such as the assistive environment. As a result, both of the above-mentioned environments can challenge interaction stability, as shown in the results.

### 4.5.1 Power Assistive Force Field

In the first phase, the stabilizer was evaluated for power assistive environment, in four steps. For the first three steps the controller was turned on. During the first step ($t \leq 28$ s), some sudden sharp disturbances were applied to the robot when the user was not holding the robotic handle (zero grasp pressure). In this situation, the stabilizer was considerably challenged since no dissipation was applied by the user’s hand. The velocity and force trajectories can be seen in Figs. 4.13a, 4.13b, and 4.13c when $t \leq 28$ s. As shown in these figure, the controller was able to stabilize the system and the robot behaved in a safe manner and the trajectories quickly converged to zero after the disturbances were applied. In fact, using the identified GPS map of the user’s hand and the measured grasp pressure, the calculated EOP was zero while the nonpassive assistive therapy was being applied. Consequently, the controller was automatically activated to damp out the energy and stabilize the system.
Figure 4.13: The controller is turned on: (a) the received force at the user’s side versus the modified force in the X-direction, (b) the force trajectories in the Y-direction, (c) the velocity trajectories, (d) the power trajectories, (e) the grasp pressure.
In the second step (28s ≤ t ≤ 50s), the user provided a soft grasp while moving the robot in 2 degrees of freedom. In this step, since the user provided some grasp pressure, the calculated EOP was not zero and the controller allowed part of the non-passive energy to be delivered to the user’s hand since it could be partially absorbed by it. The force and motion trajectories are shown in Figs. 4.13a, 4.13b and 4.13c for 28s ≤ t ≤ 50s. As can be seen in Figs. 4.13a and 4.13b, the controller has modified the delivered force to guarantee stability. In addition, the power modification is shown in Fig. 4.13d. As shown in the figure, during this step, since the amplitude of the received power packets (solid blue line) was higher than the power that could be absorbed by the user’s hand (solid green line), the controller has modified the energy (solid red line) through force modification. As a result, the user could feel the assistive nonpassive forces in the same direction as that of the delivered forces, while the amplitude was modified based on the knowledge of the energy absorption capability of the user’s hand. The corresponding grasp pressure is shown in Fig. 4.13e when 28 s ≤ t ≤ 50 s.

In the third step of this experiment, the user provided higher grasp pressure (shown in Fig. 4.13 when t > 50s) while moving the robot in 2 DOF. In this situation, the amplitude of the power absorption capability of the user’s hand was higher than the delivered non-passive assistive power (this can be seen in Fig. 4.13d when t > 50s). Consequently, the controller allowed all the non-passive power to be reflected back to the user’s hand without sacrificing the stability of the system, as shown in Fig. 4.13d for t > 50s. As a result, the user was able to feel all the assistive forces (shown in Figs. 4.13a and 4.13b when t > 50s) since the controller did not change the reflected nonpassive forces/power and the transparency of the system is completely preserved despite the existence of communication delays and nonpassive assistive environment.

Note that the system behaved in a stable manner during all three steps when the controller was turned on. In the fourth step of the first phase, the controller was turned off and the user tried to gently move the robotic handle. The force and velocity trajectories are shown in Fig. 4.14. As shown in Fig. 4.14 once the user touched the robot, the system became unstable and went out-of-control. The trajectories grew in an exponential manner and the robot slammed into the boundary of the workspace.
4.5. Experimental Evaluation of GPS-map Stabilizer

Figure 4.14: The controller is turned off: (left) the force trajectories, (right) the velocity trajectories.

4.5.2 Resistive Viscous Force Field

In the second phase of the experiment, the stabilizing behavior of the controller is shown for the delayed resistive viscous environment. Similar four steps (conducted for phase 1) have been tested for phase 2. In the first three steps ($t < 75s$), the controller was turned on and different disturbances, motion trajectories and grasp pressures were applied to the robotic handle. The corresponding motion (velocity and position) trajectories are shown in Fig. 4.15 when $t < 75s$. As can be seen in Fig. 4.15, during the first three steps, the system behaved in a completely stable manner. In addition, the grasp pressure and the power modification are shown in Figs. 4.16a and 4.16b, respectively.

In the forth step, the controller was turned off and the user provided gentle movement that resulted in instability in the form of out-of-control high-frequency diverging oscillations. The corresponding motion profiles are shown in Fig. 4.15 when $t > 75s$. Due to the intense instability, the mechanical transmission cable of the robot broke.

The results shown in this section, validate the performance of the proposed technique and illustrate that the GPS-map Stabilizer can guarantee stability and interconnection safety based on the real-time estimate of the capability of the user’s hand biomechanics in absorbing interaction energies in different directions of interaction. If the user provides enough energy absorption, the controller does not change the reflected forces and allows the non-passive energy to be completely delivered. This results in a perfectly stable and transparent system in the presence of communication delays and a non-passive environment.
4.6 Conclusion

In this chapter, Grasp-based Passivity Signature (GPS) of the human upper-limb was studied in the context of the strong passivity theorem. The proposed GPS map provides a graphical tool to assess and analyze the capability of a user’s hand in absorbing interaction energies. For this purpose, a user study was conducted consisting of 11 participants to analyze their arm’s and wrist’s (both right and left) excess of passivity (EOP), with respect to changes in grasp pressure and geometry of interaction. It was shown that there is a statistically-significant correlation between the change in EOP and (a) the provided grasp pressure, (b) the geometry of interaction. Further statistical investigations may shed more light on different characteristics of the proposed GPS map. Some interesting research questions are the following: “Does the GPS map have a typical shape?”; “Is there any similarity between the shape for right and left hands?”; “Does human handedness affect the shape of the map?”; and “How do gender, age and disabilities affect the shape of the map?”. In this chapter, GPS map was proposed for the first time and used in the design of a new controller called the GPS-map Stabilizer. The controller was shown to be capable of guaranteeing human-robot interaction safety through the use of the proposed GPS map. The stabilizer was motivated by application in haptics-enabled rehabilitation technologies where special attention needs to be paid to ensure patient-robot interaction safety. The proposed theory can also be used for conventional haptic and haptic teleoperation systems. The goal of the proposed stabilizer was to minimize transparency.
distortion using knowledge of the capabilities of the human upper limb in absorbing energy and changes in this capability due to a variable grasp pressure. The stabilizer behaves like a force reflection gate which is completely open if a user provides enough EOP, but otherwise closed just enough to ensure stability. Statistical evaluation and experimental results were reported in support of the proposed technique and the developed theory.
Bibliography


Chapter 5

A Supervised Therapist-in-the-Loop Technique for Training of Haptics-enabled Robotic Rehabilitation Systems

The material presented in this chapter has been submitted to the IEEE/ASME Transactions on Mechatronics, 2016.

5.1 Preliminaries

According to clinical statistics and gerontological studies, one of the leading causes of movement disabilities in the rapidly increasing population of aged people is stroke [1, 2]. It has been shown that early, repetitive and goal-oriented motor rehabilitation can help post-stroke patients to regain some of their lost vital motor functions which increases their quality of life and level of independence. It is believed that the mentioned improvement is due to a phenomenon called Neural Plasticity (NP) that enhances damaged neural pathways and empowers less-damaged redundant pathways [3].

Considering the increasing population of post-stroke patients, there is a need for increasing accessibility to rehabilitation therapies through the use of neuromechatronic technologies [4]. Programmable Virtual-Reality (VR)-based Haptics-enabled Robotic Rehabilitation (HRR) systems have shown great potential in accelerating NP and enhancing the quality of motor perfor-
Figure 5.1: The Quanser upper-limb rehabilitation robot and the implemented VR environment used in this chapter. The VR environment is displayed to the user via a head-mounted display. The target is shown by the green square. The patient movement is shown as the motion of the orange circle. The location of the target changes based on (a) the proximity of the patient to the defined target, and (b) the elapsed time for each motion. The possible locations of the targets are shown by the small purple squares.

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motion. In fact, AT amplifies the patients’ motor power to keep them engaged with the goal of better triggering NP. RT is delivered when patients can manage to perform simple motor tasks. As a result, the robot provides a virtual viscous environment to dissipate parts of the energy generated by the patients to make the task more challenging for them. The goal of RT is enhancing motor control and equalizing the muscle power [7, 9].

There are three major components with HRR systems, namely (a) a powerful haptics-enabled rehabilitation robot which delivers the programmed therapeutic force field; (b) a VR environment that provides the patients with the required visual cues needed to perform the tasks in a goal-oriented manner; (c) a Programmable Virtual Therapist (PVT) algorithm that is responsible for calculating the required forces to be delivered by the robot during task execution [7, 9] [10]. The HRR system discussed in this chapter is shown in Fig. 5.1 which includes an upper-limb table-top planar rehabilitation robot from the industrial partner of this study, Quanser Inc. (Markham, Canada).

In [11] and [12], comprehensive literature reviews have been presented on multi-modal stimulation of motor learning including haptics-enabled rehabilitation therapy. As discussed in [11] and references therein, one of the open problems regarding the use of haptics-enabled robotic rehabilitation technologies is the design of the amount of the assistive/resistive therapeutic force fields (called “therapy intensity” in this chapter) to be delivered to the patient’s impaired limb. This intensity is correlated to the choice of control parameters (such as the stiffness of the virtual guidance) considered for delivering haptic therapy. Although the control parameters are conventionally set as fixed values, it is believed that these parameters need to be adaptively tuned by taking into account (a) specific kinematics and biomechanics of each patient during a task, (b) the motor control capability of the patient in performing the task, and (c) characteristics of neuromechanical deficits caused by the stroke [12]. In addition, if more haptic guidance is delivered than needed, it can result in excessive reliance of the user on the guiding feedback. This can cause passive participation of the user during therapy instead of the interactive participation required to stimulate NP [11, 12]. Accordingly, automated adaptive (such as assist-as-needed and fading feedback) techniques have been proposed in the literature to provide some level of adaptation considering the motor performance of the user [11–13].

Although through the use of the above-mentioned adaptive techniques, the performance of
HRR systems can be improved, it is not possible to find an automated algorithm that matches the knowledge and experience of a skilled expert therapist. In addition, although in general the literature supports the effectiveness of robotic rehabilitation systems, there are reports showing that in some cases robotic therapy can be even less effective than conventional human rehabilitation [14, 15]. It is believed that the aforementioned observation is due to the lack of flexibility in tuning the control parameters (which may result in improper choice of parameters) compared to conventional therapy where the human therapist is capable of appropriately modifying the “strategy” and “amount of haptic guidance” [11, 12] during therapy. This modification of therapy by therapists is known to be a key factor for delivering effective rehabilitation [16]. The above-mentioned challenge regarding the practical use of robotic rehabilitation systems for a wide range of patients with different neuromechanical characteristics provides the main motivation for this work.

The rest of this chapter is organized as follows. In Section 5.2, the motivation, overview and main contributions are highlighted. In Section 5.3, the method for implementing the framework is described. In Section 5.4, experimental results are presented. Conclusions are given in Section 5.5.

### 5.2 Introduction and Problem Statement

Recently, machine learning techniques have been suggested for training assistive robots in smart home environments [17]. In this chapter, we propose a new framework that fuses the concepts of *machine learning* and *rehabilitation robotics* to address the issue mentioned in Section I. The proposed framework has two major phases, namely (A) Supervised Therapy Demonstration (STD) phase, when the therapist is in the loop of interaction with the patient for delivering haptic rehabilitation, and (B) Regeneration through Modeling (RTM) for reproducing therapeutic behavior similar to that demonstrated in the first phase for the patient when the therapist is not in the loop.

During the first phase (i.e., STD), the therapist controls the intensity and strategy of therapeutic force production. In the next phase (i.e., RTM), the distribution of the therapeutic intensity/strategy are modeled (for the purpose of therapy regeneration) using a Neural Network
(NN) algorithm. The learned kinesthetic behavior of the therapist will then be regenerated for the patient while the therapist can use his/her time to work with another patient. These steps can be repeated as many time as needed and the therapist can change the strategy repetitively. This architecture is an alternative to tuning the intensity and strategy of the required therapy and brings the conventionally-absent kinesthetic supervision of a human therapist during robotic therapy. The specific design of the proposed platforms, which is compatible with cloud-based communication, allow for transferring the expertise of therapists over distances. This responds to the current interest in tele-rehabilitation and cyber-medicine [18–20]. Another outcome of the framework is a new visualization technique that can provide a heat map of the intensity of the delivered therapy by the therapist for each session. The map can be used by clinicians for monitoring progress of a patient’s motor performance over several sessions of therapy.

To implement the proposed framework, two platforms have been suggested in this chapter as described below:

A) **Haptics-enabled Teleoperated Supervised Training (HTST):** This platform is a telerobotic system, whose feasibility was shown recently by the authors [21, 22]. This system is composed of two haptic devices, one at the therapist’s side and the other at the patient’s side. The control algorithm used in this chapter provides a virtual viscoelastic coupling between the motions of the therapist and those of the patient. It should be noted that in this chapter, the term “viscoelasticity” refers to a system with both “viscosity” and “elasticity” components. HTST architecture allows the therapist to directly tune both the intensity and the strategy of therapy. In fact, the therapist can assist the patient by leading his/her motion towards the target in the shared VR environment, or can resist the patient’s movements thus, changing the therapy strategy. With the proposed viscoelastic coupling, the patient is allowed to make mistakes in tracking the target while performing motor tasks. This is an important factor for motor learning [11], as opposed to rigidly controlling the patient’s motions. The intensity of the therapy can be tuned by the therapist based on the distance between his/her position and that of the patient in the shared VR. This architecture enables haptic awareness for the therapist and allows him/her to feel the forces delivered to the patient’s hand. The detailed design of the architecture is given in the next section and a corresponding schematic of the implemented HTST platform is shown in Fig. 5.2.
Figure 5.2: A schematic of the implemented HTST platform used in this chapter. The VR environment is shared between the therapist and the patient where the orange and yellow circles correspond to the patient’s and therapist’s movements respectively. The therapist’s side robot is a 5-DOF $HD^2$ haptic device from Quanser Inc. whose rotations and $Z$ direction motion are locked to provide kinematics similar to the patient-side robot. The patient-side robot is a 2-DOF upper-limb rehabilitation robot from Quanser Inc.

B) EMG-based Indirect Supervised Training (EIST): This is a new platform, proposed in this chapter, which is less expensive compared to the HTST platform but does not enable direct haptic awareness for the therapist during the STD phase. This platform still allows keeping the therapist in the loop of robotic rehabilitation and makes it possible for him/her to tune the strategy and the intensity of therapy. For this purpose, the platform proposes to utilize a intuitive therapy modification machine using which the therapist can quickly, easily (preferably in a hands-free manner), and in real-time tune the strategy and/or intensity of therapy. Among several possibilities, we propose to utilize wireless measurement and analysis of the therapist’s gesture based on EMG measurements of the therapist’s muscle activities using multi-electrode EMG armbands. The benefits of this choice are: (a) real-time implementation, (b) hands-free performance, (c) no restriction of the motion and workspace of the therapist, (d) intuitive intensity modification, and (e) quick calibration (as explained later in this chapter).

For this purpose, two wearable wireless EMG armbands are considered to be used by the therapist. The muscle activities of the therapist are analyzed and mapped to the required level of assistance (using the right arm) and resistance (using the left arm). The therapist can tune the
strategy and the intensity by making different types of postures (e.g., tight fist versus relaxed fist) for different arms (right or left). Fist posture is called therapy posture in this chapter. Using the EIST platform, the strength of the therapy posture provided by the therapist is mapped to the position difference that is kept between the patient and the therapist in the shared VR environment when the viscoelastic coupling exists between the two motions. As a result, one arm of the therapist (the right arm) can provide leading forces towards the target in the shared VR environment to deliver assistance, and the other arm (the left arm) can provide lagging forces to deliver resistance. This design provides an intuitive way of therapy modification performed by the therapist. Slowly fading dynamics for the delivered therapy are also considered to ensure that the therapist prefers to keep a specific intensity of therapy during a motor task. Detailed design of the architecture is given in the next section and a corresponding schematic of the implemented EIST platform is shown in Fig. 5.3.

It should be emphasized that both HTST and EIST platforms fuse the advantages of using conventional HRR systems and having the skills of a human therapist in the loop of therapy. The common goal is to provide patients with an “augmented” therapeutic environment that incorporates the therapist’s expertise instead of conventional “virtual” therapy. Both platforms use the shared VR environment which is more closely shown in Fig. 5.4.
Figure 5.4: The shared VR environment: the orange and yellow circles correspond to the patient’s and therapist’s movements respectively. The red line is the virtual viscoelastic coupling between the motions of the therapist and the patient.

5.3 Method

In this section, the design of the proposed framework is described. The framework consists of two separate phases STD, and RTM. STD is conducted using the two different platforms, namely HTST and EIST, while the second phase is the same for both platforms.

5.3.1 Phase A: Supervised Therapy Demonstration

During the first phase of the proposed framework, the therapist provides rehabilitation to the patient and tunes the intensity and the strategy of therapy based on her/his knowledge of the needs of the patient. For this purpose, two alternative platforms are proposed, as explained below.

Platform #1: Haptics-enabled Teleoperated Supervised Training: The first platform is a haptics-enabled telerobotic system that enables the therapist to directly interact with the patient and feel the kinesthetics of rehabilitation during task performance. In other words, this platform can provide the therapist with haptic awareness of interaction. A Two-channel Haptics-enabled Architecture (THA) is considered to design the system. THA is an extension of Lawrence’s four-channel telerobotic architecture \cite{23}. The patient is placed at the conventionally-called “master” console of the telerobotic system, where she/he can provide the required motion to perform a task in the shared VR environment. The therapist is placed at
the “slave” console where she/he can feel the motions generated by the patient and can provide therapeutic forces to be reflected back to and felt by the patient.

To investigate the performance, first, the haptic interaction models at the therapist’s side and the patient’s side are defined. After applying a local feedback linearization algorithm \[24\] to compensate for nonlinearities, the patient-robot haptic interaction model is obtained

\[
\delta_m(t) \ast v_p(t) = u_{cm}(t) + f_p(t). \tag{5.1}
\]

In (5.1), \(\delta_m(t)\) is the impulse response of the linearized model of the master robot, \(\ast\) is the convolution operator, \(t\) denotes time, \(u_{cm}(t)\) is the control input for the master robot to deliver the appropriate therapy. The design of \(u_{cm}(t)\) is explained later. In addition, \(v_p(t)\) is the patient’s hand velocity, and \(f_p(t)\) is the force applied by the patient to the handle of the master robot. The force felt by the patient is in the opposite direction to \(f_p(t)\) which means that

\[
f_p'(t) = -f_p(t). \tag{5.2}
\]

For \(f_p(t)\), we have the following decomposition:

\[
f_p(t) = f_p^s(t) - \zeta_p(v_p, t). \tag{5.3}
\]

In (5.3), \(f_p^s(t)\) is the voluntary component of the force applied by the patient to perform the task and \(\zeta_p(v_p, t)\) is the nonlinear reactive component of the force which results from the biomechanical response of the patient’s hand to the movement applied by the robot.

Similar to the above, the therapist-robot haptic interaction model can be described by

\[
\delta_s(t) \ast v_{th}(t) = u_{cs}(t) + f_{th}(t), \\
f_{th}(t) = f_{th}^s(t) + z_{th}(v_{th}(t), t). \tag{5.4}
\]

In (5.4), \(\delta_s(t)\) is the impulse response of the linearized model of the slave robot and \(u_{cs}(t)\) is the control input for the slave robot. The design of \(u_{cs}(t)\) is explained later. In addition, \(v_{th}(t)\) is the therapist’s hand velocity, and \(f_{th}(t)\) is the force applied by the therapist to the slave robot to administer the therapy. In addition, \(z_{th}(v_{th}(t), t)\) denotes the nonlinear reaction dynamics of the
therapist’s hand and $f_{th}^r$ is the exogenous force applied by the therapist to generate the haptic therapeutic response based on the patient’s need.

After developing the local haptic interaction models, the control signals $u_{cm}(t)$ and $u_{cs}(t)$ should be designed to develop the viscoelastic coupling between the therapist’s and the patient’s movements. The suggested designs and the corresponding functions are explain below.

$$u_{cm}(t) = c_1(t) \ast v_p(t) + \hat{f}_{th}(t)$$  \hspace{1cm} (5.5)

where $c_1(t) = \delta_m(t)$;

$$u_{cs}(t) = -\gamma(t) \ast (\hat{v}_p(t) - v_{th}(t)) + c_2(t) \ast \hat{v}_p(t)$$  \hspace{1cm} (5.6)

where $c_2(t) = \delta_v(t)$.

In (5.5) and (5.6), $\hat{f}_{th}(s)$ is the therapeutic force which is received at the patient’s side. In addition, $\hat{v}_p(t)$ is the patient’s hand velocity which is received at the therapist’s side. In this chapter, particular attention is paid to the design of $\gamma(t)$. In fact, $\gamma(t)$ makes the mentioned viscoelastic coupling between the therapist’s and the patient’s movements.

Note that $\gamma(t) = \mathcal{L}^{-1}[\Gamma(s)]$, where $\mathcal{L}(\cdot)$ denotes the Laplace transform, “s” is the Laplace operator and $\Gamma(s)$ is

$$\Gamma(s) = \Delta_v(s) - \frac{K_v}{s} \theta_v s \hspace{1cm} \text{where} \hspace{1cm} \Delta_v(s) = \mathcal{L}[\delta_v(t)] \hspace{1cm} (5.7)$$

In (5.7), $K_v$ is the stiffness constant and $\theta_v$ is the viscosity constant of the aforementioned virtual viscoelastic constraint provided by the proposed haptics-enabled telerobotic system between the motions of the patient and those of the therapist. To clarify how this design generates the required viscoelastic constraint, we combine (5.1) to (5.7) to obtain:

$$F_p^r(s) = \hat{F}_{th}(s);$$

$$F_{th}(s) = (K_v + \theta_v s) \cdot (P_{th}(s) - \hat{P}_p(s)).$$

(5.8)

The first equation in (5.8) states that the force felt by the patient is equal to the force generated by the therapist. In addition, the second equation indicates that the therapeutic force is the output of the considered viscoelastic dynamics (whose stiffness and viscous parameters are $K_v$,
5.3. Method

The aforementioned dynamics are stimulated by the position error (as the input signal) generated by the therapist between his/her and the patient’s movements. As a result, the therapist can assist or resist the patient’s movement by providing various position-error profiles. The system gives both users the feel of haptic interaction through a virtual viscoelastic coupling. Allowing the therapist to feel the coupling forces enables haptic awareness for him/her.

The therapist can change the intensity of the therapy by modifying the magnitude of the position error. In addition, he/she can change the strategy (assistive or resistive) by changing the sign of the error. Consequently, if the therapist does not touch the slave robot, the error will remain zero and the patient will not received any therapeutic forces. This error-based therapist-in-the-loop approach is motivated by the commonly accepted need for providing freedom during interaction to accommodate motor learning. This concept will be also used in the second platform.

**Platform #2: EMG-based Indirect Supervised Training:** The second platform is a new architecture which can also keep the therapist in the loop of robotic rehabilitation. It is proposed to log the therapist’s intention in changing the intensity and strategy of therapy through the therapist’s hand posture. In this chapter, the fist posture is considered as the posture of interest though the system has the capability of considering a different posture for therapy. The platform is shown in Fig. 5.3 and a closer look at the armband together with an example of one out of eight available EMG readings during a fist-and-relax test are shown in Fig. 5.5.

As mentioned earlier, in order to implement the EIST platform two EMG armbands (from Thalamic Labs Inc., ON, Canada) are utilized. The use of the wearable wireless armbands
provides movement freedom for the therapist and this is one advantage of the EIST system over HTST. In addition to the above, currently each armband costs about US $200. This means that at the therapist-side the EIST setup costs about US $400 whereas the cost of having a second robot at the therapist’s side (for HTST) can be several orders of magnitude higher. As a result, the design of the EIST system is cost-effective which is an advantage of this platform over HTST. However, EIST system is not capable of providing the therapist with direct kinesthetic awareness. This means that, the therapist cannot directly feel the kinesthetic forces applied to the patient’s hand which would be needed to better tune the therapy.

In order to implement the EIST platform, a three-step protocol is designed. The goal of the first step is to collect enough data which is then used in the second step to learn (for detection) the posture of interest to be used in the third step. The third step maps the detected posture of interest to the intended therapy which will be then provided to the patient using the rehabilitation robot. The steps are described below.

**Step #1)** The therapist wears the two EMG armbands lower than his/her elbow joints. There is no need for accurate placement of the armbands. In addition, there is also no need for normalization of the EMG readings using activities of the muscles during maximum contraction. Instead, every time that the therapist wears the armbands, a two-minute calibration procedure should be conducted as explained below. The goal is to match the current positioning of the electrodes to find the posture of interest based on the EMG readings. The therapist will be asked to perform the following postures: (a) waving out, (b) waving in, (c) expanding fingers, (d) making fist, and (e) four thumb-to-finger touching postures. The postures are shown in Fig. 5.6. The first four postures are similar to the basic ones suggested by the software provided for the armbands. In the protocol suggested here, each one of the aforementioned postures needs to be kept for at least 5 seconds while having at least 2 seconds rest in between. The posture of interest should be kept no less than 15 seconds. A binary foot pedal is considered for the setup. The pedal needs to be pushed by the therapist only during the posture of interest. As mentioned earlier, here we chose the *making fist* posture to register the therapist’s intention for tuning the therapy. The output of the pedal is a binary value that is used to distinguish the posture of interest from other postures in the logged data. The output of the pedal is “1” during the posture of interest and is “0” during other postures. The above-mentioned procedure forms
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Figure 5.6: Calibrating Postures

step #1 of the protocol and the time needed to run this step is about 1 minute for each arm (i.e., 2 minutes in total).

**Step #2** The functionality of the second step of the protocol is to find a mapping between the 8-dimensional space of the EMG measurements (provided by each armband) and the 1-dimensional space of the detected posture of interest (given by the foot pedal). The mapping is named *EMG Analyzer*. Based on the observations made in this step, in order to find an appropriate mapping, it is required to take into account the history of the EMG measurements and consider dynamical characteristics. For this purpose, in addition to the 8 original raw EMG measurements, two digital low-pass filters have been applied in the pre-processing step. The Z-transform of the aforementioned filters are $\frac{0.01}{(z-0.99)}$ and $\frac{0.002}{(z-0.998)}$, when the sampling frequency for the filters is $1KHz$. The first filter is considered to provide short-term memory for the posture identification procedure and the second filter is considered to provide longer-term memory. As a result, 24 signals (8 raw signals plus 16 filtered signals) are considered to find the aforementioned mapping. In order to identify the mapping, a feed-forward neural network is utilized. The architecture considered for the network is composed of three hidden layers where the first and the third layers have 5 perceptrons and the second layer has 15 perceptrons. A linear transfer function is considered for the first and third layers while a log-sigmoid function is considered for the second layer. The training algorithm for the network is Levenberg-Marquardt back-propagation. A schematic of the utilized NN and the corresponding inputs and output is shown in Fig. 5.7. In order to represent the functionality of the above-mentioned...
identification procedure, the result for one arm is discussed below when after eleven iterations, the NN converges to the mean-square error of 0.0001. After training the NN, its performance is evaluated for various postures including a new one (i.e., arm pronation-supination). The results are shown in Fig. 5.8 where the raw EMG measurement is given in Fig. 5.8a and the output of the trained NN is given in Fig. 5.8b. As can be seen in the figures, the trained NN is capable of appropriately detecting the fist posture and distinguishing it from other postures.

**Step #3** The third step is denoted as *EIST-based Therapy Production*. The main purpose of this step is to map the detected posture of interest to an intended therapeutic behavior for applying various forces and tuning the therapy’s strategy and intensity. In other words, this step maps the identified posture of interest to a kinesthetic stimulus, which will then be delivered to the patient’s hand by the robotic rehabilitation device. For this purpose, first the following dynamics are defined:

\[ E_{th}(n) = \text{Sat}_{[-E_m, E_m]} \left\{ \eta \cdot \varepsilon_{th}(n) \right\}, \text{ where} \]

\[ \varepsilon_{th}(n) = \alpha \cdot \varepsilon_{th}(n-1) + \beta \cdot \left( EMG_{NR}(n) - EMG_{NL}(n) \right). \]
The dynamics given by (5.9) define the position error $E_{th}(t)$ to be delivered through the viscoelastic constraint as a part of the proposed VR environment (please refer to (5.8) for definition of position error and the resulting force). In (5.9), Sat{$\cdot$} is the saturation function whose limits are $[-E_m, E_m]$, and $n$ represents the time samples. In addition, $\eta$ is a scaling factor for normalization to cover the range of position error to be used in the VR environment. Also, $EMG_{NR}(n)$ is the output of the neural network trained for the right arm, and $EMG_{NL}(n)$ is the output of the neural network trained for the left arm. Accordingly, $\left(EMG_{NR}(n) - EMG_{NL}(n)\right)$ is termed differential muscle activity factor provided by the therapist. Let us initially assume $\alpha = \beta = 1$. The functionality of $\alpha$ and $\beta$ is explained latter in this section. Based on the above definitions, the therapeutic force generated by the EIST platform is

$$F_{th}(s) = (K_v + \theta_v s) \cdot \Xi_{th}(s),$$

where $\Xi_{th}(s) = \mathcal{L}[E_{th}(t)]$. (5.10)

In other words, using (5.9), in order to generate the supervised therapeutic forces, the therapist can tune the position of the object (corresponding to his/her motion) in the VR environment (like the yellow circle in Fig. 5.4) through providing various postures for his/her right and left arms. In this way, the therapist can tune the intensity and strategy of therapy based on
his/her intention. As a result, the patient will feel the kinesthetic forces generated by the virtual viscoelastic constraint, which is stimulated through the existence of $E(t)$. Accordingly, positive values for $E(t)$ result in generation of assistive therapeutic forces and negative values for $E(t)$ result in resistive forces. Here, the position corresponding to the therapist’s actions (used in the VR environment) is calculated as

$$p_{th}(t) = p_p(t) + E_{th}(t) \cdot Q(t)$$

where $Q(t) = \left( \frac{p_p(t) - p_{T}(t)}{\|p_p(t) - p_{T}(t)\|_2} \right)$. \hfill (5.11)

In (5.11), $p_p(t)$ is the position of the patient, $E_{th}(t)$ is the position error generated by the therapist to provide therapeutic forces through the viscoelastic constraint, $p_{T}(t)$ is the position of the target, and $Q(t)$ is the normalized unit vector that connects the concurrent position of the patient to the one for the target.

Note that in (5.9), $E_{m}$ is a positive value considered to provide the maximum and minimum limits for delivery of the position error by the therapist. This value can be tuned based on the size of the robot’s workspace. The right and left arms of the therapist are considered to identify his/her intention for delivering assistance and resistance, respectively. As a result, considering the dynamics given by (5.9), when the output of the NN trained for detecting the therapist’s right fist increases, the $E(t)$ will gradually increase. When the output of the NN trained for detecting the therapist’s left fist increases, the $E(t)$ will gradually decrease. Continuous reduction in $E(t)$ value can make it negative. As a result, using the proposed architecture, the therapist is able to tune the intensity and strategy of therapy by providing various postures in left and right arms.

**Remark 5.1.** Regarding the functionality of $\alpha$: this parameter works like a forgetting factor and should be chosen as $0 \geq \alpha \geq 1$. As a result, if $\alpha = 0$, no memory is considered for the generated therapeutic behavior. This means that once the therapist provides the posture of interest, the resulting position error in the VR environment will change correspondingly and when the therapist stops the posture, the position error in the VR environment will become zero. As a result, the therapist needs to keep the posture to deliver the intended therapeutic forces. However, for $\alpha = 1$ the therapist can provide the intended therapy through a “pumping-like” motion. Once the therapist provides the posture of interest, a position error will be set for
5.3. Method

the patient even if the therapist relaxes his/her hand. The therapist can still decrease/increase
the position error using his/her arm postures. As a result, the therapist can “pump-in” and
“pump-out” the position error. An $\alpha$ value close (but not equal) to unity results in a similar
behavior for the system; however, it introduces a leakage of error in the VR environment. As a
result, if the therapist stops providing the posture, the position error will \textit{gradually} converge to
zero. The leakage rate correlates with the choice of $\alpha$ (the lower the $\alpha$ value, the faster will be
the leakage). This can help the therapist in tuning the required assistance/resistance.

\textbf{Remark 5.2.} Regarding the functionality of $\beta$, it should be noted that this parameter works
like a responsiveness factor that increases the sensitivity to the differential muscle activity
provided by the therapist. The higher this parameter, the faster the position error will grow
in response to $\left(EMG_{NR}(n) - EMG_{NL}(n)\right)$. In other words, by increasing this parameter, the
therapist can quickly change the strategy and intensity of the intended therapy while providing
less differential muscle activity.

In order to evaluate the behavior of the design proposed in (5.10), the following experiment
was conducted. The user was required to follow a desired trajectory of an object in the intro-
duced VR environment. The trajectory was a periodic triangle wave signal with a frequency of
0.2\,Hz and an amplitude of 6\,cm. The user was required to perform the task by tuning the dif-
ferential muscle activity. The goal of this experiment was (a) to show that using the proposed
EIST platform it is possible to accurately provide varying position error in the VR environment
to be used for tuning the intensity and strategy of the intended therapy, and (b) to find default
values for $\alpha$ and $\beta$ which result in an appropriate control of the therapy. The results are shown
in Fig. 5.9 where the solid red line shows the required trajectory in the VR environment and
the solid blue line shows the position generated by the user in the VR environment. The chosen
default values for $\alpha$ and $\beta$ are 0.999 and 0.1, respectively which were used in this experiment
and provided straightforward control over the task. As can be seen in Fig. 5.9, the user was
capable of accurately tracking the corresponding position of the moving object in the VR en-
vironment. It should be noted that in practical situations, the therapist usually does not change
the strategy (which corresponds to changing the sign of the position error here) and intensity
(which corresponds to the amplitude of the trajectory) as frequently. Here, we confirmed the
capability of this new platform in mapping the intention of the user to track the required be-
behavior in the VR environment through providing differential muscle activities. This can then been utilized to produce therapeutic forces (as explained before).

5.3.2 Phase B: Regeneration Through Modeling

During the second phase of the proposed framework, first the behavior of the therapist, which is registered during the first phase (using either the EIST or HTST platform) in connection with adjusting the strategy and the intensity of the therapy is modeled. Then, the modeled therapeutic behavior is regenerated for the patient when the therapist is not engaged. The therapist can assign a duration for therapy regeneration through the RTM phase so that she/he can work with another patient. Consequently, the proposed framework learns the behavior of the therapist based on the first phase, then regenerate the learned behavior for the patient during a specific amount of time. In this way, the therapist does not need to spend all of his/her time with one patient and can share it between several patients. This addresses an essential need of under-resourced healthcare systems. In addition, this allows the therapist to intuitively supervise the intensity and strategy of the therapy delivered by the HRR robotic systems. The following two steps are to be followed during the second phase of the framework.

**STEP 1)** The first step is to model the therapeutic behavior delivered by the therapist whose corresponding data is logged during the first phase. For this purpose, first, the distribution of the therapeutic position error delivered over the workspace by the therapist is calculated. The distribution represents the therapist’s intention in tuning the strategy and intensity of the therapy. Then, the calculated distribution is fed to the therapy modeling module. The module is responsible for fitting an NN representation of the therapy, which can be saved and used in
the second step where the therapeutic behavior is regenerated. The neural network used in this part is composed of three hidden layers where the first and the third layers have 5 perceptrons and the second layer has 15 perceptrons. A linear transfer function is considered for the first and the third layers while a log-sigmoid function is considered for the second layer. In addition to the above, the training algorithm considered for the network is Levenberg-Marquardt back-propagation. It should be noted that the output of the NN over the workspace of the therapy can be graphically plotted as a heat map. The plot is denoted as Therapeutic Intensity Map (TIM). This can be utilized as a graphical representation of the therapy in follow-up sessions, which can intuitively inform the therapist about the therapeutic behavior delivered in the last session. Comparing several TIMs of consecutive sessions can be a useful tool for therapists to monitor the progress of motor performance. In Section IV, examples of the TIM are shown.

**STEP 2** The second step is when the modeled therapeutic behavior is regenerated and generalized in the workspace of therapy for the patient. The therapist can leave the patient to repetitively perform various rehabilitation tasks while the therapist works with another patient. During this step, the trained NN will be utilized to map the current position of the patient in the workspace of therapy to the modeled therapeutic intensity and strategy delivered by the therapist during the first phase. For example, if during the first phase, the therapist provided higher intensity of assistive therapy in parts of the workspace (that can be due to high muscle tone of the patient in that area because of the stroke), the patient will feel more assistive forces (during the second phase) when her/his motion trajectories pass through that area. Consequently, the
input to the trained NN is the current position of the patient in the workspace of the therapy and the output is the corresponding position error with respect to the target needed to regenerate the required therapeutic intensity and the resulting forces (using (5.10)).

The proposed framework is summarized in Fig. 5.10.

5.4 Results

In this section, experimental results are given in support of the proposed framework. For this purpose, both HTST and EIST platforms are implemented and tested. The following steps are implemented to conduct the validation.

5.4.1 Virtual Reality Environment and the Task

The VR environment is shown in Fig. 5.4. Also, the corresponding workspace of the HRR device is shown in Fig. 5.11. In Fig. 5.11, the possible positions of the target are shown by the blue stars and the home position is shown by the red star. The target randomly switched its location in a sequence with a homing motion after each switch. One example of the sequence of switching was [Location #1-Home-Location #4-Location #7-Home-...]. The allowed maximum time for each home-to-target or target-to-home movement in the provided VR environment was considered to be 3 seconds. The target switched its position if (a) the elapsed time for each motion exceeded the 3-second window, or (b) the target was reached by the robot within
the required time window. The definition of reaching was to have a targeting error (Euclidean distance) less than 0.5 cm.

5.4.2 Simulating Post-stroke and Healthy Users

To provide a consistent evaluation, motor behaviors of a healthy user and a post-stroke patient were simulated for the robot. The simulated patient was then assisted using

(a) Therapist-In-the-Loop HTST scheme (TIL-HTST),

(b) Therapist-In-the-Loop EIST scheme (TIL-EIST),

(c) NN trained by the HTST scheme (NN-HTST),

(d) NN trained by the EIST scheme (NN-EIST).

This allowed us to analyze different features of the platforms under similar conditions. For this, the patient-side robot was programmed to conduct the tracking tasks in the VR environment using two different control capabilities (one corresponding to the simulated healthy user and the other corresponding to the simulated disabled user).

In order to simulate the behavior of a healthy user, a finely tuned classical trajectory controller [25] was utilized which enabled the robot to track the target in the VR environment within the aforementioned 3-second window. In order to simulate the behavior of a post-stroke patient who (a) has imbalanced high muscle tone in his/her arm due to the stroke and (b) cannot provide enough controlling force to track the target, the following steps were conducted:

1) First the control gains of the above-mentioned trajectory controller considered for tracking the target in the 3-second window was reduced by 70%. This was done since post-stroke patients usually represent weak control forces to track an object.

2) In addition, to simulate the high muscle tone caused by a stroke, a nonlinear viscous force field was generated in the workspace, as can be seen in Fig. 5.12. The post-stroke high tone in muscles usually restricts movement in one direction or parts of the workspace. For example, a clinician may realize high forces are needed to stretch a patient’s arm beyond the resting point while retracting the arm is easier. This concept is used to simulate the imbalanced tone through the the viscous force field.
After implementing the simulation of a post-stroke patient, the tracking task in the VR environment was conducted. The results can be seen in Fig. 5.13 and can be compared with the tracking results of the simulated healthy user. As shown in Fig. 5.13a and 5.13c, the simulated healthy user was capable of tracking the target in various parts of the workspace during 5 minutes of experiment. The task was completed properly. The workspace was covered and the simulated healthy user was capable of reaching all the considered targets within the 3-second window for each motion in the VR environment.

In contrast, for the case of the modeled post-stroke patient, the trajectories were not properly tracked. This can be seen in Fig. 5.13b and 5.13d. In the right side of the workspace ($X \geq 0$), the length of the trajectories were considerably reduced and none of the 5 targets in that region were reached. This was due to the existence of a high viscous force field in that region ($X \geq 0$) which corresponds to the modeled high muscle tone. In addition, in the left half side of the workspace ($X < 0$), although the trajectories are larger than the right side, still the robot was not able to reach two of the targets within the 3-second window; in addition, there was high lateral deviation, which was due to the poor control capability of the simulated patient. As a result, the simulated patient was not capable of accurately performing the assigned task. This was due to the reduced control power (mentioned earlier in this section).

After confirming that, as expected, the simulated patient has poor tracking performance in comparison with the defined reference (which is the simulated healthy user here), the next step was to use these models to evaluate the performance of the defined 4 schemes (TIL-HTST,
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Figure 5.13: The resulting trajectory for the task performance: (a) the modeled healthy user (overlaid 2D path), (b) the modeled post-stroke patient (overlaid 2D path), (c) the modeled healthy user (trajectory over time), (d) the modeled post-stroke patient (trajectory over time).

TIL-EIST, NN-HTST, NN-EIST) under similar conditions.

5.4.3 Evaluation of the HTST Platform

As mentioned earlier in the chapter, using the proposed HTST platform, we can deliver direct kinesthetic supervision of a human therapist in-the-loop to provide therapeutic trajectories for a post-stroke patient. In this part, the performance of the TIL-HTST platform is shown. For this purpose, a human operator used the $HD^2$ haptic device (therapist-side robot in the implemented HTST platform) to provide therapeutic forces in order to recover the target tracking performance of the modeled post-stroke patient. Fig 5.14a and 5.14b show the recovered path in 2D and the motion trajectory over time respectively. The experiment was conducted for 5 minutes.
As can be seen in Fig 5.14, using the implemented HTST platform, the operator was capable of delivering assistive and coordinative forces that resulted in rectifying the motion trajectories of the simulated patient. Consequently, using the TIL-HTST platform, the operator playing the role of the therapist provided variable coordinative assistance to overcome the reduced control power of the modeled patient and the increased tone in the right side of the workspace. The information in this stage is logged and is utilized in the next section to train the neural network, which can learn and model the assistive behavior of the operator playing the role of the therapist.

### 5.4.4 Neural Network Training and Therapy Regeneration based on the HTST Platform

As mentioned earlier, in this chapter, the information regarding the intensity and strategy of the therapy logged during rehabilitation using the HTST platform was used to train a neural
network. In this part, the performance of the trained neural network is shown. For this purpose, during this step, the trained neural network provided therapeutic forces and was responsible for delivering therapy to the simulated post-stroke patient in order to recover the degraded motion control performance. The result of trajectory tracking can be found in Fig. 5.15. As can be seen in Fig. 5.15, the trained neural network was capable of properly delivering the required therapy to rectify the trajectories affected by the modeled stroke. As a result, the size of the trajectories on the right side of the workspace is recovered, all the targets are reached and the deviations are reduced. In other words, the trained neural network was capable of regenerating and generalizing the kinesthetic behavior of the therapist to help the patient’s motion tracking capability with no information about the characteristics of the simulated patient and by only utilizing information collected during the TIL-HTST trial.

The therapeutic position error created by the neural network and the corresponding therapeutic force profile can be seen in Figs. 5.16 and 5.17 respectively.

As can be seen in Figs. 5.16 and 5.17 in the right side of the workspace ($X \geq 0$) where
As mentioned earlier, the trained neural network can be evaluated at different points of the workspace and the result can be plotted as a heat map that shows the intensity of the trained therapy. The resulting map encapsulates information regarding the level of infirmity and reduced capability of the patient based on the behavior of the therapist during the TIL-HTST trial. The clinician can use the resulting heat map as a new image modality to evaluate the disability of the patient and analyze improvement by comparing the proposed heat map of consecutive sessions. The resulting heat map of the conducted experiment is shown in Fig. 5.18.
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Interestingly, the resulting map of the therapy matches the simulated level of disability. As mentioned before, the simulated patient has high muscle tone on the right side of the workspace which results in reduced tracking capability in that region. This can also be interpreted from Fig. 5.18 which shows that the intensity of the trained therapy delivered on the right side is higher than the one delivered on the left side of the workspace.

5.4.5 Evaluation of the EIST Platform

In this subsection, the performance of the TIL-EIST platform is shown. For this purpose, a human operator playing the role of a therapist used the implemented EIST platform to provide therapeutic forces in order to recover the target tracking performance of the modeled post-stroke patient. Figs. 5.19a and 5.19b show the recovered path in 2D and the motion trajectory over time, respectively. The experiment was conducted for 5 minutes. As can be seen in Fig 5.19, using the implemented EIST platform, the operator playing the role of the therapist was capable of generating assistive and coordinative forces at the patient-side robot, which resulted in recovering the motion trajectories of the simulated patient. Consequently, using the TIL-EIST platform the operator playing the role of the therapist provided variable coordinating forces to overcome the reduced control power of the modeled patient and the increased tone in the right side of the workspace. The information in this stage was logged and is used in the next section to train the second neural network, which can learn the therapeutic behavior of the operator playing the role of the therapist.
5.4.6 Neural Network Training and Therapy Regeneration Based on the EIST Platform

The information regarding the intensity and strategy of the therapy logged during rehabilitation using the EIST platform was utilized to train the second neural network. In this part, the performance of the trained neural network is shown. For this purpose, the trained neural network provided therapeutic forces based on the trained behavior and was responsible for delivering therapy for the simulated post-stroke patient in order to recover the degraded motion control performance. The result of trajectory tracking can be found in Fig. 5.20. As can be seen in the figure, the trained neural network was capable of properly delivering the required therapy to recover the trajectories affected by the modeled stroke. As a result, the size of the trajectories on the right side of the workspace was rectified, all the targets were reached and the deviations were reduced. In other words, the trained neural network was capable of reproducing the behavior of the therapist to recover the tracking performance without any information about
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Figure 5.20: The capability of the NN-HTST scheme in recovering the motion of the modeled post-stroke patient: (a) overlaid 2D path, (b) motion trajectory over time. The graphs on the left are taken from Figs. 5.13b and 5.13d.

The characteristics of the simulated patient and by only utilizing information collected during the TIL-EIST trial. The generated therapeutic position error in the VR environment and the corresponding therapeutic force profile can be seen in Figs. 5.21 and 5.22 respectively.

As can be seen in Figs. 5.21 and 5.22 in the right side of the workspace ($X \geq 0$) where the simulated patient showed high muscle tone and less control capability, the provided therapeutic position error and the corresponding forces were considerably higher. Same as in the case of HTST-based heat map of the therapy, the designed neural network using the EIST platform was utilized to find the therapeutic heat map. The generated map is shown in Fig. 5.23.

The resulting map encapsulates information regarding the level of infirmity and reduced capability based on the behavior of the therapist during the TIL-EIST trial. Similar to the case of the HTST-based therapy map, the map shown in Fig. 5.23 also matches the simulated level of disability. The map shows that the intensity of the trained therapy delivered on the right side was higher than that the one delivered on the left side of the workspace.
Based on the results shown in this section, both EIST and HTST platforms were capable of delivering TIL rehabilitative cues, which can help a post-stroke patient perform the tasks. The information logged during therapy delivery by the proposed platforms can be utilized to train neural networks to regenerate the same therapeutic behavior while the therapist is outside of the therapy loop. The proposed training technique can encapsulate the rehabilitative preference of a skilled human therapist for delivering kinesthetic therapy and can fill the gap between conventional robotic rehabilitation systems and standard therapist-in-the-loop hand-over-hand therapy.

Figure 5.21: The position error generated by the neural network trained to deliver therapy based on the logged behavior of the therapist during the TIL-EIST trial.

Figure 5.22: The therapeutic forces generated by the neural network trained to deliver therapy based on the logged behavior of the therapist during the TIL-EIST trial.
5.5 Conclusion

In this chapter, a new framework was proposed to tune the intensity and strategy of haptic rehabilitation systems based on the registered therapeutic behavior of a human therapist. The proposed framework has two phases, namely: Supervised Therapy Demonstration (STD) and Regeneration through Modeling (RTM). The HTST and EIST platforms were considered as alternatives which can register a human therapist’s intention for modifying the intensity and strategy of the therapy over time during the STD phase. Although in contrast to the EIST platform, the HTST platform can provide haptic awareness for the therapist during the STD phase of the framework, the EIST platform is more cost-effective. Both platforms are capable of enabling the therapist’s kinesthetic supervision for robotic therapy to address the existing challenge regarding the lack of flexibility in tuning the delivered therapy by robotic rehabilitation systems. During the RTM phase, the registered therapeutic behavior of the therapist is considered to be modeled using a neural network that can then regenerate the behavior for the patient. As a result, a therapist can demonstrate a brief session of kinesthetic rehabilitation for the patient (through the use of one of the two introduced platforms). Then, she/he can set a length of time for the patient to independently practice based on the modeled behavior of the therapist. This saves the therapist’s time, which is an important benefit to an under-resourced healthcare system.
Bibliography


Chapter 6

Characterization of Upper-limb Pathological Tremors: Application to Design of an Augmented Haptic Rehabilitation System

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6.1 Introduction and Preliminaries

Based on official statistics, the population of adults over the age of 65 is rapidly increasing worldwide. This trend is anticipated to continue due to the increase in life expectancy, and reduced fertility rate. It is anticipated that the number of senior adults will be more than twice by 2050 compared to the corresponding number in 2013 [I]. As a result of this ageing society, it is expected that there will be a significant increase in the incidence rate of age-
related sensorimotor disorders and diseases such as Parkinson’s Disease (PD) and Essential Tremor (ET). PD and ET are known to affect coordination, targeting and speed of motion while causing involuntary hand tremor [2–4]. Processing of hand motion and real-time extraction of the involuntary components while introducing minimum lag is an active line of research. This has attracted a great deal of interest for designing assistive, wearable and rehabilitative technologies by utilizing kinesthetic inputs and electrical stimulations (see, e.g., [5–9]).

Adaptive filters developed based on a Fourier Linear Combiner (FLC) algorithm have demonstrated appropriate performance in extracting hand tremors while introducing minimum latency compared to classical filtering [10–15]. The original version of recursive FLC-based filters, i.e., Weighted-frequency Fourier Linear Combiner (WFLC), was developed based on the assumption of having a single dominant frequency [10] for the targeted signals. The filter was used to design hand-held surgical tools in order to cancel physiological tremor of surgeons’ hands, in real-time (a practical need for delicate microsurgery) [11]. The assumption of a single dominant frequency was relaxed by proposing the BMFLC technique which can track multiple harmonics of a signal. The original motivation was to extract physiological hand tremor in healthy subjects [12–14]. The BMFLC filter has been utilized to extract physiological hand tremor [16] for surgical applications [17, 18] and its performance has been compared with that of the WFLC filter in quantification of hand tremors of microsurgeons and considerable improvement has been reported [13]. Due to appropriate performance of BMFLC filters in extracting physiological tremors, a recent study has investigated the possibility of using the technique for pathological hand tremors (such as those in PD) [15]. For this purpose, in [15], a new modification of the BMFLC filter was proposed to find the dominant frequency of the signal. Although the performance of the technique in [15] was slightly inferior to that of the conventional BMFLC filter, it was able to automatically find the dominant frequency of interest.

It should be noted that there are distinct differences between pathological and physiological tremors in terms of (a) amplitude, (b) frequency content, and (c) variability. In contrast to physiological tremors, pathological involuntary movements caused by PD and ET have closer range of frequencies to voluntary actions. However, for physiological hand tremor, the frequency range of involuntary movements is considerably higher than that for voluntary compo-
6.1. INTRODUCTION AND PRELIMINARIES

nents of the motion. This makes it possible to deal with the voluntary components of motion through the use of a bias term in the model for the case of physiological tremor [12, 13]. The close frequency range of pathological hand tremors to the voluntary components can challenge the estimation problem using various filtering techniques, specially in real-time applications. In addition to the frequency range, the nature, amplitude and existence of the tremor is considerably variable for the case of pathological tremors and they change considerably during task performance. Characteristics of pathological tremors in PD and ET patients depend on position, velocity, posture, task, and loading conditions. As an example, in Fig. 6.1 the hand tremor of a patient (participant #23 in our study, a 84 years old male with ET) is demonstrated for the cases of no-load posturing (Fig. 6.1a) and with-load posturing (Fig. 6.1b). In this test, the patient is asked to keep the posture steady while holding a cup under two loading conditions (i.e. empty cup and 1-pound loaded cup). Each loading condition is performed for 10 seconds. We overlaid 10 snapshots of each condition during the corresponding period of the test to produce Figs. 6.1a and 6.1b. In addition, the results of measuring the hand accelerations in 3 DOF are given in Fig. 6.1c. As can be seen, there is almost no tremor during no-load posturing for this participant while high-amplitude tremors start right after adding the 1-pound weight to the cup. This is just one example of how variable the pathological tremors can be under different conditions.

The BMFLC filters were designed originally for physiological tremors. Consequently, using them for pathological hand tremors should be statistically studied. For example, since there are considerable variations in the nature of hand tremors for each patient in different posturing, motion and load conditions, the filter needs to have low sensitivity to parameter tuning. In other words, when we tune the main parameter of the BMFLC filter (which is a corrective gain, defined later in this chapter), we need to be confident that the filter will keep good performance during the task, even if the type and nature of a hand tremor changes. It will not be practical if the filter is sensitive to the tuning of the corrective gain. The reason is that in this case, for each part of the task (which may require a different load or posturing condition) the filter may need a different corrective gain to deliver appropriate performance. This is not practical.

Consequently, although the use of the BMFLC filter is promising for extracting pathological tremors, the performance of this filter needs to be statistically analyzed for a group of
pathological patients and the possibility of enhancing performance should be evaluated to be compatible with the characteristics of pathological tremors.

### 6.1.1 Focus of This chapter

Motivated by the above issues, in this chapter we propose a new two-step modification to make the filter more accurate in extracting tremors and less sensitive to parameter tuning and intra-patient variabilities. The two-step modifications are (a) modulating the filter’s memory, and (b) enriching the harmonic model for extracting the hand tremor. The filter proposed in this chapter is called “E-BMFLC”.

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Figure 6.1: Participant #23 Holding the cup while maintaining a posture: (a) overlaid 10 snapshots during 10 seconds for the case of an empty cup, (b) overlaid 10 snapshots during 10 seconds for the case of a loaded cup, (c) hand accelerations in X-direction (solid blue line), Y-direction (solid red line), and Z-direction (solid black line) for the case of the empty cup experiment (left) and the loaded cup experiment (right). In (b), the blurred image of the patient’s hand is due to high amplitude tremor.
6.1. Introduction and Preliminaries

In the next step, we conducted an evaluation based on collected data from 14 PD and 13 ET patients to analyze the efficacy of the proposed filter in comparison with the conventional BMFLC technique. Using statistical analysis, we showed that E-BMFLC not only significantly enhances the accuracy of the proposed filter, but it also substantially reduces the sensitivity to the design of the filter’s parameters and intra-patient variabilities. To the best knowledge of the authors, this is the first work showing how to improve the performance of BMFLC filters in a statistically-significant manner for patients living with pathological hand tremors.

In the second part of this study, we investigate the possibility of using the proposed E-BMFLC filter to develop a new Haptics-enabled Robotic Rehabilitation (HRR) architecture which is capable of delivering energetically-active assist-as-needed therapy for PD and ET patients while adaptively controlling their hand tremor and avoiding unsafe Tremor Amplification (TA). TA is a restrictive factor when using non-passive robotic systems (that elevate the energy of the human-robot interaction) for patients having hand tremors. Active HRR systems amplify the energy provided by the patient and reflect it back to him/her to enhance coordination and movement speed. However, when the patient has involuntary hand tremor, elevating the total energy of the patient’s hand is equal to elevating the energy of the hand tremor. This can result in an unsafe unwanted condition (i.e. TA). TA can simply degrade the performance and usability of HRR systems for patients living with hand tremor. In the literature, the use of HRR systems in patients living with hand tremors are mostly limited to assessment and analysis of the disease and not multi-modal interactive rehabilitation and intelligent exercises [19–21].

In order to address the aforementioned challenge, we propose Augmented Haptic Rehabilitation (AHR) architecture. AHR is motivated by new evidence showing that interactive Virtual Reality (VR)-based rehabilitation can considerably accelerate Neuro-Plasticity (NP) and enhance sensorimotor health and targeting accuracy for patients living with pathological tremors, such as PD [22–25] and ET [26–28]. The initial concept of the architecture was briefly explained in the conference version of this work [29]. The AHR system presented in this chapter is an adaptive dual-action augmented haptic platform designed based on monitoring the energy of the voluntary and involuntary components of motion. The proposed architecture provides an adaptive viscous environment (resistive therapy) in parts of the frequency spectrum of the patient’s motion to resist (not counteract) the hand tremor up to a point that it reaches a minimum
energy level. This action of the AHR system is like an adaptive energy cap which gradually forces the energy of the patient’s hand tremor to converge to a small under-control value. This action avoids TA and makes the HRR system compatible for use for tremor patients. At the same time, the AHR system provides assistive action for the voluntary component of the motion. The energy of the voluntary component and tracking error is also monitored. The assistive force field enables the patient to have an acceptable tracking performance based on the monitored energy of the voluntary movement. The intensity of the assistive therapy is adaptively and gradually tuned in a new energy-based assist-as-needed manner to provide the patient with minimum needed assistance while keeping the patient in the loop of interaction. Consequently, the proposed dual-action behavior of the AHR system allows for delivering assistance to the voluntary component of the motion while restricting the involuntary component of motion in order to avoid potential TA. This is achieved taking advantage of the accurate decomposition of the voluntary and the involuntary components of the patient’s motion using the proposed E-BMFLC filter. This motion processing is the heart of the proposed AHR architecture which makes it possible to use interactive multi-modal environment of assistive HRR systems for rehabilitating slowness, coordination deficits and motion range problems (typical symptoms in PD and ET patients), in a safe manner. Fig. 6.2 shows the proposed AHR architecture. The architecture is implemented in this chapter and experimental evaluations are reported.
Remark 6.1. The contributions of this chapter are summarized below:

a) Showing two issues with the conventional design of BMFLC filters which can reduce the quality of the results for pathological tremor estimation, namely: infinite memory and old tremor projection.

b) Proposing two new solutions to significantly enhance the accuracy of the filter, reduce the sensitivity to parameter tuning and variation in the frequency content of the signal, and deal with the two issues mentioned above.

c) Statistically analyzing the performance of the proposed E-BMFLC filter for 27 pathological tremor patients in order to validate the functionality of the proposed technique.

d) Proposing a new AHR technique which enables delivery of a new assist-as-needed rehabilitation therapy for PD and ET patients while controlling the energy of involuntary movements and avoiding unsafe amplification of hand tremors due to the active nature of robotic therapy.

e) Experimental evaluation of the functionality of the proposed AHR system.

The rest of this chapter is organized as follows: The conventional BMFLC filter is introduced in Section 6.2. The new E-BMFLC filter is proposed in Section 6.3. In Section 6.4, the developed AHR architecture is defined. The statistical results of the patient-based study on the performance of the filter are given in Section 6.5. The AHR architecture is evaluated and experimental results are reported in Section 6.6. Concluding remarks are given in Section 6.7.

### 6.2 Conventional Adaptive BMFLC Filtering

In this section a quick overview of the conventional BMFLC filter is given, based on [12–14]. It is known that hand movement of patients living with pathological tremor is a modulated signal which has low-frequency voluntary actions and high-frequency involuntary components [6]. Accordingly, the hand motion can be modelled as:

\[
M_p(t) = M_{p-v}(t) + M_{p-i}(t)
\]  

(6.1)

In (6.1), \(M_p(t)\) is a signal which corresponds to the motion of the patient’s hand that can be the hand position \(P_p(t)\), velocity \(V_p(t)\), or acceleration \(A_p(t)\). Accordingly, \(M_{p-v}(t)\) is the
voluntary component of the hand motion and $M_{p-i}(t)$ is the involuntary component. The main goal of the BMFLC filtering is to find an estimate for $M_{p-i}(t)$ in a real-time manner while minimizing error and lag. The output can then be used in actuated devices such as the one used for hand-held anti-tremor surgical tools [12–14].

A BMFLC filter considers a truncated Fourier model for the frequency window $[\omega_a, \omega_b]$ of the hand tremor as:

$$Y(t) = \sum_{i=0}^{i=\beta(\omega_b-\omega_a)} \lambda_i \sin(\omega_a t + \frac{i}{\beta} t) + \vartheta_i \cos(\omega_a t + \frac{i}{\beta} t). \quad (6.2)$$

In (6.2), $Y(t)$ is the signal to be modeled, $\omega_a$ and $\omega_b$ define the frequency window of interest (which correspond to the tremor frequency). $\beta$ is the number of harmonics considered for one unit of frequency. Also, $\lambda$ and $\vartheta$ are coefficients of the truncated Fourier combiner model.

The linear regressors formulation of the truncated model (6.2) considering the band-limited frequency window for the hand tremor $[\omega_a, \omega_b]$ can be written as:

$$Y(t) = \theta^T \phi(t), \quad (6.3)$$

where we have:

$$\phi(t) = \left[ \sin(\omega_a t + \frac{0}{\beta} t), \ldots, \sin(\omega_a t + \frac{\beta(\omega_b-\omega_a)}{\beta} t), \right.$$

$$\cos(\omega_a t + \frac{0}{\beta} t), \ldots, \cos(\omega_a t + \frac{\beta(\omega_b-\omega_a)}{\beta} t) \right]^T, \quad (6.4)$$

and $\theta = \left[ \lambda_0, \ldots, \lambda_{\beta(\omega_b-\omega_a)}, \vartheta_0, \ldots, \vartheta_{\beta(\omega_b-\omega_a)} \right]^T. \quad (6.5)$

The regressors model, defined in (6.3)–(6.5), is then utilized in a recursive Least Mean Squares (LMS) algorithm to estimate the tremor in real-time and track its amplitude and the frequency content. It should be highlighted that the LMS algorithm has been conventionally and recently used in the design of BMFLC filters [12–15]. LMS has been also replaced with Kalman filtering in some studies [16, 30]. Although the use of Kalman filtering may enhance the performance, it significantly increases the computational cost of the filter [31]. In [31] it has been reported that for $N$ operations needed through the use of the LMS technique in BMFLC filters, $3N^2$ operations are needed for Kalman filtering. For example, if we need 160 operations to extract a tremor through the use of LMS in the BMFLC filtering technique, 76800 opera-
tions would be needed if we use Kalman filtering [31]. In [30], it has been reported that if the Kalman filter is utilized in the design of the BMFLC technique, having frequency resolution of the model less than 0.5\(Hz\) can prevent real-time implementation of the filter (when 512\(Hz\) sampling rate is assumed as the definition of real-time implementation). Note that for the case of haptic interaction, the sampling frequency is suggested to be at least between 1\(KHz\) and 1.5\(KHz\). In addition to the above, as can be seen in [16, 30], using the Kalman filter for BMFLC filtering, the linear state-space model of the system will not be time-invariant. This does not match with requirements of the classical Kalman filters with guaranteed stability and it has been shown that it can result in an unexpected diverging behavior [32–34], especially since the measurement and the model are uncertain (which is the case for pathological hand tremor). Finally, it should be added that in order to use the Kalman filtering technique in practice, the covariance matrices for the model and observation uncertainties should be properly tuned based on knowledge of existing measurement noises and model uncertainties [32, 33]. The possible diverging behavior of the Kalman filter is closely related to the tuning of the covariance matrices [33]. This makes it even more challenging to use the Kalman+BMFLC technique. As a result, in this chapter we propose two new modifications (for the LMS+BMFLC) which can significantly enhance the accuracy of the conventional BMFLC filter (as shown later in this chapter) without adding further complications for extracting pathological tremors. The LMS algorithm is shown below:

\[
\hat{Y}(t) = \hat{\theta}^T(n) \phi(t)
\]

(6.6)

where

\[
\hat{\theta}^T(n) = \hat{\theta}^T(n - 1) + 2\eta\phi(n)E(t)
\]

and \(E(t) = S(t) - \hat{Y}(t)\). (6.7)

In (6.7), \(\eta\) is the LMS corrective gain, \(E(t)\) is the estimation error, \(S(t)\) is the input signal, \(\hat{Y}(t)\) is the estimated signal, \(\hat{\theta}\) is the estimation of the coefficient vector of the Fourier combiner model. Since the model is truncated, the estimated signal will be an estimation of the high frequency components of the hand motion \(M_{p-i}(t)\) [12, 14].
6.3 Proposed Enhanced-BMFLC Technique

In this section, we indicate two facts that can degrade the performance of the BMFLC filter, then we propose solutions which form the new design called E-BMFLC.

6.3.1 Challenges with the Conventional Design of BMFLC

There are two problems associated with the conventional formulation of the BMFLC filter in (6.4)-(6.7):

1) Inaccurate Error Calculation: In (6.7), the error is represented as \( E(t) = S(t) - \hat{Y}(t) \), where \( \hat{Y}(t) \) is the estimated tremor. However, the input signal \( S(t) \) is equal to the modulated hand motion \( M_p(t) \), the only measurable characteristic of the hand’s motion. It is known that the actual measure of hand tremor \( M_{p-i}(t) \) is not accessible and estimating it is the main objective of the filter. Consequently, we cannot obtain the actual error between the hand tremor and the estimated tremor. In the conventional design of BMFLC filter, it is assumed that since the model is truncated, the output of this estimation will converge to the content of the tremor frequency window. Although this assumption is not incorrect, it is not accurate either. In the utilized LMS technique (6.7), the estimation parameters \( \hat{\theta} \) concurrently change in the recursive design of the filter to minimize the estimation error \( E(t) \). Consequently, although the considered model is truncated, the changing parameters can bring other frequencies out of the window of interest (i.e. \([\omega_a, \omega_b]\)) to make the error between the modulated hand motion \( M_p(t) \) and the filter’s output \( \hat{Y}(t) \) zero. This reduces the accuracy of the filter since the output of the filter should converge to \( M_{p-i}(t) \) not \( M_p(t) \). As an example, even if at some point, the output of the filter ideally matches with the actual hand tremor \( M_{p-i}(t) \), the LMS technique still observes the existing error \( E(t) \) since the error is calculated considering the value of \( M_p \) not \( M_{p-i} \). Consequently, the filter tries to move the estimation away from that point (which was ideal) and make the error between \( M_p \) and \( \hat{Y}(t) \) as small as possible. Based on this, we note the following:

Remark 6.2. We hypothesize that the aforementioned inaccuracy in error estimation will cause considerable sensitivity to the tuning of the corrective gain \( \eta \). The reason is that for the conventional design of the BMFLC filter, shown in (6.4)-(6.7), increasing the corrective gain makes the dynamics of the LMS algorithm faster (more responsive). This results in higher
6.3. PROPOSED ENHANCED-BMFLC TECHNIQUE

Effort of the filter in pushing the estimated signal closer to \( M_p \) and away from \( M_{p-i} \) by quickly changing the estimation parameters \( \hat{\theta} \). On the other hand, it is known that having small values for the corrective gain \( \eta \) in LMS algorithm decreases the convergence rate and estimation accuracy. Consequently, for the design of the BMFLC filter, either increasing or decreasing the gain can result in higher error. This makes it difficult to find an appropriate gain for the BMFLC filter in estimating pathological tremors. This hypothesis (sensitivity to the change in \( \eta \)) is shown in Section V. •

**Remark 6.3.** Note that the features of the pathological tremors are considerably variable compared to physiological hand tremor. Consequently, even if we choose a value for the corrective gain \( \eta \) which works in one situation for the hand tremor of a patient, it does not necessarily work for the same patient, in the same session under slightly different condition which can change the characteristics of the hand tremor. The reason is that the new tremor signal may need a different value of \( \eta \). In other words, considerable variability in the characteristics of pathological tremor necessitate having low sensitivity to the choice of \( \eta \) factor. For the case of physiological tremor, since the variability is not as much as the one for pathological tremor, the inaccuracy might be less. Analyzing the performance of the BMFLC filter for the case of physiological tremor is out of the scope of this work. The mentioned sensitivity issue is shown in Section V for the case of pathological tremor. •

**Remark 6.4.** In addition to the above, since the frequency range of pathological tremor is closer to the voluntary components (in comparison with physiological tremor), higher \( \eta \) values can more easily push the output away from \( M_{p-i}(t) \), in the design of the conventional BMFLC filter. •

**Remark 6.5.** Since the calculated error for the conventional BMFLC filter \( E(t) \) is the difference between the whole modulated hand motion \( M_p(t) \) and the estimated tremor \( \hat{Y}(t) \), it is not an appropriate measure of accuracy for the model considered in the LMS technique. Consequently, it is not possible to evaluate the performance of the filter and the chosen parameters by monitoring the error \( E(t) \). The error might be quite high while the output still matches with the hand tremor. •

Considering the above remarks, there is a need to enrich the model in a way that (a) represents less sensitivity to \( \eta \), and (b) provides a proper measure of modelling accuracy.
2) **Infinite Memory:** The other problem of conventional BMFLC filtering is the considered infinite memory of the filter for estimating the coefficients of the truncated Fourier combiner model. Considering (6.7), the dynamics of the recursive formulation used to estimate the hand tremor keeps the impact of old information similar the one of new information. In other words, the estimated values in the current time sample get affected by all old values *in a recursive manner*. Considering that the regressors model used in the design of BMFLC filter is based on the Fourier linear combiner, having infinite memory means that we have assumed a periodic nature for the tremor. This is the main assumption of conventional BMFLC filters. However, due to the considerable variability in pathological tremor, although assuming a quasi-periodic nature could be correct, the assumption of completely periodic model is not valid. Keeping the impact of old information similar to the new one and trying to find a Fourier combiner model for the whole signal, means that the behavior of the signal is assumed to be periodic and the whole input signal (from the $t = 0$ to the current time sample) can be modelled by one Fourier combiner. Consequently, if the input signal has a specific pattern at the beginning of time, this pattern will be repeated in future estimation of the tremor. This phenomenon is called “Old Tremor Projection (OTP)” in this chapter and can considerably reduce the accuracy of the estimation, over time. The existence of OTP is discussed in Section V.

### 6.3.2 Enhanced-BMFLC Filter

In this part, we propose E-BMFLC filter to deal with the aforementioned issues in two phases of enhancement.

**Phase #1 ) Harmonic Model Enrichment:**

To deal with incorrect error calculation, we propose to first use an enriched model and then extract the tremor out of the enriched model. This allows us to isolate modelling and tremor extraction steps. The following steps are taken:

**Step I:** in the first step, instead of using a truncated model considering the frequency window of the tremor $[\omega_a, \omega_b]$, the whole frequency spectrum of the “modulated signal” $M_p(t)$ is modelled using the frequency window of $[\omega_{\text{min}}, \omega_{\text{max}}]$. $\omega_{\text{min}}$ is the minimum frequency which is considered in the spectrum of $M_p(t)$, and $\omega_{\text{max}}$ is the maximum frequency of it. In this chapter,
6.3. Proposed Enhanced-BMFLC Technique

\( \omega_{\text{min}} \) is considered to be 0 Hz and \( \omega_{\text{max}} \) is considered to be 20 Hz for the acceleration data of patients’ hands. Considering \( L \) number of harmonics for the Fourier combiner model of \( M_p(t) \), when \( L = \beta(\omega_b - \omega_a) + 1 \), we have:

\[
M_p(t) = \theta_{M_p}^T(t)
\]

\[
\text{where } \phi_{M_p}(t) = 
\begin{bmatrix}
\sin(\omega_{\text{min}}t + \frac{0}{\beta}t), \ldots, \sin(\omega_{\text{min}}t + \frac{\beta(\omega_{\text{max}} - \omega_{\text{min}})}{\beta}t), \\
\cos(\omega_{\text{min}}t + \frac{0}{\beta}t), \ldots, \cos(\omega_{\text{min}}t + \frac{\beta(\omega_{\text{max}} - \omega_{\text{min}})}{\beta}t)
\end{bmatrix}^T,
\]

\[
\theta_{M_p} = 
\begin{bmatrix}
\lambda_0, \ldots, \lambda\beta(\omega_{\text{max}} - \omega_{\text{min}}), \vartheta_0, \ldots, \vartheta\beta(\omega_{\text{max}} - \omega_{\text{min}})
\end{bmatrix}^T.
\]

The complete model of the input signal (6.8) is then used in recursive LMS algorithm for the filter, as follows:

\[
\hat{M}_p(t) = \hat{\theta}_{M_p}^T(n)\phi_{M_p}(t)
\]

\[
\text{where } \hat{\theta}_{M_p}^T(n) = \hat{\theta}_{M_p}^T(n-1) + 2\eta\phi_{M_p}(n)E_{M_p}(t)
\]

\[
\text{and } E_{M_p}(t) = M_p(t) - \hat{M}_p(t).
\]

In (6.11), (6.12), \( \hat{M}_p(t) \) is the estimation of \( M_p(t) \). Also, \( E_{M_p} \) is the difference between the estimated value \( \hat{M}_p(t) \) and \( M_p(t) \). In addition, \( \hat{\theta}_{M_p}^T(n) \) is the coefficient vector for the estimated model for \( M_p \). Consequently, the estimation error \( E_{M_p} \) is a real measure of accuracy for the LMS algorithm (in contrast with the conventional BMFLC). Accordingly, we can monitor/utilize \( E_{M_p} \) to evaluate the efficacy of the filter. In addition, gradually increasing the corrective gain \( \eta \) results in a more accurate estimation up to a point that the measure of accuracy \( E_{M_p} \) shows an acceptable matching between the considered Fourier model for \( M_p \) and the real value of \( M_p \). In summary, using the enriched model, the behavior of the filter is more predictable in comparison with the conventional BMFLC and the tuning procedure of \( \eta \) is more straightforward.

**Step II)**: After finding an accurate model for the modulated signal \( M_p \), now we can consider different band-limited windows of frequency to extract various frequency ranges (considering the need of the application). In fact, using the proposed technique, the signal modelling and
frequency truncation are decoupled, while in the conventional formulation of BMFLC filter these two steps were fused. In this chapter, we considered two frequency ranges: $[\omega_{a-v}, \omega_{b-v}]$ for the voluntary component of the motion and $[\omega_{a-i}, \omega_{b-i}]$ for the involuntary component of the motion. We have:

$$\omega_{max} \geq \omega_{b-i} \geq \omega_{a-i} \geq \omega_{b-v} \geq \omega_{a-v} \geq \omega_{min} \geq 0$$  \hspace{1cm} (6.13)

Accordingly, the estimation of the voluntary component of the motion (i.e. $\hat{M}_{p-v}$), and the involuntary component of the motion (i.e. $\hat{M}_{p-i}$) can be obtained as given below:

$$\hat{M}_{p-v}(t) = \hat{\theta}^T_{Mp-v}(n)\varphi_{Mp-v}(t)$$  \hspace{1cm} (6.14)

$$\hat{M}_{p-i}(t) = \hat{\theta}^T_{Mp-i}(n)\varphi_{Mp-i}(t)$$

$$\hat{\theta}^T_{Mp-v}(n) = \left[ \hat{\theta}_{Mp}(n)\{i = \gamma_0\},...,\hat{\theta}_{Mp}(n)\{i = \gamma_1\},\right.$$  \hspace{1cm} (6.15)\[\left. \hat{\theta}_{Mp}(n)\{i = \gamma_2\},...,\hat{\theta}_{Mp}(n)\{i = \gamma_3\} \right]$$

$$\hat{\theta}^T_{Mp-i}(n) = \left[ \hat{\theta}_{Mp}(n)\{i = \gamma_4\},...,\hat{\theta}_{Mp}(n)\{i = \gamma_5\},\right.$$  \hspace{1cm} (6.16)\[\left. \hat{\theta}_{Mp}(n)\{i = \gamma_6\},...,\hat{\theta}_{Mp}(n)\{i = \gamma_7\} \right]$$

$$\varphi^T_{Mp-v}(n) = \left[ \phi_{Mp}(n)\{i = \gamma_0\},...,\phi_{Mp}(n)\{i = \gamma_1\},\right.$$  \hspace{1cm} (6.17)\[\left. \phi_{Mp}(n)\{i = \gamma_2\},...,\phi_{Mp}(n)\{i = \gamma_3\} \right]$$

$$\varphi^T_{Mp-i}(n) = \left[ \phi_{Mp}(n)\{i = \gamma_4\},...,\phi_{Mp}(n)\{i = \gamma_5\},\right.$$  \hspace{1cm} (6.18)\[\left. \phi_{Mp}(n)\{i = \gamma_6\},...,\phi_{Mp}(n)\{i = \gamma_7\} \right].$$
6.3. Proposed Enhanced-BMFLC Technique

In (6.15)-(6.18), \( \theta_{Mp}(n) \{ i = k \} \) and \( \phi_{Mp}(n) \{ i = k \} \) are the \( k \)-th element of \( \hat{\theta}_{Mp} \), and \( \phi_{Mp} \) vectors at \( n \)-th time stamp, respectively. Also, we have:

\[
\begin{align*}
\gamma_0 &= \beta (\omega_a - \omega_{min}) + 1, \\
\gamma_1 &= \beta (\omega_b - \omega_{min}) + 1, \\
\gamma_2 &= L + \gamma_0, \\
\gamma_3 &= L + \gamma_1, \\
\gamma_4 &= \beta (\omega_a - \omega_{min}) + 1, \\
\gamma_5 &= \beta (\omega_b - \omega_{min}) + 1, \\
\gamma_6 &= L + \gamma_4, \\
\gamma_7 &= L + \gamma_5.
\end{align*}
\] (6.19)

Consequently, the Fourier-based signal modelling and tremor extracting are decoupled. This allows us to first accurately model the modulated signal \( M_p \), and then extract \( M_{p-i} \) and \( M_{p-v} \). Consequently, more precise extraction of tremor and less sensitivity to the choice of \( \eta \) are expected. This is statistically demonstrated in Section V.

Phase #2 ) Memory Manipulation

Here we propose to use windowed memory instead of the conventional infinite memory for the filter. This allows us to adapt better to change in characteristics of the tremor. The sliding memory window results in greater impact from recent values than from old values. For this purpose the recursive formulation of the filter (6.12) is modified as

\[
\hat{\theta}^T_{Mp}(n) = \rho \hat{\theta}^T_{Mp}(n-1) + 2\eta \phi_{Mp}(n)E_{Mp}(t) \\
\text{where } E_{Mp}(t) = M_p(t) - \hat{M}_p(t), \\
\rho = \delta \sqrt{\alpha}, \text{ and } \delta = \frac{1}{\Delta T} T_p.
\] (6.20)

In (6.20), \( \rho \) defines the pole of the discrete dynamics of the memory windowing for the filter in the Z-domain. The lower the \( \rho \) value, the faster the forgetting dynamics will be. This parameter can directly be chosen based on the desired speed that we would like to forget older data (which correlates with the variable nature of the signal to be filtered). Based on our observation which will be reported later in this chapter, for extracting pathological tremor of PD and ET patients, \( \rho = 0.999 \) can be used as the default value which can significantly enhance the performance of the filter. Using (6.20), we can tune the \( \rho \) value when (a) the sampling frequency is different from the one chosen in this chapter; and (b) we would like to filter a signal with a different variable nature compared with pathological hand tremor of PD and ET patients. In (6.20), \( \Delta T \) is the sampling time (in seconds), \( T_p \) is the width of the considered memory window (in
seconds), and $\alpha$ is the considered minimum gain within the time window which corresponds to the latest value in the window. The suggested default value for $\rho$ is calculated as follows. The width of the memory window is considered to be $T_p = 2s$. This means that we want to consider a window of 2s for keeping the impact of past values. Here, “impact” corresponds to having scaling gain more than $\alpha$ whose default value is set at 5%. For the data used in the evaluation given this chapter, the sampling frequency was 1.5 $KHz$ which means that $\Delta T = (1/1500)s$. The resulting sliding memory window for the designed filter is shown in Fig. 6.3.

This technique gradually forgets the old information affecting tremor estimation and uses recent data from a limited past time-window. Consequently, the assumption of periodic behavior is relaxed and it is just limited to the considered time-window. As a result, the signal can behave in a “quasi-periodic” manner without violating the assumptions of the designed filter. The combination of the proposed Harmonic Model Enrichment and Memory Manipulation forms the proposed design for E-BMFLC.

### 6.4 Proposed AHR Architecture

In this section, the E-BMFLC filter is used in the design of a new therapeutic architecture for pathological tremor patients. The architecture is called Augmented Haptic Rehabilitation (AHR) and performs the following two actions:

- **Action 1)** damping out the extracted hand tremor to avoid amplification of the tremor energy and enhance patient-robot interaction safety;

- **Action 2)** assisting the voluntary component of motion to help the patient in finishing therapeutic tasks.
The modulated force designed by AHR architecture is

\[ F_M(t) = F_{R-i}(t) + F_{A-v}(t), \]  

(6.21)

where \( F_M \) is the modulated force field applied by the rehabilitation robot to the patient’s hand; \( F_{R-i}(t) \) is the resistive component designed to “damp out” the tremor energy based on the definition of dissipative haptic systems [35]; and \( F_{A-v}(t) \) is the assistive component designed to help the patient in finishing the task. The designs of \( F_{R-i}(t) \) and \( F_{A-v}(t) \) are given in the rest of this section.

### 6.4.1 Modulated Force Field

To damp out the tremor energy, \( F_{R-i}(t) \) is calculated as

\[ F_{R-i}(t) = B(t)\hat{V}_{p-i}. \]

(6.22)

In (6.22), \( \hat{V}_{p-i} \) is the estimated velocity of the tremor calculated using the proposed E-BMFLC filter. \( B(t) \) is the adaptive damping coefficient. This design realizes a viscous environment in the frequency range of the tremor. Consequently, \( F_{R-i} \) acts like a damper for the hand tremor and dissipates the corresponding energy. The adaptation rule to calculate \( B(t) \) for each patient is based on a performance measure corresponding to the severity of the tremor (explained later in this section). In addition, to assist the patient’s motion in the frequency range of voluntary movement (extracted by E-BMFLC) \( F_{A-v}(t) \) is applied to help the patient in following a desired therapeutic trajectory, as

\[ F_{A-v}(t) = C(t)E_{p-v}, \]

where, \( E_{p-v} = X_{des} - \hat{X}_{p-v} \)

(6.23)

In (6.23), \( \hat{E}_{p-v} \) is the trajectory tracking error, \( C(t) \) is the adaptive coordinative gain, \( X_{des} \) is the desired position trajectory which should be tracked by the patient, and \( \hat{X}_{p-v} \) is the estimated position of the voluntary component (calculated by E-BMFLC). The adaptation rule to calculate \( C(t) \) for each patient is based on a performance measure that corresponds to the accuracy of trajectory tracking which is explained later in this section.
6.4.2 Performance Measures

In order to calculate $B(t)$ and $C(t)$ for each patient, two performance measures $PM_i$ and $PM_v$ are defined for the proposed resistive and assistive components of the modulated force field, respectively. $PM_i$ provides a quantitative measure of the severity of hand tremor during a rehabilitation task, and $PM_v$ provides a quantitative measure of accuracy for tracking the rehabilitation trajectory using the voluntary component of the hand motion.

The design of $PM_i$ is as follows:

$$PM_i(t) = \frac{\xi_{\text{tremor}}(t)}{\xi_{\text{max}} - 1}, \quad (6.24)$$

In (6.24), $\xi_{\text{tremor}}$ is the real-time measure of the energy of the involuntary hand velocity. To eliminate time-dependence of $PM_i(t)$, windowed energy is considered for $\xi_{\text{tremor}}$:

$$\xi_{\text{tremor}}(t) = \int_{t-T_w}^{t} \hat{V}_{\text{p-i}}(\tau)^2 d\tau. \quad (6.25)$$

In (6.25), $T_w$ is the width of the time window which is considered to be 10 s in this chapter. In addition, $\xi_{\text{max}} - 1$ is a rough estimate of the maximum value for $\xi_{\text{tremor}}$, designed to normalize the proposed performance measure. $\xi_{\text{max}} - 1$ can be achieved through a preoperative test when the patient is asked to hold/move the robotic handle while the force field is turned off. The ultimate goal is to increase the damping coefficient $B(t)$ until $\xi_{\text{tremor}}$ converges to a small value. The design of $PM_v$ is as follows:

$$PM_v(t) = \frac{\xi_{\text{E-track}}(t)}{\xi_{\text{max}} - 2}, \quad (6.26)$$

In (6.26), $\xi_{\text{E-track}}$ is the energy of the tracking error of the voluntary component while considering an acceptable tracking error (i.e. $E_{\text{min}}$). To eliminate time-dependence of $PM_v(t)$, windowed energy is considered for $\xi_{\text{E-track}}$:

$$\xi_{\text{E-track}}(t) = \int_{t-T_w}^{t} (E_{p-v}(\tau) - E_{\text{min}})^2 d\tau. \quad (6.27)$$

In (6.27), $E_{\text{min}}$ is an acceptable threshold for the tracking error which is considered to be 10
percent of the maximum amplitude of the desired trajectory. Also, $E_{p-v}$ is the tracking error of the voluntary component of the patient’s hand motion. In addition, in (6.26), $\xi_{\text{max}}$ is the normalizing maximum value for the tracking error which is calculated prior to the operation. The value is achieved assuming that the patient is completely incapable of tracking the target (worst case scenario). The ultimate goal is to gradually increase $C(t)$ using the second adaptation rule (explained later) until $\xi_{\text{E-track}}$ converges to a small value.

### 6.4.3 Adaptation Rules

Two adaptation rules are proposed to tune $B(t)$ and $C(t)$ based on the needs of the patient:

**The First Adaptation Rule:** The goal of the first rule is to gradually increase the dissipation gain $B(t)$ for the tremor and keep $PM_i$ under control to make it as small as possible that results in avoiding TA. The adaptation rule is:

$$B(t) = \mu_i(t)B_{\text{max}}, \quad (6.28)$$

where

$$\mu_i(n) = g_i\mu_i(n-1) + PM_i\Delta_i. \quad (6.29)$$

In (6.28), $B_{\text{max}}$ is the maximum damping factor considered for dissipating the hand tremor. This value can be tuned based on the capabilities of the utilized robot. In this chapter, the default value for $B_{\text{max}}$ is $250\text{N.s/m}$. In addition, $\mu_i$ is the adaptive scaling gain which is calculated using (6.29) based on the severity of the tremor. In (6.29), $g_i$ is the forgetting factor and $\Delta_i$ is the growth rate constant for $B(t)$. To better understand the functionality of the proposed rule, first assume $g_i = 1$. In this case, if the patient shows a severe tremor (which means $PM_i \to 1$) the adaptive scaling gain $\mu_i$ gradually increases with the rate of $\Delta_i$. Increasing $\mu_i$ results in having higher $B(t)$ which results in having less tremor and better performance measure $PM_i$. This reduces the growth rate of $B(t)$. At the same time, considering the forgetting factor $g_i$ slightly less than unity results in slowly forgetting early information and allowing the patient to experience a lower dissipation, if he/she represents a less severe tremor after some point. Finally, $\mu_i$ will converge to an equilibrium value which is specifically achieved for this patient to minimize his/her tremor. To better understand the functionality of $g_i$, suppose that the hand tremor suddenly stops at some point. This does not of course happen in practice. We are
assuming it to clarify the behavior of $g_i$. In this case, if $g_i = 1$, the dissipative gain $B(t)$ will stay at the previous value, while there is no tremor. However, by having $g_i$ slightly less than unity the dissipative gain $B(t)$ will gradually reduce. Note that if at any point, the severity of the tremor changes, this will be observed by $PM_i$ and it results in changing $\mu_i$ and setting a new equilibrium point for it. Consequently, taking advantage of having both $g_i$ and $\Delta_i$, an appropriate value for $B(t)$ can be achieved which minimizes $PM_i$ while providing minimum needed resistance. This technique is called Energy-based Resist-as-Needed (ERN) approach. The default value for $g_i$ is 0.99995. This value can make $\mu_i$ less than half in 15 s when $PM_i = 0$, considering sampling time of 1 $KH$z. Also, the default value for $\Delta_i$ is 0.0005 which can result in reaching the maximum $B(t)$ in 2 s when $g_i = 1$ and $PM_i = 1$.

**The Second Adaptation Rule:** The goal of the second rule is to gradually increase the assistive coordination gain $C(t)$ for the voluntary component and keep $PM_v$ as small as possible. This will result in having an acceptable tracking performance in an assist-as-needed manner. The ultimate purpose is to provide the patient with minimum assistance just needed to perform the task and not to provide him/her with too much assistance. If too much assistance was provided, the patient would rely on the robot and would not get involved in the interactive procedure. The rule is achieved using similar concept mentioned above as

$$C(t) = \mu_v(t)C_{max}, \quad (6.30)$$

where

$$\mu_v(n) = g_v\mu_v(n - 1) + PM_v\Delta_v. \quad (6.31)$$

In (6.30), $C_{max}$ is the maximum coordination factor considered for delivering assistance to the voluntary component. This value can be tuned based on the capabilities of the utilized robot. The default value for $B_{max}$ is 800 $N/m$. In addition, $\mu_v(t)$ is the adaptive scaling gain which is calculated using (6.31) based on the severity of the coordination deficit. In (6.31), $g_v$ is the forgetting factor and $\Delta_v$ is the growth rate constant for $C(t)$. The functionality of the adaptation rule given in (6.31) is similar to that of (6.29). The goal is to find the minimum assistance needed for the patient. Having $g_v$ slightly less than unity allows us to always challenge the patient and try to keep him/her involved in the loop. In fact, this choice of $g_v$ allows for evaluating the patient’s capability in tracking the trajectory and automatically tuning $C(t)$ to
provide corresponding assistance. If we consider \( g_v = 1 \) and the patient’s trajectory tracking is inaccurate at the beginning of the task, \( \mu_v \) will converge to a high equilibrium value and will stay there. In this situation, if trajectory tracking becomes more accurate, since we had \( g_v = 1 \), the assistive gain \( C(t) \) will not be reduced and the robot will keep on providing assistance. However, by considering \( g_v \) slightly less than unity the coordination gain will gradually drop when the patient starts to behave in a more accurate manner. This results in an assist-as-needed approach which we call Energy-based Assist-as-Needed (EAN) technique. The default values for \( g_v \) and \( \Delta_v \) are 0.9998 and 0.0002, respectively. The designed AHR system is shown in Fig. 6.2.

### 6.5 Filter Evaluation and Patient-based Evaluation

In this section, the patient-based evaluation of E-BMFLC filter is presented. The goal is to evaluate the accuracy, and the corresponding sensitivity to the tuning of \( \eta \) and intra-patient variability, in comparison with BMFLC filter.

#### 6.5.1 Demographic data

This study includes data collected from 27 patients (14 PD, and 13 ET). The patients were aged from 36 to 86 (mean: 67.85, S.D.=11.46). The population involved 17 males and 10 females. Patients were recruited from the Movement Disorders Centre at University Hospital, London Health Sciences Centre (London, Ontario, Canada). The study protocol was approved by the Research Ethics Board at Western University. Written consent forms and details of the protocol were provided to the patients prior to their participation.

#### 6.5.2 Experimental Setup and Task

The experimental setup (shown in Fig. 6.4) consists of a full upper-limb kinematic measurement system from Biometrics Ltd. Motion sensor data was collected at 1500Hz and transmitted to the PC interface MyoResearch from Noraxon. In this chapter, we used measurement data of a 3 DOF Cartesian accelerometer on hand. Each patient has been asked to perform a random target tracking task in free space for 20 seconds by repetitively moving the hand from nose to
a pen showing the target. The target positions are set such that the patient needs to fully stretch out his/her arm. After one 20-second episode of target tracking the patient is asked to perform other tasks in series (each for 20 seconds) i.e. holding an empty cup, holding a loaded cup, resting hands on lap, resting hands on a support table. These tasks are chosen to change their tremor conditions and trigger different characteristics. This allows us to evaluate their tremor in different situations. The procedure is repeated three times (three trials) for each patient. Consequently, for all 27 patients we have 3DOF acceleration for 3 separated episodes. As a result, each patient provides 9 sample signals of 20-second target tracking. Considering all 27 patients, we have 234 sample data, in total.

### 6.5.3 Evaluation Protocol

An evaluation protocol is needed to be repeated for all sample data. The question to be addressed is: “what are the ideal references (for voluntary and involuntary motions) which should be considered to calculate the accuracy and sensitivity?” For this goal, the following protocol has been conducted. For each sample signal:

**Step 1**) Fast Fourier Transform (FFT) is calculated.

**Step 2**) A $7^{th}$-order linear polynomial is fitted to the absolute value of the calculated FFT.

**Step 3**) The analytical derivative of the 7-order polynomial is calculated. This is used to find the two suprema of the polynomial which correspond to the peaks in the central frequencies of the voluntary and the involuntary components. Also, the cut-off frequency that can separate the components is calculated.
6.5. Filter Evaluation and Patient-based Evaluation

Step 4) The internal product of the FFT of the signal and a separating vector $V_{sep}$ with the same size is calculated. $V_{sep}$ has values equal to one for frequency less than the cut-off frequency and zero for frequencies higher than that. The result is the ideal FFT of the voluntary component of motion.

Step 5) The same procedure is repeated while replacing the separating vector by $1 - V_{sep}$. The result is the FFT of the involuntary component of the hand motion.

Step 6) The achieved ideal FFT vectors of the voluntary and involuntary motions are named $H_v(f)$ and $H_i(f)$, respectively. $f$ is frequency in Hz.

Step 7) The inverse FFTs of both the voluntary and involuntary components are calculated. These are used as the ideal references for evaluating the output of the filters. The achieved ideal references in the time-domain are named $R_v(t)$ for the voluntary component and $R_i(t)$ for the involuntary component. Note that the mentioned procedure is a post-processing technique representing how to realize an offline ideal filter.

This procedure is displayed in Fig. 6.5 for motion in the X-direction of participant #21.

6.5.4 Method and Evaluation Metrics

In this part, the method used to evaluate and compare the performance of the filters is discussed. After calculating the cut-off frequencies and finding the references to perform evaluation in frequency-domain and in time-domain, both the BMFLC and E-BMFLC filters have been implemented in real-time for three corrective gains $\eta$, as explained as follows. Based on our observations, $\eta = 0.004$ is a rational value to be considered for the filters. This observation is made by checking 10 random signals out of the 234 items of data. To evaluate the sensitivity of the filters to the change in $\eta$, and to evaluate/compare the performance of the filters, we run both BMFLC and E-BMFLC techniques for two more $\eta$ values, which are $0.004 \pm 50\%$. It should be noted that changing the $\eta$ value considerably more than 50% of the nominal value (i.e. 0.004) resulted in diverging behavior for the conventional BMFLC filter in some of the mentioned 10 randomly chosen signals. Although the diverging behavior could be a good validation of the high sensitivity of the conventional filter, it would not allow us to quantitatively
Figure 6.5: The results of the proposed post-processing protocol to calculate $R_v(t)$, $R_i(t)$, $H_v(f)$, $H_i(f)$ for participant #21 in the X-direction. (a) The visualization of the proposed protocol; (b) the modulated hand acceleration versus the extracted voluntary component $R_v(t)$; (c) the extracted involuntary component of motion $R_i(t)$.

compare the sensitivity of the two filters. As a result, 50% deviation is considered to analyze and compare the sensitivity of the two filters (BMFLC and E-BMFLC) to the change in $\eta$ value. As a result of the above mentioned method, each signal (out of the 234 signals) is filtered for 3 times by the BMFLC filter and for other 3 times by the E-BMFLC filter.

The Normalized RMSE (NRMSE) values of the extracted tremors (applying both the BMFLC and E-BMFLC filters) are calculated in the time-domain, using the ideal reference $R_i(t)$. 
Also, the NRMSE values of the extracted tremors (applying both the BMFLC and E-BMFLC filters) are calculated in the frequency-domain using $H_i(t)$.

Consequently, applying the BMFLC filter on each hand signal, we calculate three NRMSE values in the time domain which corresponds to the three $\eta$ values; also, we have three NRMSE values in the frequency domain. In addition, applying the E-BMFLC filter on each signal we will calculate three NRMSE values in the time-domain and three NRMSE values in the frequency-domain. Using the achieved NRMSE values, six metrics are designed which will be used in the next part (“Part E”) to statistically compare the performance of the filters.

**Metrics #1 and #2** In order to calculate the extent of improvement potentially achieved using the proposed E-BMFLC filter, the first metric is calculated for all 234 signals in the time-domain, as follows:

$$IMP_{Error(t)} = \frac{NRMSE_{conv-t} - NRMSE_{enhanced-t}}{NRMSE_{conv-t}},$$ \hspace{1cm} (6.32)

In (6.32), $NRMSE_{conv-t}$ corresponds to the conventional BMFLC filter. It is the minimum NRMSE value (best performance) in the time-domain, considering the three NRMSE values calculated by applying the three $\eta$ values. Consequently, for each signal (out of the 234 signals) we have one $NRMSE_{conv-t}$ value. In addition, $NRMSE_{enhanced-t}$ corresponds to the proposed E-BMFLC filter. It is the minimum NRMSE value achieved in the time-domain out of the three NRMSE values calculated by applying the three $\eta$ values. As a result, $IMP_{Error(t)}$ represents the improvement achieved for tracking error in the time-domain, by applying the E-BMFLC filter and in comparison with the BMFLC filter. Consequently, we have 234 $IMP_{Error(t)}$ values and the statistical distribution of it will be analyzed in Part E of this subsection. $IMP_{Error(t)} = 0$ indicates no improvement, and $IMP_{Error(t)} = 1$ indicates 100% improvement.

The same procedure is repeated to calculate the second metric which is the potential improvement achieved by applying the E-BMFLC filter, in the frequency-domain. The definition of the second metric is:

$$IMP_{Error(f)} = \frac{NRMSE_{conv-f} - NRMSE_{enhanced-f}}{NRMSE_{conv-f}},$$ \hspace{1cm} (6.33)

In (6.33), $IMP_{Error(f)}$ is the improvement achieved for estimating error in the frequency-
domain.

**Metrics #3 and #4** In addition to the above, to quantitatively evaluate the consistency of the filter in estimating hand tremor and statistically compare the filters from the point of view of the sensitivity to the choice of \( \eta \), the third and forth metrics are designed. The third metric is:

\[
IMP_{\eta VAR(t)} = \frac{V_{\text{conv} - t} - V_{\text{enhanced} - t}}{V_{\text{conv} - t}}.
\]  (6.34)

In (6.34), \( V_{\text{conv} - t} \) is the variance of the three NRMSE values for each signal which correspond to the considered three values of \( \eta \) for the conventional BMFLC filter, in the time domain. Also, \( V_{\text{enhanced} - t} \) is the variance of the three NRMSE values which correspond to the considered three values of \( \eta \) for the proposed E-BMFLC filter, in the time domain. Consequently, \( IMP_{\eta VAR(t)} \) is a quantitative metric which can tell us how much improvement is achieved applying E-BMFLC filter (in comparison with conventional BMFLC filter), from the point of view of sensitivity to the change in \( \eta \) value. Having \( IMP_{\eta VAR(t)} \) close to unity means that under the same condition, the E-BMFLC filter demonstrates little performance change (less sensitivity) in comparison to the BMFLC filter. On the other hand, having \( IMP_{\eta VAR(t)} \) close to zero means that the E-BMFLC filter behaves similar to the conventional BMFLC filter from the point of view of sensitivity to the change in \( \eta \). The third metric will be calculated for all 234 signals and the statistical distribution of it will be evaluated in Part E.

The sensitivity of the filters can be also compared in the frequency-domain using the fourth metric, \( IMP_{\eta VAR(f)} \), as:

\[
IMP_{\eta VAR(f)} = \frac{V_{\text{conv} - f} - V_{\text{enhanced} - f}}{V_{\text{conv} - f}}.
\]  (6.35)

In (6.35), \( V_{\text{conv} - f} \) is the variance of the three NRMSE values for each signal which correspond to the considered three values of \( \eta \) for the conventional BMFLC filter, in the frequency-domain. Also, \( V_{\text{enhanced} - f} \) is the variance of the three NRMSE values which correspond to the considered values of \( \eta \) for E-BMFLC filter, in the frequency-domain.

**Metrics #5 and #6** We are also interested in comparing the sensitivity of the filters to changes in motion characteristics of patients and account for intra-patient variabilities. For this goal and to evaluate the consistency of the filters in extracting hand tremors of different patients with various characteristics, the fifth and sixth metrics are designed. These metrics show how
much improvement is achieved in reducing the variation in performance under different motion conditions associated with different patients. These metrics are achieved for all 27 patients. The fifth metric is:

\[ IMP_{ΩVAR(t)} = \frac{W_{\text{conv}−t} - W_{\text{enhanced}−t}}{W_{\text{conv}−t}}. \] (6.36)

In (6.36), \( W_{\text{conv}−t} \) is the variance of the nine NRMSE values which correspond to the nine best performances achieved by applying the BMFLC filter for estimating nine motion data for each patient in the time domain. The explanation of how to calculate \( W_{\text{conv}−t} \) is as follows: For each patient we have 9 measured signals (3DOF measurements for 3 trials). Each signal is filtered using three different values of \( η \). The best performance for filtering each signal is the minimum NRMSE value out of the three NRMSE values achieved by applying the defined three \( η \) values. Accordingly, for each signal we have one best performance. Considering nine signals for each patient, we have nine best performances for each patient. The variance of these nine best performances is \( W_{\text{conv}−t} \) for the BMFLC filter in the time-domain. Consequently, for each patient we have one \( W_{\text{conv}−t} \) value in the time-domain.

Also, \( W_{\text{enhanced}−t} \) is the variance of the nine minimum NRMSE values which correspond to the best performances achieved applying the E-BMFLC filter for estimating the nine motion data for each patient in the time-domain. Consequently, for each patient we have one \( W_{\text{enhanced}−t} \) value in the time-domain. Accordingly, \( IMP_{ΩVAR(t)} \) can be calculated for each patient as given in (6.36), which is the improvement achieved in reducing the variation in the performance by applying the E-BMFLC filter. Finding \( IMP_{ΩVAR(t)} \) for all 27 patients, we can statistically analyze the corresponding distribution. This is done in Part E.

Similarly, the consistency of the filters can be compared in the frequency-domain using the sixth metric, \( IMP_{ΩVAR(f)} \):

\[ IMP_{ΩVAR(f)} = \frac{W_{\text{conv}−f} - W_{\text{enhanced}−f}}{W_{\text{conv}−f}}. \] (6.37)

In (6.37), \( W_{\text{conv}−f} \) and \( W_{\text{enhanced}−f} \) are the variance of the nine minimum NRMSE values in the frequency-domain for the BMFLC filter and the E-BMFLC filter, respectively.
6.5.5 Implementation Results and Statistical Analysis

In this part, first, various aspects of the proposed E-BMFLC filter are separately analyzed. Then, the results of the statistical comparative study on the efficacy of the filter for extracting tremors of 27 patients are given.

I) Analyzing Old Tremor Projections: As mentioned before, one of the challenges with conventional BMFLC filter is the infinite memory of it, besides the assumption of fully-periodic input signal. This can result in repetitive OTPs which can degrade the efficacy. To show the existence of OTPs in the conventional BMFLC filter, and to isolate it from other potential sources of error, the following steps are taken. First, motion data for one patient have been randomly chosen. In this case, we chose the hand motion of Participant #4 (a 55 years old male with PD) in the X-direction, during the first trial. While applying no change to the first 3 seconds of the signal, we cut the remaining part of the signal (from \( t = 3 \) s to \( t = 20 \) s) and make it zero. This is just to highlight and extract the effect of OTPs. The result of applying conventional BMFLC filter is shown in Fig. 6.6a. As can be seen, although the original signal is flattened after \( t = 3 \) s, repetitive projections exist in the estimated value. These are the predicted OTPs. As mentioned, the OTPs are the result of assuming the fully periodic model in BMFLC besides having infinite memory. Applying the proposed memory windowing technique for the same filter (\( \rho = 0.999 \)) results in Fig. 6.6b. As can be seen in Fig. 6.6b, the OTPs are completely eliminated. This result validates existence of OTPs and effectiveness of the proposed memory windowing technique. In Fig. 6.6c, the estimated coefficients of the utilized Fourier combiner are plotted, over time. As it is shown in Fig. 6.6c for the conventional BMFLC filter, the coefficient values still vary after \( t = 3 \) s. The reason is that the filter assumes that the complete hand signal from \( t = 0 \) to the current time stamp should be modelled by a periodic nature. Better view of the coefficients are given in Fig. 6.7a. After applying the proposed memory windowing, the coefficients gradually converge to small values (after \( t = 3 \) s) eliminating the OTPs. This is shown in Fig. 6.6d and Fig. 6.7b.

II) Analyzing Sensitivity to the Design of \( \eta \): As mentioned earlier, we hypothesize that the design of the proposed E-BMFLC filter is more robust to the change in \( \eta \) value in comparison with BMFLC filter. This is statistically evaluated at the end of this section. Here, an example for one signal is given to discuss the behavior of E-BMFLC and the conventional BMFLC
Figure 6.6: (a) The existence of OTPs in the output of BMFLC filter; (b) elimination of OTPs by applying the proposed memory windowing; (c) the estimated coefficients of the Fourier model for the case of BMFLC filtering; (d) the estimated coefficients after applying memory windowing.

for three different $\eta$ values (i.e. 0.002, 0.004, 0.006). The data of Participant #4 is analyzed here. For this purpose, we have considered hand motion in the $X, Y,$ and $Z$ directions, for the defined three trials. So, in total we have the following 9 data samples: Sample #1: $X$-direction, Trial #1; Sample #2: $X$-direction, Trial #2; Sample #3: $X$-direction, Trial #3; Sample #4: $Y$-direction, Trial #1; Sample #5: $Y$-direction, Trial #2; Sample #6: $Y$-direction, Trial #3; Sample #7: $Z$-direction, Trial #1; Sample #8: $Z$-direction, Trial #2; Sample #9: $Z$-direction, Trial #3.

The above 9 signals have been used to evaluate both the BMFLC and E-BMFLC filters, while considering the defined three $\eta$ values for each filter and each signal. The corresponding NRMSE values in the time-domain and in the frequency-domain are calculated. The results are shown in Fig. 6.8. In this figure, red lines correspond to BMFLC filter. Each line is the result of one $\eta$ value. Also, the blue lines correspond to the proposed E-BMFLC filter.

Considering the results in Fig. 6.8, the E-BMFLC filter not only provides a more accu-
rate tremor estimation (lower average NRSME value), it has represented (a) less performance change (less sensitivity) applying different $\eta$ values, and (b) less variation in performance applying different inputs (considering different signals). In fact, the difference between the results of using different $\eta$ values is not even easily distinguishable in the figure for the E-BMFLC filter. However, the performance of the conventional BMFLC filter changes dramatically by changing the $\eta$ values and by using the same filter for a different data point.

Consequently, it can be concluded that for the considered participant, the E-BMFLC filter has shown a more robust, more accurate and less sensitive performance.

The outputs of the filters are plotted over time for the Z-direction during the first trial, in Fig. 6.9. As expected, the figure shows more accurate estimation achieved by using the E-BMFLC filter in tracking the hand tremor of this participant when comparing with the conventional BMFLC filter, under the same condition. To ensure that the achieved conclusion is statistically significant and consistent, we need to evaluate the filters for a group of patients and run a standard statistical test, as given in the following part.

**III) Patient-based Evaluation and Statistical Analysis**: In this part, the effectiveness of the proposed E-BMFLC filter is statistically evaluated in comparison with the performance of the conventional BMFLC technique. For this purpose, the statistical distributions of the aforementioned six metrics are evaluated. The average values and standard deviations for the six metrics are calculated. The standard statistical *T-test* is utilized to analyze the significance of the calculated improvements. The results are summarized in Table 6.1. In addition, the corresponding box plots of the distributions are plotted in Fig. 6.10 for metrics #1 to #6.
6.5. **FILTER EVALUATION AND PATIENT-BASED EVALUATION**

![Graphs showing NRMSE values for E-BMFLC and conventional BMFLC techniques](image)

Figure 6.8: The NRMSE values for the proposed E-BMFLC filter (blue lines) and the conventional BMFLC technique (red lines). Each line corresponds to applying one $\eta$ value out of the considered three values. (a) Results in the time-domain; (b) results in the frequency-domain.

It can be seen in Table 6.1, the average improvement achieved for NRMSE in the time-domain ($IMPE_{\text{Error}(t)}$) is 59.73% and the standard deviation is 9.59%. Also, the average improvement for NRMSE value in the frequency-domain ($IMPE_{\text{Error}(f)}$) is 68.22% with standard deviation of 6.03%. The significance of the results are validated using the *T-test* which results in a p-value < 0.001. This shows that the achieved improvements are statistically significant. The same analysis is performed for other defined metrics and the results are shown in Table 6.1.

Considering the results summarized in Table 6.1, the proposed E-BMFLC filter, has statistically significant improvement in accuracy of the filter for estimating hand tremor. This is interpreted based on the statistical analysis of $IMPE_{\text{Error}}(t)$ and $IMPE_{\text{Error}}(f)$. Also, the sensitivity to the change in $\eta$, is significantly reduced. This is interpreted based on the statistical analysis of $IMPE_{\eta\text{VAR}}(t)$ and $IMPE_{\eta\text{VAR}}(f)$. In addition, the proposed filter shows considerable improvement in reducing the sensitivity to the change in tremor characteristics of different patients. This is interpreted based on the statistical analysis of $IMPE_{\Omega\text{VAR}}(t)$ and $IMPE_{\Omega\text{VAR}}(f)$. All the results are statistically significant in both the time-domain and the frequency-domain. Consequently, the proposed filter consistently shows significant improvement in extracting hand tremors of patients living with PD and ET. This validates the hypotheses of this chapter.
Figure 6.9: Tremor extraction for Participant #4 in the Z-direction, during the first trial. The red line is the actual hand tremor, and the blue line is the output of the filter. (a) The result of applying the proposed E-BMFLC filter; (b) the result of applying the conventional BMFLC filter.

Figure 6.10: Statistical distribution of the six improvement metrics.

6.6 Experimental Evaluation of the Augmented Haptic Rehabilitation Architecture

In this section, the proposed AHR system is implemented and experimentally evaluated. Upper-limb rehabilitation robot from Quanser Inc. is used, shown in Fig. 6.2. The user wears a head-mounted display visor which provides visual cues and the location of the moving target to track. The experiment is designed to evaluate different features of the AHR system including the proposed adaptive assistance and resistive algorithms. It should be noted that in pathological tremor patients, the involuntary movement is due to involuntary activation of hand muscles which results in an involuntary force field. Consequently, in this experiment, while a healthy
Table 6.1: Summary of the Statistical Analysis

<table>
<thead>
<tr>
<th>Metric</th>
<th>$\text{IMP}_{\text{Error}}(t)$</th>
<th>$\text{IMP}_{\text{Error}}(f)$</th>
<th>$\text{IMP}_{\text{DVAR}}(t)$</th>
<th>$\text{IMP}_{\text{DVAR}}(f)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>59.73%</td>
<td>68.22%</td>
<td>98.68%</td>
<td>99.11%</td>
</tr>
<tr>
<td>#2</td>
<td>9.59%</td>
<td>6.03%</td>
<td>4.36%</td>
<td>3.29%</td>
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<tr>
<td>#3</td>
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user handles the robot, the tremor of participant #21 is chosen randomly to design a tremor-like force field for the user to mimic the interaction between a tremor patient and the system. It should be highlighted that the generated force field in this experiment might be different from the one felt by the user during data collection. As mentioned, in this section we aimed to analyze the performance of the proposed AHR system. As a result it was needed to make a tremor-like force field to analyze the reactions of the system. For this purpose, the data collected for Participant #21 has been used as a model to make the force field which represents a realistic frequency content of a human with pathological hand tremor.

6.6.1 Experiment Design

The experiment is designed in three phases. In the first phase ($0s \leq t < 27s$), the user holds the robot while the robot perturbs the user’s hand by applying the designed tremor-like force field. During this phase, the robotic therapy is turned off and no assistive/resistive force is delivered to the user. It is expected that the user’s hand continues shaking in a tremor-like manner. During the second phase ($27s \leq t < 60s$), the designed resistive force field is turned on. It is expected that the intensity of the dissipative force gradually increases due to the proposed adaptation rule (6.28) and (6.29). This should result in a reduction in the amplitude of the hand tremor. During the third phase ($t \geq 60s$), the assistive force field is also turned on. It is expected that during this phase, the intensity of the assistive force field gradually increases.
(due to the proposed corresponding adaptation rule \((6.30)\) and \((6.31)\)). This should result in an increase in the amplitude of the low-frequency of the hand motion and a reduction in the tracking error.

It should be highlighted that during the third phase, for \(t \leq 100\text{s}\), the user just holds the robotic handle and does not try to track the target trajectory in order to mimic the behavior of a severely impaired patient. Consequently, the robot should take the full authority, increase the coordinative gain and push the user’s hand towards the correct path of motion. After \(t = 100\text{s}\), the user starts to act like a less-impaired patient by putting effort in tracking the target. Consequently, if the designed adaptation rule works, it is expected that the intensity of the assistance force field should reduce and the system should give some authority to the user. This means that the equilibrium point for the coordinative gain should drop after \(t = 100\text{s}\).

### 6.6.2 Results

The results of the experiment are shown in Figs. 6.11 and 6.12. In Fig. 6.11a, the hand velocity is shown for the proposed three phases of the experiment. As can be seen in the figure, during the first phase, the hand of the user shakes due to the applied tremor-like force field, while the therapeutic forces are turned off. When the resistive therapy is started (as Phase 2), the amplitude of the hand tremor considerably reduces as expected. The amplitude of the tremor during the second phase is 8.6 times smaller than that during the first phase. This is due to the gradual increase in the dissipative gain which can be seen in Fig. 6.12b. In addition to the above, by the start of the third phase in Fig. 6.11a, the amplitude of the low-frequency motion increases which is due to the increase in the coordinative gain. The coordinative gain is shown in Fig. 6.12a. This results in gradual reduction in the tracking error (as can be seen in 6.11b). The target movement is shown by the solid red line in Fig. 6.11b, where the voluntary component of the hand motion is shown by the solid blue line. The total modulated force provided by the proposed controller during the second and the third phases is shown in Fig. 6.11c. During the second phase, the aforementioned modulated force has high-frequency components to resist the hand tremor. During the third phase and before \(t = 100\text{s}\) the modulated force has significant low-frequency components (to guide the user’s hand towards the correct path) together with the high-frequency components to resist the hand tremor. Considering Fig.
6.7 Conclusion

In this chapter, a new design of the BMFLC filter was proposed which we have called E-BMFLC technique. The new filter uses an enriched Fourier combiner model together with a windowed memory. The goals were to reduce the error in extracting pathological hand tremor as well as the sensitivity of the filter to the choice of the corrective gain used in the filter and
intra-patient variabilities. To evaluate the performance of the filter, recorded hand motions of 27 patients (PD and ET) were used in the comparative study. The proposed E-BMFLC filter showed a statistically-significant improvement (p-value < 0.001) in estimation accuracy, in comparison with the conventional design of the BMFLC filter. The tremor tracking accuracy and the sensitivity to the choice of corrective gain and intra-patient variabilities were significantly improved using the proposed filter. In the second part of this chapter, the designed filter was utilized in developing a new haptics-enabled rehabilitation strategy, called AHR (Augmented Haptic Rehabilitation). The AHR is capable of delivering therapeutic forces (in an assist-as-needed manner) while keeping the hand tremor under control and avoiding unsafe amplification of tremor energy. This architecture makes it possible for patients living with pathological hand tremor to take advantage of robotic rehabilitation. The design of the proposed AHR architecture is motivated by recent evidence showing the impact of multi-modal rehabilitation for enhancing motor control in patients living with pathological hand tremor. The proposed AHR architecture was implemented using an upper-limb rehabilitation robot from Quanser Inc. (Markham, Ontario, Canada), and its performance was evaluated experimentally. It was shown that using the proposed AHR architecture, assistance can be delivered to the voluntary component of the hand motion (in an adaptive manner) while the system can control involuntary hand tremors. Future work in this study is to longitudinally analyze the improvement that can be achieved by the use of the proposed AHR system on a group of PD and ET patients.
Bibliography


Chapter 7

Application to other Neurological Movement Disorders: A Telerobotic Platform for People with Cerebral Palsy

The material presented in this chapter has been accepted for publication in the Journal of Medical Robotics Research, 2016.

7.1 Introduction and Preliminaries

Cerebral palsy (CP) is an umbrella terminology for a range of non-progressive neurological sensorimotor deficits that initiate in young children. The onset of CP is known to be brain damage prior, during and/or after birth. It affects a wide range of motor performances and results in various movement symptoms. Spastic CP, Ataxic CP, and Athetoid CP are some major categories of this condition [1–3]. Note that, in this chapter, the terminology “individual with CP” is used for an individual who is living with cerebral palsy. Spastic CP is a common condition for individuals with CP, which refers to hypertonic muscles that increase muscular tone and result in a reduced range of motion and stiff, jerky or uncoordinated movements [4]. Individuals who have Ataxic CP and Athetoid CP have reduced or fluctuating muscle tone (hy-
potonic muscles). Ataxic CP affects the balance and fine tuning of movements and can involve an intention tremor when attempting movements. Athetoid CP exhibits writhing involuntary movements. Individuals can have two or more types of CP, which is called mixed CP [1, 5, 6]. In summary, different types of CP involve various motor control impairments including (a) a **limited range of motion**, (b) **coordination problems**, and (c) **non-smooth motion execution** (such as hand tremor and other involuntary motor behaviors). This condition considerably disturbs the capabilities of individuals with CP in interacting and engaging with their surrounding physical environments [7].

Based on developmental theories, interactional motor experiences, such as exploration and manipulation, are key factors in cognitive and perceptual development of children [8–10]. Children with CP have considerable difficulties in performing object manipulation [11] and may therefore miss the chance for meaningful interaction with environments in early stages of their development [12, 13]. Consequently, due to the young onset of CP, the limited physical interaction capabilities can result in further secondary conditions such as cognitive development delay, learning deficits, and social skill issues. As an example, movement disorders caused by CP degrade engagement of young individuals with CP in free play environments, where children physically interact with objects, make decisions, perform different self-regulated goal-oriented tasks, think about cause-and-effect relationships and understand consequences. In the literature, it has been shown that these actions are crucial for cognitive, sensorimotor, and psychological development of children (see [12, 14, 15] and the references therein).

Technologies that are capable of allowing disabled people to perform (even indirectly) in a real play environment have attracted interest in recent years. In this regards, play-oriented robots (such as Lego robots) have been studied in the literature. These robots can be controlled using various access methods (e.g., push-down switches or eye gaze) by a child who has disabilities. Corresponding works can be found in a new literature review [12], in [16, 17] and prior research of K. Adams (author #7) [14, 15, 18–20]. Children with severe physical limitations control the aforementioned robots by high-level supervisory commands. With high-level commands, when a user makes a simple movement (e.g., pushes a switch), the robot performs an autonomous subtask (and usually keeps doing that) while waiting for a new command. Some examples of high-level supervisory commands are reach the target, drop the object, and come
back to home position. An example of a switch controlled robot system is shown in Fig. 7.1. Although the users are able to perform some tasks using the above-mentioned systems, there is still a considerable lack of “controlled, direct, instant and coordinated” interaction between the user and the play environments [21]. In other words, although these systems can indirectly realize task performance in play environments, they are incapable of realizing motion-controlled hand-eye coordinated physical interaction with real objects and they do not correlate the user movement (e.g., pushing a switch) with interaction in the environment (the robot performs a multi-step task).

Remark 7.1. Using the multi-action guidance delivered by the proposed system, the motions of the task-side robot can be controlled by the disabled user and would be correlated to the motion of the user’s hand. For example, if the user tries to move the user-side interface (e.g., a motorized haptic device) to the left, the task-side robot correspondingly and instantly will go to the left. If children could exert controlled coordinated physical interaction to manipulate objects in the environment, it is anticipated that it could lead to positive effects on their cognitive, social and sensorimotor development in the long term. •

Remark 7.2. In this chapter, we propose a new haptics-enabled telerobotic platform that can help individuals with CP in interacting with real physical environments mostly by aug-
menting their motion capabilities and also by making it possible for them to feel the interaction forces. When interacting with play objects, individuals need to be able to reach them, use smooth and fluid movements, and perform hand-eye coordination with the appropriate force and/or speed [22]. The goal of the proposed system is to allow individuals with CP to perform instant under-control tasks through a telerobotic medium that can compensate for the limited range of motion, the non-smooth tremor (and/or involuntary actions), and coordination problems that individuals with-CP may exhibit. This system makes it possible for individuals with CP to utilize their own movement strategies and motion capabilities and instantly interact with various physical environments. The main responsibility of the proposed telerobotic system is to extend the capabilities of individuals with CP and allow them to experience interaction with environments.

**Remark 7.3.** The main focus of this chapter is to propose a new mechatronic design which can facilitate interaction with physical environments for individuals with CP, as a new assistive paradigm. The design is motivated by evidence showing that physical interaction is a crucial factor for developing sensorimotor and cognitive skills, and that individuals living with a lack of interaction may develop corresponding secondary delays [8-10,12,13]. Analyzing the long-term effectiveness of the proposed system to cognitive and sensory development will require longitudinal long-term studies, which are part of our ongoing work, but outside of the scope of this chapter.

It should be noted that, telerobotic systems have been utilized in a wide variety of applications such as surgical, under-water and space operations [23]. A common goal for telerobotic systems is to extend the capabilities of human users beyond their limitations. In addition, it is possible to quantify movement capabilities (such as for skill assessment during robotics-assisted surgery) [23]. Using the same concept, in this chapter, the new telerobotic system is proposed to help disabled users extend their capabilities beyond limits imposed by their movement disorders to allow them to experience interaction with environments while the system logs all motion and force profiles.
7.1.1 Overview of the Proposed System:

The telerobotic architecture proposed in this chapter consists of (I) a user-side robot, (II) a task-side robot, (III) a Virtual Assistive (VA) computer algorithm, and (IV) a physical play environment. The system architecture has two major signal pathways namely: forward path and backward path. In the forward path, (a) the individual with CP generates motions by moving the user-side robot, (b) the VA algorithm modifies the generated motion (to enhance the task performance), and (c) the task-side robot mimics the motions modified by the VA algorithm to perform the task on the play environment. In the backward path, the VA algorithm generates a resistive compensatory force field (explained later), which is applied by the user-side robot to the individual’s hand to kinaesthetically restrict his/her involuntary movements. Consequently, the proposed system is a medium which makes it possible for individuals with CP to interact with a play environment (placed at the location of the task-side robot), while the system compensates for their limited range of motion and non-smooth movements. In addition, it provides a compensatory force field for the user to kinaesthetically restrict the involuntary movements. The mentioned functionality allows an individual with CP to engage in interactions with environments that they can not engage in without the use of this system. A schematic of the proposed telerobotic system is shown in Fig. 7.2. The proposed architecture has a triple-action design as follows:

**Action #1: Motion Range Correction:** Scale the user’s limited convenient range of motion at the user-side robot to that needed for performing the task at the task-side robot;

**Action #2: Voluntary Movement Tracking:** Filter out the motion signal transferred to the task-side robot in order to only use the voluntary component of the provided motion for task performance;

**Action #3: Involuntary Movement Dissipation:** Apply a dissipative force field to the user’s hand by the user-side robot to damp-out and resist the high-frequency involuntary component of the hand motion while keeping the dissipative resistance small for the voluntary component (that is typically a low-frequency signal [24, 25]).

The play environment can support many tasks like sorting objects, path following, obstacle avoidance or push-pull tasks. In order to verify the functionality of the system, the proposed
The experimental setup and a schematic of the proposed triple-action telerobotic architecture. The user-side robot is a table-top rehabilitation robot from Quanser Inc. (Canada) and the task-sided robot is a Phantom Premium 1.5A from Geomagic (US).

architecture was implemented using a table-top upper-limb rehabilitation robot (from Quanser Inc., Canada) as the user-side device, and a Phantom Premium 1.5A robot (from Geomagic, US) as the task-side device. Each action of the implemented system was evaluated with one non-disabled subject. The implemented system was demonstrated to therapists and their feedback was utilized to optimize the design and make the protocol of this study. Using the designed protocol, the system was tested with one individual with CP. Force and motion trajectories were collected to analyze the performance of the system.

The rest of this chapter is as follows. In Section 7.2, the design of the telerobotic system and the proposed virtual assistive algorithm are explained in detail. In addition, the triple-action performance of the proposed architecture is evaluated for the non-disabled individual. In Section 7.3, the evaluation method is introduced to analyze the effectiveness of the system for the individual with CP. The results and discussion are given in Section 7.3. The chapter is concluded in Section 7.4.
7.2 The Proposed Telerobotic Architecture and Virtual Assistive Algorithm

The design of the proposed telerobotic system shown in Fig. 7.2 is described in more detail, in this section, and experimental results are reported to evaluate different functions of the system.

7.2.1 Components and the Design of Actions

The components of the designed system are as follows.

(a) User-side Robot: The user-side robot is a 2 degrees of freedom upper-limb rehabilitation robot (from Quanser Inc., Markham, Ontario, Canada). The specification of the robot (including the shape and size of the workspace, resolution, weight, etc) can be found in [26, 27]. The robot can apply forces up to 50 N in Cartesian domain. The function of the user-side robot is to register the individual’s hand motion and provide him/her with a compensatory force field generated using the Virtual Assistive algorithm, detailed later in this section.

(b) Task-side Robot: The task-side robot is a Phantom Premium 1.5A robot (from Geomagic, US). The specifications can be found in [28]. The task-side robot is considered to follow the “modulated” motion trajectories of the individual with CP in order to perform the intended task. In this chapter, one of the considered functional tasks is a pick-and-place sorting activity explained latter in this section. A small electromagnetic lifter is attached at the tip of the task-side robot to perform the task. The motion trajectory to be followed by the task-side robot is based on the individual’s hand motion and is modulated by the VA algorithm.

(c) Virtual Assistive Algorithm: The VA is an algorithm that controls the behavior of both the user-side and the task-side robots. The algorithm first analyzes the individual’s hand motion and extracts the involuntary and voluntary components. For this purpose, a low-pass Band-limited Multiple Fourier Linear Combiner (BMFLC) filter (see [29–32]) is implemented to extract the involuntary component of the hand motion, which has a high-frequency nature in comparison with voluntary component of the motion [24, 25]. The BMFLC filter is an adaptive technique which is utilized to extract involuntary movements while introducing minimal
filtering latency into the interaction. The design of the filter can be found in \[29\,\text{–}\,32\].

**Remark 7.4.** The BMFLC filter used is a member of a family of adaptive filters which are designed based on Fourier Linear Combiner (FLC) modeling. This family considers summation of discrete harmonics over a large window of frequencies (for example from 0 Hz to 20 Hz) for modeling a signal that has high-frequency and low-frequency components. The filter adaptively and in real-time tunes the coefficients of the FLC model, using a recursive technique which is usually the Least-Mean-Square (LMS) technique, to find the best frequency-based decomposition of the targeted signal. FLC-based filters have demonstrated good performance in extracting involuntary movements introducing minimum delay in comparison with classical filtering techniques \[29\,\text{–}\,31\,\text{,}\,33\,\text{–}\,34\]. The original format of FLC-based filters, assumes a single dominant frequency \[35\] for the signal to be filtered. This was utilized to extract and cancel out physiological hand tremor of surgeons in the development of motorized surgical tools with the goal of increasing accuracy in surgical tasks \[34\]. The above-mentioned assumption (single dominant frequency) was then relaxed by the newer version of the filter i.e., the BMFLC technique. BMFLC is designed to track multiple harmonics of a signal \[29\,\text{–}\,31\] and showed higher accuracy compared to conventional FLC-based filters \[30\]. In the literature, BMFLC filtering has also been used for extracting physiological hand tremor of surgeons \[36\,\text{–}\,38\] and recently has shown good performance in extracting pathological involuntary motions \[33\].

Using the BMFLC filter, the extracted involuntary and voluntary motions are

\[
\xi_i(t) = \text{BMFLC}(M_p(t)), \quad (7.1)
\]

\[
\xi_v(t) = M_p(t) - \xi_i(t), \quad (7.2)
\]

respectively. In (7.1) and (7.2), \(M_p(t)\) is the total hand motion which has both of the voluntary and involuntary components. In addition, \(\xi_v(t)\) is the estimated low-frequency voluntary component of the hand motion and \(\xi_i(t)\) is the estimated involuntary component. When \(M_p(t)\) is considered to be the hand “velocity”, then \(\xi_v(t)\) and \(\xi_i(t)\) are voluntary and involuntary component of the hand’s velocity, respectively. The same interpretation is valid for position trajectories. After estimating \(\xi_v(t)\) and \(\xi_i(t)\), the VA provides the three actions, explained in the following.
**Action #1: Motion Range Correction:** The algorithm provides range correction to the transferred motion. For this purpose, prior to the task execution, the system operator asks the individual with CP to explore the limits of his/her comfortable range of motion using the user-side robot. The maximum range of motion needed to perform the task is known based on the specific dimensions of the task environment. Accordingly, the needed scaling can be calculated for the individual with CP, on a user-specific basis, to map his/her comfortable motion range to the one needed for task performance. For this purpose, scaling factors $C_x$ and $C_y$ are calculated as follows (for 2D tasks):

$$C_x = \frac{\text{Max}(X_p)}{\text{Max}(X_T)},$$  \hspace{1cm} (7.3)

$$C_y = \frac{\text{Max}(Y_p)}{\text{Max}(Y_T)}.$$  \hspace{1cm} (7.4)

In (7.3), $C_x$ is the mapping coefficient for the $X$ direction that relates the maximum reachable distance of the individual’s hand ($\text{Max}(X_p)$) in his/her comfortable range of motion to the maximum amplitude of motion needed in the $X$ direction to perform the designed task ($\text{Max}(X_T)$). Note that $X_p$ stands for the individual’s hand position in the $X$ direction and $X_T$ stand for the task-side robot movement in the $X$ direction. Accordingly, $C_y$ is designed similarly for the motion in the $Y$ direction. Consequently, the range-corrected motion trajectory for the task-side robot is

$$M_s(t) = \begin{pmatrix} C_x & 0 \\ 0 & C_y \end{pmatrix} \cdot \xi_v(t)^T.$$  \hspace{1cm} (7.5)

In (7.5), $\xi_v(t)$ refers to the voluntary component of the individual’s position trajectory in 2 degrees of freedom ($X$ and $Y$ directions). The task-side robot follows the corrected (scaled-up) trajectory of the individual’s hand. Consequently, the individual with CP will be able to perform large-scale tasks using her/his comfortable workspace range. In Section 3 a systematic approach is proposed to tune default values for $C_x$ and $C_y$. In addition, explanations are provided to show how to choose the cut-off frequency of the BMFLC filter to separate the voluntary and involuntary movements. Note that, the clinician will be always able to tune these parameters. This is a widely utilized approach in the literature [39, 40].

**Action #2: Voluntary Movement Tracking:** In order to provide better coordination for the individual with CP, instead of transferring the total movement of the hand (i.e. $M_p(t)$), only
the voluntary component $\xi_v(t)$ is considered to be sent to the task-side robot. The goal is to make the robot follow the voluntary component of the hand motion to perform the task. Consequently, when an individual who has CP moves the user-side robot with a movement containing both low-frequency movements (i.e., a movement generally towards the target) and high-frequency movements (i.e., a jerky or shaky movement), only the low frequency movements will be transferred to the task-side robot.

**Action #3: Involuntary Movement Dissipation:** The goal of the third action is to provide the individual with CP with resistive dissipative forces in the high frequency range to damp-out the energy of his/her involuntary hand motion. This provides the user with better coordination of the task and smoother, controlled motions. In addition, using this action, a better hand-eye coordination will be provided for the individual with CP. The reason is that using this action, the involuntary component of the hand motion dampens out, which matches the visual feedback from the task-side robot controlled to track the voluntary component of hand motion (based on Action #2). In order to implement Action #3, the involuntary component of the hand motion, which is extracted by the BMFLC filter, is utilized in the design of the resistive dissipative force field. It should be highlighted that the force field is implemented in the high-frequency domain and provides the user the feeling of moving in a viscous environment only for the involuntary component of the user’s motion. Consequently, the force field provides minimal to no resistance in response to the voluntary components of the user’s movements. The design of the proposed force field is as follows:

$$F_i(t) = \begin{pmatrix} B_x & 0 \\ 0 & B_y \end{pmatrix} \cdot \xi_i(t)^T. \quad (7.6)$$

In (7.6), $F_i(t)$ is the designed force field, $B_x$ and $B_y$ are dissipation coefficients that define the intensity of the resistive force field. The higher the intensity, the higher the magnitude of the generated resistive forces in response to the same input (i.e. involuntary component of hand velocity). It should be noted that since the dissipation coefficients are applied to the involuntary velocity of the individual’s hand at the user-side robot, the intensity of the dissipation converges to zero for voluntary movements.

**Remark 7.5.** Note that $B_x$ and $B_y$ define the intensity of the resistive force field. Feedback
from the patient and clinicians is considered to tune these parameters. The reason is that the intensity delivered using the proposed architecture depends on (a) the musculoskeletal power of the patient, (b) the level of intensity that the therapist/clinician would like to deliver to the individual’s hand, and (c) the level of comfort that the individual feels during the trial. Considering feedback from a therapist/clinician is common for neuro-rehabilitation robotic systems, where the therapist/clinician gradually tunes the difficulty level while the patient performs tasks \cite{39, 40}. As a result, we suggest to allow the clinician to tune $B_x$ and $B_y$ based on their understanding of the needs of the individual with CP and considering the individual’s comfort level during the interaction. The tuning procedure is explained in more detail in Section III.

**Remark 7.6.** Although the functionality of different actions of the system can be evaluated separately, the actions are designed to work simultaneously for individuals with CP. The reason is that if we just utilize Action #1 (scaling up the motions), we amplify not only the individual’s voluntary motions, but also the involuntary motions. In this case, the individual with CP would have more difficulty controlling the task-side robot. That is why the proposed architecture is designed to only assist the voluntary component while kinesthetically resisting and avoiding tracking the involuntary components of motion.

**d) Task Environment:** The other component of the proposed telerobotic architecture is the designed functional task environment. The geometry of the environment is decided considering the motion-capabilities of the task-side robot. Also, specific attention is paid to make the task environment “flexible”. Our clinical partners expressed that the environment needed to be flexible in order to quickly change the tasks based on the needs and interests of the individual with CP and the therapist. In this chapter, one of the main implemented tasks was to sort 10 magnetic happy face objects based on their colour when the initial pick-up position and the target drop-off locations were separated by 33 cm in the $X$ direction. There were two side-by-side target bins one for the red happy faces and one for the blue ones. The individual needed to use the proposed telerobotic system to sort the magnetic objects. This task is shown in Fig. 7.2 in the physical play environment. This is one example possible tasks and there are more possibilities. Sorting can also help children learn about the attributes of objects (like colour and shape), as they sort them into categories.
7.2.2 Experimental Evaluation

In this part, data from the experimental evaluation with a non-disabled user of the three actions of the proposed VA algorithm are presented. The experiments were performed in three phases where each phase corresponds to one of the defined actions.

Phase 1: Experiment for Motion Range Correction (Action #1): This phase was designed to evaluate the functionality of the proposed Action#1 of the developed VA. The experiment started at $t = 20$ seconds. First, the operator moved her hand for 30 seconds while the scaling factors for both X and Y directions were equal to unity. The generated motion trajectory of the user is compared to the one followed by the task-side robot in X and Y directions in Figs. 7.3a and 7.3b, respectively. Also, the 3D trajectory is shown in Fig. 7.3c. As expected, the task-side robot tracked the trajectories generated by the user. For the second part, at $t = 70$ seconds, the corrective gains $C_x$ and $C_y$ were increased by 50 percent. The trajectories for the $t \geq 70$ seconds can also be seen in Fig. 7.3. As expected in this condition, the task-side robot followed the scaled-up trajectory even though the user performed smaller motions.

Phase 2: Experiment for Voluntary Movement Tracking (Action #2): In this phase, to only evaluate the performance of Action #2, the dissipative force field was disabled. The force field is exclusively studied in the third phase of this experiment. First, the non-disabled operator provided motions only in a high-frequency manner in the X-direction. Since the high-frequency behavior was provided by a human operator (not programmed software), it is not possible to report the frequency. However, providing motions this way enabled testing the performance of the proposed action. It was expected that the task-side robot would not move much due to the proposed Voluntary Movement Tracking action of the system (Action #2). Next, the operator provided motions in a low-frequency manner. It was expected that the task-side robot would track the user-side robot, since applying Action #2, the low-frequency movements should pass through the VA algorithm. Then, the operator provided a hand motion which had both high-frequency and low-frequency components. It was expected that in this case, the robot would follow only the low-frequency component.

The results are show in Fig. 7.4, which confirms the functionality of Action #2 of the proposed VA algorithm. Considering Fig. 7.4a, when the motion had mostly high-frequency components, the task-side robot did not move much. However, when the operator moved the
robot in a low-frequency manner, the task-side robot followed the generated trajectory in Fig. 7.4b. When the motion had both high and low frequencies, the task-side robot mainly followed the low-frequency component, as shown in Fig. 7.4c. Since perfect filtering is not theoretically possible, some small high-frequency components can still be observed in Figs. 7.4a and 7.4c.

**Phase 3: Experiment for Involuntary Movement Dissipation (Action #3):** In this phase of the experiment, the dissipative force field (designed for suppressing involuntary motion through delivering a viscous force field in high-frequencies, applied by the user-side robot) was enabled and the same procedure as the one given in Phase 2 was repeated. Consequently, during the first part of the experiment, the non-disabled operator moved the robot in a high-frequency manner. Afterwards, during the second part of the experiment, she moved the robot in a low-frequency manner, and finally during the third part of the experiment, she moved the robot in a mixed-frequency manner (which included both high-frequency and low-frequency components). It was expected that the user would feel high amplitude compensatory resistive
7.2. Telerobotic Architecture and Virtual Assistive Algorithm

Figure 7.4: Motion trajectories in the X-direction: The user provided (a) high-frequency movements (first part), (b) low-frequency movements (second part), (c) movements that had both high-frequency and low-frequency components (third part).

forces in the first part (when only high-frequency motions are applied) and the third part (when mixed-frequency motions are applied) of this procedure, thus dampening the energy of the high frequency component. It was also expected that the user would not feel much resistance during the second part of this experiment. The generated force (for all the three parts) is shown in Fig. 7.5a. As can be seen in the figure, the designed VA algorithm has applied high amplitude forces in the first \((t < 45\text{s})\) and third \((t > 80\text{s})\) parts when there was high-frequency involuntary components in the motion. The dissipating energy provided by the proposed VA algorithm is given in Fig. 7.5b. The energy is calculated as follows:

\[
E_{\text{dis}}(t) = \int_{0}^{t} F_i(\tau) \cdot \xi_i(\tau)^T d\tau. \tag{7.7}
\]

Using (7.7), a high negative slope means a high rate of energy dissipation and a positive slope means energy generation over time. Considering Fig. 7.5b during the first and the third parts of
the experiment, the system considerably dissipates the interaction energy (the average slope for the first part was $-105 \frac{N\cdot m}{s}$ and for the third part was $-336 \frac{N\cdot m}{s}$) while during the second part of the experiment the energy dissipation was close to zero (the average slope was $-4.3 \frac{N\cdot m}{s}$).

As can be seen in Fig. 7.5, the designed VA algorithm has met our expectations and has dissipated the energy of the high-frequency component of the motion (in the first and the third parts of this phase) and not the low-frequency one (the second part). This can be seen by the negative slope of the energy curve during the first and the third parts, while the slope is almost zero during the second part. This experiment confirms the functionality of the proposed Action #3 of the VA algorithm. The above-mentioned experiments and results confirm the functionality of the proposed system and shows that the implemented VA algorithm and the proposed telerobotic architecture are performing as expected during the experiments involving a non-disabled user.

### 7.3 Protocol, Results and Discussion

In order to evaluate the effectiveness of the proposed architecture in assisting individuals with CP, the following protocol was conducted with one individual with CP. The ultimate goal of the protocol was to analyze the performance of the individual when the three actions were enabled (modulated interaction) in comparison to the situation when the actions were disabled (normal interaction). The individual is an adult with mixed CP which affects her upper and lower limbs. She is classified as Level IV in the Gross Motor Function Classification System Expanded and
Revised (GMFCS-E&R) [41], meaning she can perform self mobility with limitations (she uses a powered wheelchair). On the Manual Ability Classification System (MACS) [42], she is classified at Level III, meaning she can handle objects with difficulty, and needs help to prepare and/or modify activities.

**Step 1: Preparation-Part#1 (Familiarization):** During the first step, the individual was given time to get familiar with how moving the user-side robot resulted in movements of the task-side robot, and how the user-side robot exerted forces. The goal was to minimize the potential effects of adaptation on the results.

**Step 2: Preparation-Part#2: Workspace Identification for Motion Range Correction (needed for Action #1):** During the second part of the preparation, the individual was asked to explore the boundaries of her convenient workspace. This was done to find the needed scaling factors so that the individual could reach the targets in the task. The convenient motion range, and the needed workspace to perform the task are shown in Fig. 7.6. Based on (7.3) and (7.4), the results show that the participant needed 1.65 scaling up for the X direction and 1.3 scaling up for the Y direction. In other words, considering the designed workspace, cerebral palsy has reduced the participant’s motion range in the X direction by almost 40 percent and in the Y direction by almost 33 percent.

**Step 3: Preparation-Part#3: Filtering Frequency Identification (needed for Actions #2 and #3):** In order to find the cut-off frequency for the BMFLC filter, which is utilized to implement Actions #2 (Voluntary Movement Tracking) and Action #3 (Involuntary Movement Tracking).
Dissipation), the hand velocity of the individual was analyzed. For this purpose, two objects were placed on the boundaries of the designed workspace and the individual moved the user-side robot so that the task-side robot moved between the objects repetitively for 30 seconds. The frequency power spectrum is shown in Fig. 7.7 for the \( X \)-direction motion. Based on the results, the cut-off frequency (i.e. the frequency that can separate voluntary and involuntary motions) was calculated as 0.7 Hz which is shown by the black line in Fig. 7.7. In this chapter, the cut-off frequency was manually selected as the value between the main high and low frequency peaks.

**Step 4: Preparation-Part#4: Dissipation Gain Identification for Involuntary Movement Energy Dissipation (needed for Action #3):** In this part of the experiment, the dissipation gain in (7.6) was increased by 20 N.s/m steps from 0 to 100 N.s/m, while the user performed random movements at the user-side robot. The goal was to determine the best dissipation gain chosen based on observations of the user’s performance and the individual’s feedback. The individual moved the user-side robot at each dissipation gain, and rated the perceived exertion from: “easy, slightly difficult, fairly difficult, difficult, and very difficult”. A dissipative gain of 40 N.s/m for both the X and Y directions was selected for the study, as it was the value preferred by the individual that could provide enough control over the task for her. Feedback from a therapist could also help to tune this factor. After finding the parameters, to evaluate the effectiveness of the system in smoothing the movement trajectories and enhancing coordination accuracy, a two-phase task was designed, as explained in steps 5 and 6.
7.3. **Protocol, Results and Discussion**

**Figure 7.8**: Absolute error, using the *modulated interaction* (when the proposed three actions of the system are enabled), and for the *normal interaction* (when the actions are disabled).

**Step 5: Task-Phase #1 (Navigation Game)**: For this task, the user navigates the task-side robot between three locations. Two targets were located at the boundaries of the workspace (i.e., the ferromagnetic object pick-up location at the right and between the drop-off bins at the left in Figure 1). The two targets were separated by 33 cm in the X direction. The third target was a home position between the two targets. The individual moved the task-side robot (through the telerobotic medium and by providing motion at the user-side robot) from the left target to the home position, and then from the home position to the right target, and vice versa. She was asked to try to stay on each target for 4 seconds. She was given verbal cues about the timing of movement. This experiment was designed to analyze accuracy and smoothness. The individual repeated this motion eight times, first with all the three proposed Actions of the system disabled and then eight times with all of the Actions enabled. The targeting accuracy and motion smoothness are shown in Figs. 7.8 and 7.9. As can be seen in Fig. 7.8, the targeting accuracy, which is measured as the distance from the centre of the target averaged over the 4 seconds, is considerably enhanced when the three actions were enabled (modulated interaction), in comparison to when the actions are disabled (normal interaction).

In addition, the Fast Fourier Transform frequency content analysis of the movement velocity on the user-side robot, given in Fig. 7.9, shows that when the proposed three actions of the system are enabled, the power spectrum of the movement velocity contains lower frequency components whereas considerable more high-frequency components can be observed when the proposed three actions of the system are disabled. This result confirms the motion smoothing
feature of the system for task performance. It should be highlighted that the low-frequency components of the movement velocity for the case of modulated interaction is close to the normal interaction. This means that the system does not considerably affect the low-frequency movements while the high-frequency involuntary component of the movement is dissipated. In summary, the movements are smoother and the coordination is more accurate, which serves the very purpose of the proposed architecture.

**Step 6: Task- Phase #2 (Pick and Place Game):** In order to better evaluate the functionality of the system, the second phase of the task was developed. In this phase, the individual was asked to sort the ferromagnetic happy face objects based on their colours (red or blue). For this purpose, as mentioned before, on the right side of the designed workspace, an initial position is considered for the magnetic happy faces. On the left side of the workspace, two colour-coded target locations for the objects were placed side-by-side. The designed workspace can be seen in Fig. 7.2. The initial position and the targets are separated by 33 cm in the X direction. In total, the user sorted 10 objects. The individual was asked to placed the objects in the corresponding target position one after the other. A research assistant put the magnetic happy faces on the initial pick-up location (one by one).

The experiment was conducted successfully and the individual was able to sort the objects while the system smoothed her motions and increased her movement range, which ultimately resulted in a more accurate coordination and control over the task execution, despite the fact...
that the targets were placed out of her convenient workspace.

The resulting movement trajectories were analyzed in the frequency-domain (as shown in Fig. 7.10) similar to the previous step of the study (Navigation game). In addition, velocity profiles of the modulated interaction and the normal interaction are compared in Fig. 7.11. Also, movement in the X and Y directions together with the 2D movement trajectory are shown in Fig. 7.12 (for the case of modulated interaction) and in Fig. 7.13 (for normal interaction).

As it can be seen in Fig. 7.10, the involuntary components of the motion are considerably dissipated by the use of the proposed modulated interaction in comparison with the normal interaction. Also the use of the proposed modulated interaction has resulted in smoother position and velocity trajectories, which can be seen in Fig. 7.11 for the movement velocity profile and can be also observed by comparing Figs. 7.12 and 7.13 for the movement position profile.

In addition, for the modulated interaction, the motion execution (moving from the home position to the target) conducted by the individual is more coherent. This can be seen by comparing the 2D motion in Figs. 7.12c and 7.13c, and also by comparing the 2D histograms of the motion trajectories shown in Fig. 7.14. It should be noted that as shown in Fig. 7.2, the two target bins are placed side-by-side on the target line shown in Figs. 7.12c and 7.13c. Regarding the coherency of motion, for the modulated interaction, it can be seen that the trajectories are more directed towards the targets, and the individual covers a wide range of workspace (full range of needed workspace on the target line which was 17 cm at the task-side robot) to
Figure 7.11: Movement velocity in the X-direction: (a) for the case of modulated interaction, and (b) for the case of normal interaction.

laterally separate and distribute the objects; in addition, the deviation from the target line in
the X-direction ("overshoot") is minimal, which indicates that the individual was capable of
stopping accurately at the target locations to perform the task. However, for the case of normal
interaction, several non-smooth deviations can be observed. Based on the histograms shown in
Fig. 7.14, for the modulated interaction, the individual had the control to hover over top of the
targets (which resulted in brighter spots on the target line) rather than overshoot them.

In addition, for the case of normal interaction, the individual was only able to use a small
portion of the target line (42% of the defined needed full range of motion on the target line) to
distribute the objects along the line. Also, due to the inability of the individual to stop accu-
rately over the target locations non-smooth movements on the target line and overshoots can
be observed in the motion trajectory. The histogram of the normal interaction is taller in the X
direction (because of the overshoots) and is thinner in the Y direction (due to the limited capa-
bility in covering the needed workspace especially on the target line). The improved motion
cohere to corresponds with better coordination and better motion capabilities.

In summary, using the proposed system, the individual was capable of using her convenient
workspace to reach and perform the tasks, the motions were smoother in both position and
velocity domains and the individual showed better coordination accuracy and motion execution
while performing tasks. This was realized using the proposed architecture, which assisted the
individual to manage the involuntary actions and enhance her movement capabilities.
The results illustrate the potential of the proposed system and show that using the telerobotic architecture, it is possible to augment the motion capabilities of an individual with CP and assist them to provide smoother and more controlled movements for performing tasks. This presents a new assistive compensatory paradigm for people living with cerebral palsy.

7.4 Conclusion

In this chapter, a new telerobotic architecture is proposed that enhances physical interaction with real objects for individuals living with CP. The design of the proposed architecture is specific for the neurological motor deficit causing coordination issues and involuntary motions. The system is composed of four main components, namely: the user-side robot, the task-side robot, the virtual assistive algorithm, and the task environment. The proposed system has a triple-action design. It extracts the voluntary movements of the user to be transferred from the user-side robot to the task-side robot, then it corrects the motion range to fit the transferred
Figure 7.13: Motion trajectories for the normal interaction (when the proposed actions are disabled): (a) X-direction, (b) Y-direction, (c) 2D movement.

Figure 7.14: The histogram of movement for (left) modulated and (right) normal interactions. The histograms show the amount of time spent on different locations of workspace; the brighter a pixel is, the higher amplitude of the histogram, and the longer length of time spent at that spot.
motion within the needed workspace of the task, and finally it provides the user with a resistive force field implemented in high-frequency motion domain to only dissipate involuntary energy of the hand motion. The proposed telerobotic architecture is motivated by evidence showing that interaction with physical environments is crucial for individuals with CP to help prevent various secondary symptoms and further sensorimotor deficits. The proposed architecture is implemented using a Quanser upper-limb rehabilitation robot and a Phantom Premium robot. The implemented system was initially evaluated for a non-disabled participant where various functions of the designed architecture were evaluated. Afterwards, the system was studied for an individual who lives with CP to evaluate potential benefits that can be achieved from the point of view of interaction enhancement. The results support the capability of the system in enhancing physical interaction for the individual with CP through the designed triple-action architecture. This work suggests that the designed system could be used as a new compensatory assistive platform for people living with CP. Future tests and analyses will help to further investigate the effectiveness of the system, evaluate the long-term effects, and define a range for the system coefficients.
Bibliography


Chapter 8

Application to other Neurological Movement Disorders: Haptic Feedback Manipulation for Focal Hand Dystonia

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8.1 Introduction and Preliminaries

Writer’s cramp disease is an important task specific focal hand dystonia that generates mild to severe involuntary contraction of upper limb muscles during some fine motor control tasks such as writing [1]. It can result in pain, dystonic hand tremor, disorder in controlling hand kinematics, problem in force and motion control during fine motor tasks [2–4], abnormal manipulation of tools (such as pen) needed to perform tasks, abnormal frequency and legibility of writing [3, 5], muscle fatigue [4] and ultimately, disability in performing a wide range of fine motor tasks, specifically writing [6, 7]. In the literature, some therapies have been suggested for this condition including motor rehabilitation [8], Transcranial Magnetic Stimulation...
(TMS) [9], and Botulinum toxin injection therapy [10–14]. However, the nature of this condition, the affecting parameters, and the main pathophysiology is still not completely understood.

Appropriate control of motor outputs requires an optimal processing of perceptual inputs (such as vision, haptics and proprioception), in addition to a capability of accurately tuning motor outputs based on perceived information about the task, the environment, biomechanics of musculoskeletal system and sensory information. This procedure is called Sensorimotor Integration (SMI) in the literature [15–17].

In contrast to the traditional understanding of FHD which mostly focuses on motor components, the current widely-accepted pathogenesis of FHD is SMI deficits in the brain [15]. This has been suggested using functional Magnetic Resonance Imagine (fMRI) which has shown that SMI abnormalities in basal ganglia, cortex and cerebellum can be the potential cause of this condition [15, 18–21]. Cueing-based training (i.e., making the patient aware of the onset of dystonia in order to train them how to tune their motor output) has also been studied for writer’s cramp (through auditory cueing [22]) and for primary dystonia in children (using visual and friction-based cueing [23]). In addition, short-time error-enhancing through a perturbation technique (when a patient receives some disturbance forces during task execution) has shown potential after-effect benefits (regarding the optimality of path control) for children with primary dystonia [24]. A recent literature survey [15] provides existing evidence supporting the correlation between SMI disorders and FHD. Better understanding of the underlying reasons and the affecting parameters can result in developing new treatment, rehabilitation and assistive techniques to help this category of patients lead a better quality of life.

Various components of the SMI pathways are separately studied for FHD. The reported examples of perceptual deficits caused by FHD are tactile, spatial, and temporal discrimination disorders [25]. Examples of motor output deficits caused by FHD are hand kinematics and grip force control problems [2, 3, 26], in addition to, motor preparation, motor execution [27] and motor imagination [19] deficits. Besides the observed disorders in different components of SMI, there are also reports suggesting that FHD is a result of sensory processing dysfunction [28, 29]. It has also been shown that prolonged rehabilitation of FHD patients can result in somatosensory cortical plasticity which corresponds to enhanced motor performance in this category of patients [8]. This observation also makes the correlation between SMI and FHD
even stronger. This study focuses on the contribution of haptic sensory input on the pattern and severity of FHD and suggest a new possible relation between SMI deficits and FHD.

8.1.1 Closed-loop Interaction with Physical Environments

It should be noted that even the simplest interaction with a physical object involves a complex multi-modal closed control loop. The loop starts from a decision making step for performing a task, and contains the following steps: (a) generating an appropriate motor command, (b) transferring the command to the musculoskeletal system, (c) applying the required force/motion profiles on the physical environments, (d) perceiving (through the sensory system) the mechanical responses of the physical environment to the generated actions applied by the musculoskeletal system on the object, (e) transferring back the perceived responses, (f) fusing the transferred sensory information and the concurrent motor states to instantly design the required tuning of the motor commands. As mentioned, both the sensory system and the SMI pathways in the brain of patients living with FHD are believed to be abnormal [15, 18–21].

Based on the above-mentioned comments and the current literature, a simple schematic of the closed-loop interaction for FHD patients is shown in Fig. 8.1 to visualize the basic concept of the closed-loop interaction and illustrate various affecting components and the corresponding information flow. This diagram will then be used to clarify the contribution of this chapter.

8.1.2 Basic Concept, Underlying Theories and Motivation

In order to explain the motivation for this work, some basic concepts are utilized from nonlinear control theory and haptics concerning the performance of multivariable closed-loop control systems [30,31]. Based on the aforementioned theories, abnormalities (such as sensory system disorder, and/or irregular delays in processing and transferring signals) in a closed-loop control system can result in an undesirable motor output. It should be noted that when dealing with a physical object, one component of the closed-loop system is the mechanical response of the
Figure 8.1: Representative information flow schematic of components for interaction with a writing surface during a writing task which includes several steps. First, the patient makes the decision of writing; this decision is transformed to motor commands executed by the muscles and applied on the writing surface. Higher rigidity of the writing surface results in larger reaction forces from the surface in response to small position changes. The reaction force is sensed by the patient’s sensory system and is fused with other modalities in the brain during writing (such as vision and proprioception). The result is processed in the brain to control muscle activities to accomplish the task. The red lines show the flow of sensory input (feedback path), the dark lines show the flow of action information (feedforward path). The yellow components denote information processing and fusion process in the brain.

Remark 8.1. In the case of a writing task, the environment is the writing surface. Consequently, the mechanical response of the environment is the reaction force which corresponds to the rigidity of the surface. As a result, higher rigidity of the writing surface generates larger reaction forces during the similar writing task. If the rigidity of the writing surface is reduced, the patient will feel less reaction forces while writing.

Remark 8.2. Based on the mathematical evaluation of closed-loop haptics-enabled systems, it should be noted that a mechanically-stiff environment results in high loop gain and increases sensitivity to small abnormalities and movements. In the field of haptic interaction and control engineering, loop gain corresponds to the intensity of a responsive output to stimulations, where high-loop gain is known to be a factor that increases “sensitivity” to abnormal phenomena. The concepts of sensitivity and loop gain are mathematically investigated in control engineering particularly based on robust control and Small-Gain theories, where several sensitivity functions of a closed-loop system are characterized and analyzed for dealing with
uncertainties, noises, disturbances, delays, etc. [32–35]. This concept can be applied to any interactive loops and has been applied for haptics and force-enabled systems (e.g., [36–39]).

For the writing tasks, a rigid writing surface results in a high-amplitude mechanical force response which is then preserved and analyzed by the control system to generate a corrective motion/force profile. However, existence of deficits in the control procedure can result in abnormal generation of the corrective forces which can then result in further motor output problems and task performance degradation. A solution suggested is to reduce the loop gain which reduces the sensitivity to deficits in the control system. This is supported by the general concept of managing ill-behaved closed-loop control systems (in the context of nonlinear control theory) and indirectly has provided the motivation for this work.

In this chapter we evaluate the effect of writing surface rigidity on FHD patterns and investigate the potential benefits that can be achieved by reducing the loop gain (through a reduction in the surface rigidity).

8.1.3 Contribution and Hypothesis

Based upon the notes and the literature discussed above, in this chapter, the contribution of haptic inputs on altering Dystonia Severity (DS) is investigated for FHD patients, while the FHD participants were undergoing treatment with BoNT-A therapy. For this purpose, initially, severity and characteristics of dystonia is investigated for 11 participants at baseline (pre BoNT-A therapy in the first session of the trial). In addition, DS is tracked for 7 participants during 5 sessions of assessment and BoNT-A therapy. The therapy was delivered in Sessions #1 and #3. The goal was to study the effect of kinesthetic manipulation as a potential assistive technique besides BoNT-A therapy. The trial includes writing, hovering, and spiral/sinusoidal drawing tasks. In each session, the test is repeated two times when (a) a participant uses a normal pen for performing the tasks, and (b) when the participant uses a robotics-assisted system which provides a compliant virtual writing surface in order to manipulate the kinesthetic sensory input. The experimental setup is shown in Fig. 8.2.

In this chapter, we investigate the hypothesis that “reducing writing surface rigidity can intrinsically reduce average DS for FHD patients”.

To better clarify the contribution of this chapter the closed interaction loop which was
Figure 8.2: The experimental setup used in this study to manipulate haptic sensation for FHD patients. The setup consists of one Phantom Premium haptic device from Geomagic, an NDI motion grabber and a ATI Gamma force sensor. The participant (second row) was diagnosed with FHD.

originally shown in Fig. 8.1 is modified as shown in Fig. 8.3. The loop is changed in two ways. The results of this study validated that reducing the writing surface rigidity, changes the cramp pattern and considerably decreases the overall dystonia severity. In addition, the results support that reduction in dystonia severity, achieved by using the robotic system, was statistically significant (p-value < 0.001). Also, when the therapy was delivered, it was still possible to reduce dystonia severity through the use of the proposed robotic system. In addition, in this chapter it is shown that using the proposed haptic manipulation strategy, patients show better control over their grip pressure while writing. This was statistically validated (p-value < 0.001) based on the grip pressure information logged during writing and is in agreement with the literature which correlates the severity of dystonia to the extent of grip pressure [22,40–42].

The above results are then utilized in the design of an actuated pen as a writing-assistance tool. We have called the motorized pen a Dystonia Writing Assistance Pen (D-WAP). It can provide the compliant haptic interaction with the writing surface without using a table-top grounded robot.

**Remark 8.3.** The results of this chapter support the point that dystonic cramping in FHD is
8.1. Introduction and Preliminaries

Figure 8.3: The modified version of Fig. 8.1 showing how the information flow of the closed interaction loop is modified in this chapter in order to conduct the study. The orange blocks show the proposed modification of the interaction loop, the red lines show the flow of sensory input (feedback path), the black lines show the flow of action information (feedforward path). The yellow components denote information processing and fusion process in the brain.

closely related to haptic sensory input, and is not just the result of posture and position control deficits. Note that when a patient uses the proposed robotic system, the posture and the position trajectories are similar to the situation where the patient is not using the system. In other words, the results of this chapter highlight the point that FHD is not only a motor output problem but that it relates to the sensory input processing. This validates contribution of SMI dysfunction in FHD patients.

The rest of this chapter is as follows. In Section 8.2, the implemented method is described. In Section 8.3, the statistical results regarding the performance of the proposed haptic manipulation technique in reducing (a) dystonia severity and (b) excessive grip pressure are given. Conclusions are given in Section 8.4. The conceptual design of the proposed D-WAP system is presented in Appendix I (Section 8.5).
8.2 Method

8.2.1 Demographic data

This study included 11 patients in total (7 males and 4 females), with task specific focal hand dystonia during writing, aged from 52-70 (mean: 58.91, S.D.=6.75). The mean value of the number of years since disease diagnosis was 9.27. Eight patients were right-handed, two were left-handed and one was ambidextrous. Patients were excluded if they had a history of BoNT-A therapy during one year before the trial. All participants completed the dystonia rating scales. Patients were recruited from the Movement Disorder Centre at the London Health Sciences Centre, University Hospital (London, Ontario, Canada). The study protocol was approved by the local Health Sciences Research Ethics Board (HSREB# 18643). The approved letter of information was provided to the patients and consent was signed prior to their participation. It should be noted that patient #10 was ambidextrous and was diagnosed with FHD in both his hands. In fact, he had been initially left handed and due to the onset of FHD, he started writing with his right hand. However, he was then diagnosed with FHD in his right hand as well. This patient participated in this study separately for both his right-side and left-side FHD. In total 44 sessions of the patient-based trial were completed across all participants. Seven patients completed 5 sessions of assessment where they received BoNT-A therapy at the end of the first session and the third session. Also two other patients participated in this study for 3 sessions. For the type of Botulinum toxin, we used BOTOX® (onabotulinumtoxin A), 6 U/kg for adult humans [43].

Remark 8.4. The participation chart is shown in Table 8.1. It should be noted that the study included two cycles of BoNT-A therapy (Sessions 1,2,3 for the first cycle and Sessions 3,4,5 for the second cycle). The injections were administered at the end of the first visit of each cycle (i.e. the first and the third sessions). The second visit of each cycle was planned for when the effect of medication was at the maximum level (6-weeks post-injection, as studies have shown that the peak clinical effect of BoNT-A occurs approximately 6 weeks post-treatment). Each cycle was a 16-week interval to include a 1-month wash-out period (to observe the lasting effects of BoNT-A) as typical BoNT-A therapy follow 12-week intervals. Consequently, the planned intervals between the sessions were as follows: 6 weeks between, session #1 and session #2,
10 weeks between session #2 and session #3, 6 weeks between session #3 and session #4, and 10 weeks between session #4 and session #5. As mentioned, BoNT-A treatment was planned to be delivered at the end of the first session and the third session. Consequently, the effect of injection was large for sessions #2 and #4 (the post-injection sessions). In addition, the effect of injection was reduced for session #3 and was small for session #5, and none for the first session (because the participating patients did not have any history of BoNT-A therapy during one year before the trial).

The design of the 5-session assessment protocol was planned to better observe potential fluctuations resulting from BoNT-A therapy, optimize the pattern of injection and analyze the effect of haptic modulation while the patient was on therapy in comparison with the situation when the patient was off therapy. In Tables 8.2 and 8.3, details of the demographic data in addition to the pattern of injection are given. The abbreviations used in Table III are explained in Table IV. Please note that in Table II, the Dystonia and Movement Disability Scale (DMDS) is part of the Burke-Fahn-Marsden dystonia rating scale, which is used in the literature to classify generalized dystonia symptoms [44, 45]. The handwriting item of the above-mentioned rating scale was utilized to calculate DMDS, as all other items did not rate the severity of FHD symptoms. The score is calculated based on the severity of the condition observed before the start of the trial in the first session.

**Remark 8.5.** As shown in Table I, out of 11 patients, seven participants finished all the 5 sessions. The other four did not finish all the sessions of the study (some of them were due to personal reasons). It should be noted that Botulinum toxin injection therapy can affect many daily activities (such as brushing teeth, handling the steering wheel in a car, holding a cup, moving objects at home) while the disease itself is mostly task-specific. The effect of the injection could alleviate task-specific dystonia but could have an adverse effect on other tasks which may be troubling for some patients. This was a reason for some of the participants who preferred not to receive the first or the second BoNT-A therapy. As a result, they were excluded from the rest of the study and did not finish all 5 sessions. The aforementioned adverse effect of BoNT-A therapy is an important motivation for developing task targeted assistive technologies, which do not affect other tasks.
8.2.2 Study Design

The protocol designed for this study includes two main tasks namely: Normal Writing (NW), and Robotics-Assisted Writing (RAW). For the NW task, the participants were asked to use a normal pen for performing a set of writing/drawing subtasks explained later. For the RAW task, the participants were provided with the robotic system (which supports the pen) to perform the subtasks. The RAW system is composed of a Phantom Premium haptic device (from GeoMagic, US) connected to the writing pen. The robot was programmed in a way that produces a compliant writing surface 2 cm above the actual page. Rigidity of $350 \text{ N/m}$ is generated by the robot for the writing surface throughout the robot’s workspace. The system is shown in Fig. 8.2. The subtasks in both RAW and NW tasks are: a) hovering the pen over a black dot; b) writing the following sentence “Today is a bright and sunny day.”; c) drawing over two sets of printed sinusoidal waveforms with different amplitudes and frequencies, from left to right and right to left; d) drawing within two spiral shapes (one small, one large), from inside to outside and outside to inside; e) connecting two dots located between two parallel lines when the lines are close together (fine motion control) and when they are farther apart (coarse motion control).

Remark 8.6. The aforementioned subtasks were designed to simulate different components of motion control to observe the dystonic symptoms as much as possible. In Fig. 8.4, a snapshot of the drawing subtasks is shown. It should be noted that, the design of the subtasks were
Table 8.2: Demographic Data

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Dominant Hand</th>
<th>Gender</th>
<th>Age</th>
<th>Symptom Duration</th>
<th>Dystonia Movement and Disability Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>R</td>
<td>F</td>
<td>55</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>P2</td>
<td>R</td>
<td>M</td>
<td>52</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>P3</td>
<td>R</td>
<td>M</td>
<td>70</td>
<td>15</td>
<td>2</td>
</tr>
<tr>
<td>P4</td>
<td>R</td>
<td>F</td>
<td>60</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>P5</td>
<td>L</td>
<td>M</td>
<td>55</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>P6</td>
<td>R</td>
<td>M</td>
<td>58</td>
<td>45</td>
<td>3</td>
</tr>
<tr>
<td>P7</td>
<td>R</td>
<td>F</td>
<td>55</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>P8</td>
<td>L</td>
<td>M</td>
<td>66</td>
<td>3</td>
<td>2</td>
</tr>
<tr>
<td>P9</td>
<td>R</td>
<td>F</td>
<td>62</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>P10</td>
<td>L &amp; R</td>
<td>M</td>
<td>55</td>
<td>7</td>
<td>1</td>
</tr>
<tr>
<td>P11</td>
<td>R</td>
<td>M</td>
<td>70</td>
<td>11</td>
<td>2</td>
</tr>
</tbody>
</table>

motivated by the literature (such as that used in [46] which is designed for tremor assessment) and were modified for writer’s cramp while adding other subtasks such as the hovering task (to examine the effect of constant posture alone), and sinusoidal drawing (with high and low frequencies, high and low amplitudes and from left to right and right to left). Note that the pattern of cramping and the responsible muscles are different for different patients. This can be interpreted from various patterns of injection shown in Table III. Accordingly, the study is designed to simulate different components of motion control for patients with different pattern of cramping. For example, small spiral and high frequency sinusoids are for stimulating fine motor control that requires more fingertip motion, while the big spiral and the large sinusoidal motions are considered for stimulating upper muscles. In addition, drawing from right to left and left to right was done to simulate the effect of writing habits (which is from left to right in English). A writing task is also considered that is common for studying writer’s cramp.

During each subtask, the patients were asked to indicate when they felt the onset of dystonia. In addition, at the end of each task, the participants were asked to rank the severity of dystonia from 0 to 4 (values with decimals were allowed), where 0 is little or no sensation of cramp/tension/pain/tremor/discomfort and 4 is very severe cramp/tension/pain/tremor/discomfort. The dystonia severity and starting time were recorded.

Remark 8.7. As mentioned in the Introduction, Writer’s Cramp creates mild to severe in-
Haptic Feedback Manipulation for FHD Patients

Table 8.3: BoNT-A Therapy Pattern

<table>
<thead>
<tr>
<th>Patient ID</th>
<th>Injection Pattern L1</th>
<th>Injection Pattern L3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>PQ(10), PT(10), ECR(10), ECU(10)</td>
<td>PQ(10), PT(10), ECR(10), ECU(10)</td>
</tr>
<tr>
<td>2</td>
<td>FCU(30), FCR(30), BRD(20), BIC(20)</td>
<td>FCU(40), FCR(40), BRD(30), BIC(25)</td>
</tr>
<tr>
<td>3</td>
<td>FCR(10), ECR(10), FCU(10), ECU(10)</td>
<td>FCR(15), ECR(10), FCU(15), ECU(10)</td>
</tr>
<tr>
<td>4</td>
<td>FPL(5), FPB(5), FCR(10), FCU(10), BIC(20), TRIC(20), BRD(20)</td>
<td>FPL(7.5), FPB(7.5), FCR(15), FCU(15), BRD(30), BIC(30), TRIC(30)</td>
</tr>
<tr>
<td>5</td>
<td>ECR(15), ECU(15), FCR(10), FCU(10)</td>
<td>ECR(15), ECU(15), FCR(10), FCU(10)</td>
</tr>
<tr>
<td>6</td>
<td>FDS(10), FPL(10), FCR(15), FCU(15)</td>
<td>FDS(15), FPL(15), FCR(20), FCU(20)</td>
</tr>
<tr>
<td>7</td>
<td>ECU(10), ECR(15), SP(15), FCR(10), E(5), EPLB(5)</td>
<td>ECU(10), ECR(10), SP(10), FCR(10), E(5), EPLB(5)</td>
</tr>
<tr>
<td>10</td>
<td>PC(10), TM(15)</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>PQ(10), ECR(10), ECU(20), PT(10)</td>
<td>PQ(10), ECR(10), ECU(20), PT(10)</td>
</tr>
</tbody>
</table>

*Numbers in this table show the injected units of botulinum toxin.

voluntary contraction of upper limb muscles during task-specific motor control. It has a wide variety of symptoms, which are different for different patients. Some patients feel excessive pain or discomfort due to cramping and some have tremulousness, or involuntary tension or fatigue-like feelings. Consequently, the pattern of cramping is different for each patient. For this reason, it was essential to ask patients to indicate the onset of dystonia through their sensation of cramp/tension/pain/tremor/discomfort.

8.3 Results

In this section, the results of the study are presented, statistically evaluated and discussed.

8.3.1 Dystonia Severity and Effect of Haptic Manipulation

In this part, the effect of the proposed haptic manipulation on reducing severity of FHD is evaluated. For this purpose, first the average value of the reported dystonia severity is calculated
8.3. Results

### Table 8.4: Abbreviations

<table>
<thead>
<tr>
<th>Injected Muscles and Their Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PQ: Pronator Quadratus</td>
</tr>
<tr>
<td>PT: Pronator Teres</td>
</tr>
<tr>
<td>ECR: Extensor Carpi Radialis</td>
</tr>
<tr>
<td>ECU: Extensor Carpi Ulnaris</td>
</tr>
<tr>
<td>FCR: Flexor Carpi Ulnaris</td>
</tr>
<tr>
<td>FCU: Flexor Carpi Radialis</td>
</tr>
<tr>
<td>BRD: Brachioradialis</td>
</tr>
<tr>
<td>PC: Pectoralis</td>
</tr>
<tr>
<td>EPLB: Extensor Pollicis longus/brevis</td>
</tr>
</tbody>
</table>

for each task in each session, as

\[
DS_i^k = \sum_{j=1}^{n} \frac{\text{Severity of Dystonia in Subtask} \text{"j"}}{\text{Number of Subtasks}}. \tag{8.1}
\]

In (8.1), \( k \in [1, 2, 3, 4, 5] \) is the session number, \( i \) is the task index where \( DS_1^k \) corresponds to the DS value for the NW task (in the \( k \)th session) and \( DS_2^k \) corresponds to the DS value for the RAW task (in the \( k \)th session). In addition, \( j \) is the index of subtasks. As a result, after one full session of assessment, two DS values were calculated, one for the NW task and one for the RAW task. To extract the effectiveness of the proposed haptic manipulation system, the DS value of the RAW task is normalized using the corresponding value for the NW task. In this way, the effect of BoNT-A injection is excluded (which is studied separately later in this chapter) and only the effects of haptic manipulation can be observed. This has been done to evaluate the main hypothesis of this chapter. By simple algebraic manipulation, the normalization can be then transformed to a quantitative measure of percentage improvement in reducing dystonia severity achieved by the proposed haptic manipulation strategy in the \( k \)th session of the trial:

\[
IMP_{RAW}^k = 100 \times \left(1 - \frac{DS_2^k}{DS_1^k}\right). \tag{8.2}
\]
In (8.2), $IMP^k_{RAW}$ represents the percentage of improvement achieved through the RAW task. The higher this value the greater reduction there is in DS. Note that $DS_1^k$ and $DS_2^k$ correspond to similar sessions of assessment (i.e. the $k^{th}$).

In the next step, the distribution of the $IMP^k_{RAW}$ values have been calculated and analyzed. Consequently, the results of considering only the first session of assessment are shown in Fig. 8.5a and the results of considering all 44 sessions of assessment are shown in Fig 8.5b.

Based on the results shown in Fig. 8.5b using the proposed manipulation of haptic feedback it was possible to reduce the dystonia severity of participants by an average value of 52.8% and standard deviation of 35.3%. Using the standard t-test statistical analysis, it is observed that the positive average improvement is statistically significant (p-value < 0.001). This is the most important result of this chapter which validates the main hypothesis of the study. It should be highlighted that in 13 cases, using the proposed haptic manipulation, it was possible to achieve $IMP^k_{RAW}$ value greater than 90% and in 8 cases it was 100%. This means that the proposed technique was able to dramatically eliminate the symptoms of FHD in those cases.

In addition to the above, considering the results shown in Fig. 8.5a if we only consider the first session of the trial for all participants, the average value of the reduction in dystonia
8.3. RESULTS

Figure 8.5: Distribution of the improvement achieved by the proposed haptic manipulation technique: (a) the results for the first sessions when patients were not on medication, (b) the result for all included sessions. The p-values have been calculated using one-sample t-tests and show that the positive average improvements in (a) and (b) are statistically significant ("Average", "SD" and "N" are the mean value, the standard deviation and the sample size of the distribution, respectively).

severity was 57.9%, the standard deviation was 27.8%, and the p-value was smaller than 0.001. This result also validates the effectiveness of haptic manipulation in reducing the severity of dystonia. The reason for separately analyzing the result of the first assessment session is that some of the patients who respond well to the BoNT-A therapy showed very little dystonia during the later sessions of the trial. This may result in not being able to accurately observe the effectiveness of the haptic manipulation. However, even without considering this point, the distribution shown in Fig. 8.5b shows the significant improvement achieved by the proposed haptic manipulation.

Remark 8.8. Please note that as mentioned earlier, Participant #10 participated in this study separately for both his right and left FHD and showed different pattern of cramping for his right and left hands. The statistical numbers shown in Figs. 8.5a and 8.5b are given including results from both his right and left hands. Excluding the right hand of this patient (that went through only one session and provided only one data point) from the study does not significantly affect the analysis. For Fig. 8.5a, the exclusion results in having an average improvement of 54.15% (instead of 57.9%), standard deviation of 25.8% and p-value< 0.001.
Figure 8.6: $IMP^k_{RAW}$ value achieved using the proposed haptic manipulation strategy throughout the 5 trial sessions for: (a) Participant #1, (b) Participant #3 and (c) Participant #4.

For Fig. 8.5b, the exclusion results in having an average improvement of 51.7% (instead of 52.8%), standard deviation of 34.98% and a p-value < 0.001. As can be seen the average improvement is still more than 50% and the results are still significant.

In addition to the above, the $IMP^k_{RAW}$ value for three participants are given in Fig. 8.6. Note that each point in the graphs shown in 8.6 represents the improvement achieved in the normalized dystonia level through the use of the proposed haptic manipulation strategy. As mentioned earlier, the values are normalized using the dystonia level at each session. As can be seen in the figures, in some cases (such as for Participants #3 and #4) the dystonia is considerably reduced.

In the next part of the analysis, to observe the effectiveness of the proposed technique be-
8.3. Results

Besides the standard BoNT-A therapy, the normalization technique mentioned earlier is modified as follows:

\[ Total_{IMP-i}^{k} = 100 \times (1 - \frac{DS_{1}^{k}}{DS_{1}^{i}}) \]  

(8.3)

The main difference between (8.3) and (8.2) is that in (8.3) the \( DS_{1}^{1} \) value is considered for normalizing the dystonia severity for all sessions, instead of the corresponding value in each session (i.e. \( DS_{1}^{k} \)). In other words, using the second normalizing strategy (shown in (8.3)), the level of dystonia in all sessions of trial is normalized by the initial level of dystonia before the start of BoNT-A therapy measured in the first session of the trial. This results in not excluding the effect of BoNT-A therapy and studying the state of dystonia during this trial compared to the beginning of the trial. It should also be noted that using (8.3), two values for improvement are calculated for each session namely, (a) \( Total_{IMP-1}^{k} \) which is the improvement achieved for reduction in the dystonia severity level by only delivering the BoNT-A therapy through the study; and (b) \( Total_{IMP-2}^{k} \) which is the improvement achieved by the use of both BoNT-A therapy and the proposed haptic manipulation strategy together. The \( Total_{IMP-i}^{k} \) values for the three participants are given in Fig. 8.7 and the corresponding distributions are shown in Fig. 8.8.

Regarding the effectiveness of BoNT-A therapy, the following observations can be made. As can be seen in Fig. 8.7 the severity of dystonia reduced for the three participants during the BoNT-A therapy trial. However, it should be mentioned that this was not the case for all the patients in all the sessions as (a) the pattern of injection might not be optimal from the first injection; and (b) a patient may show a variable pattern of dystonia during the trial. This can be seen in Fig. 8.8 (right) when the negative values correlate with the mentioned point. As shown in Fig. 8.8 (right), the average value of improvement achieved by only delivering BoNT-A therapy was 39.2%, the standard deviation was 35.2% and the p-value (calculate using the standard t-test statistical analysis) was less than 0.001. This result tells that the BoNT-A therapy was able to reduce the dystonia level (as expected) and the positive average improvement is statistically significant. However, as mentioned the improvement was not always positive and it was not linear either. For example, considering Fig. 8.7c the participant does not show considerable improvement as a result of the delivery of BoNT-A therapy (alone) in the first injection session. However, the improvement achieved by BoNT-A therapy was considerably
Figure 8.7: Total improvement in reducing the dystonia level. The red line corresponds to $Total_{IMP-1}^k$ which shows the improvement achieved by delivering BoNT-A therapy and the blue line corresponds to $Total_{IMP-2}^k$ which shows the improvement achieved by delivering both BoNT-A therapy and the proposed haptic manipulation: (a) Participant #1, (b) Participant #3 and (c) Participant #4.

enhanced after the second injection delivered in the third session of the trial.

Regarding the effectiveness of the proposed haptic manipulation strategy besides BoNT-A therapy, the following observations can be made. Considering Fig. 8.8 (left), including the haptic manipulation strategy in the procedure, there was considerable increase in the average improvement in reducing the dystonia level. In fact the average value is increased to 64.3%, while keeping almost the same standard deviation (i.e. 35.7%). Also, the corresponding p-value is still less than 0.001. In addition, using the paired-samples t-test the two distributions shown in Fig. 8.8 have been compared and a p-value < 0.001 has been achieved. The above
8.3. Results

Figure 8.8: Distribution of $\text{Total}_{IMP-i}^{k}$ values for $k = 2$ (left), and for $k = 1$ (right). The p-values in the figure have been calculated using the one-sample t-test and show that the positive average improvements shown in both distributions are statistically significant. In addition, the paired-samples t-test was conducted (for comparing the two distributions) and demonstrated statistical significance (p-value < 0.001). This indicates that not only is the net improvement achieved by the use of the proposed haptic manipulation besides BoNT-A therapy statistically significant, but it is statistically also higher than just administering BoNT-A therapy.

Observations indicate that not only is the net improvement achieved by the use of the proposed haptic manipulation besides BoNT-A therapy statistically significant, but it is statistically also higher than just administering BoNT-A therapy.

This result suggests that the proposed haptic manipulation technique can significantly enhance the effectiveness of BoNT-A therapy and reduce the level of dystonic symptoms. In some cases, the further improvement achieved by the proposed haptic manipulation strategy was substantial. For example, as can be seen in Fig. 8.7b, 60% improvement was achieved by using the proposed strategy for Participant #3 in the first session. Also, almost 100% improvement was achieved by the proposed haptic manipulation strategy for Participant #4 while during the second and the third sessions only 20% improvement was achieved using only BoNT-A therapy. This result suggests that by applying the proposed haptic-manipulation strategy, not only is it possible to reduce the dystonia severity but it is also possible to enhance the effectiveness of BoNT-A therapy.

8.3.2 Grip Pressure and the Effect of Haptic Manipulation

In this part, the effect of the proposed haptic manipulation on reducing the excessive grip pressure is evaluated. In recent studies it has been shown that patients with FHD exert excessive
Table 8.5: Statistical Results for the Reduction in Grip Pressure achieved Using the Proposed Haptic Manipulation Strategy

<table>
<thead>
<tr>
<th>Metric #1 (Reduction in RMS of GP)</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>20.8%</td>
<td>80.2%</td>
<td>54.7%</td>
<td>20.1%</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Metric #2 (Reduction in Average of GP)</td>
<td>27.1%</td>
<td>81%</td>
<td>56.2%</td>
<td>19.5%</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Metric #3 (Reduction in Max of GP)</td>
<td>10%</td>
<td>78.7%</td>
<td>58%</td>
<td>20.6%</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

abnormal Grip Pressure (GP) during writing [22, 40–42]. The measure of grip force has been suggested in the literature as a strong descriptor of FHD which is independent of the kinematics of writing. In this regard, abnormality in grip force (excessive grip force) is reported as a more frequent descriptor of dystonia in FHD patients in comparison to the abnormality in the kinematics of writing [3].

Grip force can be used not only to generate assessment techniques in order to evaluate the severity of the condition but also to develop assistive treatment approaches (such as the one given in [22] and the one suggested in the next section of this chapter). In [22], auditory cueing was used to inform patients when they were applying too much grip pressure. The definition of normal grip pressure was considered by studying normal grip pressure of healthy people [22]. It was shown that teaching patients to reduce grip pressure can reduce the severity of dystonia and the resulting pain. Motivated by the above-mentioned literature, the pen used in the work reported in this chapter is sensorized using two FlexiForce pressure sensors to register the grip pressure applied by the patient’s thumb and index finger on the body of the pen during writing. The amounts of grip pressure measured by the two sensors were summed and the resulting value was recorded when the patients wrote the standard sentence during the RAW task to compare with the recorded value during the NW tasks. The GP of 11 patients were analyzed for the first session (before the start of BoNT-A therapy). To compare the GP value of the NW and RAW tasks, the RMS, average and maximum values of the reduction in grip pressure achieved using the proposed haptic manipulation strategy were calculated. The results are summarized in Table V and the statistical distributions are shown in Fig [8.9].
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Figure 8.9: Distributions of the Reduction in Grip Pressure achieved using the Proposed Haptic Manipulation Strategy. The p-values of the distributions are given in Table V and have been calculated using the one-sample t-test.

As shown in Table V and Fig. 8.9, when the haptic sensation of the participants are manipulated during RAW task the grip pressure is significantly reduced (by an average of 56.2% and standard deviation of 19.5%). Further statistical results are given in Table V. The observed positive improvement in reducing grip pressure was statistically evaluated using the standard t-test approach. The p-values obtained confirm the significance of the result which validates the effectiveness of the proposed approach in enhancing the performance of patients living with FHD. Using the proposed haptic manipulation strategy, patients do not need to run the procedure of thinking and intentionally reacting to the provided additional sensory inputs (such as auditory feedback) and trying to modify their motor output (which is grip pressure here) while experiencing uncomfortable involuntary painful dystonia. In this study, the patients were not asked to change their grip pressure during these experiments. Consequently, the results obtained show an involuntary and intrinsic improvement in the control of grip pressure (an aspect of motor control). The proposed approach requires much less information processing by the users (compared to providing additional inputs) while enabling significant enhancement of their motor control and reduction in the severity of their dystonia. This result confirms the effectiveness of the proposed haptic manipulation strategy and can be used to develop new assistive technologies for FHD patients, as explained latter.
8.3.3 Summary of the Results and Discussion

The patients received Botulinum-toxin injection therapy at the end of the first and the third sessions. In addition, patients were excluded if they had a history of Botulinum-toxin injection therapy during one year prior to the trial. Therefore, during the first session, they were not under the effect of the medication.

The evaluation provided in this study can be categorized in three different analyses:

For the first statistical evaluation, we compared the patients’ performance pre- and post-use of the robot (both in the first session prior to any injection). In this way, we calculated patient-specific improvement, then we analyzed the distribution of the improvement over the population of participants. The result of this first evaluation can be seen in Fig. 8.5(a) for the effect of haptic manipulation on the severity of dystonia, and in Fig. 8.9 for the effect on grip pressure (an indicator of FHD validated in the literature). This evaluation indicates that the effect of the proposed haptic manipulation on FHD is statistically significant (average improvement more than 50% and p-value < 0.001 using the one-sample t-test). This is an important result and alone validates the main hypothesis of this chapter.

The remaining statistical investigation was to extract more information about the effect of haptic manipulation when the patients underwent BoNT-A therapy.

For the second statistical evaluation, the dystonia severity during robotics-assisted writing was normalized by the corresponding baseline value of the same session (when the same participant did not use the robot in that session). This has been done to calculate the average improvement achieved by the proposed haptic manipulation strategy when the patient was in different biomechanical states (due to the administration of the therapy). The goal was to reject the null hypothesis that when the patient received the injection, the proposed haptic manipulation would not remain effective. For this purpose, we considered distribution of improvement over multiple sessions. The corresponding statistical distribution of the improvement can be seen in Fig. 8.5(b). As can be seen, the average improvement is more than 50% and this result is statistically significant (p-value < 0.001 using the one-sample t-test). As a result, the null-hypothesis is rejected.
For the third statistical evaluation, in order to evaluate the “net improvement” (achieved by using robot besides injection and to compare that with the effect of “injection alone”) we proposed the second mathematical normalization technique, shown in equation (3). The goal was to see if the proposed haptic manipulation could be considered as a complementary technique for augmenting the improvement achieved by the injection. For this purpose, the level of dystonia in all sessions of the trial was normalized by the initial level of dystonia before the start of the BoNT-A therapy. The baseline is measured in the first session. This is done to take into account the effect of BoNT-A therapy besides the proposed haptic manipulation. The result is shown in Fig. 8.8. Using the one-sample t-test technique (for the separate distributions) and paired-samples t-test (for comparing the two distributions shown in Fig. 8.8), statistical significance was demonstrated (p-value < 0.001). This tells us that the net improvement achieved by the use of the proposed haptic manipulation besides Botulinum toxin therapy is (a) statistically significant (this is based on the one-sample t-test), and (b) higher than just administering the therapy (this is based on the paired-samples t-test).

In addition to the aforementioned three evaluations, individual examples are also given in Fig. 8.7 to show examples of the pattern of improvement during the sessions. For example, considering Fig. 8.7(c), when that patient (Participant #4) just received haptic manipulation, it reduced cramping by about 30%. When the patient was under the effect of the first treatment (in the second session), the effect of BoNT-A therapy alone was only 20%. However, when in the same session the patient received haptic manipulation, the reduction in cramping was more than 90% (almost no cramping). This shows that haptic manipulation augments the effectiveness of BoNT-A therapy.

Remark 8.9. In this chapter, the distribution of improvement was analyzed over the population of participants. The improvement for each patient was calculated based on his/her own cramp pattern during normal writing. One patient may find one task more difficult than another patient. In addition, one patient may benefit from haptic manipulation more during one subtask while another may benefit more during another subtask. This is due to the differences in the pattern of motor impairment in FHD. In other words, FHD is very heterogeneous. Some patients have difficulty in very fine writing/drawing, and some patients have difficulty in coarse motion. It was observed that some patients found the small sinusoidal motion even more difficult than
writing. This could be due to its continuous nature and/or the need for accurate tracking of a path. The effect of separate subtasks across patients is very different and is not directly related to the focus of this chapter. To address this heterogeneity while analyzing the hypothesis of this chapter, the same protocol was considered for robotic and non-robotic writing tasks. In addition, by averaging the descriptors of dystonia across different writing/drawing subtasks for each patient, and by comparing the average values pre- and post-use of the robot, the improvement that the one specific patient has shown was determined. Then the distribution of the improvements was analyzed across the population of the participants. By calculating the mean, standard deviation, and p-value of the resulting distributions, the effect of the proposed haptic manipulation strategy was validated as explained in the three statistical evaluations given in this subsection. Particularly, using the conducted one-sample t-test technique, we showed the statistical significance of the achieved positive mean value of the improvements (against a distribution with average zero improvement). More statistical evaluations have been conducted as explained in this subsection. It should also be noted that the data used in the evaluations passed the normality test, before conducting the t-test analysis. To the best knowledge of the authors, this work is one of the earliest studies showing that (a) there is a potential correlation between the kinesthetic sensory input and the symptoms of FHD; (b) modulating the kinesthetic input can help patients in managing the symptoms of dystonia.

8.4 Conclusions

In this chapter, the effect of haptic manipulation on the severity of dystonia in FHD patients has been investigated. For this purpose, 11 participants who live with FHD were included in the study. Seven participants underwent BoNT-A therapy. In order to manipulate haptic sensation, the writing pen was connected to a haptic device which provided the mechanism for reducing the rigidity of interaction. Based on the data obtained, it was shown that reducing the surface rigidity can significantly reduce the severity of dystonia. In some patients, it was possible to completely eliminate the dystonic symptoms. This result highlights the contribution of haptic sensation in FHD, in contrast to the assumption that FHD is just a motor output dysfunction. In addition, it was observed that using the proposed haptic manipulation, it is
possible to enhance the effectiveness of BoNT-A therapy. It was also shown that using the proposed haptic manipulation strategy, patients had a better control over their grip force while writing. This was statistically validated based on the grip force data (a strong descriptor of FHD, validated in the literature) logged during writing. To the best knowledge of the authors, this work is one of the earliest studies showing that (a) there is a correlation between the kinesthetic sensory input and the symptoms of FHD; (b) modulating the kinesthetic input can help patients in managing the symptoms of FHD.

8.5 Appendix I: Possibility of Designing a Dystonia Writing Assistance Pen (D-WAP)

This appendix suggests the concept of an assistive technology (D-WAP) designed for FHD patients and motivated by the outcomes of this chapter. The D-WAP system has not been clinically tested yet and this appendix is provided to outline the concept of how the results of this chapter may be translated to designing a portable assistive haptic pen for FHD patients.

This chapter supports the hypothesis that reducing the mechanical rigidity of interaction can significantly reduce the severity of dystonia in FHD patients. Motivated by this, a motorized pen was designed and is denoted as D-WAP. The design is shown in Fig. 8.10. The pen is implemented as shown in Fig. 8.11. The actuator is a Faulhaber Linear DC-Servo motor (ID#
LM1247) which is capable of applying forces up to 10.7 N and a speed of 3.2 \( m/s \). The writing rod connected to the pen tip can travel up to 3.5 \( cm \). The motor is connected to a processor via a motion controller. One choice is the Faulhaber MCLM3002, which provides an internal (on-board) control loop update rate of 10 KHz running. When using the processor to externally tune the impedance characteristics of the pen during writing, the update rate is limited to approximately 125 Hz due to the RS232 command interpreter of MCLM3002. However, by choosing the new Faulhaber EtherCAT MC5004 motion controller we can achieve an external update rate (processor in the loop) of 1 KHz.

In the proposed design of the D-W AP system, specific attention has been paid to (a) make the pen movement quick and responsive; and (b) provide good weight balance when a user holds the pen.

### 8.5.1 Functionality

The D-WAP system is one-directional haptic system which can in real-time manipulate (reduce) the mechanical rigidity felt by the user during writing/drawing. The design of the rigidity reduction function of the pen is based on an admittance control technique [47]. The controller estimates the interaction forces and in response moves the writing rod according to the programmed rigidity. Since the motor is directly driven and there is no gear or indirect power transmission, it is possible to use the electric current in the motor to estimate the interaction forces. Using the D-WAP system, it is possible to program a specific rigidity level that can be tuned by the user or a clinician.

### 8.5.2 Possibility of Adaptive Stiffness Variation

As mentioned earlier, recent studies have shown that an excessive amount of grip pressure correlates with the severity of dystonia [22][40-42]. Motivated by this fact and based on the results of this chapter, the design of the proposed D-WAP system can be improved by adding two pressure sensors on the parts of the pen that are gripped. The primary use of the proposed design is to log the amount of grip pressure during normal daily writing in order to assess the condition over a long period of time. This can help the clinicians to tune the therapeutic strategies
(such as the dosage of BoNT-A therapy). However, the main goal of the suggested design is that the interaction rigidity delivered by D-WAP can be adaptively tuned according to the grip pressure. As a result, the more stiffly the patient grips the pen, the less interaction rigidity will be delivered. It is expected that this closed-loop system can adaptively help patients to manage dystonic cramping conditions. The reason is that higher grip pressure is an indication of more severe cramp [22, 40, 41] which can be addressed by further reduction in interaction rigidity. As a result, the amount of the delivered rigidity will be cramp-specific. It is known that cramp severity can vary for different writing tasks. Usually the finer the required motor task, the more cramp is likely to occur. Using the proposed system, when the patient experiences more dystonia, more reduction in rigidity will be delivered by the adaptive D-WAP system. Based on the results obtained so far, oOat investigating potential benefits of the proposed D-WAP system.
Bibliography


Chapter 9

Conclusions and Future Work

This chapter provides concluding remarks concerning the research presented in this thesis. In addition, it gives suggestions for possible future lines of research based on the theoretical and technological developments reported in the thesis.

9.1 Conclusions

- **In Chapter 2**, the design, implementation and safety of a novel haptics-enabled bilateral teleoperated rehabilitation system were presented. The system was designed with the goal of fusing the capabilities of rehabilitation robots and skills of a human therapist. To guarantee patient-robot interaction safety, the stability of the system was studied in the context of the small-gain theory. The proposed framework can stabilize the system while relaxing classical assumptions on the passivity, time-dependence and linearity of the terminals and the network, regardless of the type of therapy.

- **In Chapter 3**, a new stabilizing framework was proposed in the context of strong passivity theory with the main goal of enhancing the performance and transparency of the proposed non-passive telerobotic rehabilitation system. The result of Chapter 3 can be used for both conventional robotic rehabilitation systems and the proposed tele-rehabilitation system. The stabilizer (M-TDPC), utilizes a lower bound for the biomechanical capability of the patient’s arm in absorbing interactive energy, to tune the allowable mechanical energy which can be reflected to the patient’s arm. This enables delivering both non-passive and passive therapies.
over a delayed communication channel while enhancing the performance.

- **In Chapter 4**, the stability framework developed in Chapter 3 was extended through consideration of “variability” in the biomechanical capability of the human upper-limb in absorbing interactive energies. The goal was to maximize (in the context of strong passivity theory) the transparency and performance of the system. For this purpose, the Grasp-based Passivity Signature (GPS) map was proposed and studied. The GPS map considers variability in the geometry of the interaction and the grasp condition to interpolate the Excess of Passivity (EOP) of the patient’s hand in every time stamp. A user study was conducted consisting of 11 healthy participants to statistically evaluate the characteristics of the map for the upper-limb. The GPS-map was then used to design a new controller capable of significantly reducing the transparency distortion based on knowledge regarding the capabilities of the human upper-limb in absorbing energy and the “changes” in those capabilities.

- **In Chapter 5**, the goal was to (a) use the proposed tele-rehabilitation technology to train and model (using neural networks) the kinesthetic behavior of the therapist (delivered through two proposed systems); and (b) use the learned model to replicate the prescribed therapy for several iterations. In this way one can increase the use of a therapist’s time and share it between more patients. In addition, the architecture can be used as a replacement for the current software-based therapy tuning algorithms whose performance and effectiveness have been challenged with regard to their capability in designing an appropriate kinesthetic regime compatible with the needs of a patient in different parts of the workspace.

- **In Chapter 6**, the goal was to increase the population of patients who can take advantage of the proposed telerobotic and robotic rehabilitation technologies. Specifically, the considered population consists of patients with involuntary movements who cannot use conventional systems due to the possibility of tremor amplification (which can jeopardize safety) in the active (with respect to energy) robotic and telerobotic rehabilitation environments. A new architecture was proposed and denoted by AHR. The architecture is capable of delivering therapeutic forces (in an assist-as-needed manner) for the voluntary components of motion while keeping hand tremor under control and avoiding unsafe amplification of tremor energy. To implement the AHR system, a new adaptive filter was proposed to characterize in real-time the involuntary component of the motion. The effectiveness, accuracy, and robustness of the proposed filter
were statistically validated (in comparison to the classical tremor estimation technique) using clinical data from 14 Parkinson’s Disease (PD) and 13 Essential Tremor (ET) patients.

- In Chapters 7 and 8, two specific applications to other neurological movement disorders were reported to show how proper manipulation of haptic information can not only be used to enhance the transparency and safety of robotic/telerobotic rehabilitation systems, but also has the potential to be used for assisting patients with force and motion control impairment. In Chapter 7, a new telerobotics-assisted platform was designed and implemented, using the results of Chapter 6 for enhancing interaction with physical environments for people living with Cerebral Palsy (CP). The main objective was to locally control the energy of the involuntary movements and utilize the scaled up voluntary component to perform tasks through the telerobotic medium in a play environment. This was motivated by evidence showing that lack of interaction with real environments can result in further secondary sensorimotor and cognitive issues in people who grow up with CP. The second application (reported in Chapter 8), utilized the concept developed in Chapter 2 regarding the effects of reducing the loop gain of an interconnected system for enhancing the stability and reducing the sensitivity to the small abnormalities. In Chapter 8 this concept was applied for analyzing the sensorimotor integration loop in Focal Hand Dystonia (FHD) patients. Through a patient-based study, it was shown that reducing the writing surface rigidity (which reduces the loop gain) significantly decreases the severity of dystonia and results in better control of grip pressure. It was also shown that the proposed haptic manipulation strategy can augment the effectiveness of BoNT-A therapy. The outcome of this study was then used in the design of an actuated pen as a writing-assistance tool for FHD patients.

9.2 Future and Ongoing Work

An ultimate future aim of this project is to take a step toward equipping modern homes with kinesthetic rehabilitation technologies which can deliver safe supervised and semi-supervised physical rehabilitation exercises for patients in need. This is motivated by the increasing population of senior adults and excessive pressure on the under-resourced healthcare system. This aim comes under the umbrella of tele-medicine which is a top line of research and involves
topics such as tele-rehabilitation, cyber-rehabilitation and smart homes.

Some of the ongoing and future lines of research associated with the results of this thesis are outlined below.

1) In this thesis, a frequency window (i.e., less than 3 Hz) near to the range reported in the literature for Activities of Daily Livings (ADLs) as well as that used in rehabilitation exercises is considered to characterize the biomechanical capabilities of the user’s hand in absorbing interaction energy. However, for general-purpose haptic and haptics-enabled telerobotic systems and for other applications such as in telerobotic surgery, the frequency window can be wider and different. In this regard, a future line of research is to develop a frequency-based 3D GPS map. The third dimension of the map will represent the frequency context of the interaction. The concept will be similar to the Bode plot in the context of linear control systems. For this purpose, the EOP of the user’s limb should be evaluated in segmented windows of interaction frequencies and the corresponding correlation between the shape of the map and the change of the interaction frequency should be statistically analyzed.

2) During robotic rehabilitation exercises, the position and posture of the patient are usually fixed (sometimes using belts) mostly to avoid compensatory movements which can reduce the involvement of the affected limb(s). An example of the compensatory strategies is the trunk-forward movement instead of arm extension. However, for other applications, the user may change the posture during task execution. This can change the kinematics of the limb interacting with the robot and may change the shape of the user’s GPS map. Evaluation of this issue is a future line of research. If a statistically significant correlation is observed, the kinematics of the limb can be considered as another factor which can affect the EOP. In this case, during task execution, the kinematics of the patient’s arm can be tracked (for example using optical trackers or sensorized wearable suits), to better estimate the EOP.

3) It can be shown that by measuring the interaction forces during task execution, it is not possible to identify the mentioned inherent characteristic of the user’s limb in absorbing interaction energy. The reason is that the measured forces would be affected by both
the inherent biomechanical characteristics and the voluntary forces applied by the user. However, to relax the need for the offline identification phase, it may be possible to extract the inherent characteristics of the user’s limb by analyzing the EMG activities of the muscles. Two different types of muscle activation have been identified in the literature during task execution, namely (a) “selective changes in the patterns of activations in individual muscles to generate task-oriented force generation [1]” and (b) “co-contraction of the muscle groups, with no endpoint force changes [1]”. These two types of EMG activation can be separately detected. We hypothesize that the EOP of a human’s limb is correlated with the co-contraction of their muscles. Evaluation of this hypothesis is a future line of this research. A relevant research question to be addressed is whether the EMG activities can be used to directly and in real-time estimate the EOP value of a user’s limb? The second question is whether the EMG information correlate with the absolute value of the EOP or the changes in this value?

4) To relax the need for the identification phase an alternative solution is to first make an atlas of the GPS maps for a statistically well distributed group of people. In this step a database will be generated which includes GPS map of the group together with some basic biomechanical measures such as their age, gender, weight, height, length and diameter of the limbs. In the next step, using supervised intelligent classifiers and statistical pattern recognition techniques, the closest match can be found for a new user of the system. This offline atlas-based technique may replace the implemented identification phase used in this thesis. Statistical analysis is needed to evaluate the accuracy and conservatism of this approach.

5) Although the focus of this thesis was on the upper-limb robotic rehabilitation, the results given in Chapters 2, 3 and 5 can be directly used for lower-limb robotic rehabilitation and exoskeleton systems. However, since the framework given in Chapter 4 utilized the change in the grasp pressure, it cannot be applied for the case of lower-extremity. In this regard, an ongoing line of research, partially mentioned above, is to monitor the EMG activities of the muscles to detect in real-time active “co-contractions” which affects the viscoelasticity of a limb. This can be done for lower-extremity as a replacement for monitoring the grasp pressure suggested in this thesis for interpolation of the EOP. The
map generated using EMG will be called EMG-based Passivity Signature (EPS). Similar statistical analysis will be conducted for the proposed EPS map. Similar to the results presented in Chapter 4, the EPS map can then be used to develop a specific stabilizer for lower-extremity applications.

6) The proposed GPS map was tested for 11 healthy subjects considering their right and left wrists and arms. Evaluating this technique for post-stroke patients can help us to understand the change in the GPS map during motor development throughout a rehabilitation regime. We have hypothesized that the proposed GPS map can be used not only as a tool to guarantee patient-robot interaction safety, but also as a technique to visualize and assess the changes in patient’s biomechanics. Relevant clinical evaluations can clarify the capabilities of this technique as an assessment tool.

7) The results of this thesis allow for realizing safety-guaranteed in-home kinesthetic telerobotic rehabilitation under direct and indirect supervision of a therapist. Testing the system under a longitudinal study forms a future line of research for this work. To the best of our knowledge this will be one of the earliest remote kinesthetic tele-rehabilitation tests. We are aiming to perform patient-based evaluation of the system.

8) The adaptive filter used in the proposed AHR architecture was evaluated using data collected during tests involving PD and ET patients. However, the complete implementation of the AHR architecture still needs to be clinically analyzed. This forms a future line of research for this work.

Robotic rehabilitation has revolutionized the field of motor therapy. The lack of (a) flexibility in tuning the parameters of the system, (b) techniques that guarantee safety while maximizing performance, and (c) direct kinesthetic interaction between the therapist and the patient, are some of the existing challenges which were studied in this thesis. Addressing these issues can help to extend the benefit of this technology. This has the potential to reduce the cost of therapy and the burden on the under-resourced healthcare system.
Bibliography

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