Myoelectric Control of a Robotic Exoskeleton for Rehabilitation

by

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ABSTRACT

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A primary challenge in the design of human-robot interfaces for rehabilitation after neurological injury, such as stroke or spinal cord injury, is the detection of user intent, needed to maximize the efficacy of the therapy. Common approaches to rehabilitation robot interfaces, including the current implementation of the MAHI Exo-II upper extremity therapeutic exoskeleton at Rice University, rely on impedance control schemes. Another approach, surface electromyography (sEMG), is gaining attention. This interface is appealing as the recorded signal is related to the individual’s desired torque about the joint the muscle actuates. In this thesis, an sEMG interface and associated control schemes are proposed and investigated for the MAHI Exo-II. A known drawback of sEMG interfaces are lengthy subject- and session-dependent calibration procedures to develop muscle-force mappings. In this thesis, a relaxed calibration procedure and various control schemes are proposed to enable practical integration into therapy protocols. Agonist-antagonist muscle groups were related following normalization based on sub-maximal isometric contraction in the exoskeleton. Pilot experiments were conducted on healthy subjects to assess the usability of the exoskeleton in the proposed control modes of operation given simple sEMG interface. The results of these experiments support the implementation of the proposed sEMG interface. Future experiments will focus on validation in impaired populations.
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## Contents

Abstract ii  
Acknowledgments iii  
List of Illustrations vii  
List of Tables xi

1 Introduction 1

1.1 Background ................................................. 1
  1.1.1 The Nature of Spinal Cord Injury and Stroke .......... 1
  1.1.2 Rehabilitation ........................................... 2

1.2 Robotics and Rehabilitation ............................... 3
  1.2.1 Implementing Robots for Rehabilitation .............. 5
  1.2.2 Efficacy of Rehabilitation Robots .................... 6
  1.2.3 Quantifying Movement Quality .......................... 7

2 The MAHI Exo-II: A Robotic Exoskeleton for Rehabilitation 10

2.1 System Overview .............................................. 10
  2.1.1 Design .................................................. 10
  2.1.2 Forward Kinematics .................................... 13
  2.1.3 Inverse Kinematics ..................................... 15
  2.1.4 Jacobian ................................................ 16
  2.1.5 Manipulability and Workspace .......................... 18
  2.1.6 Verification of Theoretical Kinematics and Workspace ... 20
2.1.7 Device Characterization ........................................ 20
2.1.8 Safety Considerations ........................................ 22

2.2 Control Schemes .................................................. 24
  2.2.1 Impedance Control ........................................... 24
  2.2.2 Assist-as-Needed ............................................ 26
  2.2.3 Brain-Machine Interface ..................................... 27

3 Electromyography .................................................... 29
  3.1 Origin of the Myoelectric Signal ............................... 29
  3.2 The Force to EMG Relationship .................................. 31
  3.3 Controlling Systems with Surface Electromyography .......... 33
    3.3.1 Non-Pattern Based Interfaces ............................. 33
    3.3.2 Pattern Based Interfaces .................................. 36

4 Employing Surface Electromyography to Control the MAHI Exo-II .................................................. 38
  4.1 Signal Acquisition and Hardware Integration .................. 38
  4.2 Control Modes ................................................... 45
    4.2.1 Calibration .................................................. 46
    4.2.2 Triggered ................................................... 46
    4.2.3 Velocity Control ........................................... 51
    4.2.4 Assistive .................................................. 52
    4.2.5 Assessment ................................................ 55
    4.2.6 User Interface ............................................ 55
  4.3 System Performance ............................................. 57
    4.3.1 Calibration Quality ......................................... 58
    4.3.2 Effect of Assistive Torque on Tracking Performance During Wrist Flexion-Extension .......................... 62
4.3.3 Velocity Dependence of Assistive Mode  . . . . . . . . . . . . . 76
4.3.4 Degree of Freedom Specific Considerations  . . . . . . . . . . . 77

5 Conclusions and Future Work 80

Bibliography 83
Illustrations

1.1 Approaches to human-robot interfaces and their associated control designs ........................................ 4
1.2 An incomplete SCI subject completing an ARAT reach and place task while a therapist scores the activity .................. 8

2.1 MAHI Lab Rehabilitation Robots ........................................... 11
2.2 Kinematic structure of the MAHI Exo-II (Figure adopted from [26]) . 14
2.3 Sideview drawings of the RiceWrist, $Z_c = 0.09 \, m$ ...................... 19
2.4 Condition Number for different RiceWrist orientations .................. 19
2.5 Example test cases for RiceWrist forward and inverse kinematics and workspace ........................................... 20
2.6 Passive mode controller, joint-space implementation ................... 25
2.7 MAHI Exo-II brain machine interface during closed-loop control trials 28

3.1 Schematic of sEMG signal acquisition. sEMG signal recorded from the long head of the triceps brachii during a max voluntary contraction after 1000x gain with no filtering .................. 31
3.2 Filtered sEMG signal with associated sEMG amplitude computed from a 300 ms running RMS calculation. Measured above the extensor carpi radialis ........................................... 32
3.3 A chronic stroke survivor completes triggered movement therapy with the MIT Manus (figure adopted from [44]) .................. 34
3.4 sEMG devices employing sEMG control for rehabilitation following neurological injury (figures (a) and (b), adopted from [45] and [46], respectively) .................................................. 35

4.1 Comparison of recorded signal periodograms from the long head of the triceps brachii in two conditions .................................................. 39

4.2 Comparison of baseline signal periodogram following hardware and digital filtering noise reduction measures ........................................... 41

4.3 Importance of noise reduction measures becomes apparent when comparing (a) and (b). Muscle activation for typical exoskeleton operation (c) is markedly lower than a MVIC (d) ................................. 42

4.4 Summary of sEMG amplitude estimation for a single channel. Blocks 1 and 2 are accomplished with the Bagnoli-8 Desktop EMG system, block 3 is accomplished with a Quanser Q-2 USB data acquisition device, and blocks 4-6 are accomplished using the controller software 43

4.5 Location of agonist-antagonist muscles pairs. Pairs are color matched for the elbow (grey), forearm (orange), wrist flexion-extension (blue), and wrist radial-ulnar deviation (gold) DoF ........................................ 44

4.6 The trajectory following PD controller for wrist flexion-extension. Sensing and actuation of the MAHI Exo-II occur at the joint-space level, manipulating link lengths, $l_i$, while the controller is implemented at the user task-space level, or about wrist flexion-extension angle, $\alpha$ .............................................. 48

4.7 An example wrist extension movement in the sEMG triggered mode. Stop mode behavior is visible at approximately 4 s and 6.9 s. Vertical dashed lines denote a transition between states. ...................... 50

4.8 An example wrist flexion followed by wrist extension in the exoskeleton PI velocity control mode ................................................................. 53
4.9 The closed loop sEMG PI velocity controller for the MAHI Exo-II.

The discrete derivative of position is the controlled variable.

53

4.10 The sEMG assistive mode for the MAHI Exo-II.

54

4.11 The sEMG control panel provides an interface for the experimenter

or clinician to operate the exoskeleton and accomplish data logging.

56

4.12 The subject user interface provides visual feedback using a cursor

(grey sphere), bounds for a goal trajectory (vertical bars), and a goal

position (red target).

57

4.13 During calibration, sEMG amplitude is displayed to the left of the

virtual exoskeleton position.

57

4.14 Elbow Flexion-Extension Calibration Curve, error bars reflect

standard error across the 10 isometric contractions.

59

4.15 Wrist Flexion-Extension Calibration Curve, for flexor carpi radialis

(FCR) and extensor carpi ulnaris (ECU), error bars reflect standard

error across the 10 isometric contractions.

59

4.16 Wrist Radial-Ulnar Deviation Calibration Curve, for extensor carpi

radialis brevis (ECRB) and flexor carpi ulnaris (FCU), error bars

reflect standard error across the 10 isometric contractions.

60

4.17 Forearm Pronation-Supination Calibration Curve, error bars reflect

standard error across the 10 isometric contractions.

60

4.18 Variability in calibration for wrist flexion-extension, error bars reflect

standard error across the calibration perturbations.

62

4.19 Variability in calibration for wrist radial-ulnar deviation, error bars

reflect standard error across the calibration perturbations.

63

4.20 A subject holds the virtual cursor over the left target during the

target tracking task.

65

4.21 Order of blocks and number of associated movements.

66

4.22 Regions for analysis highlighted for example movements.

66
4.23 . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 67
4.24 Mean position error while target stationary during last 20 movements.
   Mean calculated collapsing across subjects. Standard error shown . 68
4.25 Interaction between $K_{EMG}$ and direction. Mean calculated collapsing
   across subjects. Standard error shown . . . . . . . . . . . . . . . . . 69
4.26 Position error for tracking a dynamic target. Mean calculated
   collapsing across subjects. Standard error shown . . . . . . . . . . . 70
4.27 Position error while target stationary. Mean calculated collapsing
   across subjects. Standard error shown . . . . . . . . . . . . . . . . . 70
4.28 Change in iEMG recorded in channel one during wrist flexion. Mean
   calculated collapsing across subjects. Standard error shown . . . . 71
4.29 Change in iEMG recorded in channel one during wrist extension.
   Mean calculated collapsing across subjects. Standard error shown . 72
4.30 Change in iEMG recorded in channel two during wrist flexion. Mean
   calculated collapsing across subjects. Standard error shown . . . . 72
4.31 Change in iEMG recorded in channel two during wrist extension.
   Mean calculated collapsing across subjects. Standard error shown . 73
4.32 sEMG power normalized to MVIC power. Time normalized to time
   required to complete the movement. Mean calculated collapsing
   across subjects. Shaded region represents standard error . . . . . . 74
4.33 Dependence of tracking error on time allotted to complete minimum
   jerk profile, standard error shown . . . . . . . . . . . . . . . . . . . 76
4.34 Positioning of the thumb during forearm pronation-supination and
   wrist brace . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 78
Tables

2.1 Actuation Scheme Parameters ........................................... 21
2.2 Comparison of MAHI Exo-II to ADL Range of Motion and Torques . 22
2.3 Relevant Experimentally Characterized Parameters for MAHI Exo-II
  Control ................................................................. 23

4.1 Chosen muscles and channels for each DoF ............................ 44
Chapter 1

Introduction

A primary challenge in employing robots for rehabilitation is the detection of user intent. Impaired individuals are often incapable of significant motor function impeding beneficial human-robot interaction (HRI). This thesis presents a new myoelectric interface for the MAHI Exo-II, an upper-extremity therapeutic exoskeleton, and associated control modalities aimed at improving intent detection in impaired populations. Chapter 2 will discuss requisite technical aspects of the rehabilitation system, Chapter 3 will highlight previous research with myoelectric control, and Chapter 4 will present the new interface and capabilities for the MAHI Exo-II. A brief review of rehabilitation and robotics provides context for the current work.

1.1 Background

1.1.1 The Nature of Spinal Cord Injury and Stroke

Stroke and spinal cord injury (SCI) are two common causes of disability in the United States. There are approximately 795,000 instances of stroke each year. Annual direct cost for stroke exceeded $36.5 billion in recent years with a mean annual outpatient rehabilitation cost of $11,145 for each individual [1]. Although affected population demographics vary more than with stroke, 12,000 new instances of SCI occur with an estimated 273,000 individuals currently living with SCI. Less than 1% of those injured completely recover by time of hospital discharge and 59.3% of individuals experience
incomplete SCI. Long-term impairment increases unemployment rates in survivors on
top of the direct economic costs of hospitalization and outpatient care. For example,
a year after injury, only 11.8% of SCI survivors are employed. Employment rates
slowly increase to 34.9% by 20 years post-injury, or roughly 60% of the original pre-
injury rate [2]. Increasing rehabilitation efficacy may reduce the economic impact of
these two causes of neurological impairments and increase the individual’s quality of
life.

Although the mechanism of injury varies, both stroke and SCI involve lesions in
an individual’s nervous system tissue. During a stroke, either a blood clot prevents
the supply of oxygen to part of the brain starving the cells of oxygen, or an artery
swells, potentially leaking blood. In both instances, the result is damaged cell tissue
around the site of the clot or leak. Motor function impairment may occur depending
on the location of the damaged tissue. Prevalence of disability following a first stroke
is high, with an estimated 77.4% of stroke survivors experiencing upper limb motor
deficit [3]. SCI involves a traumatic event that severs or partially severs, in the case of
an incomplete SCI, peripheral nervous system tissue in the spinal column. Individuals
with a SCI will experience some form of impairment for parts of the body more distal
than the site of the injury. For impairment of the upper limb, the injury will occur
at a level higher than the third thoracic vertebrae.

1.1.2 Rehabilitation

The primary goal of rehabilitation is to regain lost motor function. Post-injury re-
habilitation became increasingly prominent in recent decades after numerous studies
supported the concept of neural plasticity, the ability of the nervous system to re-
organize and change in response to environmental stimuli. In the practice of stroke
rehabilitation, there was evidence suggesting repetitive and constrained movement improved motor function [4]. Subsequent efforts employing functional magnetic resonance imaging, transcranial magnetic stimulation, aside other assessment tools, supported repetitive therapy practices by observing measurable and lasting changes in the motor cortex [5, 6]. In SCI rehabilitation, the mechanism of recovery is less certain, although the prospect for improvement in motor function is significantly greater for victims of incomplete SCI versus complete SCI [7]. There is evidence, however, suggesting neuroplasticity is an important aspect of recovery and that repetitive training of the affected limbs improves functionality measured with accepted clinical measures [8]. These recent findings have led to a shift for clinicians handling SCI from compensatory practices like braces and assistive devices to active therapy [9]. For both stroke and SCI, current rehabilitation protocols incorporate multiple sessions with repetitive movements of the affected limb spread over multiple weeks. The objective of these treatments, again, is to promote neuroplasticity and recovery of motor function.

1.2 Robotics and Rehabilitation

In the past couple of decades, robotic systems have emerged at the forefront of rehabilitation research. The differences between rehabilitation robots, prostheses and orthoses are noteworthy. Prosthetic devices and orthoses replace the function of lost limbs or augment the function of impaired limbs. The purpose of prostheses and orthoses is to become extensions of the user’s body, essentially minimizing user engagement while improving motor function. They realize a compensatory role. However, user engagement is crucial to promoting neuroplasticity [6]. Consequently, prostheses and orthoses are not rehabilitative, except in cases of overlapping function. The robotic systems discussed in this thesis will be rehabilitative in nature.
As engagement is necessary for successful rehabilitation, volitional muscle activation from the central nervous system improves therapeutic outcomes. Fully assistive movements while subjects observe an interface provide a marginal benefit during therapy [10]. Maintaining patient engagement mentally and physically is difficult, especially in impaired populations where the subject may not be capable of significant movement. Several human-robot interfaces have emerged to increase engagement in therapy including impedance controllers, electromyography (EMG), and electroencephalography (EEG). These interfaces and control designs have the potential to interact with varying levels of impairment as described in Figure 1.1.

Figure 1.1: Approaches to human-robot interfaces and their associated control designs

Although these approaches vary regarding implementation of hardware and calibration, they all fundamentally strive to accurately discern patient intent and promote active participation during therapy. Current velocity/force and EEG based control schemes will be discussed more thoroughly in Section 2.2. EMG based control methods will be discussed in detail in Chapters 3 and 4.
1.2.1 Implementing Robots for Rehabilitation

Robots possess numerous characteristics making them well suited to a rehabilitation role. Among these qualities is that robots do not fatigue. They are able to provide consistent training during therapy sessions. Further, sensors employed for controlling the robot can be exploited to quantify movement quality and provide data for metrics of motor function recovery [11]. A rehabilitation robot needs a robust actuation scheme and structure with appropriate sensors. Lastly, robotics in a rehabilitation scenario have the potential to reduce clinician workload due to their autonomy. A robot-assisted clinician may be able to treat numerous individuals simultaneously. Due to their strengths and potential benefits, significant efforts have been put forth in developing rehabilitation robots.

Aside from their strengths for application in rehabilitation, the design of robotic systems must meet certain requirements for clinicians and users to accept them in practice. Zinn et. al suggested that the robot must appear safe and behave in a safe manner [12]. Practically, the hardware must have rounded edges, sufficient cushioning, and appropriate controllers for HRI. Further, the robot must be capable of accommodating the diverse range of user limb sizes and ranges of motion [13]. A major design consideration is the number of degrees of freedom (DoF) the system will posses.

Rehabilitation robots need to have DoF that correspond to human anatomy. There is debate, however, as to whether the system must be capable of completing isolated, single DoF movements focusing on individual joints as opposed to compound movements that match chosen activities of daily living (ADL). Langhammer and Stanghelle suggested that subject motivation improves when the movement matches ADLs and improves rehabilitative outcomes [14]. In contrast, Kahn et. al found evidence to
support that training specific movements generalizes to increased motor function in other movements accomplished with the same limb. They did note, however, if a specific movement serves as an outcome measure, training for that movement will yield improved results when compared to transferring skill from training other movements [15]. Another study supported these findings, but again, suggested that breaking complex movements into simple movements improves outcome when haptic feedback is high [16]. Recently, another pilot study found no difference between training in one DoF movements or coordinated functional movements [17]. There is evidence suggesting a benefit to training both isolated and compound movements in rehabilitation; therefore, the desired type of movement during therapy will motivate design choices.

Rehabilitation robots can be classified into two primary groups: end effector designs, including the ubiquitous MIT Manus, and exoskeletons, including the UCI ARM Guide. Each of these implementations has its merit. An end effector design can adapt to varying limb sizes and allow more complex movements as they are less restrictive due to a single point of contact with the patient [13]. Exoskeletons are more constraining on the user due to multiple points of contact but advantageous in supporting weak limbs and preventing compensatory movements. Although different in fundamental design, researchers have successfully implemented both end effector and exoskeleton designs in rehabilitation robots [13].

1.2.2 Efficacy of Rehabilitation Robots

While robotic systems may reduce overall therapy cost [18], the design, construction and implementation of a system is non-trivial. It is worthwhile to ensure their usefulness in the clinical realm given the high initial investment. Much of the early robotic
research focused on stroke rehabilitation. Aisen et. al published the first clinical assessment of rehabilitation robots in 1997 [19]. In a double blind study, twenty acute stroke patients underwent therapy with either the MIT Manus or a control treatment. The objective of the study was to compare robotic rehabilitation to standard therapy practices. Results indicated that both treatment groups improved in motor function but the robotic therapy group showed greater improvement. Following this initial study, numerous researchers continued pursuing rehabilitation robotics with positive results. Employing their own exoskeleton design, Reinkensmeyer et. al generalized the results to chronic stroke patients in a study employing the UCI ARM Guide, suggesting an optimistic outcome for many individuals regardless of time since injury [20]. As early as 2005, numerous studies supported the efficacy of robots for stroke rehabilitation, and focus began to widen to investigate other impairments.

More recently, studies investigated the usefulness of robotics applied to incomplete SCI rehabilitation. In two single case studies, results suggested improvements in motor function following intense training for the incomplete SCI subject while employing the MAHI Exo-II exoskeleton [21] and a wrist-forearm exoskeleton [22]. A recent follow-on study investigated eight subjects with incomplete SCI [23]. Improvement in post-treatment clinical assessments when compared to baseline scores support implementation of rehabilitation robotics for incomplete spinal cord injury.

1.2.3 Quantifying Movement Quality

Clinicians and researchers have traditionally measured therapy outcomes using functionality scales. These measures require an evaluator to score subjects while they complete tasks related to ADLs as in Figure 1.2. These metrics include, but are not limited to, the Fugl-Meyer Assessment of Motor Recovery after Stroke, Action
Research Arm Test (ARAT), and American Spinal Cord Injury Association (ASIA) Impairment Scale upper extremity motor score. These scales serve to quantify impairment levels based observer scores of a patient completing the exam.

Figure 1.2: An incomplete SCI subject completing an ARAT reach and place task while a therapist scores the activity.

Robots, however, enable the quantification of movement quality through the analysis of kinematic data. These data, recorded during patient movements, provide a method for objective assessment, while potentially reducing clinician workload. Various researchers sought to validate robotic metrics in a clinical setting. Colombo et. al found significant correlation between robotic metrics and numerous clinical measures, including the ARAT and Fugel-Meyer test [24]. Initially, Celik et. al found a strong correlation between robotic measures and clinical measures [25]. Later, Zaiffa et. al also found a significant correlation between the robot metrics and several clinical metrics, including the ARAT, in 12 incomplete SCI subjects [11]. They do caution, however, that the metrics employed must match what the researcher intends to mea-
sure, just as in the clinical measures. For example, if a clinical measure incorporates
movement speed, the robotic metric must also depend on speed. For the clinician as-
sessing changes in motor function, these findings support employing robotic metrics
as a diagnostic tool.
Chapter 2

The MAHI Exo-II: A Robotic Exoskeleton for Rehabilitation

2.1 System Overview

At Rice University, the Mechatronics and Haptic Interfaces (MAHI) Lab has developed numerous robotic exoskeletons for rehabilitation and HRI research applications as mentioned in Section 1.2.1. The following sections will present the MAHI Lab hardware employed in this thesis and demonstrate the requisite knowledge for successful employment as a rehabilitation device.

2.1.1 Design

The MAHI Exo-II, shown in Figure 2.1(a), is a five degree of freedom robotic exoskeleton designed for stroke and SCI rehabilitation. It has four actuated degrees of freedom corresponding to elbow flexion-extension, forearm pronation-supination, wrist flexion-extension and radial-ulnar deviation. The fifth, passive degree of freedom allows for shoulder adduction-abduction to assist in user fit. The exoskeleton is nearly symmetric about its longitudinal axis enabling easy transition between a user’s left and right arm through adjustment of the passive degree of freedom and a 5 kg counterweight [26]. The kinematic structure of the MAHI Exo-II wrist is identical to that of the RiceWrist exoskeleton, Figure 2.1(b), a 3RPS (revolute-prismatic-spherical) serial-in-parallel device also designed for rehabilitation of neurological impairment.
A parallel mechanism offers certain advantages that make it desirable for the RiceWrist’s application as a rehabilitation exoskeleton. Parallel manipulators have higher structural rigidity to weight ratios when compared to serial devices. All of the wrist actuators can be placed at the base of the wrist increasing power efficiency. This relative increase results from a drawback of serial robots where more proximal motors must support the actuators and transmissions of the more distal links. This increased rigidity to weight ratio is critical in the application of haptic devices as it reduces the inertial effects on the user’s movement while providing enough force to interact with a user [27].

The MAHI Exo-II employs five DC motors (Maxon, Inc) and capstan cable drives for actuation of its active DoF. Compared to other actuators, DC motors are heavier, but were still chosen for the MAHI Exo-II. The concerns regarding weight of the motors were offset by the benefits of a parallel mechanism. Additionally, other actuation schemes presented significant drawbacks. Pneumatics are undesirable as they would
have introduced non-linear control challenges. Cable drive systems have inherent advantages compared to other drive systems. In backdrivable haptic devices, backlash is a highly undesirable characteristic, which made gears unsuitable for application in the MAHI Exo-II. Additionally, Bowden cable drives would have required an unnecessarily complex actuation scheme to allow bidirectional control for each DoF and introduced higher friction, reducing backdrivability. Sensing is provided by precision encoders. Physically, the exoskeletons meet the requirements of a rehabilitation robot outlined in Section 1.2.1.

The following sections will more thoroughly discuss technical aspects of the MAHI Exo-II necessary for successful implementation in its role as a rehabilitation robot. As the first two DoF, elbow and forearm, are revolute joints that directly align with virtual axes of the human elbow and forearm (pronation-supination) of the user, controller implementation occurs at the joint-space level. The parallel mechanism, however, requires task-space control as the pose of the end effector, or handle, provides rotation about the wrist in flexion-extension and radial-ulnar deviation. The actuation mechanisms control parameters that do not directly correspond to these last two anatomical axes. For task-space control, we employed forward kinematics and the Jacobian and calculated the device manipulability to determine the workspace. Inverse kinematics were derived for completeness. Sections 2.1.2 - 2.1.5 will focus on these aspects of RiceWrist parallel mechanism for controller implementation. The derivation of the forward kinematics, inverse kinematics, Jacobian, and manipulability were completed in collaboration with Andrew Erwin.
2.1.2 Forward Kinematics

Forward kinematics describe the position of the device end effector relative to the base frame in terms of joint-space parameters. Forward kinematics are necessary in implementing the various controllers of the RiceWrist. Figure 2.2 shows the geometric location of the kinematic parameters and reference frames. For the RiceWrist, the base frame, \( \{3\} \), aligns with the forearm frame, \( \{2\} \), and is offset by a fixed distance, \( d \), and rotation, \( \gamma \), which corresponds to forearm pronation-supination. The end effector is the handle that the user grips and is a fixed relative to the wrist platform frame, \( \{4\} \). When the user wears the exoskeleton correctly, the handle is adjusted so that the virtual axes of user’s wrist are centered at the origin of \( \{4\} \). The RiceWrist’s parameters are given in the general state vector:

\[
q' = [\theta_1 \ l_1 \ \theta_2 \ l_2 \ \theta_3 \ l_3 \ \alpha \ \beta \ \gamma \ x_c \ y_c \ z_c]^T
\]

(2.1)

where \( \theta_i \) are the angles of the links connecting the base platform and wrist platform, \( l_i \) are the lengths of the links connecting the base platform and wrist platform, \( [\alpha \ \beta \ \gamma] \) are the XYZ Euler angles describing the rotation of \( \{4\} \) and \( [x_c \ y_c \ z_c] \) are the coordinates of the origin of \( \{4\} \) relative to the origin of \( \{3\} \). The radius of base platform and wrist platform are fixed at 0.105 m and 0.053 m, respectively. Defining the ratio of the two platform radii is useful in the derivation of the forward kinematics:

\[
\varphi = \frac{r}{R} = 0.5
\]

(2.2)

In a parallel mechanism without redundant DoFs, defining constraint equations allows determination of device unknowns. For the RiceWrist, the three known, or controlled, parameters are \( l_1 \), \( l_2 \) and \( l_3 \). Unknown parameters of interest are the
end effector Euler angle $\alpha$, Euler angle $\beta$, and $Z_c$, which constitute the reduced state vector:

$$q = [\alpha \beta Z_c]^T$$  \hspace{1cm} (2.3)

where $\alpha$ corresponds to wrist flexion-extension, $\beta$ corresponds to wrist radial-ulnar deviation, and $Z_c$ is the distance between the origin of $\{3\}$ and origin of $\{4\}$. Constraint equations were determined through inspection of geometric relationships. For example, the location of the spherical joints relative to the revolute-prismatic joints
are shown in Equations 2.4-2.6.

\[
P_{B_1}^T = \begin{bmatrix} -l_1\cos(\theta_1) \\ 0 \\ l_1\sin(\theta_1) \end{bmatrix} \tag{2.4}
\]

\[
P_{B_2}^T = \begin{bmatrix} \frac{1}{2}l_2\cos(\theta_2) \\ -\frac{\sqrt{3}}{2}l_2\cos(\theta_2) \\ l_2\sin(\theta_2) \end{bmatrix} \tag{2.5}
\]

\[
P_{B_3}^T = \begin{bmatrix} \frac{1}{2}l_3\cos(\theta_3) \\ \frac{\sqrt{3}}{2}l_3\cos(\theta_3) \\ l_3\sin(\theta_3) \end{bmatrix} \tag{2.6}
\]

Three closed paths allow nine constraint equations, Equation 2.7, as there are three equations for each \(x\), \(y\) and \(z\) direction:

\[
\varphi_i = 3 P_i T + R_i P_i T + R_4 P_4 T - 3 P_4 = 0, \ i = 1, 2, 3 \tag{2.7}
\]

where, the first term represents the transformation matrix from the origin of \{3\} to the prismatic joints, the second term is given in equations 2.4-2.6, the third term is the transformation matrix from the ball joints to the origin of \{4\} and the fourth term is the transformation from \{3\} to \{4\}. The nine constraint equations and three known link lengths allow determination of the the parameters of equation 2.1, including the parameters of interest from Equation 2.3.

### 2.1.3 Inverse Kinematics

The inverse kinematic solution provides a method of calculating required link lengths based on a desired pose of the wrist platform. Numerically determining the inverse
kinematic solution eliminates concerns regarding multiple solutions to the pose by providing a single solution within an adjustable error tolerance. Ghorbel et. al showed the kinematic solver applied in this derivation [28]. Initially, a matrix, $\Psi$, consisting of the constraint Equations 2.7 and the reduced state vector, Equation 2.3, were differentiated with respect to $q'$ from Equation 2.1, producing $\Psi'$. Next, the matrix $\bar{\Psi}$ was defined as in Equation 2.8. The inverse of this matrix, $\bar{\Psi}^{-1}$, then provides equations relating the inverse kinematic relationship.

\[
\bar{\Psi} = \begin{bmatrix}
\phi \\
q'
\end{bmatrix} - \begin{bmatrix}
0 \\
q
\end{bmatrix}
\]  
(2.8)

Applying the following equation, presented in [29], allows determination of the inverse kinematic solution:

\[
q'_i = q'_{i-1} - [\bar{\Psi}(q'_*)]^{-1}\bar{\Psi}(q'_{i-1}, q), \ i = 1, 2, 3
\]  
(2.9)

where $q'_*$ is any valid inverse kinematic solution solved using forward kinematics. Solving the equation in an iterative manner, the current guess of the inverse kinematics, $q_i$, is updated until the estimate falls within the defined error tolerance.

2.1.4 Jacobian

The device Jacobian, $J$, maps forces and torques for the RiceWrist during controller implementation and allows determination of the device manipulability. Initially, equations for link length [30], equations 2.10-2.12, were differentiated with respect to the three reduced state variables in equation 2.3. The link lengths were given by:
\[ L_1^2 = 1 + \varrho^2 + X_c^2 + Y_c^2 + Z_c^2 - 2X_c \]
\[ + 2\varrho(C_\alpha^2 C_\beta + S_\alpha^2)(X_c - 1) \]  
\[ + \varrho(C_\beta - 1)S_{2\alpha}Y_c - 2\varrho S_\beta C_\alpha Z_c \]  
\[ (2.10) \]

\[ L_2^2 = 1 + \varrho^2 + X_c^2 + Y_c^2 + Z_c^2 + X_c - \sqrt{3}Y_c \]
\[ - \varrho[C_\alpha^2 C_\beta + S_\alpha^2 - \sqrt{3}C_\alpha S_\alpha(C_\beta - 1)][X_c + 1/2] \]
\[ - \varrho[S_\alpha C_\alpha(C_\beta - 1) - \sqrt{3}(S_\alpha^2 C_\beta + C_\alpha^2)][Y_c - \sqrt{3}/2] \]
\[ + \varrho S_\beta[C_\alpha - \sqrt{3}S_\alpha]Z_c \]  
\[ (2.11) \]

\[ L_3^2 = 1 + \varrho^2 + X_c^2 + Y_c^2 + Z_c^2 + \sqrt{3}Y_c \]
\[ - \varrho[C_\alpha^2 C_\beta + S_\alpha^2 + \sqrt{3}C_\alpha S_\alpha(C_\beta - 1)][X_c + 1/2] \]
\[ - \varrho[S_\alpha C_\alpha(C_\beta - 1) + \sqrt{3}(S_\alpha^2 C_\beta + C_\alpha^2)][Y_c + \sqrt{3}/2] \]
\[ + \varrho S_\beta[C_\alpha + \sqrt{3}S_\alpha]Z_c \]  
\[ (2.12) \]

where, \( C_\alpha = \cos(\alpha) \), \( C_\beta = \cos(\beta) \), \( S_\alpha = \sin(\alpha) \), \( S_{2\alpha} = \sin(2\alpha) \), and \( X_c, Y_c, Z_c \), and \( L_i \) are normalized with respect to \( R \). The result is a 3x3 matrix mapping from joint-space to task-space velocities and torques as shown in Equations 2.13 and 2.14.

Pre-multiplying by the transpose of the Jacobian results in the mapping from joint-space to task-space velocities and torques.

\[
\begin{bmatrix}
\dot{\alpha} \\
\dot{\beta} \\
\dot{Z}_c
\end{bmatrix} = J(q')
\begin{bmatrix}
\dot{L}_1 \\
\dot{L}_2 \\
\dot{L}_3
\end{bmatrix}
\]  
\[ (2.13) \]
\[
\begin{bmatrix}
\tau_\alpha \\
\tau_\beta \\
F_z
\end{bmatrix} = J(q')
\begin{bmatrix}
F_1 \\
F_2 \\
F_3
\end{bmatrix}
\] (2.14)

### 2.1.5 Manipulability and Workspace

The manipulability of a device describes how well a particular design is able to apply forces and velocities in different poses. One method of determining the manipulability of the RiceWrist is using condition number, Equation 2.15, employing eigenvalues from the product of the RiceWrist Jacobian, Equation 2.16, and Jacobian inverse. The condition number calculation accounts for the singularities that may be present in the RiceWrist. A singularity occurs when one of the eigenvalues is equal to zero and indicates a point in the workspace where an actuator is incapable of changing the device pose. As shown in Figure 2.3(b), this pose physically occurs when one of the links aligns with the wrist platform. The actuator is incapable of changing the pose of the platform regardless of force output. A spatial contour plot of the condition number shows the theoretical bounds of a device’s workspace.

\[
Condition\ Number = \sqrt{\frac{\lambda_{min}}{\lambda_{max}}}
\] (2.15)

\[
\lambda = eig(J^{-1}J)
\] (2.16)

Figure 2.4 shows the theoretical workspace of the RiceWrist for two different wrist platform heights. The white regions show regions of singularity. Noting the differences between figures 2.4(a) and 2.4(b), the workspace of the wrist is dependent on \( Z_c \). As the platform height decreases, the size of the theoretical workspace decreases.
During controller implementation it is necessary to ensure the device never enters these regions with condition number = 0. Near singularities, kinematic instabilities will ensue as commanded torque or desired velocity rises asymptotically to infinity. In the RiceWrist’s current physical implementation, it is impossible to reach the theoretical boundaries of the workspace as the wrist platform’s spherical joints limit
the attainable $\alpha$ and $\beta$.

### 2.1.6 Verification of Theoretical Kinematics and Workspace

Solutions for the theoretical forward kinematics, inverse kinematics, and workspace of the RiceWrist were verified using visualizations of the base ring and wrist wring in MATLAB. Example test cases and associated wrist platform poses are presented for varying $\alpha$ (Figure 2.5(b)) and simultaneously varying $\beta$ and $Z_c$ (Figure 2.5(c)).

![Visualization of theoretical kinematics and workspace](image)

Figure 2.5: Example test cases for RiceWrist forward and inverse kinematics and workspace

### 2.1.7 Device Characterization

Numerous parameters are necessary to implement a control scheme on the MAHI Exo-II. Table 2.1 presents relevant actuation scheme characteristics. The following values are provided by equipment manufacturers or specified from MAHI Exo-II design. For the wrist motors, the rotational motion of the motor is converted into the linear displacement of the links and has units rev/m. Five quadrature encoders (Avago
Technologies US, Inc.), with 2,048 counts per revolution, are co-located with the DC motors and provide position information for the motor shafts.

Table 2.1 : Actuation Scheme Parameters

<table>
<thead>
<tr>
<th>Actuator</th>
<th>Transmission Ratio</th>
<th>Motor Torque Constant (Nm/A)</th>
<th>Amplifier Gain (A/V)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow</td>
<td>10.7:1</td>
<td>0.127</td>
<td>1.8</td>
</tr>
<tr>
<td>Forearm</td>
<td>14.7:1</td>
<td>0.0603</td>
<td>1.8</td>
</tr>
<tr>
<td>Wrist</td>
<td>27.2 (rev/m)</td>
<td>0.175</td>
<td>0.184</td>
</tr>
</tbody>
</table>

As the objective of rehabilitation is to increase motor function in the patient’s day to day life, it is important to ensure the robot is capable of matching the range of motion (RoM) and torques required for ADLs. Using 24 movements associated with ADLs, Rosen et. al captured joint torques and RoM data for the elbow, forearm and wrist DoF [31]. A comparison between the MAHI Exo-II’s RoM and torque output and results of this study are summarized in Table 2.2. As discussed in Section 2.1.5, the maximum torque output of the RiceWrist depends on three link lengths. The values for the MAHI Exo-II were calculated with \( Z_c = 0.09 \, m \), a typical location for a subject in the middle of the workspace regarding wrist platform height. Overall the MAHI Exo-II delivers the required joint torques, but limits elbow flexion-extension and wrist flexion-extension when compared to ADLs. The limitation in the elbow DoF is due to positioning of safety hardstops while the limitation in the wrist flexion-extension DoF is due to the limits of the parallel mechanism’s workspace. With respect to torque, the MAHI Exo-II exceeds the requirements of ADLs.
Table 2.2: Comparison of MAHI Exo-II to ADL Range of Motion and Torques

<table>
<thead>
<tr>
<th>Joint</th>
<th>Range of Motion $(deg)$</th>
<th>Torque $(Nm)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ADL</td>
<td>Exo-II</td>
</tr>
<tr>
<td>Elbow</td>
<td>150</td>
<td>90</td>
</tr>
<tr>
<td>Forearm</td>
<td>150</td>
<td>180</td>
</tr>
<tr>
<td>Wrist (FE)</td>
<td>115</td>
<td>65</td>
</tr>
<tr>
<td>Wrist (RU)</td>
<td>70</td>
<td>63</td>
</tr>
</tbody>
</table>

In addition to RoM and torque capabilities, other parameters are necessary to ensure successful controller implementation. French et. al characterized static friction, viscous friction, inertia and spatial resolution for the MAHI Exo-II [32]. Table 2.3 summarizes these parameters for the four actuated DoF. The wrist and forearm DoFs are comparable in magnitude to other rehabilitation devices [32]. The high inertia of the elbow is due to the entire structure of the exoskeleton, including the DC motors for the wrist, and passive counterweight for gravity compensation, rotating around the elbow joint axis. High-resolution encoders provide high spatial resolution on the order of on the order of 10-100 $\mu rad$. This resolution allows accurate position information and sufficiently accurate velocity for controller implementation. Velocity is calculated from the first discrete derivative of position.

2.1.8 Safety Considerations

As impaired subjects wear the MAHI Exo-II during therapy, user safety is of utmost importance. Numerous measures are employed in the software and hardware of the
Table 2.3: Relevant Experimentally Characterized Parameters for MAHI Exo-II Control

<table>
<thead>
<tr>
<th>Joint</th>
<th>Static Friction ((Nm))</th>
<th>Viscous Friction ((Nm·s/rad))</th>
<th>Inertia ((kg·m^2))</th>
<th>Spatial Res. ((10^{-5}rad))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow</td>
<td>0.949</td>
<td>0.122</td>
<td>0.271</td>
<td>7.16</td>
</tr>
<tr>
<td>Forearm</td>
<td>0.139</td>
<td>0.0283</td>
<td>0.0257</td>
<td>5.22</td>
</tr>
<tr>
<td>Wrist (FE)</td>
<td>0.109</td>
<td>0.0283</td>
<td>0.0020</td>
<td>13.1</td>
</tr>
<tr>
<td>Wrist (RU)</td>
<td>0.112</td>
<td>0.0225</td>
<td>0.0033</td>
<td>12.2</td>
</tr>
</tbody>
</table>

exoskeleton to ensure user safety. Commanded torque sent via analogue outputs of the data acquisition card are bounded using saturation limits in the controller software. These limits on torque prevent injuring the user and damaging the hardware in the event a numerical singularity is approached as discussed in Section 2.1.5. Additionally, the on-screen user interface includes push buttons to disable the amplifiers via the digital output pins of the data acquisition card. There are two mechanical on/off switches for the power supply to the exoskeleton control box. One is a foot pedal and the other is a mechanical button on the side of the control box. Additionally, the exoskeleton has mechanical hard stops for each DoF to prevent hyper extension of the user’s arm and wrist. Lastly, fuses are in place on the data acquisition card, power supply, and amplifiers to prevent excessively high voltage commands to the DC motors.
2.2 Control Schemes

The MAHI Exo-II has numerous control schemes that have been employed in rehabilitation research. Until recently, the controllers have utilized either an impedance or an EEG-based control signal. The controllers implemented on the MAHI Exo-II have been for single DoF movements. Over time, controller development has focused on increasing subject engagement and accessing more severely impaired individuals. The following sub-sections will highlight the current controller implementations on the MAHI Exo-II [27, 33]. Section 2.2.3 will highlight current developments, including preliminary results, of a brain-machine interface (BMI) with the MAHI Exo-II.

2.2.1 Impedance Control

Three modes were originally implemented on the MAHI Exo-II: patient passive, triggered, and constrained. In the passive mode, a proportional-derivative (PD) controller follows a pre-defined trajectory to complete a point to point movement. The controller is implemented in joint-space controlling each motor according to the following control law:

\[ u = K_p(q_{i,d} - q_i) - K_d\dot{q}_i, \quad i = 1, 2, 3, 4, 5 \quad (2.17) \]

where \( u \) is the commanded task space torque, \( K_p \) is the proportional gain, \( q_{i,d} \) is the desired position of the joint variable, \( q_i \) is the current position of the joint variable, \( K_d \) is the derivative gain and \( i \) corresponds to each of the five joints controlled by the DC motors. During implementation the exoskeleton moves the user’s limb without any input from the subject. A block diagram for this configuration is shown in Figure 2.6. The linear trajectory is time scaled allowing adjustment of the movement speed.
A visualization shows a cursor corresponding to the current exoskeleton position and a target over the desired exoskeleton position.

Figure 2.6: Passive mode controller, joint-space implementation

The triggered mode controller is similar to the passive controller and represents an incremental step toward increasing user engagement. The triggered mode employs the same trajectory following, joint-space controller as in the passive mode. However, the user must initiate the movement by exerting a certain force against the same controller with a set-point at the initial position. After the user exceeds the pre-defined threshold, the exoskeleton carries the subject through the rest of the movement. The threshold required to trigger and the exoskeleton speed along the trajectory are adjustable.

In the constrained mode, the exoskeleton does not control movement. Rather, it provides a resistive torque proportional to movement speed. The motor command is simply the derivative term of the PD controller presented in equation 2.17. The user is able to move freely through a viscous field. Increasing the damping gain increases the amount of resistance the exoskeleton provides. A visualization is still shown but now there is no assistive torque to drive the user to the target position. Historically, this mode has been employed to quantify movement quality with the MAHI Exo-II, as it allows the user to move freely when the constraint is set to zero [23].
2.2.2 Assist-as-Needed

One proposed solution to increasing patient engagement during therapy is subject adaptive control, implemented as an assist-as-needed controller on the MAHI Exo-II [34]. This controller adjusts model parameters based on an update law to provide assistance to the patient only if they are incapable of meeting or maintaining performance benchmarks during a specific movement task. Similarly, if the patient exceeds the performance benchmark, the update law increases the difficulty of the movement task. The adaptive controller requires less manual tuning than the controllers presented in Section 2.2.1 as they continually adapt to the patient’s performance. The controller’s adaptability makes it well suited to handling a wide variety of impairment levels. For the MAHI Exo-II, the adaptive controller implements the following control law:

\[ u = \hat{G} - \hat{F}_p - K_D r \]  

(2.18)

where \( \hat{G} \) is the estimate gravitational force, \( \hat{F}_p \) is the estimate of the patient forces, \( K_D \) is a feedback gain matrix and \( r \) consists of the sliding mode variables consisting of the system tracking error. As the MAHI Exo-II does not have force sensors or accelerometers to estimate the interaction forces, the terms \( \hat{G} \) and \( \hat{F}_p \) are parameterized and estimated with Gaussian Radial Basis Functions spaced evenly across the workspace. Essentially, the controller in Equation 2.18 is a tracking PD controller, but contains feed forward elements of the subject and environmental factors. In practice, \( F_p \) adds to the torque command from \( r \) if the subject is incapable of keeping up with the desired trajectory. The desired trajectory is continuously updated based on the performance in each movement. If the subject is lagging behind the desired
trajectory and requiring assistance, the movement speed is reduced and vice versa. A study comparing the clinical outcomes of assist-as-needed control to triggered mode control in incomplete SCI subjects is in progress.

### 2.2.3 Brain-Machine Interface

Recent studies have shown the potential of employing non-invasive, scalp EEG in detecting cortical potentials related to movement in stroke subjects [35, 36]. Bhagat et. al investigated exploiting these measured potentials for application to robotic therapy [33]. The rehabilitative benefit arises from directly measuring the intent to move in the motor cortex. After discerning the user’s intent, the exoskeleton moves accordingly, providing positive sensory feedback to promote neuroplasticity. In an initial study, Bhagat et. al investigated open-loop calibration procedures. During calibration, the user donned the exoskeleton and completed blocks of trials moving between targets in the three modes described in section 2.2.1. From the EEG data collected, a 2-class support vector machine (SVM) classifier was developed to detect the intent to move in the form of a go or no-go command. In offline analysis, a median classification accuracy of approximately 90% was observed in the single stroke subject with classification remaining above 70% when calibration occurred in the active constrained mode.

Employing the developed calibration procedure and SVM classifier, we attempted closed-loop control of the MAHI Exo-II for elbow flexion-extension. This work was completed with Nikunj Bhagat and Anusha Venkatakrishnan. Five subjects suffering from upper limb motor deficit following stroke were recruited to participate as a proof-of-concept for real time detection of movement intent. Following calibration, subjects completed three sessions of closed-loop trials. Figure 2.7 shows one subject complet-
Figure 2.7: MAHI Exo-II brain machine interface during closed-loop control trials

ing a BMI trial, where he attempts to move the cursor on the screen, corresponding to the current elbow position, to the target, goal elbow position, through EEG triggering alone. The MAHI Exo-II operated in the same manner as described for the triggered mode in Section 2.2.1, but rather than a velocity trigger, the exoskeleton remained stationary under set-point PD control until receiving a "go" command from the classifier. Overall, the closed-loop control had a real time classification accuracy of 67%. A more extensive protocol with 15 stroke subjects is currently in-progress to further investigate the efficacy of this MAHI Exo-II BMI controller applied to stroke rehabilitation.
Chapter 3

Electromyography

Electromyography (EMG) is the practice of reading myoelectric signals, or electrical activity generated in skeletal muscle during contraction. In the broadest sense, researchers use EMG in two distinct forms: neurological EMG and kinesiological EMG. The former is concerned with a muscle’s response to an external stimuli while the latter is concerned with a muscle’s neuromuscular activation [37]. Kinesiological EMG has numerous applications in biomechanics and robotics as it provides insight into an individual’s desired movement. Exploiting the EMG signal for control applications requires an understanding of the signal origin, signal processing, and current control schemes. The following sections will discuss various aspects of kinesiological EMG relevant to rehabilitation robotics.

3.1 Origin of the Myoelectric Signal

In skeletal muscle, muscle fibers are grouped into motor units (MU). The fibers in a MU are not necessarily adjacent, but innervated by the same α-motorneuron [38]. When an α-motorneuron fires, all fibers in the MU undergo the same innervation process. During steady state rest, an ionic equilibrium exists between the inside and outside of a muscle cell. An ion-pump in the fiber membrane maintains a constant potential of approximately -85 mV. When the α-motorneuron fires, the generated electrical stimulus along the motor nerve changes the characteristics of the fiber membrane.
The result is an influx of sodium ions that raise the potential across the membrane up to approximately 30 mV. The membrane’s ion-pump immediately reverses this depolarization. This depolarization-repolarization generates a burst of electrical activity that releases calcium ions in the intercellular space, which, through another chemical process, causes shortening in the muscle contractile tissue [37]. The site of activation is approximately 2 mm² and travels along the muscle fiber at a velocity of 2-6 m/s [39]. The result is a wave of electrical activity that travels up and down each of the muscle fibers in the MU originating where the motor nerve attaches to the muscle fiber.

Measuring EMG requires a differential electrode configuration, usually achieved with electrodes on the surface of the skin. As the wave of changing electrical potential propagates down the muscle fiber, each electrode records a different point on the propagating wave. Taking the difference between the two measurement sites produces the EMG signal. An EMG electrical burst is the superposition of all muscle fibers in a MU, known as the motor unit action potential (MUAP), and the superposition of all MUAPs within detection range of the electrode. An example surface EMG (sEMG) signal after amplification along with the signal acquisition process is shown in Figure 3.1. Invasive EMG is possible through the use of fine wire electrodes and offers increased signal fidelity as subcutaneous tissues attenuate and disperse the muscles’ EMG signal. For many applications the increased preparation requirements and complications of injecting an electrode directly into the muscle make sEMG more appealing.

Numerous factors influence the measured sEMG signal [40]. Due to the differential electrode configuration, the alignment of the electrodes with the muscle fiber, distance between the electrodes, and size of the electrodes will affect the measured sEMG.
Additionally, biological influences including the MU firing rate, number of active MUs, location of the electrodes relative to the MUs, crosstalk from nearby muscles, blood flow, characteristics of the subcutaneous tissue, and electrical conductivity at the skin and electrode interface affect the recorded sEMG signal. Some of these factors can be controlled. A constant electrode size and fixed distance between electrodes is attainable. Influence of some factors can be mitigated. For example, placing electrodes on the belly, or widest part, of the muscle reduces cross talk interference and maximizes the number of MUs within detection range. The biological factors vary between subjects, between muscles in the same subject and within the same muscle over time.

3.2 The Force to EMG Relationship

The relationship between the recorded sEMG signal and torques produced at the joint is complex. To increase muscle force, the nervous system will increase MU recruitment
Figure 3.2: Filtered sEMG signal with associated sEMG amplitude computed from a 300 ms running RMS calculation. Measured above the extensor carpi radialis and/or increase MU firing rate. Many of the factors influencing the corresponding change in sEMG signal associated with these increases vary non-linearly with position and velocity due to the factors mentioned in Section 3.1. Further, the contribution of the muscle to joint torque is further complicated by the presence of elastic biological elements and numerous muscles actuating even the most simple joints like the elbow. An accurate, widely accepted model defining the relationship does not exist [40]. Often the amplitude of the sEMG signal is used to relate recorded muscle activity to the desired joint forces.

The amplitude is computed as an root-mean-square (RMS) power calculation or mean absolute value [41], and captures both the increase in MU signal and firing rate. The instantaneous amplitude is highly variable, but the relationship to individual
muscle force is monotonic in quasi-static conditions after adequate smoothing [40], as shown in Figure 3.2. Thus the amplitude still provides valuable insight to the user’s intent.

3.3 Controlling Systems with Surface Electromyography

sEMG has been proposed to control numerous systems from wheelchairs to prostheses and exoskeletons. sEMG is attractive as a control signal as it provides information directly related to the user’s motor intent. In addition to relaying using intent, onset of sEMG activity occurs 50-100 ms prior to muscle contraction [42], which can mitigate the effect of signal processing and controller delays. Depending on the complexity of the task, various approaches have been successful in controlling exoskeletons. The approaches fall into two categories: non-pattern and pattern based approaches [43]. Pattern based approaches exploit some form of machine learning, or classifier, while non-pattern based approaches rely on the amplitude of a single sEMG feature like signal power. The following sections will highlight sEMG approaches for controlling robots specifically for rehabilitation of the upper extremities.

3.3.1 Non-Pattern Based Interfaces

*Triggering:* An early form of of sEMG control in robotic therapy was based on onset analysis, or triggering. In this approach, movement onset is detected when the amplitude of the sEMG signal exceeds a predefined threshold. Employing the MIT Manus, Dipietro et. al investigated an sEMG interface for stroke rehabilitation [44]. They found noteworthy benefits to the sEMG interface when compared to velocity or force triggering. Highly impaired stroke subjects, incapable of significant movement, were still able to generate detectable sEMG activity in upper limb muscle. The sEMG
interface could make therapy available to populations of impaired subjects where it had been previously inaccessible. Additionally, they found that subjects could use compensatory movements to trigger robot motion when using a velocity based trigger that were avoided with an sEMG based trigger. For example, when the subject wanted to extend their arm from their body in the transverse plane, as shown in Figure 3.3, they could simply push forward with their shoulder to generate the trigger. With sEMG triggering, the subject had to activate the appropriate muscles of the upper limb to initiate movement.

Figure 3.3: A chronic stroke survivor completes triggered movement therapy with the MIT Manus (figure adopted from [44])

Aside from these strengths, this control scheme has limitations in that it is sensitive to the signal to noise ratio [43] and does not require active user engagement following movement onset. This passivity is undesirable in therapy, as passive moveme-
Figure 3.4: sEMG devices employing sEMG control for rehabilitation following neurological injury (figures (a) and (b), adopted from [45] and [46], respectively). 

Figure 3.4 : sEMG devices employing sEMG control for rehabilitation following neurological injury (figures (a) and (b), adopted from [45] and [46], respectively)

ements do not achieve the same level of therapeutic outcomes as when subjects are actively engaged [10].

Proportional Control: Numerous groups have employed proportional control schemes for sEMG interfaces. In one approach, these interfaces provide an assistive torque based on sEMG amplitude following normalization. A simplified model for the sEMG to force relationship was employed in the form of a linear gain based on normalized sEMG amplitude. Pilot studies employed this control scheme in chronic stroke survivors for elbow flexion-extension [45], Figure 3.4(a), and wrist flexion-extension [46], Figure 3.4(b) after normalization to the subject’s maximum voluntary contraction (MVC).

Both groups observed significant improvements in the Fugl-Meyer scale, a motor function test, and improvements in Ashworth scale, a test relating amount of muscle tone, in a total of 24 chronic stroke survivors following a treatment protocol. An advantage of these interfaces over triggered approaches is the requisite user engagement.
The assistive torque allowed impaired subjects to increase their range of motion, while reducing muscular effort during training. Other groups have proposed more complex muscle mappings, often based on Hill’s muscle model, before applying an assistive torque [47, 48]. The Hill model relates the sEMG activity to force by modelling a muscle as a contractile element in series with an elastic element and parallel elastic element. The goal is to provide a more accurate estimate of the user’s intended motion. These models are sensitive to variations in model parameters [49]. In order to develop a reliable and accurate torque mapping, however, intensive calibration procedures are required that are only valid for one subject and vary session to session. Lenzi et. al suggested that these approaches are impractical outside of the laboratory environment and demonstrated the ability of the central nervous system to adapt the imprecise torque estimate in control of an assistive elbow exoskeleton [50]. A caveat to this approach is the controller should not promote the development of new muscle synergies during rehabilitation. New muscle synergies are an appropriate solution for control of various systems [51], but potentially detrimental during rehabilitation.

3.3.2 Pattern Based Interfaces

A common approach to sEMG control is the use of artificial neural networks (ANN) for muscle mapping, especially in multi-DoF movements [52, 53]. Although highly dependent on training data, an ANN outperforms a Hill model based approach in accuracy for sEMG torque prediction [54]. This mapping approach has been employed in a proportional scheme to provide an assistive force during a upper limb reaching task in eight chronic stroke patients [55]. More complex calibration procedures enabled a muli-DoF reaching movement with robotic assistance based on an eight channels of sEMG inputs. The subjects increased the size of their workspace while
reducing effort in a majority of employed muscles. Subject performance degraded, however, with respect to time to reach the target, settling time and path length.

Although the muscle mapping was more accurate, several recommendations from this study were relevant to all sEMG based rehabilitation. The authors suggest that sEMG assistance may reduce abnormal muscle synergies present in stroke survivors by reducing the muscular effort, allowing them to train in a larger workspace and with healthy patterns of muscle activation. Drawbacks of this muscle mapping method are the unpredictability of the network outside of the range of the calibration data and requisite time spent to collect calibration data to train the network.

A recent emergence in sEMG approaches is the practice of high-density EMG (hdEMG). In hdEMG, a grid of multiple electrodes is used to provide more information about the underlying muscle, including muscle fiber conduction velocity and evaluation of a single MU through signal decomposition [56]. A recent hdEMG effort demonstrated high classification accuracies in stroke subjects, suggesting a potential for future control interfaces [57]. A drawback to this approach, again, is the cost of completing extensive calibration procedures.
Chapter 4

Employing Surface Electromyography to Control the MAHI Exo-II

The preceding chapter highlighted the benefits of an sEMG interface for therapeutic exoskeletons. As outlined in Section 2.2, the MAHI Exo-II has impedance based controllers, as well as the initial groundwork for a scalp EEG based BMI. An sEMG interface would provide currently unrealized capabilities for rehabilitation of heavily impaired subjects. In this chapter*, an sEMG interface, four different sEMG control modes, and initial sEMG pilot experiments for the MAHI Exo-II are presented.

4.1 Signal Acquisition and Hardware Integration

As an initial investigation into the feasibility of an sEMG interface for the MAHI Exo-II, a simple sEMG amplifier was assembled on a National Instruments prototyping board. Passive single use electrodes (BIOPAC, Inc), 11 mm in diameter, with silver contact and 17% chloride electrode gel were employed. An isolation circuit was implemented between the amplifier and subject. An AD620N instrumentation amplifier provided an approximate gain of 456x. The signal was then recorded using the MAHI Exo-II’s Q-8 USB (Quanser Consulting, Inc) data acquisition card at 1

*Portions of this chapter originally appeared in a paper submitted for inclusion in the proceedings of the 2015 Dynamic Systems and Control Conference (DSCC), and I gratefully acknowledge my collaborators, Amy A. Blank and Marcia K. O’Malley, in this publication. This work, though, has been expanded to include new analysis and commentary.
Figure 4.1: Comparison of recorded signal periodograms from the long head of the triceps brachii in two conditions

sEMG signal amplitude was estimated using a moving window RMS calculation. For exoskeleton controller implementation, a running RMS calculation was chosen for signal smoothing and estimation of the sEMG amplitude. In general, the signal to noise ratio (SNR) increases as the square root of the increase in window length [58]. SNR was calculated as the standard deviation of the signal amplitude divided by mean signal amplitude for a fixed window. A window length of 300 ms was chosen. The 300 ms window produced the recommended maximum latency due to window length for control, while providing the most smoothing [43]. In this case, the RMS smoothing introduced a latency of 150 ms, or half of the window length.

Substantial electromagnetic interference was observed with this initial set up due to the close proximity of the exoskeleton’s DC motors and numerous high voltage currents in wires to the aluminum frame. Much of the background exoskeleton noise
overlapped with large portions of the primary sEMG power spectrum (20-400 Hz). Figure 4.1 shows a comparison of the exoskeleton background noise recorded while the (a) subject rested in the exoskeleton during set-point PD control and (b) the sEMG signal recorded during a maximum voluntary isometric contraction (MVIC) outside of the exoskeleton. Both were calculated during a 1 s window using a fast Fourier transform. The sEMG signal was accompanied by low frequency interference, with a signal power of 20-40 dB above the recorded signal from a MVIC. During control of the exoskeleton, the SNR was lower than suggested in Figure 4.1 as the MVIC represents a best case scenario, where the sEMG signal power is at its highest. As maximum exoskeleton torques were much lower than a healthy subject’s MVIC, interactions with the exoskelton would consist of a signal power approximately an order of magnitude lower. sEMG electrodes attached to the triceps brachii experienced the highest interference due to their close proximity to the elbow joint’s DC motor. Various digital filter designs were investigated, but the overlap between sEMG signal and exoskeleton interference resulted in inadequate SNR’s. In all DoF, SNR was less than 1. Measures to improve the interface’s SNR were necessary.

To overcome these challenges, a Bagnoli-8 desktop sEMG amplifier (Delsys, Inc), was used. The system utilized active electrodes (300x gain at the detection site) with parallel 10 mm x 1 mm silver contacts with a common mode rejection ratio of -92 dB and shielded lead wires. Overall, the system provided a 1000x gain of the recorded signal and analog filtering with a 20-450 Hz band pass. Additionally, a second DAQ was used to record the sEMG signal after amplification. This two DAQ set-up allowed sEMG wires and analog processing to be physically separated from the exoskeleton control box. Additionally, elbow motor leads were re-routed to maximize spacing between the frame and motor command current. The results of these measures are
shown in Figure 4.2(a). The periodograms were again generated using 1 s of data recorded from the long head of triceps brachii while resting in the exoskeleton during set-point PD control. Recorded background interference power was reduced following these measures on the order of 15-40 dB, depending on frequency.

![Figure 4.2](image)

(a) Resting in exoskeleton  
(b) Resting in exoskeleton with elliptic filter design

Figure 4.2: Comparison of baseline signal periodogram following hardware and digital filtering noise reduction measures

Following implementation of these noise reduction measures, detrimental noise was still observed in a pilot subject during wrist flexion-extension. Additional noise reduction measures were undertaken in the form of digital filter implementation. An eight order, elliptic filter with a band pass of 25-450 Hz was implemented. This filter design was chosen for its steep roll off and nearly flat pass band. The attenuated signal below 25 Hz and above 450 Hz is visible in Figure 4.2(b). In order to quantify the SNR, the exoskeleton was operated in the sEMG calibration mode, which will be
Figure 4.3: Importance of noise reduction measures becomes apparent when comparing (a) and (b). Muscle activation for typical exoskeleton operation (c) is markedly lower than a MVIC (d)

(a) Resisting a 1 Nm perturbation in exoskeleton with elliptic filter design
(b) MVIC outside of exoskeleton with elliptic filter design

further discussed in Section 4.2.1. In this mode, the exoskeleton was commanded to provide a constant 1 Nm torque while the subject held their wrist stationary. After five perturbations in each direction, the SNR increased in another subject from 9.6 ($SE = 3.9$) to 12.96 ($SE = 3.4$) for the channel associated with flexion and from 12.77 ($SE = 1.9$) to 20.2 ($SE = 2.0$) for the sEMG channel associated with extension. Additionally, subjects’ arms were covered with a neoprene wrap (Horseloverz.com) to reduce interference due to the exoskeleton frame. The observed effect of this change in one subject was less profound with the resultant SNR increase to 12.4 ($SE = 2.4$) in the channel associated with flexion and to 15.5 ($SE = 4.2$) in the channel associated with extension. Grounding of the exoskeleton frame to earth
ground resulted in worsening or no change in the SNR. An example periodogram of the sEMG signal during a 1 Nm perturbation and MVIC is presented in Figure 4.3. Even while opposing a relatively small torque for a healthy subject, 1 Nm, the signal generated in the triceps brachii (long head) is approximately 20 dB above background interference (Figure 4.2(b)) across the primary sEMG spectrum, 20-450 Hz, following noise reduction measures. The overall approach to signal acquisition, or estimation of the user sEMG amplitude, is summarized in Figure 4.4.

Figure 4.4: Summary of sEMG amplitude estimation for a single channel. Blocks 1 and 2 are accomplished with the Bagnoli-8 Desktop EMG system, block 3 is accomplished with a Quanser Q-2 USB data acquisition device, and blocks 4-6 are accomplished using the controller software.

Following amplitude estimation, the control signal for the exoskeleton was generated through the relation of agonist-antagonist muscle pairs. A single sEMG channel was placed over each muscle in the agonist-antagonist pair. After generation of the
sEMG signal amplitude, the signals were normalized to a sub-maximal voluntary isometric contraction (SMVIC). Obtaining the normalization factor will be discussed in Section 4.2.1. Chosen agonist-antagonist muscle pairs for each MAHI Exo-II DoF are presented in Table 4.1 and Figure 4.5. Although a single channel was employed for each direction, a similar electrode configuration to a previous sEMG exoskeleton control study was chosen [59]. Electrodes were placed as close as possible to the center of each prescribed muscle in order to reduce cross-talk interference from nearby muscles.

Table 4.1: Chosen muscles and channels for each DoF

<table>
<thead>
<tr>
<th>DoF</th>
<th>Channel 1</th>
<th>Channel 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow</td>
<td>Biceps Brachii</td>
<td>Triceps Brachii (Long Head)</td>
</tr>
<tr>
<td>Forearm</td>
<td>Pronator Teres</td>
<td>Supinator</td>
</tr>
<tr>
<td>Wrist (FE)</td>
<td>Flexor Carpi Radialis</td>
<td>Extensor Carpi Ulnaris</td>
</tr>
<tr>
<td>Wrist (RU)</td>
<td>Extensor Carpi Radialis Brevis</td>
<td>Flexor Carpi Radialis</td>
</tr>
</tbody>
</table>

Figure 4.5: Location of agonist-antagonist muscles pairs. Pairs are color matched for the elbow (grey), forearm (orange), wrist flexion-extension (blue), and wrist radial-ulnar deviation (gold) DoF.
This signal normalization provides a simple linear mapping between sEMG amplitude and the contribution of that channel to the desired torque about the currently controlled joint. Potential limitations of this approach are restriction to single DoF movements and imprecise torque estimates. These capabilities were lost in a trade-off to obtain a robust and simple system that requires minimal calibration and tuning. Following the linear torque mapping, the difference in normalized signals is computed to generate a control signal, $\Delta \hat{V}_{EMG}$.

4.2 Control Modes

Several sEMG control modes were developed for the four MAHI Exo-II DoF based on the normalized sEMG signals. Sections 4.2.2-4.2.4 present the controllers in order of decreasing constraint on the user. Three target positions are chosen for each user: a center position, and two extreme positions in the RoM for the controlled DoF. All inactive DoF positions are held in place using PD control with set-points corresponding to their task-space center positions. Further, users’ hands are wrapped to the exoskeleton handle using a bandage to reduce muscular cross-talk due to the subject’s grip. Prior to electrode placement, the user’s skin is lightly abraded with fine sandpaper and cleaned with isopropyl alcohol using recommended procedures [37]. Further, ground reference for the sEMG signal was attached either to the left elbow or right acromion process. The following sections will cover the calibration procedures, the three sEMG control modes, and the user interface. Real time code was programmed in Simulink (The MathWorks, Inc) then compiled into C++ using Quarc software (Quanser Consulting, Inc). As all controllers follow the same primary design across DoF, Sections 4.2.1-4.2.6 will present the controller for wrist flexion-extension. DoF specific considerations will be discussed in Section 4.3.4.
4.2.1 Calibration

Before controlling the MAHI Exo-II, a short calibration procedure must be accomplished to normalize agonist-antagonist muscle pairs. Initially the exoskeleton is commanded to place the user in the center of the workspace. After arriving at this position, 5 s of baseline sEMG amplitude are recorded to determine subject specific baseline noise. Next, the exoskeleton ramps up to a constant commanded torque for 4 s about the active DoF while sEMG data are recorded for channel 1. The mean signal power during the last 2 s is used to generate the SMVIC torque mapping. A visual display with a cursor corresponding to the current wrist position and a target corresponding to the center position are shown on screen along with signal traces for the two channels. The visual display will be discussed in Section 4.2.6. Users are presented visual feedback of the two sEMG amplitudes and are instructed to avoid co-contraction by minimizing the displayed signal trace associated with the antagonist muscles while holding the cursor on the target by activating the agonist muscle. The SMVIC is repeated 5 times. The exoskeleton then reverses the perturbation torque direction and repeats the calibration for the second direction. Static friction values, previously characterized for the exoskeleton (Section 2.1.7) are added to the torque command. To prevent damage to the exoskeleton, the torque command is attenuated, eventually reaching zero, as subjects approach the edges of the physical workspace.

4.2.2 Triggered

An sEMG triggered control mode was developed and implemented for the MAHI Exo-II. When compared to previously described triggered control modes that only seek to identify initial movement intent [44], the proposed triggered control mode attempts to increase engagement by requiring the subject to maintain activation throughout
the movement. Employing a finite state machine (FSM), a task-space trajectory is created for the active DoF. The exoskeleton then follows the trajectory with a task-space PD controller, without gravity compensation, according to the following control law:

\[ u = K_p(e) + K_d(\dot{e}) \]  

(4.1)

where, \( e \) is the position error, defined as:

\[ e = \theta_d - \theta \]  

(4.2)

During the triggered control mode, the one DoF system dynamics can be expressed using the following [60]:

\[ M(\theta)\ddot{\theta} + C(\theta, \dot{\theta})\dot{\theta} + G(\theta) = u + F_{user} \]  

(4.3)

where, \( M \) is the inertia, \( C \) is the Coriolis and centrifugal terms, \( G \) is the force of gravity, \( u \) is the controller input and \( F_{user} \) is the force of the user on the system. Gains \( K_p \) and \( K_d \) are manually tuned to minimize steady state error while providing a critically damped response for a step input of 10°. In steady state, acceleration and velocity are zero, and substituting in Equation 4.1, Equation 4.3 becomes:

\[ G(\theta) = K_p(e) + F_{user} \]  

(4.4)

Solving for \( e \):

\[ e = \frac{1}{K_p}(F_{user} - G(\theta)) \]  

(4.5)
Therefore, to minimize steady state error and minimize the influence of the user disturbances and gravity, the gain $K_p$ is maximized. Increasing this gain, however, increases the energy of the system. Increasing $K_D$ helps dissipate this energy to provide a critically damped response for the tuning step input. In practice, $K_p$ and $K_D$ are limited by the velocity calculation. As velocity is calculated from the discrete derivative of position, if $K_D$ is set too high, chatter due to quantization error can result in an unstable response. Velocity is filtered using a second order Butterworth design, 100 Hz low-pass filter, following differentiation. During operation, all motor commands are attenuated for 3 s to allow filter settling time. The high level controller block diagram is shown in Figure 4.6.

Figure 4.6: The trajectory following PD controller for wrist flexion-extension. Sensing and actuation of the MAHI Exo-II occur at the joint-space level, manipulating link lengths, $l_i$, while the controller is implemented at the user task-space level, or about wrist flexion-extension angle, $\alpha$.

Although there are discrete transitions in states, a piecewise continuous trajectory is generated by the FSM. Transitions between states are based on the magnitudes of the normalized agonist-antagonist channels. The user defines three thresholds:
the normalized agonist sEMG activity required to initiate movement \((ag_{req})\), the normalized agonist sEMG activity required to maintain movement \((ag_{mant})\), and the maximum allowed normalized antagonist sEMG activity allowed at any time \((an_{allow})\). These thresholds are expressed as a percentage of the calibration SMVIC. Movement begins when agonist activity exceeds \(ag_{req}\) and antagonist activity is below \(an_{allow}\).

Each time movement is initiated, a new trajectory associated with the minimum jerk profile is calculated from the current position to the goal position. The minimum jerk profile was chosen as it provides the smoothest movement between target positions and has been proposed as the natural profile for point to point movements in humans. This profile is given by [61]:

\[
\theta(t) = \theta_i + e_i \left( 10 \left( \frac{t}{T} \right)^3 - 15 \left( \frac{t}{T} \right)^4 + 6 \left( \frac{t}{T} \right)^5 \right)
\]  

where \(\theta\) is the position of the currently actuated joint, \(e_i\) is the initial error, \(t\) is the time elapsed since entering the movement state, and \(T\) is the user defined time to complete the movement.

If the final target position is reached within a certain tolerance, the movement direction switches. If agonist activity drops below \(ag_{mant}\) or antagonist activity exceeds \(an_{allow}\) during movement, the exoskeleton follows a parabolic trajectory with constant decreasing speed to a set-point slightly ahead of the position when the state switches to the stop mode. An sEMG triggered mode that only requires the subject to initiate movement, as in Section 2.2, is available by setting \(ag_{mant} = 0\%\) and \(an_{allow} = 100\%\). Figure 4.7 shows the relationship between sEMG amplitude and exoskeleton behavior for one subject during movement between the extremes of the workspace. User engagement is forced, as the subject must continually push against the handle to generate the necessary sEMG activity, while the exoskeleton moves
Figure 4.7: An example wrist extension movement in the sEMG triggered mode. Stop mode behavior is visible at approximately 4 s and 6.9 s. Vertical dashed lines denote a transition between states.

again, reducing resistance felt by the user. During the initial 3 s, the increase in position error is accompanied by the increase in sEMG activity of the agonist muscle while the subject pushes against the handle to generate the necessary sEMG activity to trigger movement. Although with this healthy subject there was no difficulty in relaxing the antagonist muscle, the threshold $a_{\text{allow}}$ would help train healthy muscle synergies in impaired subjects and promote relaxing of antagonist muscle groups. Further, user adjusted thresholds allow the exoskeleton user to tune exoskeleton to account for subject specific SNR. Benefits of this multiple threshold approach include continuous engagement and relaxation of the antagonist muscle.
Although the FSM triggering approach constrains the user-exoskeleton interaction, i.e. the controller does not vary speed or direction in response to the relative magnitude or sign of the sEMG signal, this constraint may be beneficial for some subjects. In some cases, heavily impaired subjects may have the ability to generate an sEMG signal but little control over the signal. Some sEMG control strategies would cause the exoskeleton to behave in a manner undesirable for therapy [62]. For example, a subject may intend to move in the flexion direction but muscle spasticity results in increased sEMG activity in the antagonist muscle. An sEMG controller may give a command in the extension direction during bidirectional control. The presented sEMG triggered mode would not allow significant movement in the antagonist direction, requiring the subject to generate an appropriate muscle synergy for the desired movement.

4.2.3 Velocity Control

Although unobserved in rehabilitation robotics, sEMG based velocity control has been shown to provide an intuitive sEMG control scheme and may offer unique benefits for robotic rehabilitation [51]. As an incremental increase in user engagement over the triggered mode, a proportional-integral (PI) velocity controller was developed for the MAHI Exo-II. In this control mode, a maximum desired angular velocity, $\dot{\theta}_{max}$, is mapped to the calibration torque value. $\Delta V_{EMG}$ then controls the desired angular velocity of the active DoF according to the following control law:

$$u = K_p(e_v) + K_i \int_0^t e_v \, d\tau$$

(4.7)

where,
\[ e_v = \dot{\theta}_d - \dot{\theta} \] (4.8)

and,

\[ \dot{\theta}_d = \Delta \hat{V}_{EMG}(\dot{\theta}_{max}) \] (4.9)

This mode enables the subject to control direction of movement and relative velocity of the movement without position dependent forces, such as gravity or stiffness of biological elements, significantly influencing the system equilibrium position. For user safety, the magnitude of \( \Delta \hat{V}_{EMG} \) is limited to 1. This mode may be useful for subjects that are have some control over their muscle activity, but require training in promoting healthy synergies. Further, it may assist in training to increase RoM as the integral term effectively stiffens the system, providing a base for the subject to push against.

The gains \( K_P \) and \( K_I \) are manually tuned, again, for minimal steady state error and for a step input of half of the maximum allowed velocity. An example wrist flexion-extension movement in this control mode is presented in Figure 4.8. As seen in the upper plot, as the agonist muscle activity increases, the antagonist muscle relaxes resulting in wrist flexion. Without instruction, the subject naturally increases co-contraction at the two extremes of the workspace to send a zero velocity command to the exoskeleton, while increasing their joint stiffness to reject the disturbances at approximately 3.2 s, 4.6 s and at 7.6 s. The developed controller high level block diagram is presented in Figure 4.9.

4.2.4 Assistive

The assistive mode is a feed-forward torque controller with closed-loop velocity feedback. This mode is less constraining than the modes presented in Sections 4.2.2 and
Figure 4.8: An example wrist flexion followed by wrist extension in the exoskeleton PI velocity control mode.

Figure 4.9: The closed loop sEMG PI velocity controller for the MAHI Exo-II. The discrete derivative of position is the controlled variable.
4.2.3 but augments the user’s muscle strength at low velocity. The velocity feedback effectively reduces the bandwidth of the controller. The low velocity sEMG assistance allows the subject to increase their RoM and reduce muscular effort. Previous sEMG work postulated these outcomes have therapeutic benefit in promoting healthy muscle synergies [55]. As $\Delta \hat{V}_{EMG}$ is based on a linear torque mapping, a feed-forward torque is commanded based on this difference in normalized sEMG activity. As the normalization is based on SMVIC at the center of the workspace and only employs two channels, the torque estimate is less accurate under dynamic conditions and at the extreme positions of the workspace. The velocity feedback essentially attenuates the sEMG command signal when conditions increasingly deviate from the calibration condition and provides increasing resistance if the subject is capable of moving at a high enough velocity. The difference in normalized sEMG signals is then multiplied by a user selectable gain, $K_{EMG}$. Figure 4.10 presents the high level controller block diagram.

![Diagram](image)

Figure 4.10 : The sEMG assistive mode for the MAHI Exo-II

As the feed forward command adds energy to the system, when the gain $K_D$ is set equal to zero, the system is potentially unstable. For safety of the user and hardware,
the torque command is attenuated near the boundary of the physical workspace. Compared to the triggered and velocity control modes, this mode imposes less constraint on the user. It relies on the user to stabilize and exploit the assistive torque. Section 4.3.2 will investigate the ability of healthy subjects to control a system with an sEMG based torque.

4.2.5 Assessment

An sEMG assessment mode was also programmed for the purpose of providing a mode for evaluating unassisted movements of the upper limb. In this control mode, the exoskeleton does not provide any actuation in the active DoF. Rather, the subject back-drives the exoskeleton. sEMG activity is still recorded and as well as kinematic data allowing assessment of movement quality, as discussed in Section 1.2.3, in the MAHI Exo-II. This control mode produces the least constraint on the user allowing free movement about the active DoF with only the low inertia and low friction of the exoskeleton, Section 2.1.7, impeding their movement.

4.2.6 User Interface

There are two user interfaces (UI’s) for the MAHI Exo-II sEMG implementation. A control panel, presented in Figure 4.11, provides an interface for an experimenter or clinician to accomplish various functions to operate the MAHI Exo-II in sEMG mode. Subject data logging is possible including storage of exoskeleton fit data, calibration values, and model parameters, such as $K_{EMG}$.

The second UI provides visual feedback for the subject. On screen, a cursor corresponds to the current position of the active DoF (Figure 4.12). Targets are presented at the desired goal positions corresponding to the center and extreme positions of
Figure 4.11: The sEMG control panel provides an interface for the experimenter or clinician to operate the exoskeleton and accomplish data logging in the workspace. During tracking tasks, two vertical bars, spaced at the width of the cursor, are presented and move between targets following a programmed trajectory.

During calibration, the second UI also shows signal traces of recorded sEMG power to help train the subject. The subject holds the cursor on the center target during the perturbation. The lower signal trace in Figure 4.13 corresponds to activity in the extensor channel during wrist flexion-extension calibration. The initial peak in sEMG amplitude coincides with the subject moving the cursor back to the center position following the initial perturbation. The upper signal trace shows the relaxation of the antagonist muscle.
Figure 4.12: The subject user interface provides visual feedback using a cursor (grey sphere), bounds for a goal trajectory (vertical bars), and a goal position (red target).

Figure 4.13: During calibration, sEMG amplitude is displayed to the left of the virtual exoskeleton position.

4.3 System Performance

After developing the sEMG interface for the MAHI Exo-II, several pilot experiments were conducted to assess the presented approach. Initial experiments focused on as-
sessing calibration methods to evaluate if a linear mapping is observed between torque and sEMG and that variability within and between subjects. Further experiments investigated the assistive mode to determine if a reduction in muscle activation was observable.

4.3.1 Calibration Quality

*Linear Trends in Isometric Contractions:* For constant force isometric contractions, a nearly linear relationship is expected between torque and sEMG activity [37]. To assess the quality of the calibration procedure presented in section 4.2.1, one subject was recruited to perform blocks of 10 isometric contractions in four DoF. Approximately two minutes of rest was given between blocks. Figures 4.14-4.17 present the results of this pilot experiment. Data for wrist flexion-extension, wrist radial-ulnar deviation, and elbow flexion-extension were collected in one session with a 500 ms moving window RMS calculation, while the forearm pronation-supination data were collected in a separate session with a 300 ms moving window after implementing DoF specific considerations that will be discussed in Section 4.3.4.

Overall, linear trends were observed in the relationship between commanded exoskeleton torque and the sEMG activity in the agonist channel, \( R^2 \geq .67 \). In several cases, the y-intercept of the least squares line contains a constant offset. This error is likely caused by a combination of biological and mechanical factors. Anecdotally, the subject reported difficulty in feeling the perturbation at low torques. It is possible the subject increased co-contraction in anticipation of the perturbation. Lastly, cross-talk in the forearm is likely a cause of increased activity in the extensor carpi radialis and extensor carpi radialis brevis due to their close proximity to the extensor digitorum, a muscle that primarily contributes to grip.
Figure 4.14 : Elbow Flexion-Extension Calibration Curve, error bars reflect standard error across the 10 isometric contractions.

Figure 4.15 : Wrist Flexion-Extension Calibration Curve, for flexor carpi radialis (FCR) and extensor carpi ulnaris (ECU), error bars reflect standard error across the 10 isometric contractions.
Figure 4.16: Wrist Radial-Ulnar Deviation Calibration Curve, for extensor carpi radialis brevis (ECRB) and flexor carpi ulnaris (FCU), error bars reflect standard error across the 10 isometric contractions.

Figure 4.17: Forearm Pronation-Supination Calibration Curve, error bars reflect standard error across the 10 isometric contractions.
An assumption in this calibration approach is that the commanded torque is the actual torque applied at the joint. As the torque is applied as an open-loop command, errors in modeling will result in errors in the torque applied around the anatomical axes. As previously observed, there appears to be an effect of direction and high variability associated with static friction in the MAHI Exo-II [32]. Additionally, the effects of gravity are likely non-negligible, even in the flexion-extension DoF due to the parallel configuration of the wrist mechanism. Further, motor torque specifications are taken from the manufacturer’s specification sheet and do not necessarily represent the exact value for the motors on the exoskeleton. During low torque commands these inaccuracies become more influential. A practical conclusion drawn from this pilot experiment is the calibration torque should be maximized to minimize the relative effects of model inaccuracies. Additionally, wrapping the subject’s hand to the exoskeleton handle can reduce cross talk due to grip. The commanded torque must remain in the range of the continuous linear output of the motor, however, limiting potential calibration torques.

Calibration Variability: Eight healthy subjects were recruited to explore the variability associated with the sEMG amplitude estimate between calibration perturbations during a single calibration block. Subjects completed the procedure for wrist flexion-extension and wrist radial-ulnar deviation. Results of the pilot experiment are presented in figures 4.18 and 4.19. Mean variation, normalized to the calibration value, was calculated at 20.2% for flexion, 13.3% for extension, 17.9% for radial deviation and 23.7% for ulnar deviation. With minimal practice, subjects were capable of producing repeatable values for low levels of muscle activity. It is possible, the variability observed at these calibration values may be explained by the variability in muscle force output rapidly increases at low force values as low numbers of MU are
Figure 4.18: Variability in calibration for wrist flexion-extension, error bars reflect standard error across the calibration perturbations.

required [63]. High inter-subject variation and variation within the same subject but across muscles highlights the importance of normalization procedures when drawing comparisons across subjects and muscles due to variability in joint stiffnesses and strength.

4.3.2 Effect of Assistive Torque on Tracking Performance During Wrist Flexion-Extension

Experimental Goals: As a pilot experiment for integration of sEMG controllers for the MAHI Exo-II, subject performance in the assistive mode, presented in Section 4.2.4, was investigated. The effect of varying levels of assistance, adjusting $K_{EMG}$, was explored during a tracking task in wrist flexion-extension for healthy subjects. It was postulated that subjects would be able to adapt quickly to the sEMG assistance,
Figure 4.19: Variability in calibration for wrist radial-ulnar deviation, error bars reflect standard error across the calibration perturbations

maintain performance, as measured by target tracking error, and reduce observed muscular effort during the task as measured by the integral of EMG (iEMG), as previously observed for elbow flexion-extension [50]. Back-driving the exoskeleton, $K_{EMG} = 0\%$, served as the control condition. For this experiment, the effect of proportional sEMG assistance was isolated, thus the gain, $K_D$, was set equal to zero.

As the normalization is based on SMVIC at the center of the workspace and only employs two channels, the torque estimate is less accurate under dynamic conditions and at the extreme positions of the workspace. Although limited sEMG information is used to provide the assistive torque, the goal was to provide intuitive assistance allowing the user to move naturally without developing new synergies for movement.

Experimental Protocol: Six healthy subjects (three male, three female, ages 20-30, right hand dominant) were recruited to participate, completing wrist movements...
with their right wrist. Following a signal check on each of the sEMG channels, the exoskeleton was then fit to the subject and center and extreme positions in the parallel mechanism's workspace were chosen. Ground reference for the sEMG signal was attached to the acromion process. As the parallel mechanism workspace varies with differing platform height, as discussed in Section 2.1.5, the extreme positions for each subject varied slightly. The RoM for this experiment was approximately $\pm 20^\circ$.

The subject then completed the calibration protocol described in Section 4.2.1. For the experimental blocks, subjects completed a tracking task, attempting to keep a cursor corresponding to wrist position between two vertical bars as they moved between two targets, as shown in Figure 4.12. The goal trajectory was calculated using the minimum jerk profile (Equation 4.6) given 2 s to complete the movement between targets at the selected left and right extremes of the workspace.

Following calibration, subjects completed 10 movements back-driving the exoskeleton to familiarize themselves with the visual interface. On the visual display, the target alternated between black and red to prompt the user to move to it. The target stopped flashing when the subject arrived within a certain threshold of the goal position (Figure 4.20). The target then remained for 1.5 s until the next target appeared at the other extreme of the visual display. The first experimental block consisted of 70 movements between a target at one extreme of the workspace to a target at the other extreme, while back-driving the exoskeleton. Length of blocks was chosen based on adaptation rates in previous sEMG studies [50, 64]. The subject the completed five more blocks of trials alternating between an experimental $K_{EMG}$ condition (50%, 100%, 150%), and back-driving the exoskeleton. Order for condition was pseudo-randomized, as shown in Figure 4.21.

Data Analysis: Data from the first and last 20 movements in each experimental
block, 10 movements in each direction, were selected for analysis. These data were averaged to account for inter-trial variability in movement and sEMG data. For each movement, data were split into two regions to assess performance during both the dynamic and static portions of the experiment. The dynamic region extended from the time the target was presented until the subject arrived within a certain threshold of the target position, approximately 2 s. The static region extented from 750 ms to 250 ms before the target switch, while holding at the extreme of the workspace.
These regions are shown in Figure 4.22. Mean absolute tracking error was calculated during each of these intervals. iEMG was calculated for the static task in the fixed 500 ms window following post-post processing full wave rectification and 3 Hz low-pass filtering. The sEMG data were not normalized as the comparisons were limited to within subjects and within the same sEMG channel. The difference in performance from the first 20 movements was compared to the last 20 movements to compare learning effects.

Results: Data were analyzed using repeated measures ANOVA in the two segments of the experimental trial. A significance level of $\alpha = .05$ was used in analysis. Post-hoc simple main effects analysis for significant main effects were completed using a false discovery rate (FDR) adjustment while contrasts were employed with a Scheffé
adjustment. Two within subjects factors, movement direction and level of sEMG assistance, were investigated. One subject was identified as a within subjects outlier (> 3 inter-quartile ranges from subject mean) in multiple metrics and removed from analysis. Figures 4.23 and 4.24, present results for tracking error. Significant effects of $K_{EMG}$ were found in the dynamic, $F(1.78, .001) = 10.45$, $p = .018$, $\eta^2_p = .72$, and static, $F(1.74, < .001) = 20.82$, $p = .001$, $\eta^2_p = .84$, portions of the task. A Greenhouse-Geisser correction was applied. No significant effects of direction or interaction between $K_{EMG}$ and direction were observed ($p > .49$).

The iEMG was calculated to estimate muscular effort. No significant effect of $K_{EMG}$ or interaction with direction was observed in the flexor channel (Figure 4.25(a)). Although not significant in the repeated measures ANOVA, it appears as if increasing the gain $K_{EMG}$ reduced activation of the flexor channel while holding at the extreme position corresponding to extension. Qualitatively, the effect of $K_{EMG}$ appears to be more variable during flexion. Two of the five subjects showed reduced sEMG activity, one showed no change in sEMG activity and two showed increasing sEMG activity.
Figure 4.24: Mean position error while target stationary during last 20 movements. Mean calculated collapsing across subjects. Standard error shown with increasing $K_{EMG}$.

In the extensor channel, no significant effect of $K_{EMG}$ was found although there was a significant interaction between $K_{EMG}$ and movement direction, $F(1.78, 21.98) = 8.52$, $p = .014$, $\eta^2_p = .68$. In all but one subject, the relationship between extensor activity during movement in the extension direction decreased monotonically with increasing $K_{EMG}$. In the flexion direction, the relationship varies subject to subject, although it appears the effect is minimal. This interaction, shown in Figure 4.25(b), was decomposed using a post-hoc linear interaction contrast. A significant linear contrast was found, ($p = .01$) suggesting the slopes were different. Combined with a simple main effects analysis, suggesting no effect of $K_{EMG}$ in the flexion direction, there is evidence to suggest $K_{EMG}$ has a linear reduction in recorded extensor activity in the extension direction.

The difference in position error from the first 20 movements and last 20 movements was also investigated to assess adaptation. For the dynamic tracking task, no
significant effect of $K_{EMG}$ was found regarding the change in performance or interaction of $K_{EMG}$ and direction ($p > .22$). Observing Figure 4.26, there appears to be minimal change in the no and low levels of $K_{EMG}$ assistance condition but an improvement in performance for the $K_{EMG} = 150\%$ condition. Observing the results for the steady state performance (Figure 4.27) a similar effect of $K_{EMG}$ appears to be present, although, again, it is not significant at the $\alpha = .05$ level ($p = .064$). No significant effect of direction or interaction of direction and $K_{EMG}$ was observed ($p > .77$).

Adaptation in the iEMG for both channels was also investigated for the flexor and extensor channel. No significant effect of $K_{EMG}$ or significant interaction of $K_{EMG}$ and direction were found ($p > .45$). Results for the difference in sEMG activity in the flexor channel are presented for flexion (Figure 4.28) and extension (Figure 4.29),
Figure 4.26: Position error for tracking a dynamic target. Mean calculated collapsing across subjects. Standard error shown.

Figure 4.27: Position error while target stationary. Mean calculated collapsing across subjects. Standard error shown.
Figure 4.28: Change in iEMG recorded in channel one during wrist flexion. Mean calculated collapsing across subjects. Standard error shown.

Discussion: The objective of this experiment was to assess the ability of healthy subjects to control and exploit an sEMG based assistive torque from the MAHI Exo-II during wrist flexion-extension. Regarding the performance metric, tracking error, subjects attained similar performance levels with low and moderate levels of sEMG assistance during the dynamic portion of the task. While holding at the extremes of the workspace, position error increased with increasing levels of $K_{EMG}$ with little change between back-driving the exoskeleton and $K_{EMG} = 50\%$. At this low level of assistance, it appears subjects were able to adapt and attain similar levels of performance to the no assistance condition. The only significant degradations in performance resulted at $K_{EMG} = 150\%$. Observing Figures 4.27 and 4.26, as subjects were improving in their ability to control the system, but it is unlikely they would have attained the same level of performance as the lower levels of $K_{EMG}$, subjects were not improving in the $K_{EMG} = 100\%$ condition. While interacting with a robotic system,
Figure 4.29: Change in iEMG recorded in channel one during wrist extension. Mean calculated collapsing across subjects. Standard error shown.

Figure 4.30: Change in iEMG recorded in channel two during wrist flexion. Mean calculated collapsing across subjects. Standard error shown.
Figure 4.31: Change in iEMG recorded in channel two during wrist extension. Mean calculated collapsing across subjects. Standard error shown.

Healthy and impaired subjects are capable of adapting to predictable disturbances [65]. It is possible though, the increasing levels of $K_{EMG}$ amplified biological noise and EMI surpassing the ability of the subject to reject unpredictable disturbances. For the proposed approach, the $K_{EMG} = 150\%$ condition resulted in a detrimental impact on performance. Future efforts will focus on distinguishing between environmental interference and biological motor noise to further reduce unpredictable disturbances.

Although decreases in iEMG were observed in the ECU, an average decrease of approximately 40\% for $K_{EMG} = 100\%$ when compared to back-driving the exoskeleton across subjects, high variability prevented statistical significance. The reduction in recorded muscle activity, however, suggests a potential for this simplified approach. A reduction in muscular activity may be beneficial to rehabilitation as assistance may help reduce abnormal synergies in impaired populations [45]. Higher variability was observed in the FCR, although a trend of reduced sEMG activity is visible for the low and middle $K_{EMG}$ conditions. This variability is likely explained by high motor sys-
tem noise at low force levels [63]. Preliminary results from another experiment, with eight subjects, suggest healthy subjects completing a similar wrist flexion-extension movement while back-driving the exoskeleton only generated 2-5% of MVIC sEMG activity (Figure 4.32(a)). In comparison, the extensor generated closer to 20% of the activity associated with a MVIC (Figure 4.32(b)).

Figure 4.32 : sEMG power normalized to MVIC power. Time normalized to time required to complete the movement. Mean calculated collapsing across subjects. Shaded region represents standard error

The only resistance to movement was low friction present in the device and elastic biological elements in the wrist, resulting in low contractile forces in these healthy subjects. Future work will include resistive forces during the tracking task to increase muscular activation in healthy subjects. In this protocol, five subjects did not provide sufficient power to resolve the observed differences in iEMG. For the conditions $K_{EMG} = 50\%$ and $K_{EMG} = 100\%$, antagonist muscle activation did not increase
during the steady or dynamic task. Co-contraction is natural method of increasing stability of performance, especially in unpracticed or unpredictable conditions [66]. The absence of an increase in co-contraction is evidence of an intuitive interface. Subjects were able to adapt and exploit the sEMG assistance at the two lower levels of assistance with little or no impact on performance in a tracking task.

These low forces also led to high variability in comparisons of iEMG between the beginning and end of a block. Although no statistically significant differences were observed, there are trends of decreasing sEMG activity between the first and last movements of the block in the flexor channel (Figures 4.28-4.29) and extensor channel (Figure 4.30). These trends suggest the subjects may be reducing muscular effort with practice, but it is likely that five subjects did not provide sufficient power to resolve these differences. Anecdotally, several subjects reported that the task became easier when they relaxed their muscles suggesting instructing the subject to relax may increase performance.

**Conclusion**: The ability of healthy subjects to use sEMG based robotic assistance during a tracking task in wrist flexion-extension was explored. Low levels of sEMG assistance did not have significant impact on tracking performance. Although no significant differences were found in muscular activity, estimated from iEMG, overall trends of decreasing activation with increasing sEMG assistance were observed. Levels of co-contraction did not increase for the low levels of sEMG assistance suggesting an intuitive interface. Further experiments will investigate simple sEMG assistance in the other MAHI Exo-II DoF and impaired populations.
4.3.3 Velocity Dependence of Assistive Mode

Following the study presented in Section 4.3.2, one of the subjects completed two more experimental blocks several days later. The goal of this pilot experiment was to investigate the effect of movement velocity on tracking performance with sEMG assistance. Initially, the subject completed 20 movements in the $K_{EMG} = 0\%$ condition to re-familiarize themselves with the task. Next they completed two experimental blocks, first $K_{EMG} = 50\%$ then with with $K_{EMG} = 0\%$. The task was the same as described in 4.3.2, except each experimental block consisted of 180 movements, where the time allotted complete the minimum jerk profile decreased from 2 s to 0.8 s, in 0.2 s increments, every 20 movements. Results are shown in Figure 4.33. Data from the last 10 movements from each velocity step were used to compute mean tracking error.

Although position error was higher with sEMG assistance, it is impossible to
discern whether this increase is due to learning effects with a single subject. A linear increase in tracking error was observed in both conditions over this range of peak tracking velocities. A t-test was conducted testing for a difference of slopes. No significant difference was found in the slopes of the two linear regression following a t-test on the slope of the line \( (p = .67) \). The effect of movement speed has a similar effect on tracking error in both \( K_{EMG} \) conditions.

4.3.4 Degree of Freedom Specific Considerations

The sEMG interface has been developed for all four DoF of the MAHI Exo-II. The basic architecture is constant across DoF, but each DoF incorporates slight variations in implementation, aside from different electrode locations. Some practical considerations are presented.

**Elbow:** The potential influence of gravity is highest for the elbow DoF as the entire mass of the forearm and exoskeleton hinges about the joint. Thus a passive counterweight is incorporated into the exoskeleton design. The counterweight must be carefully set for each subject for the center calibration position. A significant directional bias in the sEMG linear mapping is possible in either direction if the weight over compensates or under-compensates for the influence of gravity. If the active DoF is not the elbow, setting the counter weight as far back as possible to support the forearm allows the user to turn off the elbow amplifier and increase the SNR for other DOF.

Further, due to the close proximity of the muscles of the triceps brachii to the elbow actuator, care must be taken to ensure the skin does not rest on the frame of the exoskeleton near the exoskeleton baseplate. A substantial increase in background noise is experienced in this condition. With the handle in the vertical position, the
long head of the triceps brachii appears to produce the most natural interface and highest SNR in a two electrode configuration.

Regarding controller implementation, elbow DoF control is implemented at the joint-space level. The actuator directly manipulates the revolute joint through a cable capstan drive transmission.

Wrist Flexion-Extension and Radial-Ulnar Deviation: In a two electrode configuration, the influence of cross-talk is substantial. During a signal check it is prudent to check for independence of the two channels during movement in both direction. An incorrect electrode placement by 1 cm can result in an uncontrollable system. Further, gripping the exoskeleton handle or opening of the hand activates flexor and extensor muscles near the desired muscles. Wrapping the hand to the exoskeleton handle and instructing subjects to relax their grip reduces cross-talk improving controllability.
Simple gravity compensation has been implemented for the wrist radial-ulnar deviation DoF as a fixed feed-forward torque command. It is easily set in the assessment mode by trial and error until the wrist is supported while the subject is resting. sEMG signal power can be used to ensure the subject is not contracting while setting gravity compensation.

*Forearm:* Cross-talk from muscles that stiffen the wrist can easily exceed the recorded sEMG power from the muscles of interest during forearm pronation-supination. To improve control during forearm pronation-supination, a wrist brace was created to stiffen the joint. Further, placing the thumb on the same side of the handle as the fingers, as shown in Figure 4.34, provides a more intuitive to control interface. Similarly to the elbow, controller implementation occurs at the joint space level.
Chapter 5

Conclusions and Future Work

Rehabilitation robots have garnered much attention over the past couple decades due to their ability to provide consistent therapy in a clinical setting when compared to traditional therapy. A primary challenge in implementing robots for rehabilitation of neurological injury, however, is ensuring user engagement. To this end, it is necessary to discern the intent of the user and providing appropriate sensory feedback to increase the efficacy of motor therapy. One proposed method of discerning the intent of the user is sEMG. The overarching goal of this thesis was to present technical aspects of the MAHI Exo-II relevant to its implementation as a rehabilitation device and a new sEMG interface for the MAHI Exo-II.

Chapter One reviewed current evidence for the efficacy of therapy and rehabilitation robotics. In recent decades, motor therapy has become more prominent as clinicians shifted focus from compensatory practices to rehabilitation. Robots are well suited to the role of rehabilitation for various reasons, including their support of physically weak persons, consistent training, and ability to assess movement quality. Numerous studies have demonstrated their usefulness in a clinical setting including various patient-robot interfaces.

Chapter Two presented technical details of the MAHI Exo-II, upper extremity therapeutic exoskeleton. Forward kinematics, inverse kinematics, and the device Jacobian were derived to achieve task-space control of the wrist parallel mechanism. The device manipulability was determined to calculate the wrist’s theoretical workspace.
Then relevant technical aspects required to implement the device for rehabilitation were presented along with past control schemes.

Chapter Three discussed the practice of EMG recording and application of sEMG to control rehabilitation robots. Due to the origin of the sEMG signal, particular benefits arise in a clinical setting including volitional increases in the patient’s RoM, positive sensory feedback for the heavily impaired patients, reduction of compensatory movements, reduction of unhealthy motor synergies and forced active engagement. All of these factors make sEMG an attractive interface when compared to existing impedance control schemes.

Chapter Four presented the development and initial implementation of an sEMG interface for the MAHI Exo-II. Initially, efforts to obtain a reliable signal in an electrically noisy environment were shown. A calibration procedure and numerous sEMG control modalities were developed and demonstrated in the exoskeleton. Lastly, pilot experiments were conducted to assess aspects of the developed interface. It was suggested that subjects could reduce muscular effort without significant impact on performance with a relatively simple assistive control scheme, when compared to muscle mappings.

Future work for the MAHI Exo-II sEMG interface will consist of three primary efforts. Pilot experiments incorporating the presented sEMG control modes for impaired populations will be necessary. Initially, experiments in the triggered mode will assess the efficacy of the interface for heavily impaired subjects in the elbow DoF. Following successful implementation in this pilot study, a more rigorous clinical study, incorporating all DoF over multiple weeks, will be conducted. Specific control modes may be matched based on level of impairment. As a parallel effort, a more extensive sEMG to joint force mapping may be beneficial. Although the sim-
plified approach presented in this thesis will likely improve clinical outcomes, more complex controllers, such as an sEMG based assist-as-needed implementation would require more accurate joint torque predictions. A one DoF, wrist flexion-extension test bed for calibration and implementation of a time delayed artificial neural network will provide the initial steps toward this effort. Lastly, experiments should be conducted to assess the sources of noise in the sEMG signal. A protocol should be accomplished that distinguishes between the influence of nervous system noise and environmental electromagnetic interference. Knowledge of the source of noise would allow implementation of additional noise reduction measures.
Bibliography


