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Subject Adaptive Control Paradigms for Robotic Rehabilitation

by

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ABSTRACT

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As the majority of the activities of daily living involve distal upper extremity movement, effective rehabilitation of the upper limbs, especially the distal joints, is crucial. Due to their inherent capabilities to deliver intensive and repetitive therapy, robotic devices are increasingly being used for the rehabilitation of neurologically impaired individuals. However, not every robotic device or therapy protocol has been shown to promote plasticity-mediated recovery. It is necessary that the robotic therapy must be capable of engaging the participant. Furthermore, the mechanical design of the robotic device must exhibit specific properties, such as low apparent inertia and friction, isotropic dynamic characteristics, and minimal backlash, to support sophisticated interaction modes. In this thesis a subject adaptive controller, capable of adaptively estimating position-dependent subject input and providing only the required amount of assistance is presented. This controller aims to maximize the participants’ engagement in their therapy. Features of the controller were validated via simulations and experiments, and clinical validation was conducted with an elbow-forearm-wrist exoskeleton, the MAHI Exo-II. Results highlighted limitations in both the hardware’s workspace and in the controller’s performance. To address this limitations a novel wrist-forearm exoskeleton, the RiceWrsit-S, is proposed and an improved minimally assistive (mAAN) controller is presented. The controller is capable of estimating sub-
ject input as a function of time, hence it can estimate subject input regardless of position dependency, as opposed to the subject adaptive controller proposed in the first part of the thesis. Novel features of the controller algorithm for maintaining subject engagement via performance based challenge modulation while still satisfying ultimately bounded error performance are presented. The mAAN controller and consistency of the accompanying algorithms are demonstrated experimentally with healthy subjects and with one subject with incomplete spinal cord injury in the RiceWrist-S. The proposed controllers and the novel exoskeletal device provide a means for a more effective robot-aided rehabilitation of neurologically impaired individuals.
to my mother
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Chapter 1

Introduction

Neurological impairments, such as stroke and spinal cord injury (SCI), affect a significant portion of the population, and research findings show that intensive rehabilitation can induce neural plasticity, thereby affecting recovery of function and independence among these populations [4]. In the United States, about 795,000 people suffer a stroke each year. Stroke, the leading cause of long-term disability, has a significant social and economic impact with an estimated $38.6 billion annual cost [5]. Additionally, there are approximately 12,000 incidences of SCI in the United States each year [6], with estimated total yearly direct and indirect costs of $14.5 billion and $5.5 billion, respectively [7]. Both of these neurological injuries give rise to significant upper limb motor impairment. Given the clear economical impact of these conditions, and owing to the beneficial effects of intensive physical therapy, interest in robotic rehabilitation has increased greatly in recent years. The potential for robotic devices to significantly impact therapy practices, and in turn functional recovery, is attributed to the fact that robotic devices can deliver this beneficial intensive rehabilitation in a more effective manner compared to classical therapy [8].

Generally speaking, rehabilitation of patients affected by neurological lesions, including stroke and SCI, is intended to induce brain and spinal cord plasticity and to improve functional outcomes. In order to fulfill this goal, therapy must be intensive, involving high numbers of repetitions spanning multiple consecutive sessions [9]. Robotic devices are well suited to offer consistent delivery of intensive therapy, coupled
with the opportunity to perform objective and quantitative performance evaluation of patients using the vast sensor data inherently available in these robotic devices.

Not every robotic device or therapy protocol has been shown to be capable of promoting neuroplasticity-mediated recovery in stroke or SCI populations. Neuroplasticity refers to changes in neural pathways and synapses due to changes in behavior [10]. To be able to trigger neuroplasticity, robotic therapy must engage the participant, which can be achieved by sharing control of movements with the subjects through interaction controllers [11], patient adaptive control modes [12], or progressively resisting control modes [13]. Furthermore, the mechanical design of the robotic device must exhibit specific properties, such as low apparent inertia and friction, isotropic dynamic characteristics and minimal backlash to support these various interaction modes, besides providing large workspace and high torque output capabilities.

1.1 Motivation and Problem Definition

1.1.1 Control Design

One of the most critical areas of research in upper-extremity rehabilitation robotics is the development of control strategies capable of regulating physical interaction with the subject in a way that promotes plasticity, and therefore improves motor recovery [14]. Assistive strategies, which target a wide range of severely to mildly impaired subjects, are the most extensively investigated controller paradigm in the rehabilitation robotics community [14]. Since there is strong evidence that active participation induces neural plasticity [15], assistive controllers should intervene minimally in order to best promote involvement, plasticity, and recovery. Addressing this phenomenon is currently an active area of research. Several controllers, using strategies ranging from
impedance to nonlinear adaptive control have been proposed, but are still susceptible to a few shortcomings. Beyond minimal intervention, an important phenomenon about robot-aided rehabilitation is that unless properly challenged, subjects may still let the robot take control [16]. Hence, a mechanism for sustaining user engagement in an assistive control scheme is needed. Existing approaches either lack optimal intervention, or implementation of a proper challenging mechanism within the given controller scheme. Therefore, I have focused my research on development of subject adaptive controllers which aim to promote subject involvement.

1.1.2 Mechanical Design

From a mechanical design point of view, rehabilitation robots can be broadly classified into two groups, end-effector based robots and exoskeletal robots. Although end-effector based robots provide training capability encapsulating a large portion of the functional workspace, they do not possess the ability to apply torques to specific joints of the arm, a crucial functionality required in many therapy regimens. Exoskeletons, on the other hand, are designed to resemble human anatomy and their structure enables individual actuation of joints. Recently, rehabilitation engineering research has increasingly focused on quantitative evaluation of residual motor abilities in an effort to obtain an objective evaluation of rehabilitation and pharmacological treatment effects [17]. Exoskeletons offer the advantage of precisely recording and monitoring isolated joint movements of the arm and wrist and hence are a better-suited design option versus end-effector based designs for this purpose.

Besides structural transparency, an ideal robotic rehabilitation device must (a) train the complete functional workspace of a human limb, as the benefit of sensorimotor training is specific to the muscle groups and limb segments which are exercised,
(b) activate individual joints to induce exact ergonomic movements in a patient, and
(c) not cause discomfort or safety hazards for the user during movement [18].

Though a number of exoskeletal robotic devices have been proposed for the upper limb, to date none have been proposed for the distal part of the upper extremity which satisfy the aforementioned properties. Therefore, in the mechanical design part of my thesis, I focus on developing an ergonomic exoskeleton device for distal upper-extremity, which is capable of corresponding the complete workspace of human joints, while satisfying key structural transparency properties such as low apparent inertia and friction, isotropic dynamic characteristics and minimal backlash.

1.2 Objective

The objectives of this research are twofold. The first objective is to develop novel subject-adaptive control paradigms for upper extremity robot-aided rehabilitation, which are capable of inducing and maintaining subject engagement. The second objective is the development of high-fidelity robotic devices for upper extremity rehabilitation. Towards accomplishment of the first objective, I incorporated adaptive input modeling and sensorless force estimation techniques within assistive controller algorithms to induce subject engagement by providing only the required amount of assistance. Additionally, I proposed novel algorithms for directly manipulating the error bounds on the trajectory errors based on subject performance for maintaining subject engagement, while satisfying stable human-robot interaction. For the second objective, I developed a 3 DOF exoskeletal device, RiceWrist-S, for forearm-wrist rehabilitation. The RiceWrist-S is capable of covering the complete functional workspace of the user, providing high torque output, while satisfying structural transparency and ergonomic human machine interaction.
1.3 Contributions

The contributions of this thesis are categorized by their association to control design or mechanical design development domains.

1.3.1 Control Design

An adaptive controller, which uses a Gaussian network for modeling position dependent input force, is developed and implemented for the 3 DOF RiceWrist, a serial-in-parallel robot mechanism for upper extremity robotic rehabilitation. Simulation and experimental results that compare the performance of the adaptive controller to a proportional-derivative controller show that the trajectory tracking performance of the adaptive controller is better compared to the performance of a PD controller using the same values of feed-back gains. The results of this study were published in the proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR 2013) [19].

A novel subject-adaptive control algorithm, using a Gaussian network based adaptive controller in conjunction with a feedback gain modification algorithm is proposed. The developed controller is capable of changing the amount of error allowed during movement execution, while simultaneously estimating the forces provided by the participant that contribute to movement execution. Additionally, a physiologically optimal trajectory profile for wrist pointing movements is experimentally defined. The novel subject-adaptive control algorithm is validated with the RiceWrist system in an experimental study involving five healthy subjects, with the modified assist-as-needed adaptive controller decreasing its feedback control action when a subject shifts his behavior from passively riding along with the robot during movement to actively engaging and initiating movements to the desired on-screen targets. The results of this
study were published in the ASME/IEEE Transaction on Mechatronics [20].

A novel minimal assist as needed (mAAN) controller, which employs a non-linear disturbance observer, is developed. The controller is capable of estimating the subject input as a function of time in a fast, stable, and accurate manner. Two additional algorithms are introduced to further promote active participation of subjects with varying degrees of impairment. First, a bound modification algorithm is introduced which alters allowable error. Second, a decayed disturbance rejection algorithm is presented which supports subjects who are capable of leading the desired trajectory. The mAAN controller and accompanying algorithms are demonstrated experimentally with healthy subjects in the RiceWrist-S. Portions of this work is detailed in a manuscript conditionally accepted for publication in the IEEE Transactions on Robotics.

1.3.2 Mechanical Design

The mechanical design of a 3 DOF forearm-wrist exoskeletal device, RiceWrist-S, is presented. The mechanical design aims to provide a large workspace and torque output, while satisfying structural transparency and ergonomic human machine interaction. Special cable routing mechanisms allow positioning of the actuators to decrease apparent inertial and gravitational loading. Cable drive transmission provides minimal friction and zero backlash. A passive DOF at the handle corrects for any misalignments between human and robot rotation axes, and provides natural posture by adding redundancy to the mechanism. The key mechanical properties of the device were experimentally characterized to assess suitability for rehabilitation applications. This work has been published in the proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomecha-
Clinical validation of RiceWrist-S as an upper limb rehabilitation device was conducted via a single case study with an individual with chronic incomplete spinal cord injury. Both clinical measures and robotic measures of movement smoothness indicated functional gains, supporting the hypothesis that intensive upper limb rehabilitation with the RiceWrist-S would show beneficial outcomes. The results of this study were published in Cambridge University Press Robotica [23].

1.4 Organization of the Thesis

The thesis is organized as follows: Chapter 2 introduces the hardware, MAHI Exo-II, employed in the studies presented in Chapter 3 and 4. Chapter 3 presents a subject-adaptive control algorithm, using a Gaussian network based adaptive controller in conjunction with a novel feedback gain modification algorithm. Chapter 4 gives the preliminary results of a clinical study, aimed at testing the efficacy of the novel subject-adaptive controller, and discusses the observed shortcomings of both the hardware and the controller. Chapter 5 introduces the mechanical design, system characterization, and clinical validation of a novel upper extremity rehabilitation device, RiceWrist-S. Chapter 6 presents a novel minimal assist as needed (mAAN) controller, which aims to address the shortcomings of the subject adaptive controller presented in Chapter 3. Chapter 7 summarizes the overall findings and conclusions.
Chapter 2

MAHI Exo-II: Kinematic Structure and Mechanical Design

In this chapter, I present the design of MAHI Exo-II (see Fig. 2.1), a robotic exoskeleton for rehabilitation of the upper extremity after stroke, spinal cord injury, or other brain injuries. The five degree-of-freedom robot enables elbow flexion-extension, forearm pronation-supination, wrist flexion-extension, and radial-ulnar deviation.

This chapter has been adapted from [24], and is included here for completeness. Portions of this chapter were published in the Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR 2011) [25] and I gratefully acknowledge my collaborators in this publication.

Figure 2.1 : MAHI Exo-II – Elbow, forearm and wrist exoskeleton for stroke and spinal cord injury (SCI) rehabilitation.
2.1 Introduction

In this chapter the design of MAHI Exo-II, an elbow, forearm and wrist exoskeleton designed and manufactured for rehabilitation of stroke and SCI patients, is presented. The mechanical design builds upon its predecessor, MAHI Exo-I [1,26] and has a total of 5 DOF. The device offers several significant design improvements compared to its predecessor, MAHI Exo-I. Specifically, issues with backlash and singularities in the wrist mechanism have been resolved, torque output has been increased in the forearm and elbow joints, a passive degree of freedom has been added to allow shoulder abduction thereby improving alignment especially for users who are wheelchair-bound, and the hardware now can be used for treatment of both sides and enables simplified and fast swapping of treatment side.

2.2 Literature Review

Exoskeletal upper extremity rehabilitation devices possess essential advantages over end-effector based rehabilitation devices such as, the ability to apply torques to specific joints, and precisely recording and monitoring the joint movements. In the rehabilitation robotics community there have been different approaches to obtain an optimal device which can be incorporated in the upper extremity rehabilitation of neurologically impaired subjects. Although the proposed devices can be categorized in a number of ways, from a mechanical design point of view I will be evaluating them based on two important aspects: the number of employed degree of freedom (DOF), and the type of employed actuation.

One of the proposed design strategies is to correspond as many joints in the human arm as possible. The main aim with this approach is to be able to include
these devices into functional training routines. An early example of full upper-body rehabilitation devices was developed by Tsagarakis et al. [27]. The device employs 7 actuated DOF, and uses pneumatically-actuated muscles (pMAs) for a compact and lightweight design. An electrically actuated 7-DOF device developed by Rosen et al. [3] is able to achieve 99% of the range of motion (ROM) required for ADL. Mihelj et al. developed a 6-DOF, electrically actuated device, ARMin [28], which mainly focuses on creating a more natural movement in the shoulder complex of the user. A more recent upper-body exoskeleton design, X-Arm2, by Schiele et al. [29], employs 8 actuated and 6 passive DOFs in order to alleviate ergonomic interaction between device and the user.

Exoskeleton devices, in essence, aim to replicate the human kinematic in the intended joints. Hence alignment of the the rotation axes of the exoskeletal device with the user’s biological axes of rotations is an important requirement [18]. However with the increase of the number of DOF of the device, the difficulty of achieving this requirement is likely to increase and possibly require highly complex designs. Also, there have been studies showing that functional training, which is the main reason behind development of exoskeletal devices with high DOFs, does not actually provide more benefit than single DOF isolated therapies in terms of motor rehabilitation [9]. In fact, a recent robotic rehabilitation study suggests that multi-joint functional robotic training is not decisively superior to single joint robotic training [30]. Considering these respects, some research groups adopted a strategy of developing more simplified designs which focus on selected joints of the upper-extremity. BONES [31], developed by Klein et al., is a 4-DOF exoskeleton, which could accommodate shoulder horizontal flexion/extension, upper arm internal/external rotation, elbow flexion/extension, forearm pronation/supination. CAREX [32], a cable driven upper arm exoskeleton,
and L-Exos [33], a force-feedback arm exoskeleton mainly focused on proximal part of the upper extremity and could correspond three shoulder rotations and elbow flexion/extension. Although recent upper limb exoskeleton devices give primary importance to more proximal parts such as shoulder complex, there are designs which focus more on the distal part of the human arm. Wrist portion of the MIT-Manus [34] developed by Krebs et al. and 3 DOF wrist robotic exoskeleton [35] by Squeri et al. are able to accommodate wrist flexion/extension, wrist abduction/adduction and forearm pronation supination.

Pneumatic and electrical actuators are the two most widely employed actuation types for exoskeletal upper extremity rehabilitation devices. The main advantage of the pneumatic actuators is their high power to weight ratio which enables design of smaller size/lighter devices. Some of the well known pneumatically actuated devices, which employ pneumatic muscle actuators (pMAs), are Pneu-WREX [36], developed by Sanchez et al., BONES [31], developed by Klein et al., and 7 DOF exoskeleton [27], developed by Tsagarakis et al. Although the electrical actuators provide lower power to weight ratio, they do not possess intrinsic nonlinearities as pneumatic actuators do (such as dead-band, mass flow, effects of change in pressure), they are able to provide a higher band-width, and hence allow implementation of more sophisticated controllers. Consequently the electrical actuators are overwhelmingly preferred over pneumatic actuators in the rehabilitation robotics community. Main examples include, but not limited to, X-Arm2 [29], ARMin [28], CAREX [32], and L-Exos [33].

In this chapter, I present the design of an electrically actuated elbow, forearm and wrist exoskeleton, MAHI Exo-II. The structure of the chapter is as follows: Section 2.3 details the kinematic structure of the system and presents the design improvements based on the deficiencies of the previous design. Section 2.4 explains the advantages of
the new design over previous design, and presents the capabilities and characteristics of the new design.

2.3 System Description

2.3.1 Kinematic Structure

The five degree-of-freedom MAHI Exo-II is a robotic exoskeleton that enables elbow flexion-extension, forearm pronation-supination, wrist flexion-extension, and radial-ulnar deviation. Before making a detailed description of the kinematic structure of the exoskeleton, human arm kinematics will be investigated.

2.3.1.1 Human Arm Kinematics

It is fair to say that nearly all the activities of daily living (ADL) (eating, drinking, cleaning, dressing, etc.) involve upper extremity movements. So, for a stroke, spinal cord injury or any other brain injury patient, rehabilitation of upper extremities is crucial for restoring the functionality to be able to achieve ADL. Since robotic rehabilitation has been introduced to the field, exoskeletal devices have been drawing attention due to their structural features. They provide the opportunity to apply desired torques/forces throughout the desired range of motion at the specified joints of human limb. Because the limb itself becomes a part of the exoskeletal system during operation, both the capabilities and the limits of the human arm have to be considered carefully, throughout the design process. So, understanding the nature of the human arm is a vital step in the development of upper limb rehabilitation exoskeleton devices.

The human arm includes 7 DOF: shoulder vertical and horizontal flexion/extension,
shoulder internal/external rotation, elbow flexion/extension, forearm pronation/supination, wrist flexion/extension and wrist radial/ulnar deviation (as depicted in Fig. 2.2). As the primary goal of rehabilitation is to restore function in ADL, defining the torque and workspace capabilities of the human arm as target values for the device is excessive. Instead, setting the target values as the necessary values to complete the ADL will result a more reasonable set of design objectives.

Figure 2.2: Human arm kinematics – Axis 1: shoulder vertical flexion/extension, Axis 2: shoulder horizontal flexion/extension, Axis 3: shoulder internal/external rotation, Axis 4: elbow flexion/extension, Axis 7: forearm pronation/supination, Axis 5: wrist flexion/extension and Axis 6: wrist radial/ulnar deviation. (Adopted from [37])
Rosen et al. [37] performed a pilot study to determine the kinematic and dynamic requirements of an exoskeleton arm for functional use. In their study, human arm motions were recorded during 19 ADL, which included eating, drinking, general reaching tasks, functional tasks and hygiene related tasks, by using a motion capture system. Torque values were calculated using both a modeling simulation package (Cosmos/Motion, Solidworks) and an analytical approach (Autolev, Online Dynamics). The resulting torque and ROM values for every joint are given in Table 2.1.

In the development of MAHI Exo-II, the values that are presented in Table 2.1 have been taken as the target specifications, and the achieved values are presented in Section 2.4.

<table>
<thead>
<tr>
<th>Joint</th>
<th>ROM(deg)</th>
<th>Torque(Nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shoulder Vertical Flexion/Extension</td>
<td>105</td>
<td>9.6</td>
</tr>
<tr>
<td>Shoulder Horizontal Flexion/Extension</td>
<td>130</td>
<td>7.2</td>
</tr>
<tr>
<td>Upper arm Internal/External Rotation</td>
<td>120</td>
<td>3.2</td>
</tr>
<tr>
<td>Elbow Flexion/Extension</td>
<td>150</td>
<td>3.5</td>
</tr>
<tr>
<td>Forearm Pronation/Supination</td>
<td>150</td>
<td>0.06</td>
</tr>
<tr>
<td>Wrist Flexion/Extension</td>
<td>115</td>
<td>0.35</td>
</tr>
<tr>
<td>Wrist Radial/Ulnar Deviation</td>
<td>70</td>
<td>0.35</td>
</tr>
</tbody>
</table>

Table 2.1: The torque and workspace capabilities of human arm for 19 activities of daily living (ADL).
2.3.1.2 Robot Kinematics

The basic kinematic structure of the five degree of freedom MAHI Exo-II is depicted in Fig. 2.3. The exoskeleton is comprised of a revolute joint at the elbow, a revolute joint for forearm rotation, and a 3-RPS (revolute-prismatic-spherical) serial-in-parallel wrist. The first two DOF correspond to elbow and forearm rotations. Out of two rotational and one translational (distance of bottom plate from top plate) DOF of the 3-RPS platform, the two rotational DOF correspond to wrist flexion/extension and abduction/adduction. The fifth DOF accounts for minor misalignments of the wrist rotation axes with the device, which may become a problem especially during movement.

Figure 2.3 : Kinematic structure of MAHI Exo II – A 3-RPS (Revolute-Prismatic-Spherical) platform constitutes the wrist degrees-of-freedom of the robot and is in serial configuration with forearm and elbow degrees-of-freedom. (Adopted from [1])
2.3.1.3 Kinematics of Elbow and Forearm Joints

The coordinate frames assigned to the joints of the system are depicted in Fig. 2.3. Frame \{1\} is the Newtonian frame (ground), frames \{2\}, \{3\} and \{4\} are fixed to the elbow joint, base and top plate of the wrist platform respectively. The transformation between frame \{1\} and frame \{3\} accounts for the rotations at the elbow and the forearm joint (as well as the constant distance from elbow joint to the base plate) and the Denavit-Hartenberg parameters are given in Table 2.3 as

<table>
<thead>
<tr>
<th>Joint</th>
<th>(\text{rot}(x))</th>
<th>(\text{tr}(x))</th>
<th>(\text{rot}(z))</th>
<th>(\text{tr}(z))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow</td>
<td>0</td>
<td>0</td>
<td>(\theta_4)</td>
<td>0</td>
</tr>
<tr>
<td>Forearm</td>
<td>(-\frac{\pi}{2})</td>
<td>0</td>
<td>(\theta_5)</td>
<td>(d)</td>
</tr>
</tbody>
</table>

Table 2.2 : Link parameters for the Elbow and Forearm joints

where \(\theta_4\) and \(\theta_5\) are rotation angles of elbow and forearm joint respectively, and \((0, -d, 0)^T\) is the location of the base plate of the wrist in frame \{2\}. Consequently the transformation matrices between frame \{1\} and frame \{2\}; and frame \{2\} and frame \{3\} are given as

\[
^1T_2 = \begin{bmatrix}
\cos \theta_4 & -\sin \theta_4 & 0 & 0 \\
\sin \theta_4 & \cos \theta_4 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\] (2.1)
Considering that the elbow and forearm joints of the robot are coincident with the operator’s elbow and forearm joints, transformation matrices $^1T_2$ and $^2T_3$ can be used to determine the inverse and forward kinematic measurements of these joints.

### 2.3.1.4 Kinematics of Wrist Module

The wrist module of MAHI Exo-II employs a 3-RPS parallel mechanism (Fig. 2.3), which is first presented by Lee and Shah [38]. The mechanism comprises a base plate, a top plate (which are depicted as frame $\{3\}$ and frame $\{4\}$ respectively in Fig. 2.3), and three extensible links (with lengths $l_1$, $l_2$, $l_3$) which connect the base plate to the top plate. The links are connected to the base plate with revolute joints (R1, R2, R3) and to the top plate with spherical joints (S1, S2, S3). Spherical joints are placed 120° apart from each other on the top plate and similarly the revolute joints are placed equally on the base plate. The handle which is held by the patient is attached to the top plate. For the ease of calculations, the coordinate frames $x_3y_3z_3$ and $x_4y_4z_4$ are attached to the centers of base plate and top plate, whose radii are $R$ and $r$, respectively. Both $z_3$-axis and $z_4$-axis are perpendicular to the planes to which they are attached, and $x_3$-axis and $x_4$-axis point to the revolute joint $R_1$ and the spherical joint $S_1$ respectively. The coordinates of the revolute joints in frame $\{3\}$ are

\[
^2T_3 = \begin{bmatrix}
    \cos \theta_5 & -\sin \theta_5 & 0 & 0 \\
    0 & 0 & 1 & -d \\
    \sin \theta_5 & \cos \theta_5 & 0 & 0 \\
    0 & 0 & 0 & 1
\end{bmatrix}
\]
\[ R_1 = \begin{bmatrix} R \\ 0 \\ 0 \end{bmatrix} \]

\[ R_2 = \begin{bmatrix} -\frac{1}{2}R \\ \frac{\sqrt{3}}{2}R \\ 0 \end{bmatrix} \]  \hspace{1cm} (2.3)

\[ R_3 = \begin{bmatrix} -\frac{1}{2}R \\ -\frac{\sqrt{3}}{2}R \\ 0 \end{bmatrix} \]

and the coordinates of the spherical joints in the frame \{4\} are

\[ ^4S_1 = \begin{bmatrix} r \\ 0 \\ 0 \end{bmatrix} \]

\[ ^4S_2 = \begin{bmatrix} -\frac{1}{2}r \\ \frac{\sqrt{3}}{2}r \\ 0 \end{bmatrix} \] \hspace{1cm} (2.4)

\[ ^4S_3 = \begin{bmatrix} -\frac{1}{2}r \\ -\frac{\sqrt{3}}{2}r \\ 0 \end{bmatrix} \]

The transformation matrix between frame \{3\} and frame \{4\}, \(^3T_4\) can be written as
\[ \begin{pmatrix} n_1 & o_1 & a_1 & p_1 \\ n_2 & o_2 & a_2 & p_2 \\ n_3 & o_3 & a_3 & p_3 \\ 0 & 0 & 0 & 1 \end{pmatrix} \] (2.5)

where \((p_1, p_2, p_3)^T\) represents the position of the origin of the frame \(\{4\}\) in frame \(\{3\}\); and \((n_1, n_2, n_3)^T\), \((o_1, o_2, o_3)^T\) and \((a_1, a_2, a_3)^T\) are the directional cosines of the unit vectors \(x\), \(y\) and \(z\) in frame \(\{3\}\). For simplification of the calculations, all lengths and coordinates are normalized with respect to the base plate’s radius \(R\) as

\[
\rho = \frac{r}{R},
\]

\[
L_i = \frac{l_i}{R},
\]

\[
P_i = \frac{p_i}{R}.
\]

In the following sections, forward and inverse kinematic analysis of the 3-RPS mechanism by using the methodology of [38] and [1] are presented. Subsequently, real-time computation of the kinematics of 3-RPS mechanism with a symbol manipulation software, MotionGenesis (previously Autolev from Online Dynamics), is introduced.

### 2.3.1.5 Forward Kinematics

The 3-RPS mechanism has two rotational degrees-of-freedom and one translational degree-of-freedom. Because the mechanism is a parallel manipulator, it has multiple constraint equations (three equations for this particular mechanism), and the orientation and the position of the top plate are calculated, in terms of the link lengths, by solving these three configuration constraint equations simultaneously. The angle between the \(R_iS_i\) link and the base plate is \(\theta_i\) and accordingly, the coordinates of the spherical joints with respect to the frame \(\{3\}\) are
\[
^3S_1 = \begin{bmatrix}
1 - L_1 \cos \theta_1 \\
0 \\
L_1 \sin \theta_1
\end{bmatrix}
\]

\[
^3S_2 = \begin{bmatrix}
-\frac{1}{2}(1 - L_2 \cos \theta_2) \\
\frac{\sqrt{3}}{2}(1 - L_2 \cos \theta_2) \\
L_2 \sin \theta_2
\end{bmatrix}
\]

\[
^3S_3 = \begin{bmatrix}
-\frac{1}{2}(1 - L_3 \cos \theta_3) \\
-\frac{\sqrt{3}}{2}(1 - L_3 \cos \theta_3) \\
L_3 \sin \theta_3
\end{bmatrix}
\]

Considering that the distance between spherical joints is $\sqrt{3}r$, the constraint equations can be written as

\[
L_1^2 + L_2^2 - 3 - 3p^2 + L_1L_2 \cos \theta_1 \cos \theta_2 - 2L_1L_2 \sin \theta_1 \sin \theta_2 - 3L_1 \cos \theta_1 - 3L_2 \cos \theta_2 = 0
\]

(2.7)

\[
L_3^2 + L_2^2 - 3 - 3p^2 + L_3L_2 \cos \theta_3 \cos \theta_2 - 2L_3L_2 \sin \theta_3 \sin \theta_2 - 3L_3 \cos \theta_3 - 3L_2 \cos \theta_2 = 0
\]

(2.8)

\[
L_1^2 + L_3^2 - 3 - 3p^2 + L_1L_3 \cos \theta_1 \cos \theta_3 - 2L_1L_3 \sin \theta_1 \sin \theta_3 - 3L_1 \cos \theta_1 - 3L_3 \cos \theta_3 = 0
\]

(2.9)

The top plate of the mechanism is physically constrained to move on only one side of the base plate, so $p_3$ is always positive. This brings the following relation:

\[180^\circ > \theta_i > 0^\circ\]
Thus, Equations 2.7-2.9 can be solved numerically for given link lengths, and unique solutions for $\theta_i$ can be calculated. Considering that the spherical joints are located on the edges of an equilateral triangle on the top plate, the position vector of the top plate can be calculated by using the obtained $\theta_i$ values and link lengths as

$$P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \end{bmatrix} = \frac{1}{3} \sum_{i=1}^{3} S_i \quad (2.10)$$

The coordinates of the spherical joints, by using transformation matrix $^3T_4$ can be expressed as

$$\begin{bmatrix} ^3S_i \\ 1 \end{bmatrix} = ^3T_4 \begin{bmatrix} ^4S_i \\ 1 \end{bmatrix} \quad (2.11)$$

The elements of directional cosine vectors can be determined by using the Equations 2.4, 2.6 and 2.11. So the components of vector $n$ are

$$n_1 = \frac{1 - L_1 \cos \theta_1 - P_1}{\rho}$$
$$n_2 = -\frac{P_2}{\rho}$$
$$n_3 = \frac{L_1 \sin \theta_1 - P_3}{\rho} \quad (2.12)$$

and the components of vector $o$ are

$$o_1 = n_2$$
$$o_2 = \frac{\sqrt{3} - \sqrt{3}L_2 \cos \theta_2 - 3P_2}{\sqrt{3}\rho}$$
$$o_3 = \frac{2L_2 \sin \theta_2 + L_1 \sin \theta_1 - 3P_3}{\sqrt{3}\rho} \quad (2.13)$$
The orthogonality of the unit vectors $\mathbf{n}$, $\mathbf{o}$ and $\mathbf{a}$ allows to determine the components of vector $\mathbf{a}$

\begin{align*}
a_1 &= n_2 o_3 - n_3 o_2 \\
a_2 &= n_3 o_1 - n_1 o_3 \\
a_3 &= n_1 o_2 - n_2 o_1
\end{align*}  \quad (2.14)

Equations 2.10 and 2.12-2.14 can be used to determine the transformation matrix $^3T_4$ and subsequently, the Euler-$xyz$ angles $\alpha$, $\beta$ and $\gamma$ can be represented as

\begin{align*}
\beta &= \sin^{-1}(n_3)  \quad (2.15) \\
\alpha &= \text{atan2}(-o_3/\cos(\beta), a_3/\cos(\beta))  \quad (2.16) \\
\gamma &= \text{atan2}(-n_2/\cos(\beta), n_1/\cos(\beta))  \quad (2.17)
\end{align*}

The important point here is that the wrist joint of the patient is coincided with the coordinate center of the top plate during the training sessions and the Euler angles $\alpha$ and $\beta$ correspond to the wrist flexion/extension and radial/ulnar deviation respectively. If Euler angle $\beta = \pm 90^\circ$, Euler angles $\alpha$ and $\gamma$ become indeterminant, as can be seen from Equations 2.16 and 2.17, but the physical constraints prevent this situation from occurring. Another important point to consider is that the top plate cannot make any rotation around the $z_4$-axis, so $\gamma = 0$ most of the time.
2.3.1.6 Inverse Kinematics

The calculation of the necessary joint space positions to achieve a desired task space position of the end-effector can be carried out using inverse kinematics equations. The position of the end-effector of the 3-RPS mechanism (top plate) can be defined by two rotations, Euler angles $\alpha$ and $\beta$, and a translation, $P_3$. Because the Euler angle $\gamma = 0$, as stated above, the direction cosine vectors can easily be calculated. The revolute joints constrain the links $R_1S_1$, $R_2S_2$ and $R_3S_3$ to move in the planes $y = 0$, $y = -\sqrt{3}$ and $y = \sqrt{3}$. This relation, combined with the right hand side of Equation 2.11, brings

\begin{equation}
 n_2\rho + P_2 = 0 \tag{2.18}
\end{equation}

\begin{equation}
 -n_2\rho + \sqrt{3}o_2\rho + 2P_2 = -\sqrt{3}[-n_1\rho + \sqrt{3}o_1\rho + 2P_1] \tag{2.19}
\end{equation}

\begin{equation}
 -n_2\rho - \sqrt{3}o_2\rho + 2P_2 = \sqrt{3}[-n_1\rho - \sqrt{3}o_1\rho + 2P_1] \tag{2.20}
\end{equation}

Equations 2.19 and 2.20 can further be simplified

\begin{equation}
 n_2 = o_1 \tag{2.21}
\end{equation}

\begin{equation}
 P_1 = \frac{\rho}{2}(n_1 - o_2) \tag{2.22}
\end{equation}

Once $P_1$ and $P_2$ are calculated by using Equations 2.18 and 2.22, the transformation matrix $^3T_4$ can be computed. Consequently, the link lengths, $L_1$, $L_2$ and $L_3$ can be calculated by using Equation 2.11.
2.3.1.7 Real-Time Computation of the Kinematics of 3-RPS

The real-time computation of the position of the end-effector for a given set of joint variables (forward kinematics), and the joint variables for a desired end-effector position (inverse kinematics) of a robotic manipulator are crucial for control applications. Although the governing equations for inverse and forward kinematics calculations are derived, as presented in the preceding sections, a powerful and highly-advanced symbolic manipulator software, MotionGenesis (previously Autolev), has been used for real-time kinematics calculations to generate more robust solutions. MotionGenesis allows one to define a physical mechanism by using the built-in physical objects such as points, particles, frames and bodies. The software includes commands for calculating angles and distances between objects. Furthermore, the software enables one to define the rotations between objects and automatically calculates rotation matrices. The built-in solver for sets of nonlinear algebraic equations allows one to calculate inverse and forward kinematics. MotionGenesis is capable of creating compact C, MATLAB, and Fortran codes for real-time applications.

2.3.2 Design Description

The new design, while maintaining the basic kinematic structure and grounded nature of the original design, introduces a number of significant design improvements based on the deficiencies of the previous design. The issues and the proposed solutions are presented in detail below, grouped under wrist, forearm and elbow subsections.

2.3.2.1 Wrist Mechanical Design

Based on the results of pilot clinical testing of spinal cord injury (SCI) patients with MAHI Exo-I, the most important deficiency of the design in the wrist part was identi-
fied as the mechanical singularities introduced by the wrist ring connector joints. Because of these singularities, at certain configurations, patients’ wrist movements were not being satisfactorily recorded for evaluation. The main reason for the problem was that universal-revolute joints were incapable of providing the intended spherical joint characteristics at some specific configurations of the 3-RPS mechanism. Consequently, we have replaced the universal-revolute joints with Hephaist-Seiko SRJ series high precision spherical joints. Although these spherical joints resolved the problems due to the universal-revolute joints, they led to a decrease in range of motion (ROM). To improve the ROM, we used an inclined surface design on the wrist ring (see Fig. 2.4(a)). This choice also contributed to a considerable reduction in friction and backlash and resulted in a wrist mechanism with significantly more rigid and smooth operation compared to MAHI Exo-I. Besides all of these advantages offered by the use of spherical joints and the inclined wrist ring design, the overall ROM was still slightly reduced in comparison with MAHI Exo-I. A comparison in terms of ROM for both designs for various joints is given in Table 2.3 in Section 2.4. Nevertheless, the new design is still capable of spanning 100% of wrist abduction/adduction ROM and 63% of wrist flexion extension ROM during activities of daily living (ADL).

### 2.3.2.2 Forearm Mechanical Design

The improvements for the forearm joint include increasing the torque output while reducing the mechanism complexity and cost. In the previous design, Applimotion 165-A-18 frameless and brushless DC motor actuator with MicroE Systems Mercury 1500 encoder were used to drive the forearm joint. Although this design enabled implementing the desired mechanism in a limited space, it mainly suffered from low torque output. In the new design, a high torque DC motor (Maxon RE40), with
Figure 2.4: (a) CAD model of the wrist ring with inclined surface to increase wrist range of motion. (b) Manufactured inclined wrist ring attached to the spherical joint.

cable drive mechanism is implemented. Use of cable drive mechanism is justified by its backdrivable and zero-backlash nature and by the considerable reduction in cost. In the new design, desired range of motion is unaltered with an approximately 35% increase in torque output (see Table 2.3), for under one forth of the cost of the prior design. Another consideration for the new design was eliminating the complexity of the mechanism, more specifically eliminating the issues that emerged due to the misalignment of the optical encoder. In the previous design, the optical encoder was embedded in the forearm joint with the frameless brushless motor, as depicted in Fig. 2.5(a), and was vulnerable to dislocations especially inserting or removing an arm from the exoskeleton. Misalignments in the encoder grating ring required the disassembly of the forearm mechanism and a significant effort to satisfy the μm level tolerance. Consequently, instead of having the sensor and the actuator be open to effects that would lead to misalignments, in the new design they have been kept out of interference with the arm during attachment or detachment, as shown in Fig. 2.5(b). This solution also enabled easy access to the encoder and the motor in case of a malfunction.
2.3.2.3 Elbow Mechanical Design

The primary goal in the new design for the elbow subsystem was to implement a mechanism that allows both left and right arm therapy. In MAHI Exo-I, a Kollmorgen U9D-E pancake DC motor with a cable transmission system was fixed on one side of the elbow mechanism and a counterweight was attached through a moment arm to the motor shaft to provide passive gravity compensation for the forearm assembly. Because the counterweight and elbow motor would be between patient and mechanism as shown in Fig. 2.6(a) for left arm attachment, this configuration only allowed right arm therapy. To overcome this issue, a new design which employs a high torque DC motor (Maxon RE65) with cable drives is developed. Main consideration for the new design was to implement a mechanism that will enable one to change the transmission from one side to the other easily and quickly. For this reason, in the new design the elbow actuator is moved below the mounting block, the capstan arc is positioned in a way that it will not interfere with that user, and consequently changing the side of
Figure 2.6: (a) In MAHI Exo-I, elbow motor and counterweight fixed on one side allowed only rehabilitation of the right arm. (b) In MAHI Exo-II, counterweight can be attached on either side to allow both left and right arm therapy. (c) A passive DOF that tilts the whole device in the coronal plane provides improved patient comfort and posture during therapy.

the therapy only required mounting the counterweight to the corresponding side.

New elbow actuation design also led to a considerable improvement in the torque output. Although the initial design was well within the useful range for training and rehabilitation applications, the torque output for the elbow joint was further increased to enable locking of the elbow joint in specified positions for isolated wrist or forearm training. A large capstan with 15:1 transmission ratio allowed a 238% increase in torque output as compared to MAHI Exo-I (see Table 2.3).

One of the most important points to take into account during the mechanical design of a rehabilitation robot is to ensure that the system does not cause any discomfort or safety hazard for the user during the movement [18]. For this reason, a tilting mechanism (as a passive DOF) is implemented to enable the patients to have a better posture during the training/rehabilitation sessions by allowing abduction of the shoulder, as illustrated in Figs. 2.6(b), 2.6(c).
Table 2.3: Achievable joint ranges of motion (ROM) and maximum continuous joint torque output values for MAHI Exo I and MAHI Exo II. Maximum joint ROM and torque values for 19 activities of daily living (ADL) as extracted from [3] are also given for comparison.

<table>
<thead>
<tr>
<th>Joint</th>
<th>ADL ROM (deg)</th>
<th>Torque (Nm)</th>
<th>MAHI Exo I ROM (deg)</th>
<th>Torque (Nm)</th>
<th>MAHI Exo II ROM (deg)</th>
<th>Torque (Nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow Flexion/Extension</td>
<td>150</td>
<td>3.5</td>
<td>90</td>
<td>4.91</td>
<td>&gt;90</td>
<td>11.61</td>
</tr>
<tr>
<td>Forearm Pronation/Supination</td>
<td>150</td>
<td>0.06</td>
<td>180</td>
<td>1.69</td>
<td>&gt;180</td>
<td>2.30</td>
</tr>
<tr>
<td>Wrist Flexion/Extension</td>
<td>115</td>
<td>0.35</td>
<td>85</td>
<td>2.92</td>
<td>72</td>
<td>1.67</td>
</tr>
<tr>
<td>Wrist Abduction/Adduction</td>
<td>70</td>
<td>0.35</td>
<td>85</td>
<td>3.37</td>
<td>72</td>
<td>1.93</td>
</tr>
</tbody>
</table>
2.4 Results

2.4.1 System Capabilities

The ranges of motion and maximum achievable torque outputs for the elbow, forearm and wrist joints based on the mechanical design improvements outlined in the previous section are summarized in Table 2.3. Same parameters are given for the previous design (MAHI Exo-I) and for activities of daily living (ADL) as reported by Perry et al. [3] for comparison.

Both MAHI Exo-I and II are capable of providing a ROM exceeding or only slightly below the ROM of ADL for forearm pronation/supination and wrist abduction/adduction. MAHI Exo-I covers 74% of wrist flexion/extension ROM of ADL while MAHI Exo-II covers 63% of it. For the elbow, both designs cover approximately 60% of ADL ROM, from a fully extended posture to a right angle at the elbow. For the joints with a ROM beyond human ROM, both hardware and software stops are implemented for safety.

In terms of torque output capability, both versions of the exoskeleton provide more than sufficient torque to replicate torques involved in ADL, for all four DOF. MAHI Exo-II has a much higher elbow maximum continuous torque output than MAHI Exo-I, but less torque output at the wrist DOF. This is mainly due to use of lighter DC motors (Maxon RE35, 340 g) in MAHI Exo-II, as compared to DC motors used in MAHI Exo-I (Maxon RE40, 480 g). MAHI Exo-II torque output at the forearm DOF is also improved 36% compared to the previous design. The improvements in forearm and elbow torque output serve to enable locking these joints at desired positions in software to allow isolated training of remaining unlocked joints. Despite the decrease in torque output at the wrist joints, the wrist motors are still capable of providing
this locking property.

2.4.2 System Characteristics

The experimental system characterization of the device, in terms of static friction, closed loop position bandwidth, viscous friction, and inertia was conducted in order to evaluate the device’s potential for rehabilitation. A summary of these findings is presented here.

To determine the average static friction in every joint, the actuators were programmed as a virtual spring and the response of the system to a ramp position input was measured. The inertia and viscous friction values were determined using the logarithmic decrement method. The closed loop position control bandwidth of the MAHI Exo II was identified by observing the device’s ability to track a sine position input with a PD controller implemented for each individual DOF. We observed approximately 2.1 Hz, 4.1 Hz, 11.5 Hz, and 12.3 Hz bandwidths for the elbow, forearm, wrist flexion/extension, and wrist radial/ulnar deviation degrees-of-freedom, respectively. The device characteristics are reported in Table 5.3.

The main goals of the redesign have been enabling the use of the exoskeleton for therapy of both arms, and resolving the backlash and singularity issues related to the universal-revolute joints at the wrist ring. To achieve the first goal, the elbow actuator relocated and the capstan transmission of the elbow joint is redesigned in such a way that the capstan arc does not get in the way of the upper arm and the torso of the patient during elbow movements. Changing of the configuration for using the device for one arm from a configuration for the other arm is reduced to attaching the counterweight onto the side opposite to the patient. The second goal was achieved via use of high precision spherical joints, which led to
a slight decrease in ROM after including an inclined wrist ring design that allowed making most use of the available ROM envelope for the spherical joints.

In comparison with other rehabilitation robots, MAHI Exo-II poses several advantages. First, parallel design of the wrist provides increased rigidity and torque output; decreased inertia; and isometric force distribution throughout the workspace, as compared to a serial configuration. Also, the alignment of the biomechanical axes of joint rotation with the controlled DOF of the MAHI Exo-II makes it possible to constrain movement of a desired joints. This is particularly important in rehabilitation, where the therapy exercises may focus on a particular joint.

The new design offers additional benefits in comparison with MAHI Exo-I. One benefit is lowered cost due to use of all DC brush motors for all actuators, by replacing the frameless brushless DC motor on the forearm and the pancake DC motor on the elbow joint of the earlier version. Another improvement is the additional passive DOF that allowed tilting of the whole device in the coronal plane which significantly added to patient comfort, posture and ease of attachment/detachment.
<table>
<thead>
<tr>
<th>Joint</th>
<th>Static Friction (N·m)</th>
<th>Inertia (kg·m²)</th>
<th>Viscous Coeff. ($\text{Nm} \cdot \text{s}/\text{rad}$)</th>
<th>CL Position Bandwidth (Hz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elbow Flexion/Extension</td>
<td>0.912</td>
<td>0.347</td>
<td>0.238</td>
<td>2.1</td>
</tr>
<tr>
<td>Forearm Pronation/Supination</td>
<td>0.1109</td>
<td>0.0258</td>
<td>0.0112</td>
<td>4.1</td>
</tr>
<tr>
<td>Wrist Flexion/Extension</td>
<td>0.1915</td>
<td>0.0032</td>
<td>0.0161</td>
<td>11.5</td>
</tr>
<tr>
<td>Wrist Radial/Ulnar Deviation</td>
<td>0.1759</td>
<td>0.0038</td>
<td>0.0059</td>
<td>12.3</td>
</tr>
</tbody>
</table>
Chapter 3

A Subject-Adaptive Controller for Robotic Wrist Rehabilitation

In this chapter, the development of a novel subject-adaptive controller is presented. The developed controller is capable of changing the amount of error allowed during movement execution, while simultaneously estimating the forces provided by the participant that contribute to movement execution. Also presented in this chapter is the experimental validation of a physiologically optimal asymmetric wrist movement profile, utilized as the desired movement trajectory for the developed controller. This chapter also presents the validation of feedback gain modification by using the RiceWrist system, which is the wrist-forearm portion of the MAHI Exo-II presented in Chapter 2, in an experimental study involving five healthy subjects.

Portions of this chapter were published in the IEEE/ASME Transactions on Mechatronics [20] and I gratefully acknowledge my collaborators in that publication.

3.1 Introduction

Movement rehabilitation of subjects affected by neurological lesions, including stroke and SCI, is delivered with the goal of improving function leveraging on brain and spinal cord plasticity. To achieve this objective, therapy must be intensive [9]. Robotic devices are well suited to offer multiple training sessions with consistent delivery of therapy, coupled with the opportunity to perform objective and quantitative performance evaluation of subjects throughout the course of therapy. This objective and
data-driven assessment is typically not feasible with clinical tests commonly used to assess the efficacy of classical rehabilitation. Indeed, robotic devices are being increasingly included in rehabilitation protocols, and the results of clinical studies with subjects with both stroke [8], and SCI [39] support this approach.

One of the most critical areas of research in rehabilitation robotics is the development of control strategies capable of regulating physical interaction with the subject in a way that promotes plasticity, and therefore improves motor recovery [14]. In assisting control strategies, the robotic device assists a subject to move along a desired path. As one might expect, the specific role played by the robot during therapy can significantly impact the clinical outcomes.

Hogan, Krebs et al. [4] showed that continuous passive motion (CPM)-based therapy did not produce significant improvements in post-stroke patients, suggesting that plasticity-mediated motor recovery requires active participation.

To ensure active participation, controllers within the assist as needed (AAN) paradigm [14] have been developed. Such approaches attempt to minimize the assistance provided by the robot, based on some online measurement of the subject’s performance, or by defining regions of no-action, in which the robot does not assist movements. These formulations are well-suited to robotic rehabilitation, given the higher inter-subject variability of human movements. Additionally, such approaches are aligned with motor control studies showing that error is likely to be a driving signal for motor learning [40], [41].

### 3.2 Literature Review

Krebs et al. [42] presented an impedance control scheme based on a force-field tunnel, and a virtual wall which assists the subject by pushing them along the trajectory if
the movement is slower than a predefined velocity. A fixed wait time before starting
delivery of assisting forces or torques is introduced. Such an approach does not
account for a subject’s potentially non-homogeneous residual motor capabilities in
different regions of the workspace, and might require force support only to initiate
a movement, and not to complete it, or vice versa. A similar approach is described
in [43], where an impedance controller is defined around a desired trajectory specified
in the task space, and regulates the assisting forces according to the distance of the
subject from the desired trajectory. The fact that the desired trajectory is only defined
in the task space makes this controller independent of time, thus allowing movement
velocity to be completely defined by the subject. Applying the AAN approach to a
wrist rehabilitation robot, the algorithm proposed in [35] adapts the desired range
of motion according to the performance of the subject, and introduces non-linear
feedback control action to minimize assistance force/torques when the error is small.

In contrast to an impedance control approach, Wolbrecht et al. [12] modeled the
residual functional abilities of the subject and provided assistance only in the re-
gions of the workspace in which the subject had insufficient capability. Their assis-
tance scheme was based on an adaptive controller that used a Gaussian radial basis
function network for estimation purposes; their controller was implemented on the
Pneu-WREX [36], a pneumatically actuated, 4 DOF, serial mechanism. Inclusion of
Gaussian networks in adaptive control algorithms was previously proposed for both
real-time robot control [44] and for arm movement modeling purposes [45]. Addition-
ally, to ensure continuous active participation, an adaptation law was used to decrease
the assistance forces when the position error is low. A drawback of this approach is
that the quality of the estimate of the subjects’ residual capabilities is perturbed by
the forgetting factor law; moreover, this approach does not allow directly manipula-
tion of the error bounds, as is possible with force-field tunnel approaches.

In this chapter I present a subject-adaptive controller, which is based on the adaptive control approach [2] and uses a Gaussian network for estimation purposes, similar to [12], and introduces a novel feedback gain modification algorithm capable of directly manipulating the error bound according to the performance of the subject.

The chapter is organized as follows. In Section 3.3 the hardware is described. In Section 3.4 the AAN controller presented and the feedback gain modification algorithm is introduced. In Section 3.5, the definition of the nominal desired trajectory is made. The experimental results for the validation of the developed controller are presented and discussed in Section 3.6. Finally, the conclusions of the chapter and remarks for the future work are presented in Section 3.7.

![Image of RiceWrist hardware platform with a subject in neutral pose.](image)

Figure 3.1: The RiceWrist hardware platform with a subject in neutral pose.

### 3.3 Hardware Description and Modelling

The RiceWrist [46] is a wrist and forearm exoskeletal robotic device (Fig. 3.1). The basic kinematic structure of the 4-DOF serial-in-parallel mechanism is depicted in Fig.
Figure 3.2: Basic kinematic structure of the 4-DOF serial-in-parallel RiceWrist which employs a 3-RPS (revolute-prismatic-spherical) parallel mechanism at the wrist module and a revolute joint at the forearm. Reference frame 3 and 4 are attached to the base plate and end effector of the 3-RPS mechanism respectively. Rotation around $x_4$ with respect to reference frame 3 corresponds to wrist flexion/extension (FE), and rotation around $y_4$ with respect to reference frame 3 corresponds to wrist radial/ulnar deviation (RUD).

3.2. The exoskeleton is comprised of a 3-RPS (revolute-prismatic-spherical) wrist, to support wrist flexion/extension (FE) and radial/ulnar deviation (RUD), and a revolute joint for forearm pronation/supination (PS). The final DOF of the platform is translation (distance of bottom plate from top plate) and accounts for minor misalignments of the wrist rotation axes with the device. The dynamic equations of the system can be represented in the form:

$$M(x)\ddot{x} + C(x, \dot{x})\dot{x} + g(x) = F_r + F_p$$  \hspace{1cm} (3.1)$$

where $x$ is a $4 \times 1$ vector of end-effector position (independent coordinates), $M$ is the $4 \times 4$ inertia matrix, $C$ is the $4 \times 4$ matrix which represents Coriolis/centrifugal terms, $G$ is the $4 \times 1$ gravity vector, $F_r$ is the $4 \times 1$ vector of forces applied by the actuators.
and $F_p$ is the $4 \times 1$ vector of forces applied by subject at the end-effector (handle) which is mapped to the joint space by the transpose of the inverse of the Jacobian of the mechanism.

Using the formulation in [47], it can be shown that the dynamical equations of the RiceWrist can be expressed in the form of (5.2) and possess identical properties as open-chain serial mechanisms. The important distinction, however, is that the obtained dynamical model is valid only locally, i.e. the domain of the generalized coordinates ($x$) is a bounded and closed set ($\Omega$) rather than the whole $n$-dimensional real space ($n$ corresponds to the number of DOF of the device, in particular case $n = 4$) [47]:

$$x \in \Omega, \text{ where } \Omega \subset \mathbb{R}^n$$

In [19], a conservative estimate of the domain of validity of the reduced kinematic model of the parallel portion of the RiceWrist is defined which well within the requirements for wrist movement-based rehabilitation therapy. In particular, it was determined that the reduced model is valid within very large margins, for both flexion-extension and radial-ulnar deviation movements with velocities on the order of 30-100 deg/s.

### 3.4 Assist-As-Needed (AAN) Controller

In this section, I introduce the AAN controller which employs an adaptive control algorithm developed by Slotine and Li [2], and a feedback gain modification algorithm, which modifies the amount of permissible error according to the performance of the subject. First, I describe the adaptive controller and conduct the stability analysis in order to show the uniform ultimately boundedness of the errors. Then, I build the development of the error-bound alteration algorithm on the results of previous
description and analysis.

3.4.1 Adaptive Controller

In my formulation, I develop the controller in task space, because I wish to abide by
the formulation in [12] which confers a clear physical meaning to the regressor matrix,
and the construction of the regressor matrix is an integral step in the formulation of
the controller.

Having represented the dynamic equations of the system in the form of (5.2), I
define the the tracking error as  \( \tilde{x}(t) = x(t) - x_d(t) \), where \( x_d(t) \) the desired end effector
trajectory which is at least twice differentiable. Furthermore, let me define the sliding
mode variables:

\[
\begin{align*}
    r &= \dot{x} + \Lambda \tilde{x} = (\dot{x} - \dot{x}_d) + \Lambda (x - x_d) \\
    v &= \dot{x}_d - \Lambda \tilde{x} = \dot{x}_d - \Lambda (x - x_d) \\
    a &= \dot{v}
\end{align*}
\]

where \( \Lambda \) is a \( 4 \times 4 \) constant, positive definite, symmetric matrix.

Since the system dynamics are linear in terms of system parameters, they can be
represented as a multiplication of a regressor matrix, which includes the known func-
tions of the system equations, and an unknown vector. I now assume that the forces
applied by the subject \( F_p \) depend primarily on the orientation of the hand. Hence
the force field \( F_p \) is dependent on the three rotational elements of \( x, x_{\text{rot}} \), defining the
posture of the wrist joint. I further assume that \( F_p \) is linearly parameterizable.

In my formulation, different from what Slotine and Li proposed in [2], I use a
control law that only estimates the position-dependent elements (\( G(x) \) and \( F_p \)), and
does not account for the inertial and Coriolis/centrifugal terms \( M(x) \ddot{x} \) and \( C(x, \dot{x}) \dot{x} \).
Through this given modification, I relax the requirement of asymptotic stability in
favor of ultimately bounded stability (see the following stability analysis), thereby enabling direct modulation of the system error bounds.

Consider the following control law:

$$F_r = \hat{G}(x) - \hat{F}_p - K_D r$$  \hspace{1cm} (3.3)

where $\hat{G}$ is the estimate of the gravitational term, $\hat{F}_p$ is the estimate of the forces coming from the subject, $K_D$ is a symmetric positive definite feedback gain matrix.

As stated above, both $G(x)$ and $F_p$ are linearly parameterizable, and they can be modeled as

$$Y\hat{\theta} = \hat{G}(x) - \hat{F}_p$$  \hspace{1cm} (3.4)

where $Y$ is a $4 \times m$ regressor matrix which contains known functions of state $x$, and $\hat{\theta}$ is the $m \times 1$ vector containing estimates of unknown system parameters. I use Gaussian radial basis functions (RBFs) to model both $G(x)$ and $F_p$. The rationale to use Gaussian RBFs is that any continuous function, not necessarily infinitely smooth, can be uniformly approximated by linear combinations of Gaussian RBFs [48]. I partition each rotational DOF of the robot in four equally spaced intervals, yielding five nodes for every rotational DOF (located at $-20$, $-10$, $0$, $10$, $20$ degrees) and a total number of 125 points in the 3D space defined by the RiceWrist rotational DOFs. I then define 125 RBFs throughout the workspace of the RiceWrist as

$$g_n = \exp(-\|x_{rot} - \mu_n\|^2/2\sigma^2)$$  \hspace{1cm} (3.5)

where $g_n$ is the $n^{th}$ Gaussian radial basis function, $x_{rot}$ is the $3 \times 1$ current orientation of the RiceWrist’s end-effector, $\mu_n$ is the $3 \times 1$ location of the $n^{th}$ Gaussian RBF, and $\sigma$ is a constant which defines the width of the function. By keeping the number of the functions as low as possible, I aim to decrease the expense of computation and to
avoid estimation of unrealistically irregular force fields [49]. The forces coming from
the subject are parameterized using these 125 RBFs. The vector of Gaussian RBFs
is defined as
\[ g = [g_1 \ g_2 \ ... \ g_{125}]^T \] (3.6)
Consequently the regressor matrix is defined as
\[
\begin{bmatrix}
g^T & 0 & 0 & 0 \\
0 & g^T & 0 & 0 \\
0 & 0 & g^T & 0 \\
0 & 0 & 0 & g^T \\
\end{bmatrix}
\] (3.7)
In order to develop the adaptation law through stability analysis of the controller,
I first choose the Lyapunov function candidate as
\[
V(t) = \frac{1}{2}[r^TMr + \tilde{\theta}^T\Gamma\tilde{\theta}] 
\] (3.8)
where \( \Gamma \) is a \( 4 \times 4 \) constant, positive definite, symmetric matrix, and
\( \tilde{\theta}(t) = \hat{\theta} - \theta \).
Next, I differentiate (3.8) and use the following relations beside the skew-symmetry
property
\[
\begin{align*}
\dot{x} &= \dot{r} + a \\
\dot{x} &= r + v \\
Y\hat{\theta} &= \hat{G}(x) - \hat{F}_p 
\end{align*}
\]
in order to obtain following equation
\[
\dot{V}(t) = -r^TK_Dr + r^TY\tilde{\theta} + \tilde{\theta}^T\Gamma\tilde{\theta} + B 
\] (3.9)
where
\[ B = -r^T Cv - r^T Ma. \] (3.10)

I use the adaptation law suggested in [2]

\[ \dot{\theta} = -\Gamma^{-1} Y^T r \] (3.11)

The adaptation law, when substituted in (3.9), produces

\[ \dot{V}(t) = -r^T K_D r + B \] (3.12)

Hence, I show that the controller is uniformly ultimately bounded, i.e. the error always stays within a certain bound, due to the existence of \( B \). The condition

\[ r^T K_D r > |B| \] (3.13)

has to be verified, for the derivative of \( V \) to be negative. Two important points are noteworthy. First, the term \( B \) is fairly small for rehabilitation applications with low velocity and acceleration values. Second, from (3.12) it is visible that the error bound can be modulated by the \( K_D \) term. In fact, the feedback gain modification algorithm, described in the following section, exploits the ultimately boundedness of the controller and modifies the error bound by modulating the \( K_D \) term.

Note that the feedback part of the controller (3.3) is in essence a PD controller, while the feed-forward part of the controller is the estimate of the forces coming from the subject. In case of a drastic change in the subject’s force input, the controller is still providing assistance according to the previously determined estimate. In this situation, the dynamical system is equivalent to a PD controller with disturbance. The disturbance includes the wrong feed-forward estimate and the instantaneous input from the subject. Hence, considering a possibility of a drastic change in the
subject’s force input, a software stop which is based on a threshold error (15 deg) between the desired and actual positions is implemented, immediately inactivating the amplifiers when this condition is verified.

3.4.2 Feedback Gain Modification Algorithm

Although the adaptive controller described in Section 3.4.1 considers the input from the subject and adapts/adjusts the robot torque input accordingly, the subjects might still let the robot take control. To address this issue, Wolbrecht et al. [12] propose a forgetting factor algorithm which decays learned parameter estimates when error is low. I follow a different approach to AAN control, which aims to introduce error in the execution of movements during rehabilitation through the modulation of the controller feedback gain. This is motivated by motor control studies showing that error is likely to be a driving signal for motor learning [40], [41]. Through the ultimately boundedness of the formulation, the feedback gain modification directly manipulates the admissible error bounds and the amount of force support. Hence, instead of requiring the errors to become zero, this approach tolerates error and manipulates the error bound according to the performance of the subject. Furthermore, the proposed approach does not apply any modification to the adaptation law of the controller [2], hence it does not interfere with the quality of force estimation.

The algorithm is based on the definition of a minimum and a maximum feedback gain (diagonal matrices $K_{D_{\text{MAX}}}$, $K_{D_{\text{MIN}}}$), which are determined experimentally according to predetermined bounds for average errors ($r_{\text{MIN}}$, $r_{\text{MAX}}$). This is done by considering (3.12), and modifying the gain along the desired movement trajectory according to the subject’s performance. The feedback gain is updated in a discrete manner, at the end of every single movement task. The following difference equation
was used to update the scalar feedback gain $k_{D_{i,j}}$, for the task $i$, for the $j^{th}$ DOF:

$$k_{D_{i,j}} = (1 - 1/\tau)k_{D_{i-1,j}} + A/\tau$$

(3.14)

where $\tau$ is an update constant (units of task numbers), and $A$ is the convergence value of the first order difference equation, which is modified according to the relation

$$A = \begin{cases} 
  k_{D_{MIN,j}}, & \text{if } \alpha < 0 \\
  (1 - \alpha_j)k_{D_{MIN,j}} + \alpha_j k_{D_{MAX,j}}, & \text{if } 0 \leq \alpha \leq 1 \\
  k_{D_{MAX,j}}, & \text{if } \alpha > 1 
\end{cases}$$

(3.15)

where $\alpha_j$ is defined with the linear relation

$$\alpha_j = \frac{r_{av,j} - r_{min,j}}{r_{max,j} - r_{min,j}}$$

(3.16)

where $r_{av,j}$ is the average error of the subject, in DOF $j$.

### 3.5 Definition of a desired trajectory

Wrist movements have relevant dynamical differences compared to shoulder and elbow movements [50, 51]. It is thus reasonable to expect that kinematic synergies observed for planar shoulder and elbow movements might not be fully replicated in wrist movements. In particular, a recent study [52] measured multiple movement profiles for wrist pointing movements involving wrist flexion-extension and radial-ulnar deviation, using non linear least-square fitting as a benchmark to compare different analytic forms of velocity profiles. A major finding of that study was the tendency of asymmetric profiles to provide improved goodness-of-fit results, compared to profiles with inherent symmetry, such as the minimum jerk profile. Some methodological limitations (i.e. non-unicity of the fit, dependence of the solution on the initial parameters
given for the fit, tendency of estimates to converge to velocity profiles with non-zero initial and final velocities) and the inherent variability observed in wrist pointing movements prevent drawing strong conclusions such as the definition of a nominal physiological velocity profile. However, the observed asymmetry in velocity profiles seems to be a common trait of wrist pointing motion that needs to be considered when defining a desired trajectory for robot-aided rehabilitation applications.

3.5.1 Experimental study with healthy subjects

To define a physiological representation of the desired wrist movement profile during pointing movements to be employed for the adaptive control scheme presented in this chapter, an experimental study with healthy subjects was conducted.

3.5.1.1 Protocol

The experiment involved 7 healthy male individuals, ages 23-29 years, who were asked to perform movements in FE or RUD using the RiceWrist. During the experiment, the RiceWrist was powered off and used only in backdrive mode, minimally perturbing subjects’ movements due to its intrinsic backdriveability*. A graphical display was provided to visually guide subjects during the execution of a point-to-point movement. Two experiments were performed with each subject, allowing separate analysis of wrist FE and RUD movements. For either movement, two target locations were used, corresponding to a displacement away from the center of the display either to the right or left (FE), or up and down (RUD). The center of the display corresponded to the neutral wrist position. A target would change color from black to blue to suggest

*Torques required to back drive the RiceWrist are on the same order of those of the device used in [52]
a movement toward that target. For the first 0.75 s, the target would remain blue, eventually turning to red, to indicate that a pointing movement towards that target should last for 0.75 s. The target remained red for 0.75 s, before turning black as the next target changed color to blue. Eighty targets for a DOF were presented in a random order; after every peripheral target, the next movement was always towards the central target. Movement extent was set to 25 degrees. Subjects were allowed to practice freely with the device until they felt comfortable with the device and the visual display, and after this practice session, data collection began.

\subsection*{3.5.1.2 Data Analysis}

Due to the inherent unidimensionality of the task (the maximum straight line deviation of successful movements was lower than 0.5 deg), velocity profiles were calculated as time derivatives of the measured Euler Angles, using the X-Y-Z sequence in moving frame. Encoder data were acquired continuously at 1000 Hz; velocity profiles were extracted in post-processing using a Savitzky-Golay filter, performing a local 4\textsuperscript{th} order polynomial fit, in a moving window of amplitude 200 ms. Having calculated the instant $t_{max}$ with maximum instantaneous velocity $v_{max}$, segmentation of reaching movements was performed by defining the time $t_{in}$ and $t_{end}$ of movement start and end, respectively, by searching the minimum and maximum times in which the condition $|v(t^*)| > 0.05 \cdot |v(t_{max})|$ was verified in a continuous range comprising the time $t_{max}$. Segmented movement profiles were then visually inspected in order to ensure evaluation of movement profiles containing a single peak, following the same procedure reported in [52]. 104 out of 638 tasks (16\%) were discarded for FE; 187 out of 622 tasks (30\%) were discarded for RUD movements. To account for different movement durations, computed times (hereafter referred as $t'$) were mapped into a
normalized temporal $[0,1]$ range.

Two indices of symmetry of the acquired velocity profiles were considered. The first index was \textit{peak location}, defined $t_{\text{peak}} = t'_{\text{max}}$. The second index was \textit{skewness}, defined for a probability distribution function as $\text{skewness} = E \left[ \left( \frac{X - \mu}{\sigma} \right)^3 \right]$. In order to compute \textit{skewness}, the velocity profile was normalized to have unitary area, and \textit{skewness} computed numerically from the acquired velocity profile, assuming the latter as the probability distribution.

The calculated symmetry indices were subject to statistical inference tests. A Jarque-Bera test [53] was applied in order to test the null hypothesis that the samples come from a normal distribution with unknown mean and variance. Due to non-normality of the measured indices, two non-parametric tests were then applied: the Wilcoxon signed-rank [54] and the sign test [55], in order to test whether both indices of symmetry come from a distribution with a median corresponding to that of a symmetric profile.

\subsection{Results}

Symmetry indices for the 969 completed tasks are reported in Fig. 3.3. The mean value of the measured \textit{skewness} equals -0.041 (standard deviation: 0.185), while the mean value of peak location index $t_{\text{peak}}$ equals 0.52 (standard deviation: 0.078). Both indices suggest the prevalence of asymmetric profiles with a negative skewed distribution. The Jarque-Bera test was applied to test normality of distribution of both symmetry indices, showing a very high statistical significance for the rejection of the hypothesis that the symmetry indices are normally distributed ($p < 0.001$ in both cases). A Wilcoxon signed-rank test was then used to test the null hypothesis that the measured indices of symmetry come from a distribution with a median corresponding
Figure 3.3: Histograms of the extracted indices of symmetry, obtained combining results from the Flexion-Extension and Radial-Ulnar Deviation experiments. Skewness distribution mean is -0.041, standard deviation equals 0.185, while peak percentage mean is 0.52, with standard deviation 0.078.

to that of a symmetric profile \((skewness = 0 \text{ and } t_{peak} = 0.5)\). Both tests rejected the null hypothesis with strong statistical significance \((p < 0.001)\) in both cases, giving the following ranges for the median of computed indices of symmetry, at the \(p < 0.05\) confidence level: \(skewness = -0.05 \pm 0.01, t_{peak} = 0.528 \pm 0.005\). Ultimately, due to the asymmetric distributions of both indices of symmetry considered, the sign test was eventually used, rejecting the hypothesis of symmetric movement profiles \((p < 0.001 \text{ in both cases})\), and giving the following estimate of medians, at the \(p < 0.05\) confidence level: \(skewness = -0.06 \pm 0.012, t_{peak} = 0.53 \pm 0.005\), thus giving evidence for the asymmetry of single peak wrist pointing profiles.

### 3.5.2 Definition of a nominal trajectory for wrist pointing movements

Despite the abundance of proposed analytical representation of wrist pointing movements velocity profiles [56], successful integration in a robot control scheme introduces several requirements, such as continuity and ease of computation, that were not nec-
essarily considered in previous studies. As a working hypothesis to demonstrate the control approach, the desired movement profile is defined using the beta function, as:

\[ v(t) = P_1(t - P_2)^{P_3}(P_4 - t)^{P_5} \quad P_2 \leq t \leq P_4. \] (3.17)

As proposed in [57], the beta function is a convenient function that can be used to accurately describe and synthesize both human and robot movements: it can represent either symmetric or asymmetric movement profiles, and its parameters can be tuned very easily in a decoupled fashion. \( P_2 \) corresponds to the time of movement start, \( P_4 \) represents the time of movement end, \( P_1 \) is a scaling factor that can be used to represent movements of different extents, and finally \( P_3 \) and \( P_5 \) can be modified in order to obtain a given degree of (a)symmetry. In particular, the location of the single peak in the velocity profile can be calculated as

\[ t_{\text{peak},\beta} = \frac{P_3 P_4 + P_2 P_5}{P_3 + P_5}, \] (3.18)

while the profile skewness can be calculated as:

\[ \text{skewness}_{\beta} = 2 \frac{(P_5 - P_3)\sqrt{P_3 + P_5 + 3}}{(P_3 + P_5 + 4)\sqrt{(P_3 + 1)(P_5 + 1)}}. \] (3.19)

Finally, parameter \( P_1 \) accounts for movements of different extent, considering the following relation:

\[ \int_{P_2}^{P_4} v(\tau)d\tau = P_1 \frac{(-P_2 + P_4)^{1+P_3+P_5}\Gamma(1 + P_3)\Gamma(1 + P_5)}{\Gamma(2 + P_3 + P_5)}, \] (3.20)

where \( \Gamma(\cdot) \) is the gamma function. Equations (3.18 - 3.20), in combination with the initial and final value conditions

\[ v(t = P_2) = v(t = P_4) = 0, \quad P_2 < P_4 \] (3.21)

show that a generic, asymmetric, single-peaked movement profile of any duration \( t_d \) can be represented as (3.17), by setting parameter \( P_2 = 0 \), parameter \( P_4 = t_d \),
parameters $P_3$ and $P_5$ to verify some conditions on profile symmetry, and finally modulating parameter $P_1$ in order to generate smooth movements of different extent (3.20).

The proposed approach allows the definition of a smooth and natural desired trajectory for wrist movements in free space. Fig. 3.4 shows that the beta function can be successfully used to represent wrist movements during pointing tasks. Least-square fitting has been applied to the mean profile extracted during the experiments reported above (velocity profiles in the normalized time domain were normalized in amplitude), and a goodness-of-fit coefficient $R^2 = 0.9998$ was found.

![Figure 3.4: Results of least square fitting between the mean profile obtained from the 969 successful trials, normalized in amplitude and time, and a beta function profile, defined by (3.17), with error bounds representing one standard deviation above and below the mean value. $R^2=0.9998$.](image)

### 3.6 Experimental validation

Experiments were conducted to validate the developed controller, taking into special account the novel feedback gain modification algorithm for the adaptive controller.
The controller was implemented in Simulink (The MathWorks, Inc.) software translated into real time code using QuaRC (Quanser Inc.), at a sampling rate of 1 KHz. All experimental results are presented for isolated movements of one of the degrees of freedom of the robot, flexion/extension of the wrist, since it is anticipated that rehabilitation protocols will target individual degrees-of-freedom of the RiceWrist, rather than coordinated movements, since studies suggest that repetitive isolated movements have positive effect on the results of the motor rehabilitation of subjects with stroke [9], [30]. This particular degree of freedom was chosen to demonstrate the feasibility of the control implementation on the portion of the RiceWrist comprising the closed kinematic chain.

3.6.1 Experiment I: Validation of the Adaptive Controller

I first aimed at assessing whether the modified adaptive controller presented in Section 3.4.1 is able to estimate end-effector interaction forces $F_p$. In particular, I sought to determine if the implemented performance-dependent modification change in feedback gains affects the quality and accuracy of force estimation.

In Experiment I, I used a linear extension spring connected on one side to the robot handle, with the other side of the spring attached to a fixed frame. This set-up was meant to provide a reproducible model of an impaired subject with stiff tendons. The spring is connected so that it is at its equilibrium point when the robot is approximately at its neutral configuration, and resists movement only in the wrist flexion region (positive FE), while it is not engaged for extension movements. The spring provides an approximate rotational stiffness, in robot end-effector coordinates, of 1.302 Nm/rad.

For the first part of the experiment, Experiment I-a, a sinusoidal desired tra-
jectory with 22 degrees amplitude and 0.5 Hz frequency is assigned for FE rotation while other joints are kept in a neutral pose (see Fig. 3.1). The adaptation gain $\Gamma^{-1}$ ($\text{diag}(0.0025 \ 0.0025 \ 0.0025 \ 0.0025)\text{Nm}_\text{rad}^{-1}$), $\Lambda$ ($\text{diag}(60 \ 60 \ 50 \ 20)\text{s}^{-1}$), and $K_D$ ($\text{diag}(10 \ 2.5 \ 1.5 \ 1.5)\text{Nms}_\text{rad}^{-1}$) are chosen experimentally such that the average steady state position error is less than 0.45 degrees and the estimation of the feedforward part converges in approximately 140 s.

![Graph](image)

**Figure 3.5:** Experiment I-a: Validation of the Adaptive Controller. (a) Errors for the first and last ten seconds. Smaller error values can be achieved as the controller estimates the forces coming from the subject. (b) Feedforward and feedback components of the control input in task space. As the estimation progresses, the feedback decreases and feedforward dominates the response. Note that control input value is larger when the spring is resisting the movement.
Fig. 3.5(a) shows the position error values for the first and last ten seconds of \textit{Experiment I-a}, and Fig. 3.5(b) shows the feedforward and feedback part of the control input in task space. The increase of the feedforward part in the region in which the spring is maximally deformed indicates that the adaptive controller successfully estimates $F_p$.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3.5a.png}
\caption{(a)}
\end{figure}

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig3.5b.png}
\caption{(b)}
\end{figure}

Figure 3.6: \textit{Experiment I-b}: Validation of the Adaptive Controller. (a) Converged values of Gaussian RBFs located at $\mu_n = -20$, $-10$, $0$, $10$, $20$ degrees for the FE joint in \textit{Experiment I-a}. (b) Estimated values for the last 20 s of \textit{Experiment I-b} for different $K_D$ values. The presented values are coherent with each other with a maximum deviation of 0.1 Nm that is caused mainly by modelling inaccuracies such as friction.
In order to assess the quality of force estimation, the estimated values of unknown parameters related to the Gaussian RBFs after the controller reached steady state were analyzed. Since Experiment I-a involved only a rotation of the FE joint, with the other joints kept at 0 degrees, only the values of the five RBFs that are involved in this movement were considered, located at 0 degree for the RUD and PS joints, and at $-20$, $-10$, $0$, $10$, and $20$ degrees for the FE joint. Because the linear spring resists the movement in the positive direction, the estimated values for 0, 10, and 20 degrees are expected to show a linearly increasing trend, while RBF in the negative direction are unloaded by the spring and thus should estimate a negligible torque, determined mainly by unmodelled effects. Fig. 3.6(a) shows the converged values of the estimated Gaussian RBFs amplitudes, which agree well with the expected magnitudes.

Finally, I analyzed whether the implemented feedback gain modification algorithm compromises force field parameter estimation, compared to state-of-the-art, constant feedback gain adaptive controllers. For this reason, in Experiment I-b, different $K_D$ values are used for the control law, including the adaptive modification of the feedback gains described in (3.9). Fig. 3.6(b) presents the average of the estimated values for the last 20 s of Experiment I-b for different $k_{D,FE}$ values. The presented values are coherent with each other, as expected, with a maximum deviation of 0.1 Nm that is caused mainly by modelling inaccuracies such as friction.

3.6.2 Experiment II: Validation of AAN Controller

In Experiment II, the validation of the subject-adaptive controller, including the AAN controller was conducted with five healthy subjects, ages 23-30, interacting with the robot with their dominant arm. To explicitly test the capability of the controller to accommodate a subject whose force capabilities rapidly change during therapy, the
Figure 3.7: Experiment II: Validation of AAN controller for the experiment with five healthy subjects. Gray-shaded area refers to the perturbation-on, subject-passive phase. After 25 trials, the perturbation ceases and the subject is asked to complete the visually-guided movements.

validation experiment was structured in two phases. In the first phase, the subject was asked not to interfere with the robot, that was controlled through the algorithm described in the previous sections. During this phase, the robot applied a modified control action $F_{r,mod} = F_r + c$, where $F_r$ is the control input defined in (3.3), and $c$ is a constant task-space applied torque, that mimics the action of a subject. After 60 seconds, $c$ was instantaneously set to zero, and the subject was asked to move intentionally as triggered by the visual display†. The simulated instantaneous change of $F_p$ represents an exaggerated scenario of a subject rapidly undergoing improvement of functional capabilities during therapy. Results show that the subject-adaptive controller provides the desired characteristics for modification of the feedback gain.

During the perturbation on, subject-passive phase (shaded in grey in Fig. 3.7) the feedback modification algorithm first increases the assigned feedback gain, and as the

†The following set of controller parameters was used: $k_{D,FE}(1) = 5 \cdot 10^{-3}$ Nms/rad, $k_{MIN,FE} = 1 \cdot 10^{-3}$ Nms/rad, $k_{MAX,FE} = 2 \cdot 10^{-2}$ Nms/rad, $r_{MIN,FE} = 0.5$ rad/s, $r_{MAX,FE} = 15$ rad/s, $\tau = 3$, $c = 0.2$ Nm, $t_3(1,1) = 2$ s
adaptive controller estimates the constant task-space torque, decreases the gain until it settles down to a roughly constant value. While the perturbation is off, subject active phase (not shaded in Fig. 3.7) \( c = 0 \), and the subject is required to actively move. In this phase, \( k_D \) shows first-order decay dynamics, with update constant determined by parameter \( \tau \) in (3.14).

### 3.7 Discussion and Conclusion

In this chapter I have presented the development of a subject-adaptive controller that features an AAN controller with a feedback gain modification algorithm. Together, these novel features enable the application of this controller to the RiceWrist system, which is the wrist-forearm portion of the MAHI Exo-II presented in Chapter 2, and capable to rehabilitate the distal DOFs (forearm pronation/supination, wrist flexion/extension, and radial/ulnar deviation) of the upper limb.

Previous AAN controllers for robotic rehabilitation have used impedance controllers to regulate assisting forces based on deviations from desired trajectories, but cannot adapt in the case of non-homogeneous residual motor capabilities across the robot workspace. AAN controllers based on an adaptive control architecture offer this customization, and are therefore selected for the given application of wrist rehabilitation, since differential abilities to execute wrist flexion and extension movements are often observed in the main target populations of stroke and incomplete spinal cord injury. To date, however, such adaptive AAN controllers have modified the feed-forward part of the controller in order to adapt the estimate of the participant’s ability to execute movements.

I introduced a novel AAN controller, designed to obtain ultimately bounded stability properties. Inspired by motor control studies showing that error is likely to be
a driving signal for motor learning [40], [41], a novel formulation based on feedback gain modification is developed. The formulation gives direct access to modify the allowable error during movement execution, while simultaneously estimating the forces provided by the participant that contribute to movement execution. Experimental results show that the controller accurately estimates environmental forces such as would be applied by the subject during therapy.

The approach presented in this chapter translates the adaptive controller approach [2] to the field of rehabilitation robotics, and combines Gaussian radial basis functions for estimating interaction forces, as previously proposed in [44], and later proposed in [12] for rehabilitation applications. The controller presented in this chapter differs from [12] in that the proposed controller is able to directly manipulate the allowable error bounds and the amount of force support. Hence, instead of requiring the errors to become zero, the proposed controller tolerates error and manipulates the error bound in a performance-adaptive way. Furthermore, the proposed approach does not apply any modification to the adaptation law of the controller [2], and therefore does not interfere with the quality of force estimation.

The formulation is based on the working hypothesis that the subjects’ applied force field (referred to as $F_p$ in this chapter) is linearly parameterizable. Despite the simplifying nature of this assumption, the approach has been introduced in [16] for a real-time controller implementation, and in [45] for modeling of human motor control. The experimental results show that the system is capable of rapidly adapting to the changing residual capabilities of subjects, even if the actual forces applied cannot be accurately modeled as a linearly parameterizable force field $F_p$. Although alternate methods of force estimation have the potential to provide more accurate estimation, they are model-based, introduce complexity to the control algorithm, and increase
computational cost.

Because the RiceWrist is used to rehabilitate movements of the distal upper extremity, it must be ensured that the desired trajectories are physiologically appropriate for wrist movements. Much of the prior literature in trajectory generation for upper limb rehabilitation robotics is based on the notion of optimally smooth (minimum jerk) movements. Such characteristics of upper limb movements have been reliably demonstrated for whole arm reaching tasks evaluated in task-space. However, recent findings have indicated that the same characteristics are not observed in point-to-point reaching movements of the wrist joint. Therefore, the results of an experiment with healthy subjects have been presented results in order to define a physiological representation of a desired wrist movement profile that can be employed with the proposed AAN controller.

Finally, the combination of the proposed AAN controller with feedback gain modification is validated through experiments involving five healthy subjects. Experimental results demonstrate that the proposed approach provides variable levels of mechanical assistance when the subject is able to complete the movement on his own by estimating the forces provided by the subject; adapts the feedback gains so as to regulate the assistance in a performance-adaptive way.

The next chapter will focus on the implementation of the modified adaptive AAN controller in a clinical setting, in order to validate the efficacy of the proposed controller for rehabilitation of the distal upper limb after incomplete spinal cord injury.
Chapter 4

Subject testing of Subject-Adaptive Controller Robotic Therapy After Spinal Cord Injury

In this chapter an overview of the methods and the preliminary results of a clinical study, aimed at testing the efficacy of the novel subject-adaptive controller controller for upper extremity rehabilitation after incomplete spinal cord injury (SCI), are given. To test the specific added value of the subject-adaptive controller, a parallel-group controlled clinical study is carried out. The study aims directly to compare the effects of the subject-adaptive controller with a fixed gain, Subject-Triggered (ST) controller where the robot completes a movement upon the application of a trigger force by the subject.

Portions of this chapter were published in the proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR 2015) [58], and includes sections from an ongoing study in collaboration with Kyle Fitle. I gratefully acknowledge my collaborators in this publication.

4.1 Introduction

A distinguishing feature of rehabilitation robots is that they can implement several different control strategies during interaction with humans [14]. For stroke rehabilitation, it has become more or less clear which interaction modalities do and do not contribute to recovery [59]. However, for SCI this problem is still far from being definitively answered. Despite preliminary studies on animal models suggesting that
rehabilitation should leverage plasticity in a similar way to how it does for stroke rehabilitation [60, 61], this question still remains to be tested in a clinical study.

This lack of knowledge is surprising considering the continuously increasing efforts that roboticists are devoting to the formalization and implementation of shared control modes to facilitate robot-assisted rehabilitation protocols [11, 20, 62]. For such research efforts to have translational significance, it is necessary to test their efficacy in a clinical population. Especially in rehabilitation after incomplete SCI, a field still much in its infancy, such early stage trials should be aimed at giving inputs for further refinement of robot-assisted therapeutic protocols. The work described in this chapter presents preliminary results of a clinical study, aimed at testing the efficacy of a novel assist-as-needed (AAN) controller for upper extremity rehabilitation after incomplete SCI. Although the results are for a subset of the subjects, they provide an insight for the future results.

Subsequent sections present the implemented controller modes (Section 4.2), the methods used in the study (Section 4.3), preliminary results of the study (Section 4.4), and the conclusions (Section 4.5)

### 4.2 Control Modes

Two control modes were developed for this study and implemented in the MAHI Exo-II [25], a five degrees-of-freedom (DOF) exoskeleton used for isolated rehabilitation of the elbow, forearm and wrist joints. The exoskeleton is capable of two control modes, the subject-adaptive controller, and the Subject-Triggered (ST) controller, which are described in the following sections.
Figure 4.1: Block diagram of the subject-adaptive controller employed in this study. Blocks with a yellow background include components of the adaptive controller [2]. The dashed line refers to a discontinuous update of signal variables, i.e. the feedback gain is changed on a task-by-task basis.

4.2.1 Subject-Adaptive Controller

For the subject-adaptive controller (see block diagram in Fig. 4.1), the controller proposed in Chapter 6 is implemented, which includes an additional on-line trajectory recalculation beside its two main components; subject ability estimation and feedback gain modification. The algorithms briefly restated below for completeness.

The subject ability estimation algorithm is based on the adaptive controller [2]. The adaptive controller uses the following adaptation law:

$$\dot{\theta} = -\Gamma^{-1} Y(x)^T r$$  \hspace{1cm} (4.1)

where $\Gamma$ is an $n \times n$ constant, positive definite, symmetric matrix; $Y$ is a regressor matrix which contains known functions of $x$, which is the task space pose of the end-effector; $\hat{\theta}$ is the vector containing estimates of unknown system parameters; and $r$ is a weighted sum of position and velocity error, defined as

$$r = \dot{x} + \Lambda \ddot{x} = (\dot{x} - \dot{x}_d) + \Lambda (x - x_d)$$  \hspace{1cm} (4.2)

where $\Lambda$ is a weighting constant.
For the implementation described in this study, the previous formulation is extended by introducing direction dependency on the regressor matrix \( Y = Y(x, \dot{x}) \), considering that an impaired subject might have different levels of disability on their agonist and antagonist muscles. As in Chapter 6, Gaussian Radial Basis Functions (RBFs) are employed as known functions in the regressor matrix, but instead of one, double set of RBFs are used for each DOF to account for direction dependence.

Another modification introduced in the controller presented in Chapter 6 involves the logic of feedback gain modification, a component required so to modulate the amount of motion assistance in a performance-adaptive way. For this study, the change of the feedback gain, \( \Delta K_D \), is discretely updated based on the subject error performance at the end of every task. \( \Delta K_D \) is defined as

\[
\Delta K_D = \Delta K_{D,\text{max}} \frac{(r_{\text{avg}} - r^*)}{(r^* - r_{\text{min}})},
\]

where \( \Delta K_{D,\text{max}} \) is a bound on the magnitude of change of the feedback gain, \( r_{\text{avg}} \) is the average error for the previous task, and \( r_{\text{min}} \) defines the slope of the gain update curve. The gain update law shown in (4.3) is used, rather than directly assigning a feedback gain value for a given subject error performance, as done in Chapter 6. In this way it was possible to introduce an error characteristic term, \( r^* \), an upper bound to the allowable error. This term is introduced because even healthy subjects’ movement contains natural variability and providing force support to minimize error beyond such variability might be detrimental to motor learning [63].

The generation of the desired trajectory for this controller is handled by a two-part algorithm. The first part assigns an allocated time \( T_{\text{end}} \) and constructs a nominal desired trajectory based on a physiologically optimal and experimentally validated joint movement profile. The second part of the algorithm implements a conditional trajectory recalculation (CTR), so that when the position of the subject is ahead of
the nominal desired trajectory, a new desired trajectory is computed as a piecewise polynomial function. After each recalculation, $T_{end}$ is reduced until the current movement is completed and the updated value of $T_{end}$ is passed for the next task. In an attempt to differentiate between intentional subject involvement and unintentional elastic return due to muscle stretching, the CTR is enabled only if the subject is able to be ahead of the nominal desired trajectory in both center-to-periphery and periphery-to-center directions for a percentage (10%) of the last movement when CTR was disabled. This helps guarantee active subject input because the elastic return of stretched muscles typically only aids movement from periphery-to-center. If the CTR is not activated for a given task, the algorithm will increase $T_{end}$ until the subject is able to beat the nominal desired trajectory. During the CTR “off” phase, a ghost cursor following the nominal desired trajectory is displayed to the subject in the GUI in order to motivate the subject to beat the nominal trajectory (see Fig. 4.2(A)).

Since a lead-type error is not possible when the trajectory recalculation mode is switched on, the RBF amplitude estimates are mostly non-decreasing (in absolute value), in such condition. To avoid this problem, the adaptation law in (4.1) is modified to include a first-order decay of the RBF amplitude estimates only when the error drops below the value $r_{min}$.

### 4.2.2 Subject-Triggered controller

The ST controller is implemented as a two state controller. In the first state, a set point controller with high proportional-derivative gains at the start position (center or periphery) is implemented, and the subject is visually cued to apply a force towards the direction of the target position (periphery or center). When the force applied by the subject exceeds a threshold $F_{th}$, and is sufficient to break through the virtual
wall along the desired direction, the controller switches to the second state. In this phase, a trajectory controller with high proportional-derivative gains is implemented to reach the target through a minimum-jerk trajectory with duration $t_{ST}$. Although subject input is required to trigger the switch to the movement mode, subjects are not involved in controlling their movements to reach the target. The values of $F_{th}$ are increased by the therapist on a session-to-session, based on subject ability and comfort (pain and fatigue are recorded before and after each session to ensure excessive levels of each are avoided). This is done is to progressively increase the challenge to the subject to encourage active involvement throughout the course of training.

### 4.3 Methods

The purpose of the clinical study is to demonstrate that a robot-aided rehabilitation protocol that follows the subject-adaptive control paradigm can result in improve-
ments in arm and hand motor functions when compared to an alternative rehabilitation protocol, based on the Subject-Triggered (ST) controller, in subjects with incomplete spinal cord injury (SCI). Subject improvements are evaluated using both recognized clinical assessment techniques, and well established robotic data assessment methods.

4.3.1 Subject Profile and Training Protocol

This study uses a parallel groups design in which participants with motor incomplete SCI (according to American Spinal Injury Association (ASIA) Impairment Scale (AIS) C-D levels) are assigned to either the AAN control group (group A) or to the ST control group (group B). Inclusion criteria were age (comprised between 18 and 75 years), diagnosis of chronic incomplete SCI (at least 6 months prior to enrollment), while exclusion criteria were prior enrollment in robotic rehabilitation studies for the upper arm, any planned alteration in medication for muscle tone for the duration of the study, arthritis, excessive shoulder pain, joint contracture or excessive muscle tone (Modified Ashworth Scale >3).

For each group, six subjects were enrolled considering the inclusion criteria. Each subject participated to a total of fifteen visits. The first two visits involved screening for inclusion and exclusion criteria and baseline assessment on primary and secondary outcome measures, in addition to the ASIA upper extremity scale to verify the diagnosis. During the second baseline visit, each subject underwent a robotic evaluation session, in which they were asked to perform sixty point-to-point isolated reaching movements for each of four the MAHI Exo-II DOFs. One-week after the last baseline visit, subjects received robotic training, in ten 90-minute long sessions, spread over a period of three to four weeks. At the beginning of each robotic training session,
subjects executed an evaluation session. After the evaluation session, subjects underwent robotic training, which takes the form of $x$ repetitions per DOF, with $x$ adapted to result in sessions of the prescribed duration (90 minutes). Through this design, it is possible to evaluate whether a specific controller implementation was capable of maximizing the number of repetitions in a given maximum allowed session time. For the subject-adaptive controller AAN controller, both force and timing parameters estimated from the previous sessions were retained as initial guess in the subject-adaptive therapy mode, whereas for the ST controller, the therapist manually set the challenge parameters (i.e. force threshold percentage $F_p$ and time allowed for a movement $T_{ST}$) on a session-by-session basis, based on subjects performance. After the last training session, three post-treatment assessment sessions (one week, two weeks, and two months after treatment) were completed with the therapist, in addition to the evaluation sessions with the robot.

4.3.2 Clinical Assessment Measures

The improvements in arm and hand movement capability of the subjects in both groups were evaluated using recognized clinical assessment techniques. Specifically, subject’s spasticity, motor function performance, muscle strength, and sensation were tested in the baseline assessment and in the post-treatment assessment sessions. The adopted clinical measures are summarized below.

4.3.2.1 Modified Ashworth Scale (MAS)

MAS is a simple test of a subject’s spasticity. An OT or PT performs the MAS selected sets of muscles by flexing or extending the corresponding joint over a count of one second. The muscle set is then scored on a scale from 0 to 4, where 0 is no
increase in muscle tone, 2 is a more marked increase in muscle tone though most of the range of motion, but the affected part is easily moved, and 4 is the affected part or parts are rigid in flexion or extension.

4.3.2.2 Action Research Arm Test (ARAT)

ARAT mainly focuses on assessing upper limb function using observation. It consists of 19 tasks divided into four categories, grasp, pinch, grip, and gross arm movement. The tasks involve manipulating objects of different sizes and shapes such as washers, a cup of water, and a cricket ball. Each task is graded on a 0-3 point scale with 3 points given for a task completed in a normal matter, 2 points given for tasks completed with difficulty, 1 point for a partially completed task, and 0 points awarded for an uncompleted task. The grading for this study was done based on the trained observations of an occupational therapist.

4.3.2.3 Graded Redefined Assessment of Strength, Sensibility, and Prehension Test (GRASSP)

The GRASSP, explained in detail by Kalsi-Ryan et al. [64], is a measure which examines a subject’s strength, sensation, and prehension tasks relating to ADL. The sensation portion involves using a Semmes-Weinstein Monofilaments testing kit to determine the subject’s level of sensation impairment. This kit includes monofilaments of different thicknesses which will exert a precise amount of force before buckling. These are pushed against the subject’s skin surface to determine if they can detect the given amount of pressure in point contact. The assessment is performed simply by having the subject close his or her eyes and announce whether or not he or she feels a point contact and where that contact is felt while an OT or PT pushes the
filaments down onto the skin. It is rated from 0, no measurable sensation, to 4, can detect 0.4 grams of force. This test is performed on the skin surface on the dorsal and palmar regions of the each hand.

The strength portion is completed using qualitative rating by an OT or PT rating strength in each selected muscle from 0, flaccid, to 5, full range with maximal resistance. The prehension portion of the assessment involves a performance portion in which the subject must complete tasks including pouring water from a bottle, opening a jar, picking up and turning a key, transferring nine pegs on a specially made board, picking up four different-sized coins and placing them in a slot, and screwing four different-sized nuts onto bolts. Each of these tasks is graded from 0 to 5, with 5 indicating all subtasks were completed successfully in the given time limit. Prehension testing also involves rating (from 0 to 4) the subject’s ability to generate three grasps, cylindrical, lateral key pinch, and tip to tip pinch. Each of these grasps will be used in the performance portion if the subject has unimpaired use of his or her hands, and the OT/PT rates each by observation of the this portion.

4.3.3 Robotic Assessment Measures

Motion data recorded during the evaluation portion of each therapy session and the baseline and post-treatment assessments were quantitatively analyzed in order to evaluate the improvement in the upper extremity movement capability of the subjects. The velocity-profile based robotic assessment measures are briefly described below.

4.3.3.1 Speed Peaks

The Speed Peaks metric is simply the number of peaks in a speed profile. Peaks indicate an acceleration or deceleration with more peaks per movement indicating
less smooth movements. This metric has been used previously in healthy and stroke-impaired subjects [65,66], but should be used with caution because the generation of spurious peaks is possible and inconsistencies may result in speed profiles with large numbers of arrest periods. This metric is computed by simply finding the number of positive to negative sign changes in the first derivative of the velocity data.

4.3.3.2 Spectral Arc Length (SAL)

Spectral arc length, as defined by Balasubramanian et al. [67], is a movement smoothness metric which is the negative arc length of the amplitude and frequency-normalized Fourier magnitude spectrum of the speed profile. The idea behind this metric is to examine a given movement in the frequency domain with smoother movements having more low-frequency components and less smooth movements consisting of higher frequency components. This metric is defined as

\[
\eta_{sal} \triangleq - \int_0^{\omega_c} \sqrt{\frac{1}{\omega_c^2} + \frac{dV(\omega)^2}{d\omega}} d\omega \quad (4.4)
\]

where \( V(\omega) \) is the Fourier magnitude of the speed profile \( v(t) \) and \([0, \omega_c]\) is the frequency band of the movement. Smaller magnitude values of the spectral arc length indicate higher quality movements.

4.3.3.3 Normalized Speed

This relatively simple metric works on the observed phenomenon that subjects with less healthy movement tend to have speed profiles with deeper valleys and more near-stops than normal movements [66]. This results in the normalized mean speed being significantly lower for impaired subjects than for unimpaired ones. Therefore, the
normalized mean speed is examined as a quality of movement metric. The simple equation is shown here

\[ \hat{v} = \frac{\bar{v}}{v_{\text{max}}} \]  

(4.5)

where \( v \) is speed.

4.3.3.4 Smoothness Correlation Factor (SCF)

Another quality of movement metric which was examined in this analysis is based on the coefficient \( \rho \), described by Colombo et al. [68], which is based on the correlation between the velocity profile of a given movement and the corresponding minimum jerk velocity profile. In this analysis \( \rho \) was calculated as follows

\[ \rho = \frac{(V_{\text{subj}} - \bar{V}_{\text{subj}})(V_{m,j} - \bar{V}_{m,j})}{\sqrt{(V_{\text{subj}} - \bar{V}_{\text{subj}})^2(V_{m,j} - \bar{V}_{m,j})^2}} \]  

(4.6)

where \( V_{\text{subj}} \) is the movement speed of the subject and \( V_{m,j} \) is the minimum jerk speed profile (bar indicates mean).

\( V_{m,j} \) was calculated as follows:

\[ V_{m,j}(t) = \delta \frac{30t^4}{T^5} - \frac{60t^3}{T^4} + \frac{30t^2}{T^2} \]  

(4.7)

where \( \delta \) is the movement distance, \( t \) is the movement time, and \( T \) is the time to complete the movement. To calculate the smoothness correlation factor, \( \rho \) is multiplied by the coefficient of determination, \( r^2 \), between the subject’s velocity profile and a fourth-order best fit curve. This was calculated using MATLAB. This metric indicates how similar the subject’s velocity profile matched the minimum jerk profile and how well it can be represented by a fourth-order, bell-shaped curve. The metric
ranges from 0 to 1, with 1 indicating a perfect correction with the minimum jerk profile. Occasion negative values were calculated for individual movements, implying negative correlation, and were set to zero. This metric was used successfully in a study with the RiceWrist [69].

4.4 Results

4.4.1 Clinical Assessment Results

The results of the clinical assessments discussed previously were analyzed using a mixed design ANOVA with treatment group as the between subjects variable and other variables being within subjects. One outlier identified with the 3 IQRs from hinges method was removed and replaced with the grand mean for that session. The results of this analysis are presented in Table 4.1 below.

Table 4.1: Results of clinical assessments from the baseline to the post-treatment assessment.

<table>
<thead>
<tr>
<th></th>
<th>Main Effect of Sessions</th>
<th>Group-Session Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>df</td>
<td>F</td>
</tr>
<tr>
<td>MAS</td>
<td>(1, 8)</td>
<td>1.4</td>
</tr>
<tr>
<td>Grip-Pinch</td>
<td>(1, 8)</td>
<td>3.0</td>
</tr>
<tr>
<td>ARAT</td>
<td>(1, 8)</td>
<td>0.5</td>
</tr>
<tr>
<td>GRASSP Quant. Preh.</td>
<td>(1, 8)</td>
<td>0.4</td>
</tr>
<tr>
<td>GRASSP Strength</td>
<td>(1, 8)</td>
<td>19.0</td>
</tr>
<tr>
<td>GRASSP Sensation</td>
<td>(1, 8)</td>
<td>3.84</td>
</tr>
</tbody>
</table>

4.4.2 Robotic Assessment Results

The robotic position and velocity data collected at the assessment sessions and the beginning of each training session was analyzed using the four robotic metrics men-
tioned above. The statistical analysis was completed similarly to that done with the clinical measures except that outliers were replaced with the subject mean instead of the grand mean. This is the preferred method and was more feasible here where the subjects had 12 mean values for each metric as opposed to 2 as in the clinical data analysis.

The robotic data was analyzed from training session one to training session ten for the statistical pre/post analysis. The results of this analysis are shown in Table 4.2.

Table 4.2: Results of statistical analysis of robotic data. Data analyzed here is from the training session 1 to training session 10.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed Peaks</td>
<td>(2.3, 9.0) GG</td>
<td>0.6</td>
<td>.59</td>
<td>0.13</td>
<td>.96</td>
<td>2.0</td>
<td>0.19</td>
<td>0.33</td>
<td></td>
</tr>
<tr>
<td>Norm Speed</td>
<td>(2.1, 8.3) GG</td>
<td>1.1</td>
<td>.38</td>
<td>0.22</td>
<td>.94</td>
<td>1.4</td>
<td>0.3</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td>SAL</td>
<td>(2.3, 9.2) GG</td>
<td>1.2</td>
<td>.34</td>
<td>0.24</td>
<td>.20</td>
<td>1.0</td>
<td>0.4</td>
<td>0.21</td>
<td></td>
</tr>
<tr>
<td>SCF</td>
<td>(1.7, 6.9) GG</td>
<td>2.4</td>
<td>.16</td>
<td>0.38</td>
<td>.76</td>
<td>2.3</td>
<td>0.17</td>
<td>0.37</td>
<td></td>
</tr>
</tbody>
</table>

4.5 Discussion and Conclusion

This study aimed to compare the effectiveness of two different types of assistive robot-aided interaction protocol in the rehabilitation of incomplete SCI subjects. Although the preliminary results provide promise for the possible positive outcomes with higher number of subjects, they do not allow to reach definitive conclusions. In fact, via the analysis of both robotic and clinical data no significant interaction was found between the effects of group and sessions. This indicates that the controller assigned for therapy (AAN or ST) did not make a significant difference in the way
their quality of movement changed over the course of the training sessions. The results also showed a lack of main effect of the session, indicating that the subjects’ scores did not significantly change from pre-training to post-training on average.

Therefore, no definitive statements about the effect of the robotic training using this protocol can be made at this point. However, certain trends in the data may prove interesting for further research. For example, both strength measures used (Grip-Pinch and the GRASSP strength section) show small, but noticeable increases from pre to post for both groups. In addition, the trends in some robotic metrics look promising and may warrant additional research.

Despite the absence of the outright and definitive statistical significance, we have reason to believe that future iterations of assist-as-needed-type controllers may hold promise in providing effective rehabilitation. First, these results are only preliminary and do not include all subjects. The greater power gained with analyzing more subjects data could potentially change the statistical results. In addition, trends seen in some of the robotic metrics and observed in the clinical strength measures suggest that small improvements are occurring. We simply need to determine how to increase the effect of the robotic training.

Throughout the training protocols, significant observations have been made about both the robotic hardware, MAHI Exo-II, and the implemented subject-adaptive controller. An important observation about the subject-adaptive controller is that, the assumption of the position dependency of the subject capability, which is an integral step in the modelling subject capability (see Section 3.4.1), might be an over simplification for neurologically impaired individuals. Our observations suggest that expecting a consistent position dependent performance from a subject is not reasonable especially with the existence of neuro-injury induced tremors, spasticity,
and sudden muscle cramps. Additionally, it has been observed that for most of the subjects the wrist module of the MAHI Exo-II was not able to match the complete functional workspace, and the torque output capabilities of the wrist module was limited. In order to address the limitations of the existing hardware and controller, the subsequent chapters of this thesis present the next generation of a wrist module design, and a minimal assist-as-needed controller.
Chapter 5

RiceWrist-S: a Forearm-Wrist Exoskeleton For Upper Extremity Rehabilitation

In this chapter, I present the design of the RiceWrist-S, a novel forearm-wrist robotic exoskeleton for rehabilitation of the upper extremity after stroke and SCI. The 3 degree-of-freedom (DOF) device is developed to address the problems encountered at the wrist portion of the MAHI Exo-II hardware; such as small workspace and limited torque output capabilities.

Portions of this chapter were published in Robotica [23], IEEE RAS EMBS International Conference on Biomedical Robotics, and Biomechatronics (BioRob 2012) [21], IEEE International Conference on Rehabilitation Robotics (ICORR 2013) [22]. I gratefully acknowledge my collaborators in these publications.

5.1 Introduction

To facilitate the implementation of sophisticated interaction control algorithms, the design of the robotic device needs to minimize the intrinsic nonlinearities such as static friction and backlash, and provide high torque output capability. Additionally, a wearable rehabilitation device must ensure ergonomic human robot interaction by covering complete functional workspace and causing no discomfort or safety hazard at the intended joints. Furthermore, it is a common practice to use the robotic devices for the assessment of motor coordination, where subjects back-drive the robotic device and motion data are recorded for analysis. Hence it is desirable for a robotic device
to exhibit specific properties such as low apparent inertia and friction, and isotropic
dynamic characteristics to ensure the transparency of the device.

5.2 Literature Review

Nearly all activities of daily living (ADL), such as eating, drinking, cleaning, and
dressing, involve distal upper extremity movement and a certain level of manual
dexterity. In order for a person who has suffered a stroke or SCI to regain the ability to
perform these ADLs, effective rehabilitation of the upper limbs, especially the distal
joints, is required. A growing number of research groups have developed robotic
deVICES for rehabilitation of the distal joints of the upper extremity. For example,
Colombo et al. employ a one DOF wrist manipulator in conjunction with a two
DOF elbow-shoulder manipulator in their clinical evaluation of stroke rehabilitation
[70]. Although the wrist manipulator can apply large torque outputs, its actuation
is limited only to wrist flexion/extension movements. The Arm Trainer [71] and
Universal Haptic Drive (UHD) [72] are designed to actuate two out of three DOFs
of human wrist for a given configuration. Both devices use geared transmissions,
which can reduce the backdrivability of the device. Some of these limitations were
addressed by Krebs et al. who developed a compact 3-DOF wrist robot [34]. Their
system is capable of matching the complete range of motion (ROM) required for
ADLs of the wrist by employing a differential gear mechanism, that provides the
advantage of limiting the reflected inertia for flexion/extension (FE) and radial/ulnar
deviation (RU), but introduces some friction and requires expensive, high-accuracy
mechanical components. In a subsequent robot-aided stroke rehabilitation study,
Squeri et al. proposed a new 3 DOF wrist robotic exoskeleton [35]. Although the
design approximately covers the required ROM for wrist movement ADLs [3], it is
unclear how both the incorporation of gear drives and coupled movements between the actuator for wrist flexion/extension and the handle reflects on the backdrivability and transparency of the device, specifically in terms of friction and end point inertia.

This chapter presents the RiceWrist-S (Fig. 5.1), a forearm-wrist robotic exoskeleton intended for stroke and SCI rehabilitation. The RiceWrist-S is designed to provide high torque output and cover the complete functional workspace of the human wrist. Such performance is achieved while also providing minimal friction, and inertial and gravitational loading, by means of a cable drive transmission. This chapter is structured as follows. In Section 5.3, the design and characterization of the RiceWrist-S is presented, in conjunction with the details and rationale of design choices, and procedures and results of device characterization. Then, a pilot clinical evaluation of the RiceWrist-S with one subject with incomplete SCI is reported. The clinical evaluation methods are described in Section 5.4, including detailed description of performance metrics used for clinical and robotic assessment, while the results are reported in Section 5.4.2. Finally, the implications of the clinical study outcomes are discussed.

5.3 Device Description and Modelling

RiceWrist-S is a 3 DOF, electrically actuated, grounded forearm-wrist exoskeleton. The system employs, contrary to the parallel wrist portion of the MAHI Exo-II, a serial RRR manipulator, the kinematic structure of which is depicted in Fig. 5.2. RiceWrist-S is capable of actuating the user’s forearm pronation/supination (PS), wrist flexion/extension (FE), wrist radial/ulnar deviation (RU) DOFs separately. In addition to the actuated DOFs, the system also employs a passive DOF at the handle to add redundancy to the mechanism and correct for any misalignment that might
occur due to the simplifying assumption that the three axes of wrist motion intersect at a point.

Figure 5.1 : RiceWrist-S – Forearm and wrist exoskeleton for rehabilitation, shown with participant with incomplete spinal cord injury.

The main purpose of the design of the RiceWrist-S is to address the shortcomings of the wrist portion of the MAHI Exo-II. The MAHI Exo-II employs a parallel 3-RPS (revolute-prismatic-spherical) mechanism at the wrist portion. The upside of the parallel mechanisms are rigidity (due to closed chain structure), decreased apparent inertia (due to the ability to locate the actuators remotely form the end effector). However the workspace capabilities of the parallel mechanisms are limited compared to serial mechanisms. The design of the RiceWrist-S first and foremost aims to cover the functional workspace of the human joints, which is not achieved by the parallel wrist portion of the MAHI Exo-II (see Table 5.2). Furthermore, since the rotation axes of human joints are intersected with the end-effector of the 3-RPS mechanism, the torque generation from joint space to end-effector space depends on a position dependent transformation, namely the Jacobian of the mechanism. Hence the maximum torque output will depend on the position of the end-effector. The design of the RiceWrist-S eliminates the position-dependent transformation of torque generation by reducing the torque generation problem to the joint space. In this
way, the RiceWrist-S is capable of providing maximum continuous torque output throughout the complete range of motion for every joint.

Figure 5.2: Kinematic structure of RiceWrist-S, a 3-DOF serial spherical mechanism.

5.3.1 Design Details

In order to ensure zero backlash and low friction on the FE and RU joints, the RiceWrist-S uses cable drive transmissions, while the PS joint employs a frameless brushless motor in direct drive configuration. The cable transmission for the RU joint is achieved via a cable routing mechanism which allows remote placement of the actuator to minimize gravitational and inertial loading on the user (Fig. 5.3(a)).

The primary benefit of the cable routing mechanism is that it enables placement of the RU joint actuator exactly below the FE rotation axis, decreasing the endpoint inertia of the device. Additionally, the cable routing mechanism enables achievement of a 1:24 transmission ratio with a compact design, providing high torque output and increasing the sensor resolution by a factor of 24. The motor power is transferred from the motor shaft to the transmission shaft via two steel cables, both of which are first fixed on the motor shaft and wound in opposite directions on the shaft, then wound
around and fixed on the aluminum cylinders. The aluminum cylinders are threaded and coupled to the precision threaded steel transmission rod, allowing transmission of motor power to the transmission rod. To transfer power from the transmission rod to the device handle, one end of the transmission shaft is used as a capstan spool, and the capstan arc, coupled to the device handle, is driven by means of a cable drive system. The cables are pretensioned by screwing the aluminum cylinders in opposite directions. Actuation is provided by a Maxon RE-30 brushed DC motor with a CPT Avago 5540 HEDS optical encoder with 500 counts per revolution.

The cable transmission for the FE joint is designed so that the distance of the FE actuator from the PS rotation axis is minimized, in order to keep the inertia of the device as low as possible. An idle pulley is employed to avoid collisions between the actuator and other device components (see Fig. 5.3(b)). The transmission ratio for the FE joint is 1:18. I selected a Maxon RE-40 brushed DC motor with a CPT Avago 5540 HEDS optical encoder with 500 counts per revolution. The sensing resolution, actuator and transmission specifications, torque output, and ROM capabilities of the device are summarized in Tables 5.1 and 5.2.

The safety of the subject is ensured via mechanical stops that are within the reachable range of motion for an unimpaired subject. Additionally, current saturation is applied in software to limit excessive torque command to the motors. Finally, multiple mechanical emergency stop buttons are employed which can be activated by the therapist at any time.

5.3.2 Kinematic and Dynamical Performance Analysis

A critical design requirement for the RiceWrist-S is dynamic transparency which affects the ease of human-induced motion when the device is un-powered, since such an
Figure 5.3: (a) Cable routing mechanism for the RU joint: power is transferred from the motor shaft to the transmission rod via a steel cable. The transmission rod drives the RU joint capstan arc, that is coupled with the handle support. (b) Cable routing mechanism for the FE joint: an idle pulley is employed to transfer actuation to the FE joint capstan arc, via a steel cable.

Figure 5.4: Section views of the generalized inertia ellipsoid through the planes $\theta_3 = 0$ (a), $\theta_2 = 0$ (b), and $\theta_1 = 0$ (c), for different manipulator configurations.

operation mode is being relied on for assessment of subjects’ movement quality. One way to characterize dynamic transparency is to quantify the inertial forces required to actuate the manipulator when the user is driving the robot. To do so, the generalized inertia ellipsoids (GIE) of the device for the complete joint-space are calculated. GIE, defined first in [73], is a measure of required torque for a unit acceleration at a given
configuration.

Let me define the generalized coordinates and the joint space dynamic model of the RiceWrist-S as

$$\theta = [\theta_1 \theta_2 \theta_3]^T$$  \hspace{1cm} (5.1)\

$$\tau = M(\theta)\ddot{\theta} + B(\dot{\theta}, \theta)\dot{\theta} + G(\theta)$$  \hspace{1cm} (5.2)\

where $M$ is a $3 \times 3$ inertia matrix, $B$ is a $3 \times 3$ matrix which represents Coriolis/centrifugal terms, $G$ is the $3 \times 1$ gravity vector, and $\tau$ is the $3 \times 1$ vector of the back-driving torque applied by the subject represented in the joint-space. I am interested in considering the inertial contribution of the torques required to back-drive the robot, hence let me assume $B(\dot{\theta}, \theta)\dot{\theta} = 0$, and neglect $G$. As a result, (5.2) reduces to

$$\tau = M(\theta)\ddot{\theta}$$  \hspace{1cm} (5.3)\

Consider the constant unit joint accelerations, which describe the points on a spherical surface

$$\ddot{\theta}^T \ddot{\theta} = 1$$  \hspace{1cm} (5.4)\

Combining (5.3) and (5.4), the torques required to obtain a unit acceleration can be computed by solving the following quadratic form:

$$\tau^T M^{-T}(\theta)M^{-1}(\theta)\tau = 1$$  \hspace{1cm} (5.5)\

The analytical expression of the inertia matrix $M$ as a function of generalized coordinates $\theta_1, \theta_2$ and $\theta_3$ can be obtained using standard Lagrangian dynamical modeling methods [74], and allows the definition of a quadratic form, as a function of only the generalized coordinates and inertial manipulator parameters: the GIE [73]. Analysis
of the GIE allows determination of the apparent resistance to motion perceived by the user when moving at constant acceleration, as a function of the direction of motion.

The distance between a point on the surface of the ellipsoid drawn around the current manipulator kinematic status \( \theta_c = (\theta_1, \theta_2, \theta_3) \) and the point \( \theta_c \) itself gives a measure of the inertia perceived along the direction joining the point on the surface and \( \theta_c \).

The generalized ellipsoid can be represented in a more synthetic and compact way by eigenvalue decomposition of the matrix \( M^{-T}(\theta)M^{-1}(\theta) \). The eigenvectors of the matrix define the principal axes of the ellipsoid, while the reciprocals of the square of the eigenvalues define the semi-axes lengths. In the cases of the principal directions, the ellipsoid axes length gives an immediate measure of the necessary torque values to generate a unit joint acceleration along the corresponding principal direction.

For clarity of representation, section views of the GIE are reported in Fig. 5.4, obtained as a cut of the GIE through planes \( \theta_3 = 0, \theta_2 = 0, \) and \( \theta_1 = 0, \) respectively, for different manipulator configurations. The axes lengths vector \( L_{|\theta_0} \) and the principal axes matrix \( \text{Dir}_{|\theta_0} \) of the ellipsoid for the neutral position \( \theta_0 = [\theta_1 \ \theta_2 \ \theta_3]^T \) are computed as

\[
L_{|\theta_0} = [0.0185 \ 0.0105 \ 0.0033]^T \tag{5.6}
\]

\[
\text{Dir}_{|\theta_0} = \begin{bmatrix}
0.0367 & 0.1715 & 0.9845 \\
0.0905 & 0.9805 & 0.1742 \\
0.9952 & 0.0955 & 0.0205
\end{bmatrix} \tag{5.7}
\]

The joint torque values at the neutral position computed using Equations 5.6 and 5.7 are given as

\[
\tau_{|\theta_0} = [0.0201 \ 0.0138 \ 0.0047]^T Nm \tag{5.8}
\]

In order to assess the configuration-dependence of the inertia perceived with re-
spect to the device configuration, the variability of principal directions were initially evaluated, and were assessed that they are mostly parallel to the cardinal axes of the manipulator (i.e. \( \theta_1 \), \( \theta_2 \) and \( \theta_3 \)). Since the principal direction orientation changes by less than \( \pm 5 \) degrees as a function of manipulator workspace, I was able to analyze variability in intrinsic inertia by only evaluating the variability of GIE eigenvalues, throughout the manipulator’s reachable workspace (\( \pm 45 \) deg for all joints, 1031 evenly spaced points). The maximum variability is obtained for the PS joint, and approximately equals 10.8% of the value computed at the neutral position. The maximum variability of the other joints are 4% (FE) and 9% (RU), and demonstrates that variability in the eigenvalues of the inertial matrix is less than one order of magnitude compared to the values measured in the neutral position.

\[5.3.3 \text{ Device Characteristics} \]

In order to evaluate the potential of the RiceWrist-S for rehabilitation, the resolution of the device was determined using a similar approach presented in [75], along with key device characteristics that affect dynamic performance. The end effector spatial resolution (\( \Delta Q_E \)), is calculated by considering the Jacobian of the device (\( J(\theta) \)) and the joint space resolution vector (\( \delta_\theta \)), which includes the resolution values provided in Table I, for any configuration (\( \theta \)) of the work space \( W \) as

\[
\Delta Q_E = \max \{ \| J(\theta) \delta_\theta \| \} \forall \theta \in W
\]

and was determined to be \( 2.1816 \times 10^{-4} \) radians.

The mechanical characteristics of the device, including static friction, inertia, and viscous friction, are experimentally determined for every joint. The response of the system to a ramp position input is used to determine the static friction. The inertia
and viscous friction are determined by investigating the response of the system to a
step position command. While a more detailed description of these procedures can
be found in [22], the estimated parameters are reported in Table III for complete-
ness. The closed loop position control bandwidth of the RiceWrist-S is identified by
observing the device’s ability to track a sine position input with a PD controller im-
plemented for each individual DOF. The observed values are approximately 3.6 Hz,
6 Hz, and 8.3 Hz bandwidths for the PS, FE, and RU DOFs, respectively.

Comparison between the experimentally-estimated joint inertia values shown in
Table III and those obtained through dynamical modeling through (5.8) shows a
strong quantitative agreement, with a maximum percentage error of 20% for the PS
joint that corresponds to an error in the estimated inertia of only $6 \cdot 10^{-3}$ kg·m$^2$. The
model also correctly predicts that the joint with the highest reflected inertia is the
PS joint, whose value of intrinsic inertia is 1.5 times higher than that of the FE joint.
Finally, the joint with the least inertia is the RU joint, which is approximately aligned
with the axes corresponding to the lower eigenvalue of the inertia matrix, with an
inertia approximately one third of that of FE joint.

5.4 Clinical Case Study

In order to validate the use of the RiceWrist-S for clinical use in upper extremity
rehabilitation, a case study with an individual with chronic incomplete spinal cord
injury was conducted. In the following sections, the methods and results of this
pilot evaluation are described. The hypothesis is that with this novel device, the
robot-aided therapy would result in observable gains in clinical measures of motor
impairment and in improvements in movement smoothness, as observed in previous
studies of robotic rehabilitation [17].
5.4.1 Methods

A 45-year-old male, right handed, with incomplete SCI at the C3-5 level, classified as American Spinal Injury Impairment Scale (AIS) C and 83 months post-injury, participated in ten sessions of robotic-assisted arm training over 20 days of training, approximately four times per week, subject to a protocol approved by all participating institutions. The participant was highly active and independent in his powered wheelchair. Motor impairment in the distal component of his upper limb, including voluntary opening/closing of the hand or isolated finger movements, was greater when compared to the proximal components of the extremity, such as wrist and forearm movements. During the course of training, he did not participate in any other intensive occupational therapy program.

Set-up of the system and donning of the exoskeleton took approximately ten minutes. The subject was seated on a chair with his left arm placed inside the RiceWrist-S exoskeleton, and fixed to the device through Velcro and straps for minimizing the relative motion between the forearm and the device. Each session began by defining the subject’s active range of motion, for each DOF (calibration session). After calibration, an evaluation session was conducted where the subject was asked to perform visually-guided target hitting movements when back-driving the unpowered device through one of its DOFs. Later, a training session was administered, that involved the same target-hitting tasks, but with the robot commanded to display a force field proportional to the movement velocity at the intended joint, while all other joints of the device were kept stationary via control. The level of resistance was changed from session to session by the therapist according to the observed performance of the subject. The therapist aimed to increase resistance and thereby the challenge and engagement of the subject, but also was observant of the subject’s fatigue level when
choosing resistance levels. After completion of the evaluation and therapy for the first DOF, the process was repeated for the other DOFs. All training sessions were conducted by a physical therapist (N.Y.) who had previous experience with robotic-assisted training and rehabilitation of adults with incomplete spinal cord injury.

5.4.1.1 Clinical Assessment Measures

The efficacy of the robotic rehabilitation protocol was evaluated in a similar approach that described in Chapter 4. The main focus of the evaluation in this study was on the upper extremity muscle strength, motor performance function, grip and pinch forces of the subject. The strength of selected upper extremity key muscles (elbow flexors, wrist extensors, elbow extensors, finger flexors, and finger abductors) was scored according to American Spinal Injury Association (ASIA) guidelines between 0 and 5 (total score, range 0-25).

Arm and hand function performance were measured with both the Jebsen-Taylor Hand Function Test (JTHFT) and Action Research Arm Test (ARAT) [76, 77]. The JTHFT is a standardized 7-item test designed to evaluate various hand functions that resemble daily life activities, including writing, simulated page turning, picking up small common objects, stacking checkers, simulated feeding, lifting large and light objects, and lifting large and heavy objects. The sentence writing task was not included in the score due to severe hand dysfunction on the non-dominant side for the participant. Time of performance is recorded for each task. JTHFT has been used widely to measure upper extremity motor function in stroke and SCI [78] and has an established validity [79], reliability [80], and capacity for detecting changes in performance [81], [82]. The Action Research Arm Test (ARAT) is a standardized test of unilateral hand and upper limb function that consists of 19 items divided into four
sub-tests including grasp, grip, pinch and gross movement [77]. Although the ARAT was originally designed to measure arm and hand functions after stroke [83], [84], [81], it has been successfully used in SCI [85], [86]. All tasks are scored on a 4 point ordinal scale ranging from 0-3 where 0=no movement; 1=performs test partially; 2=complete test, but takes abnormally long or has great difficulty; and 3=normal movement, giving a possible range of 0-57.

In addition to these measures of arm and hand function, grip strength data were collected before and after each training session. Manual grip strength was measured with a hand-held standard adjustable dynamometer (Lafayette Instrument, Model 78010) in the sitting position with shoulder adducted, elbow flexed and forearm in mid-position. Finally, the subject was asked to rate his fatigue and discomfort/soreness level on a visual analogue scale ranging from 0-100, before and after each training session.

5.4.1.2 Robotic Data Assessment Measures

As a similar approach to that explained in Chapter 4, the motion data recorded during the evaluation portion of each therapy session were quantitatively analyzed in order to evaluate the improvement in the quality of upper extremity goal-directed movements of the subject. Movements were initially segmented into individual point-to-point movements. This was done by selecting a threshold $\alpha$ of the peak velocity $v_{\text{max}}$, measured during each movement, which was then used to define both the instant of movement start $t_{\text{in}}$ and of movement end $t_{\text{fin}}$. These points in time represent the first and last instance in which the condition $|v(t)| > \alpha|v(t_{\text{max}})|$ is verified within a movement, where $t_{\text{max}}$ is the time at which maximum velocity occurs. For the purposes of this analysis, $\alpha$ was set to 0.05. Although there is no general consensus
for the hypothesis that wrist pointing movements have symmetric velocity profiles, and preliminary studies are actually in support of their moderate asymmetry [52], this segmentation algorithm has been selected because it is standard in the robotics and motor control literature [87], and allows a direct comparison of results with those derived from other protocols and systems. Due to the inherent unidimensionality of the task (the maximum straight line deviation of successful movements was less than 0.5 deg), velocity profiles and subsequent derivatives were calculated as time derivatives of the measured joint angles. Encoder data were acquired continuously at 100 Hz; velocity profiles and higher-order derivatives were extracted in post-processing using a Savitzky-Golay filter, which has been purposively conceived to be optimal in minimizing amplified noise through differentiation, performing a local fourth order polynomial fit in a moving window of amplitude 100 ms (i.e. containing 10 samples).

Two indices of performance were calculated for each point-to-point movement, in order to verify the hypothesis that smoothness of movement would be increased by robot-aided therapy. The considered indices of performance were the Movement-Arrest-Period-Ratio (MAPR) [88] and a normalized measure of the sum-of-jerk of the measured profile (NSOJ), similar to the one used in [89].

The MAPR is a simple and robust method for assessing movement smoothness that quantifies the departure of the measured velocity profile from a single peaked, approximately bell-shaped profile, considered the “reference” movement profile for healthy point-to-point movements of the upper arm [90]. The MAPR is defined as the percentage of the total movement duration in which the measured velocity is higher than a threshold of $v_{\text{max}}$, as:

$$\text{MAPR} = \frac{T_1}{t_{\text{end}} - t_{\text{in}}},$$

where $T_1$ is defined as the total time in which the condition $v(t) > \beta v_{\text{max}}$ is verified
and can be expressed as the integral of a boolean time-series, as:

$$T_1 = \int_{t_1}^{t_{\text{end}}} (v(t) > \beta v_{\text{max}}) dt$$  \hspace{1cm} (5.11)$$

For the purposes on analysis in this study, the threshold $\beta$ was set to 0.25.

Sum-of-jerk (SOJ) metrics have been widely employed to quantify the smoothness of movements of subjects undergoing robot-aided therapy, mostly in the literature of post-stroke robot-aided rehabilitation. Computation of SOJ metrics requires differentiated encoder signals, and therefore implies applicability only to robotic systems with high resolution joint angle measurement [89]. It is considered that the mechanical structure and the sensing subsystem of the RiceWrist-S has a high accuracy in measuring the end-effector position, so that the measured profiles during pointing movements are minimally affected by quantization. In this chapter, a specific form of normalized SOJ (NSOJ) measure was considered, since it has been shown to be strictly increasing with the amount of onset time between submovements [89], and because normalization makes the calculated index insensitive to changes in movement duration [91]. The specific form used for the NSOJ metrics is obtained by normalizing the sum-of-jerk by the cube of mean velocity, as:

$$NSOJ = -\frac{1}{v_{\text{mean}}^3(t_{\text{end}} - t_{\text{in}})} \int_{t_{\text{in}}}^{t_{\text{fin}}} |\ddot{\theta}(t)| dt,$$  \hspace{1cm} (5.12)$$

where the minus sign is introduced so that NSOJ defines a measure of trajectory smoothness, and not of its inverse.

It should be noted that the fact that observed velocity profiles are asymmetric is in contrast with the minimum jerk hypothesis and thus would suggest that criteria such as NSOJ may not accurately measure deviation from the ideal profiles. However, despite the reduction in accuracy, the degree of mismatch between the minimum jerk trajectory and the average movement extracted during the experiments
with healthy subjects is fairly small [52], compared to the highly non-bell shaped movements extracted during therapy with SCI subjects, thus enabling the use of minimum jerk-based measures for heavily impaired subjects.

For each evaluation session, the values of MAPR and NSOJ were calculated for the 20 point-to-point movements performed, separately for each DOF. The values corresponding to the first and last evaluation session of the robotic therapy program were considered for statistical inference (three tests for each movement direction (FE, RU, PS), giving dof=19, and a single test including the combination of movements in all directions, all dof=59) using the non-parametric Wilcoxon signed rank test [92], in order to test the null hypothesis, for which the indices of smoothness calculated during the two sessions come from a distribution with the same median.

5.4.2 Case Study Results

5.4.2.1 Clinical Assessment

Table IV reports the values obtained through the clinical assessment tests. The results show improvements in the JTHFT as indicated by decreases in the amount of time necessary to execute functional tasks. Improvements in ARAT attributed to pinch, and increases in grip strength were found. However, the overall improvement in ARAT is lower than the minimal clinically meaningful change (5.7 points) [93]. Performance for the other clinical assessments stayed constant from pre- to post-treatment. For example, at the conclusion of therapy, the subject’s manual muscle test score did not show any change; however, a 1 point increase was observed in finger flexors (flexor digitorum profundus, middle finger, level of spinal innervation= C8). Manual grip strength improved from 11 kgf to 14 kgf, which possibly translated into improvement of lifting heavy objects in JTHFT - from a total 21 sec to 15 sec, the time necessary
to grasp, lift and release five weighted cans (0.45 kg/can). The only positive change that occurred in ARAT was in the pinch subgroup, particularly seen in holding a spherical marble between the thumb and middle finger and between the thumb and index finger (from a score of 2 to 3).

The pinch strength assessment requires the subject to pinch a gauge between the thumb and index finger in order to measure isolated pinch forces, while the ARAT pinch subtest consists of tasks which rely on dexterous manipulation and positioning of the fingers, a more dynamic task. It is hypothesized that over the course of the robotic therapy, the subject has improved overall in upper limb function, and therefore manipulating and moving small objects shows greater gains than direct measurement of pinch strength, though both assessments are focused on pinch capabilities of the subject.

The subject’s self-report on fatigue and discomfort/soreness varied after each session, compared to before training. For example, for five of the ten sessions he reported an increase in fatigue level (average 36 points), though at other times he reported no change (after one session) or a decrease (after four sessions) in fatigue level (average -14 points). A similar pattern of variability was observed for discomfort/soreness level. For two sessions he reported a decrease in discomfort/soreness (average 23 points), while for eight sessions he reported an increase in discomfort/soreness level (average 17 points). All symptoms were localized to left arm/shoulder and upper back, and did not last longer than 24 hours. Therefore, none of the training sessions were cancelled due to excessive discomfort/soreness or fatigue.
Figure 5.5: Bar plot with error bars describing the two measures of smoothness computed during the first (Pre) and last (Post) session of therapy, representing mean and standard deviation of the twenty movements for every degree of freedom conducted during the assessment. An asterisk in proximity of the bar to the right/left indicates rejection of the null hypothesis at the 0.05 significance level, with the bar on the right/left having a higher mean (increased smoothness).

5.4.2.2 Robotic Data Assessment

The analysis of robotic data measured during evaluation sessions supports the hypothesis that robot-aided training increased smoothness of the participant’s movements. Specifically, MAPR measures increased for movements in each DOF. Pre-post comparison provided strong statistical significance for increased MAPR for FE movements and for the combination of all degrees of freedom, but not for RU and PS movements alone. However, the mean MAPR value for both RU and PS increased at the end of therapy, compared with the measurement in the first session. NSOJ shows a less consistent trend, for which smoothness increased with therapy for FE and PS movements, but not for RU movements. Pre-post comparison provides statistical significance of increased smoothness for PS movements and for the combination of all movements, weak significance for FE movements ($p = 0.068$) but strong significance
for a decrease in movement smoothness for RU movements. This might be influenced by a fatigue effect given by the fact that during all sessions, the evaluation session for RU movements was administered last in the protocol, i.e. after evaluation and therapy sessions for both FE and PS. The indices of smoothness calculated and the results of the statistical analysis are reported in Fig. 5.5 and Table 5.5.

### 5.5 Discussion and Conclusion

In this chapter, I presented the novel design and pilot clinical study validation of the RiceWrist-S, a custom-developed wrist exoskeleton for incomplete spinal cord injury robot-aided therapy. The kinematic structure of the RiceWrist-S is chosen so that every actuated DOF directly corresponds to an individual human anatomic rotation. By incorporating a custom cable drive transmission that minimizes inertial and gravitational loading on the proximal joints, an increase in the dynamic transparency of the exoskeleton is realized, when it is in unpowered mode. The reduction of inertia is demonstrated through the analysis of the GIE through the three-dimensional workspace of the manipulator. The GIE analysis shows that the RiceWrist-S has configuration-independent intrinsic dynamical properties throughout the workspace, with a maximum ratio between highest inertia to lowest inertia across actuated joints equal to 5, similar to state-of-the-art systems such as the one presented in [34], [94]. However, the presented device does not require high-accuracy mechanical parts and expensive transmission components as the differential gear used in [34]. Moreover, the use of cable drive transmission contributes to the low friction characteristic of the RiceWrist-S. The maximum static friction values are smaller than 13%, 6%, and 10% of the continuous torque at PS, FE, and RU joints, with a maximum value of 0.22 Nm of static friction. Additionally, the kinematic structure reduces the measurement
of the hand orientation and control of the device to joint space tasks, removing the need for inverse or forward kinematics calculations.

In order to further validate the RiceWrist-S as clinically appropriate, a single case study with one participant is conducted, presenting with chronic incomplete spinal cord injury at the cervical level. Results from this pilot trial are significant in demonstrating that repetitive training of certain movements with the RiceWrist-S are feasible in rehabilitation of upper extremity motor functions in incomplete SCI. The clinical findings reinforce results from our prior pilot trial that repetitive training of arm and wrist movements (with MAHI Exo-II) in incomplete SCI can be associated with motor gains in hand movements [39], [69]. More specifically, the repetitive training of forearm and wrist muscles with the RiceWrist-S device has shown mild increase in hand grip and selective hand functions such as pinch grip and lifting heavy objects. Two smoothness of movement metrics have been used to assess the efficacy of the robotic training protocol by using the acquired robotic data during evaluation sessions where the participant backdrives the robot. In comparisons of pre- and post-training robotic measures, the subject showed improvement in terms of both MAPR, the percentage of the total movement duration in which the measured velocity is higher than a threshold of maximum velocity, and NSOJ, a normalization of the sum of-jerk by the cube of mean velocity.
Table 5.1: Sensor and Actuator Specifications for the RiceWrist-S Upper Limb Rehabilitation Robot

<table>
<thead>
<tr>
<th>Joint</th>
<th>Actuator</th>
<th>Transmission</th>
<th>Sensor (Resolution)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forearm PS</td>
<td>Applimotion 165-A-18</td>
<td>Direct-Drive</td>
<td>MicroE Mercury-1500 (0.002°)</td>
</tr>
<tr>
<td>Wrist FE</td>
<td>Maxon RE-40 (148877)</td>
<td>Cable Drive (1:18)</td>
<td>Avago HEDS-5540 (0.01°)</td>
</tr>
<tr>
<td>Wrist RU</td>
<td>Maxon RE-30 (310009)</td>
<td>Cable Drive (1:24)</td>
<td>Avago HEDS-5540 (0.0075°)</td>
</tr>
</tbody>
</table>
Table 5.2: Achievable joint ranges of motion (ROM) and maximum continuous joint torque output values for RiceWrist-S and the forearm-wrist portion of MAHI Exo-II. The required ROM and torque values for 19 (ADL) as extracted from [3] are also given for comparison.

<table>
<thead>
<tr>
<th>Joint</th>
<th>ADL ROM (deg)</th>
<th>Torque (Nm)</th>
<th>RiceWrist-S ROM (deg)</th>
<th>Torque (Nm)</th>
<th>MAHI Exo-II ROM (deg)</th>
<th>Torque (Nm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forearm PS</td>
<td>150</td>
<td>0.06</td>
<td>180</td>
<td>1.69</td>
<td>180</td>
<td>2.30</td>
</tr>
<tr>
<td>Wrist FE</td>
<td>115</td>
<td>0.35</td>
<td>130</td>
<td>3.37</td>
<td>72</td>
<td>1.67</td>
</tr>
<tr>
<td>Wrist RU</td>
<td>70</td>
<td>0.35</td>
<td>75</td>
<td>2.11</td>
<td>72</td>
<td>1.93</td>
</tr>
<tr>
<td>Joint</td>
<td>Static Friction (N·m)</td>
<td>Inertia (kg·m²)</td>
<td>Viscous Coeff. (Nm·s/ rad)</td>
<td>CL Position Bandwidth (Hz)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>-----------</td>
<td>-----------------------</td>
<td>-----------------</td>
<td>-----------------------------</td>
<td>----------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forearm PS</td>
<td>0.221</td>
<td>0.0258</td>
<td>0.428</td>
<td>3.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wrist FE</td>
<td>0.198</td>
<td>0.01165</td>
<td>0.085</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wrist RU</td>
<td>0.211</td>
<td>0.0048</td>
<td>0.135</td>
<td>8.3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3: RiceWrist-S Device Characteristics
Table 5.4: Functional scores before and after robotic therapy

<table>
<thead>
<tr>
<th>Test</th>
<th>Baseline</th>
<th>Post-treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASIA UEMS</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>JTHFT (seconds)</td>
<td>99.1</td>
<td>93.8</td>
</tr>
<tr>
<td>Flipping cards</td>
<td>15</td>
<td>15.2</td>
</tr>
<tr>
<td>Picking up small objects</td>
<td>27</td>
<td>28.3</td>
</tr>
<tr>
<td>Simulated feeding</td>
<td>12.4</td>
<td>11.7</td>
</tr>
<tr>
<td>Lifting big objects (light)</td>
<td>12.3</td>
<td>13</td>
</tr>
<tr>
<td>Lifting big objects (heavy)</td>
<td>20.8</td>
<td>14.6</td>
</tr>
<tr>
<td>ARAT (0-57)</td>
<td>29</td>
<td>31</td>
</tr>
<tr>
<td>Grasp (0-18)</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>Grip (0-12)</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>Pinch (0-18)</td>
<td>4</td>
<td>6</td>
</tr>
<tr>
<td>Gross Movement (0-9)</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Pinch Force (kgf)</td>
<td>3</td>
<td>2.8</td>
</tr>
<tr>
<td>Grip Force (kgf)</td>
<td>11</td>
<td>14</td>
</tr>
</tbody>
</table>
Table 5.5: Analysis of movement smoothness during the evaluation sessions

<table>
<thead>
<tr>
<th>Measure/DOF</th>
<th>MAPR</th>
<th></th>
<th></th>
<th></th>
<th>NSOJ</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
<td>Pre vs. Post</td>
<td></td>
<td>Pre</td>
<td>Post</td>
<td>Pre vs. Post</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
<td>Std</td>
<td>Mean</td>
<td>Std</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Mean</td>
<td>Std</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FE</td>
<td>0.503</td>
<td>0.159</td>
<td>0.616</td>
<td>0.126</td>
<td>0.0215</td>
<td></td>
<td>0.0131</td>
<td>0.0136</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0047</td>
<td>0.0027</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RU</td>
<td>0.525</td>
<td>0.180</td>
<td>0.598</td>
<td>0.165</td>
<td>-0.0083</td>
<td>0.005</td>
<td>-0.022</td>
<td>0.0143</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6.2·10^{-4}</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PS</td>
<td>0.520</td>
<td>0.238</td>
<td>0.605</td>
<td>0.151</td>
<td>-0.0313</td>
<td>0.0331</td>
<td>-0.0071</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3.0·10^{-6}</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>All</td>
<td>0.516</td>
<td>0.192</td>
<td>0.607</td>
<td>0.146</td>
<td>0.0084</td>
<td></td>
<td>0.0176</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.011</td>
<td>0.012</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.026</td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>
Chapter 6

Minimal Assist-as-Needed (mAAN) Controller for Upper Limb Robotic Rehabilitation

In this chapter a novel minimal assist-as-needed controller, which is designed to minimally intervene during training, is presented. The controller is capable of estimating the subject input as a function of time in a fast, stable, and accurate manner. Two additional algorithms are introduced to further promote active participation of subjects with varying degrees of impairment. First, a bound modification algorithm is introduced which alters allowable error. Second, a disturbance rejection decay algorithm is presented which supports subjects who are capable of leading the desired trajectory. The mAAN controller and consistency of the accompanying algorithms are demonstrated experimentally with healthy subjects and with one subject with incomplete spinal cord injury in the RiceWrist-S.

6.1 Introduction

Assistive strategies, which target a wide range of severely to mildly impaired subjects, are the most extensively investigated controller paradigm in the rehabilitation robotics community [14]. There is strong evidence that active participation induces neural plasticity [15], and therefore assistive controllers should intervene minimally in order to best promote involvement, plasticity, and recovery.

Several controllers have been proposed which aim to provide minimal amounts of robotic assistance. However, existing approaches either provide sub-optimal interven-
tion, or lack a proper challenging mechanism within the given controller scheme. In this chapter, I present a minimal assist-as-needed controller, which aims to help subjects complete a desired motion, while encouraging active participation by intervening minimally.

6.2 Literature Review

Providing minimal assistance only becomes possible when the subject’s functional capability is known; adaptive controllers are often applied for this purpose. In particular, Gaussian radial basis networks have attracted considerable interest due to their universal approximation property [95]. Inclusion of Gaussian radial basis networks in adaptive control algorithms was previously proposed for both real-time robot control [44] and arm movement modeling purposes [96]. This approach fundamentally assumes subject input to be position dependent, and therefore estimates subject input via Gaussian radial basis functions distributed throughout the workspace.

Wolbrecht et al. [12] first employed an adaptive controller with Gaussian radial basis functions for the purposes of robotic rehabilitation. To ensure continuous subject engagement, the authors include an adaption law which decreases assistive forces—i.e., “forgets” the estimated subject input—whenever position error is low. This approach is problematic, however, because estimates of subject input are necessarily perturbed by the forgetting factor. Pehlivan et al. [20] decoupled input estimation and engagement problems by directly manipulating the subject’s positional error bounds. Both [97] and [98] improve the estimation ability of [12] through directionally dependent radial basis functions.

In order for a Gaussian radial basis network to accurately estimate a subject’s functional capability, that subject must behave in a position dependent manner. In
the formulation of the controller presented in Chapter 3, I made the similar assumption. However, based on the observations made during the clinical study presented in Chapter 4, I concluded that, while this consistency may be reasonably expected from healthy individuals, it is not necessarily the case for neurologically impaired subjects. In fact in the literature it has been shown that, it is unlikely that neurologically impaired subjects have either position or time dependent capabilities because of (a) movement disorders, such as tremor, which irregularly affect movement capabilities [99], and (b) varying velocities, where movement speed and direction alter subject torque capabilities [100]. Furthermore, adaptation laws employed within the approaches described above do not guarantee that parameters will converge to their true values, except under special conditions. Hence the accurate estimation of subject input is not guaranteed at all times.

In this chapter a minimal assist-as-needed (mAAN) controller is introduced which utilizes sensorless force estimation independently determine subject capability at each moment in timewithout assuming any underlying patternbefore providing a corresponding assistance with adjustable bounds on the trajectory error. In this study I investigate a force estimation technique, namely a nonlinear disturbance observer outlined by [101], and employ it within the mAAN controller. Finally, in order to maintain active participation of subjects with various capability levels, I introduce two additional algorithms: a bound modification algorithm which alters allowable error, and a decayed disturbance rejection algorithm which lets able subjects exceed the desired trajectory.

This chapter is organized as follows. Section 6.3 introduces the experimental hardware, Section 6.4 presents the derivation of non-linear disturbance observer, and Section 6.5 incorporates the nonlinear disturbance observer within the proposed con-
control law. Additional algorithms to improve subject-adaptivity are detailed in Section 6.6, and the mAAN controller is subsequently tested in Section 6.7. Finally, the conclusions of the chapter and remarks for future work are presented in Section 6.8.

6.3 Hardware Description and System Modeling

The RiceWrist-S [23], a three DOF forearm-wrist exoskeleton, is used as the experimental platform (see Fig. 6.1). This serial manipulator is capable of independently actuating the user’s forearm and wrist DOFs; pronation/supination (PS), flexion/extension (FE), and radial/ulnar deviation (RU). The RiceWrist-S also incorporates a passive and redundant DOF at the handle to account for any axial misalignments between subject and mechanism.

In order to render low friction and backlash, the device employs both a brushless DC motor to directly drive the PS joint, and brushed DC actuators with cable drive transmissions for FE and RU joints. It has been previously demonstrated that the RiceWrist-S achieves low apparent inertia, corresponds with the desired range-of-motion, and provides torque outputs appropriate for rehabilitation applications [20].

The manipulator dynamics can be represented in the traditional form:

\[ M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau_r + \tau_p \]  

(6.1)

where \( q \) is a 3 \( \times \) 1 vector of joint positions, \( M \) is the 3 \( \times \) 3 inertial matrix, \( C \) is the 3 \( \times \) 3 matrix which represents Coriolis/centrifugal terms, \( G \) is the 3 \( \times \) 1 gravity vector, \( \tau_r \) is the 3 \( \times \) 1 vector of torques applied by the actuators and \( \tau_p \) is the 3 \( \times \) 1 vector of torques applied by the subject and mapped into joint space.

The subsequently proposed mAAN controller is implemented on the FE joint of the RiceWrist-S manipulator. During the implementation the unused DOFs were
physically constrained. Static friction, inertia, and viscous friction have been experimentally identified for this joint. Static friction was estimated from the system response to a ramp position input; inertia and viscous friction were determined by investigating the system response to a step position command. A modified logarithmic decrement method presented in [102], which isolates inertial and viscous effects responsible for exponential decay of the system’s free vibration, is employed.

Figure 6.1: The RiceWrist-S, a robotic rehabilitation device used to experimentally validate the proposed controller.

6.4 Sensorless Force Estimation

Force sensors can be used to measure the subject’s applied force as a function of time; however, these sensors increase system cost and raise stability concerns [103]. Motivated by a desire to avoid adding force sensors, a variety of “sensorless” force estimation methods employ motors, compliance, or position sensors already incorporated within the robot. Sensorless force estimation techniques exploit differences between the expected and actual manipulator configurations to approximate disturbances applied to the system. Here I briefly review motor and compliance-based force
estimators, before providing a more detailed analysis of model-based force estimation.

For some robots, it is possible to indirectly measure disturbances using motor torques—but motor torques are noisy, particularly if gears are present [104]. Alternatively, this force measurement problem can be converted into a position measurement problem by incorporating compliant elements. Compliance has been implemented at the mechanical level with series elastic actuators [105], and at the controls level via virtual springs [106]. Within the realm of rehabilitation robotics, compliance is particularly attractive because it improves backdrivability and safety during human-robot interaction [107]. Despite these benefits, introducing compliant elements augments design complexity; as such, for systems simply seeking force estimation, compliance might not be the most convenient solution.

In this work I apply model-based estimation, where plant dynamics and input-output data are used to mathematically extract the disturbance. Given joint positions, velocities, and accelerations, it is trivial to solve the equations of motion for disturbances; in practice, an observer can be used to measure unknown disturbances using incomplete and noisy states.

One drawback of model-based disturbance estimation is that the robot’s inertial matrix inverse must typically be calculated in real time. Another flaw is the assumption that disturbances are constant; unless a prediction of future disturbances is available—as might be the case when performing iterative tasks—the resultant estimation trails fluctuating disturbances. Finally, if the plant model is inaccurate, this method cannot correctly distinguish between responses caused by known and unknown inputs; the estimated disturbances therefore include both external forces ($\tau_p$) and unmodeled dynamics ($\tau_m$). While this effect may be undesirable, it will be shown that model-based disturbance estimation can still be quite convenient within
the robotic rehabilitation context. For now, formally denote the disturbance which model-based approaches seek to estimate as

\[ d = \tau_p - \tau_m \]  

(6.2)

Applying the disturbance definition, the robot manipulator dynamics (6.1) can be rewritten

\[ \hat{M}(q)\ddot{q} + \hat{C}(q, \dot{q})\dot{q} + \hat{g}(q) = \tau_r + d \]  

(6.3)

where \( \hat{.} \) donates the estimated value. The ensuing paragraphs describe a model-based force estimator, namely a nonlinear disturbance observer outlined by [101], that yields an approximate disturbance measurement consistent with these equations of motion.

### 6.4.1 Non-linear Disturbance Observer (NDO) Formulation

The nonlinear disturbance observer proposed by Chen et al. [101] has been employed in a variety of implementations, such as friction compensation, sensorless torque control [108], and haptic interaction control [109]. In this section, I overview the disturbance observer formulation given in [101], and as an additional step show the boundedness of the disturbance estimation errors in the case of a time varying interaction between the subject and the robotic device.

As an initial step, the formulation defines the differential equation, which describes the disturbance estimation system, as follows

\[ \dot{\hat{d}} = -L(q, \dot{q})(\hat{d} - d) \]  

(6.4)

where \( \hat{d} \) is the estimate of the disturbance term and \( L(q, \dot{q}) \) is defined with the following relation
\[ L(q, \dot{q}) \dot{M}(q) \ddot{q} = \frac{dp(q, \dot{q})}{dt} \]  
(6.5)

where \( p(q, \dot{q}) \) will be determined subsequently. The main aim of the disturbance observer formulation is to eliminate the need for acceleration measurement via inclusion of an auxiliary variable \( z \).

\[ z = \hat{d} - p(q, \dot{q}) \]  
(6.6)

Considering the relations given in (6.4-6.6) and the robot manipulator dynamics given in (6.3), the time derivative of the auxiliary variable \( z \) is given as follows

\[ \dot{z} = -L(q, \dot{q})(z + p(q, \dot{q})) + L(q, \dot{q})(\dot{M}(q)\ddot{q}(t) + \dot{C}(q, \dot{q})\dot{q}(t)) + \dot{g}(q) - \tau_r(t) - L(q, \dot{q})\dot{M}(q)\ddot{q} \]  
(6.7)

\[ = -L(q, \dot{q})(z + p(q, \dot{q}) - \dot{C}(q, \dot{q})\dot{q} - \dot{g}(q) + \tau_r) \]

Note that the above relation allows computation of the auxiliary variable \( z \) and hence the estimate of the disturbance \( \hat{d} \) without need for acceleration information. Of course in order to achieve this, the functions \( L(q, \dot{q}) \) and \( p(q, \dot{q}) \) have to be determined such that the disturbance estimation term converges to an actual value asymptotically. Let me define the disturbance estimation error term as follows

\[ e_d = d - \hat{d} \]  
(6.8)

In the case of constant (or very slowly changing over time) disturbances, one can set (or assume) that \( \dot{d} = 0 \). Considering the relation given in (6.4) the time derivative of the error term can be written as follows

\[ \dot{e}_d = -L(q, \dot{q})e_d \]  
(6.9)
The proper selection of \( L(q, \dot{q}) \) will bring asymptotic convergence of the error term to zero. Considering the equation (6.5), the selection of \( p(q, \dot{q}) = c\dot{q} \) (where \( c \) is a positive constant) gives the following relation

\[
L(q, \dot{q}) = c\hat{M}^{-1}(q) \tag{6.10}
\]

The inherent properties of the inertia matrix of robotic manipulators (symmetry and positive definiteness) lead to asymptotic convergence of the error term in equation (6.9). As a further investigation the following Lyapunov analysis is provided.

\[
V_{o, NDO} = \frac{1}{2} e_d^T e_d \tag{6.11}
\]

Differentiation of \( V_{o, NDO} \) along the solutions of (6.9) provides

\[
\dot{V}_{o, NDO}(e_d) = -e_d^T c\hat{M}^{-1}(q)e_d \tag{6.12}
\]

The above analysis guarantees that the error system (6.9) is at least asymptotically stable around equilibrium point \( e_d = 0 \).

### 6.4.1.1 Existence of Time Varying Disturbances

In the existence of time varying disturbances, the assumption of \( \dot{d} = 0 \) will not be correct. Hence the disturbance estimation error system can be redefined as follows

\[
\dot{e}_d = -L(q, \dot{q})e_d + \dot{d} \tag{6.13}
\]

In this case there does not exist an equilibrium point for the error system (6.13). However, Lyapunov stability analysis can be used to show the boundedness of the
solutions [110]. I employ the same Lyapunov function candidate (6.11) for the analysis when \( \dot{d} \neq 0 \).

\[
V_{o,NDO}(e_d) = \frac{1}{2}e_d^T \hat{N}_d
\]  

(6.14)

I assume that the magnitude of the time change of the disturbances is bounded with some constant \( D \), i.e. \( \| \dot{d} \| \leq D \). Note that \( L_2 \) norm is employed throughout the formulation for consistency. Hence, the time derivative of the Lyapunov function will bring the following result

\[
\dot{V}_{o,NDO}(e_d) = -e_d^T (c\hat{M}^{-1})(q)e_d + \dot{d}
\]

(6.15)

\[
\leq -c\lambda_{min}(\hat{M})\|e_d\|^2 + D\|e_d\|
\]

Note that the relation \( y^T x \leq \|x\|\|y\| \) is employed in the above inequality (6.15). By introducing a constant \( \theta \), such that \( 0 < \theta < 1 \), the inequality (6.15) can be represented in the following form

\[
\dot{V}_{o,NDO}(e_d) \leq -(1 - \theta)c\lambda_{min}(\hat{M})\|e_d\|^2 + \theta c\lambda_{min}(\hat{M})\|e_d\|^2 + D\|e_d\|
\]  

(6.16)

then \( \dot{V}_{o,NDO} \leq -(1 - \theta)c\lambda_{min}(\hat{M})\|e_d\|^2 \) \( \forall e_d \) if and only if the following inequality is satisfied

\[
\|e_d\| > \frac{D}{\theta c\lambda_{min}(\hat{M})}
\]  

(6.17)

Hence, as soon as the inequality in (6.17) is satisfied, the error system will behave like it is asymptotically converging to the equilibrium point. It is possible to define an ultimate bound on the disturbance estimation error \( e_d \) with a more rigorous analysis, but for the sake of briefness I use a constant \( e_{UB} \), which bounds the term in the right hand side of the inequality (6.17), as an upper bound on the disturbance estimation
error. The performance of the described NDO for a time varying disturbance is shown in Fig. (6.2).

Figure 6.2 : An experiment on a single joint of the RiceWrist-S is implemented to investigate the disturbance estimation capability of the NDO. The applied torque is a chirp signal sweeping from an initial frequency of 0.5 Hz to a maximum frequency of 4 Hz at 20 s with 1 Nm amplitude. The maximum disturbance estimation error is less than 16% of the disturbance’s amplitude at any given time.

6.5 mAAN Control Law

An AAN controller for rehabilitation exercises should help subjects complete desired motions, while encouraging active participation by intervening minimally. Accordingly, the following mAAN controller is proposed

\[ \tau_r(t) = \tau_b(t) - \hat{d}(t) \]  \hspace{1cm} (6.18)

where \( \tau_b \) signifies a baseline controller, \( \hat{d} \) indicates the model-based disturbance estimate, and \( \tau_r \) represents the total controller input. This mAAN controller has the same structure as those previously demonstrated in [12] and [20], which both employ
a PD baseline controller and feedforward disturbance rejection term. In [12] and [20], the disturbance estimate was found as a function of position—here, however, the subject force is measured as a function of time.

The logic behind this mAAN controller design comes directly from its intended application. If the estimated disturbance is equal to the applied disturbance, then system behavior is governed by a baseline controller; should that baseline controller be designed for trajectory tracking, then “perfect” disturbance rejection ensures desired movements. In practice, sensorless disturbance estimation is never exact (see Section 6.4)—as a result, applied perturbations affect tracking error and hence subject passivity is discouraged. Whenever subjects contribute to a motion, the amount of robotic assistance is reduced accordingly; on the other hand, while subjects are unable to perform a task, the mAAN controller works to offset their applied disturbance. Taken to an extreme, if the subject completes an action flawlessly, then the controller provides no aid—alternatively, if the subject remains passive, then the controller outputs torques requisite to perform the planned motion, albeit with some tracking error.

I selected the passivity-based motion control law proposed by [2] and detailed in [111] for the baseline controller. Given a twice-differentiable reference trajectory, I express the position error in joint space as $\tilde{q} = q - q^d$. I then define the sliding variables

$$v = q^d - \Lambda \tilde{q}$$
$$a = \dot{v}$$
$$r = \dot{q} - v$$

(6.19)

where $\Lambda$ is a positive definite matrix which determines the relative weight of position
errors. The baseline controller can then be written

$$\tau_b = \hat{M}(q)\dot{a} + \hat{C}(q, \dot{q})v + \hat{g}(q) - K_D r$$  \hspace{1cm} (6.20)$$

where $K_D$ is a positive definite gain matrix. Implementation of the passivity-based motion controller requires real-time knowledge of the reference path, model dynamics, and system states; these prerequisites do not alter computational demand, however, as the model equations of motion are also solved within the disturbance observer.

Combining the baseline controller (6.20), mAAN control law (6.18), and modified manipulator dynamics (6.3), I obtain

$$\hat{M}(q)\dot{r} + \hat{C}(q, \dot{q})r + K_D r + e_d = 0$$  \hspace{1cm} (6.21)$$

Imagine for a moment that $\hat{d}$ is not calculated through estimation, but is precisely measured by some external device. In this idealized case, Lyapunov stability analysis can prove $r$ to be at least uniformly ultimately bounded using the candidate function as follows

$$V_c(\dot{q}, q) = \frac{1}{2}r^T M(q) r + \tilde{q}^T \Lambda^T K_D \tilde{q}$$  \hspace{1cm} (6.22)$$

Since the system parameters employed in the controller are not the exact values, the differentiation of the Lyapunov function (6.22) along the trajectories of 6.21 results in the following equation

$$\dot{V}_c(\dot{q}, \tilde{q}) = -\tilde{q}^T K_D \tilde{q} - \tilde{q}^T \Lambda^T K_D \Lambda \tilde{q} + r^T (\tilde{M} r + \tilde{C} r)$$  \hspace{1cm} (6.23)$$

where $\tilde{M}(q) = M(q) - \hat{M}(q)$, $\tilde{C}(q, \dot{q}) = C(q, \dot{q}) - \hat{C}(q, \dot{q})$.

The function presented in equation (6.23) does not satisfy $V_c(\dot{q}, q) < 0$ for all $(\dot{q}, q) > 0$. Hence, no stability notion for the system states, in the sense of Lyapunov, can be assumed for the system 6.21. However, it is possible to use Lyapunov analysis
to show boundedness of the system solutions \((\tilde{q}, \tilde{\dot{q}})\) [110], by showing that there exists a set \(S\) such that \(\dot{V}_c(\tilde{q}, \tilde{\dot{q}}) < 0\) for all \((\tilde{q}, \dot{q}) \in S\).

For the function \(V_c(\tilde{q}, \dot{q})\) with a constant \(\eta\), which satisfies \(0 < \eta < 1\), it can be shown that

\[
\dot{V}_c(\tilde{q}, \dot{q}) \leq -(1 - \eta)\lambda_{\min}(K_D)(\|\tilde{q}\|^2 + \|\Lambda\|^2\|\dot{\tilde{q}}\|^2) - \eta\lambda_{\min}(K_D)(\|\tilde{q}\|^2 + \|\Lambda\|^2\|\dot{\tilde{q}}\|^2) + \|r^T(M\tilde{r} + \bar{C}r)\| \quad (6.24)
\]

Hence, for all \((\tilde{q}, \dot{q})\) which satisfy the following inequality, \(\dot{V}_c\) will be negative and \(V_c\) will move in the decreasing direction

\[
\|\dot{\tilde{q}} + \Lambda\tilde{q}\| = \|r\| \geq \|M\tilde{r} + \bar{C}r\| \quad (6.25)
\]

When the inequality (6.25) holds, the \(V_c\) satisfies all the features such that the system solutions behave as if the origin, \((\tilde{q}, \dot{q}) = 0\), is asymptotically stable [110].

Having independently established stability conditions for both the disturbance observer and controlled system, I now seek to verify the stability of the composite controller (6.18) which integrates \(\hat{d}\) estimates from the disturbance observer (6.4); I here follow the method developed by [112]. Because the disturbances are time variant, the numerical estimate \(\hat{d}\) is inexact—hence, I must also consider controller stability when \(e_d \neq 0\).

First, choose the Lyapunov candidate function

\[
V(\tilde{q}, \dot{q}, e_d) = V_c + V_{e,\text{NDO}} = \frac{1}{2} r^T M(q) r + \tilde{q}^T \Lambda^T K_D \tilde{q} + \frac{1}{2} e_d^T e_d \quad (6.26)
\]

By taking its time derivative, substituting the robot dynamics, and applying the
skew symmetry property gives

\[ \dot{V}(\dot{\tilde{q}}, \tilde{q}, e_d) = -\dot{\tilde{q}}^T K_D \dot{\tilde{q}} - \dot{\tilde{q}}^T \Lambda^T K_D \Lambda \tilde{q} \]

\[-e_d^T (e \tilde{M}^{-1}(q)) e_d + r^T (\tilde{M} r + \tilde{C} r - e_d) \quad (6.27)\]

Using the inequality \( y^T x \leq \|y\|\|x\| \), and remembering \( e_{UB} \) is an upper bound on the disturbance estimation error \( e_d \) and \( \lambda_{\min}(K_D) \) is a lower bound on \( K_D \)—where \( \lambda_{\min}(K_D) \) denotes the minimum eigenvalue of \( K_D \)—it is obvious that \( \dot{V} \) can be bounded as

\[ \dot{V}(\dot{\tilde{q}}, \tilde{q}, e_d) \leq -(1 - \epsilon) \lambda_{\min}(K_D)(\|\dot{\tilde{q}}\|^2 + \|\Lambda\|^2\|\tilde{q}\|^2) \]

\[ -\epsilon \lambda_{\min}(K_D)(\|\dot{\tilde{q}}\|^2 + \|\Lambda\|^2\|\tilde{q}\|^2) + \|r^T (\tilde{M} r + \tilde{C} r - e_d)\| \quad (6.28)\]

where, \( \epsilon \) is a constant, such that \( 0 < \epsilon < 1 \).

Thus, \( \dot{V} \leq -(1 - \epsilon) \lambda_{\min}(K_D)(\|\dot{\tilde{q}}\|^2 + \|\Lambda\|^2\|\tilde{q}\|^2) \) \( \forall \dot{\tilde{q}}, \tilde{q} \) if the following inequality is satisfied

\[ \|\dot{\tilde{q}} + \Lambda \tilde{q}\| = \|r\| \geq \frac{\|\tilde{M} r + \tilde{C} r - e_{UB}\|}{\epsilon \lambda_{\min}(K_D)} \quad (6.29)\]

I therefore conclude that the mAAN controller employing nonlinear disturbance observer yields bounded trajectory errors (see Fig. 6.3). Should \( \tilde{M} \to 0, \tilde{C} \to 0, \) and \( e_d \to 0 \), this analysis demonstrates \( \|r\| \to 0 \) and the system is globally asymptotically stable. Throughout this proof I assumed \( \|r\| \) to be bounded—since the amount of force which a subject can physically realize is naturally limited, it follows that the amount of induced error must be finite. Of particular interest is the inclusion of \( K_D \) within the bounded set description; by varying the user-selected gain matrix \( K_D \), I can directly manipulate the bounds on the allowable tracking error. For instance, it may
be desirable to decrease the allowable tracking error when subjects are attempting to learn a motion—once those subjects demonstrate proficiency, however, the radius of trajectory error bound can be increased to increase task challenge (or vice versa).

![Figure 6.3: Trajectory error on a single joint of the RiceWrist-S using mAAN control and disturbance observer estimates with both varying $K_D$ values and disturbance amplitudes. Applied torques were sinusoidal, with 1 Hz frequency and amplitude $D_A$. The robot was commanded to maintain a stationary pose. As $K_D$ increases the error bounds tighten; here the amount of error $r$ resulting from an identical input decreases in response to increased $K_D$. Disturbances with greater amplitude desirably create larger errors.]

**Figure 6.3**: Trajectory error on a single joint of the RiceWrist-S using mAAN control and disturbance observer estimates with both varying $K_D$ values and disturbance amplitudes. Applied torques were sinusoidal, with 1 Hz frequency and amplitude $D_A$. The robot was commanded to maintain a stationary pose. As $K_D$ increases the error bounds tighten; here the amount of error $r$ resulting from an identical input decreases in response to increased $K_D$. Disturbances with greater amplitude desirably create larger errors.

### 6.6 Subject-Adaptive Algorithms

By incorporating estimated subject forces within the mAAN controller, I aim to (a) provide minimum required assistance, (b) encourage active participation, and (c) ensure the completion of desired motions; however, unless properly challenged, subjects may still let the robot take control [16]. “Challenge” here refers to difficulty, which implies both the presence of errors and decreased robotic assistance. For more
impaired subjects, less challenge (smaller allowable errors) is necessary; conversely, for less impaired subjects or for subjects who improve their movement capability, more challenge (larger allowable errors) is suitable. In other cases, the subject may be so proficient that the absence of assistance best renders a reasonable challenge.

In order to adapt allowable error to subject capability, I include an algorithm which modulates the allowable error bound based on previous performance. I here exploit the phenomenon that errors combined with visual feedback provide an impetus for active involvement—indeed, error is likely a driving signal for motor learning [113]. Altering error bounds can be interpreted as changing the cross-sectional radius of a desired trajectory; this radius should be directly related to subject ability. Furthermore, in cases where a subject is consistently able to surpass the desired trajectory, it may be sensible to enable that subject to complete the task in less time than is typically allocated. For this purpose, I have implemented an algorithm which decays resistive forces when movement speed exceeds the given trajectory.

Viewed together, these subject-adaptive algorithms aim to ensure that all users—regardless of ability—are challenged, and therefore encourage active participation for more effective recovery.

### 6.6.1 Error Bound Modification Algorithm

Since trajectory errors are bounded by (6.25), changing the feedback gain $K_D$ modifies allowable error; a high $K_D$ tightens error bounds, while a low $K_D$ relaxes error bounds. I here introduce $r^*$, a user-specified maximum allowable average trajectory error. By comparing $r^*$ to the current tasks’s average error, $\bar{r}_i$, this algorithm updates the feedback gain for the next task, $K_{D,i+1}$. The formulation is loosely similar to what was detailed by [20]. To have a more accurate evaluation of subject performance,
however, the algorithm I propose also compares $\bar{r}_{i-1}$, to $\bar{r}_i$.

Discrete computation of the feedback gain occurs at the end of each task, and is carried out as follows

$$K_{D,i+1} = (1 + x_i)K_{D,i} \quad (6.30)$$

where $x_i$, the change rate which satisfies $0 < |x_i| < 1$, can be formulated as

$$x_i = x_{nom} \frac{\bar{r}_i - r^*}{r^*} \left( \frac{|\bar{r}_i - r^*|}{|\bar{r}_{i-1} - r^*|} \right)^{sign(r^* - \bar{r}_i)} \quad (6.31)$$

where $x_{nom}$ is a predetermined, constant, nominal change rate. The sign of $x_i$ is determined by comparing the average error in the current task to the maximum allowable error. For example, if $\bar{r}_i$ is smaller than $r^*$, the algorithm decides that the subject is able to produce better error performance than expected, and hence the feedback gain decreases for the subsequent task. The magnitude of $x_i$ depends upon the first and second multiplier terms of $x_{nom}$ in (6.31); magnitude thus considers both the difference between actual and maximum error, and performance changes over time.

### 6.6.2 Disturbance Rejection Decay Algorithm

The error bound modification algorithm constrains users within some radius of the desired trajectory. I here alleviate that constraint by allowing fast, intentional movements towards the goal while maintaining the controller’s ultimate boundedness characteristics.

In order to reduce resistance of able subjects, I modify the mAAN control law (6.18). In this modification, when (a) the subject’s position is closer to the target than the desired position, and (b) the subject is inputting force in the target direction,
the control law becomes

\[ \tau_r(t) = \tau_b(t) - F\ddot{d}(t) \]  

(6.32)

where \( F \) is a decay term which satisfies \( 0 < F < 1 \). This alteration matches with intuition; if a subject is consistently able to provide force input toward the goal, the controller should allow this “good” disturbance instead of rejecting it.

The decay term \( F \) is calculated at every sampling time

\[ F_T = (1 + \nu)F_{T-1} \]  

(6.33)

where

\[ \nu = \begin{cases} 
\nu_{\text{dec}}, & \text{if } \dot{q}_d \tau_p > 0 \\
\nu_{\text{inc}}, & \text{else} 
\end{cases} \]  

(6.34)

The above relationship decreases the term \( F \) at a rate of \( \nu_{\text{dec}} \) so long as the subject’s force input is in the direction of desired velocity—on the other hand, \( F \) increases with a rate of \( \nu_{\text{inc}} \) if the subject reverses input direction. In order to decrease disturbance rejection and move faster than a desired trajectory, consistently correct movement is required.

### 6.7 Experiments

I conducted a series of experiments to evaluate the mAAN controller’s performance and validate the consistency of the subject-adaptive algorithms. All experiments were implemented on the FE joint of the RiceWrist-S, which served as a one DOF testbed for the sake of simplicity. The controller was realized using Matlab/Simulink (The MathWorks, Inc.), and data acquisition at a sampling rate of 1 KHz was achieved using QuaRC (Quanser Inc.). Experiments involving subjects were performed with the approval from the Rice Institutional Review Board.
6.7.1 Estimation of Subject Capability

In this experiment, I seek to compare the force estimation quality of the proposed mAAN controller—which is based upon a nonlinear disturbance observer (NDO)—to widely used adaptive procedures derived from Gaussian radial basis functions (RBF). The control law (6.18) is executed on the FE joint of the RiceWrist-S for two cases: one where $\hat{d}$ is calculated using the NDO approach (6.4), and a second where $\hat{d}$ is estimated using the RBF procedure.

As indicated in Section 6.1, Gaussian RBFs have been extensively used to model human input for robotic rehabilitation applications [12,20,97,98]. This approach necessarily assumes subject torque to be position dependent, and represents that input as a weighted sum of Gaussian RBFs distributed throughout the motion workspace. Using an adaption law which considers instantaneous position and velocity errors as well as the user’s “proximity” to each RBF, this procedure “updates” the RBF weights. For a more detailed description, see [20].

Although position dependent input torques are presumably present in healthy individuals, the same is not necessarily true for neurologically impaired subjects. I therefore sought to evaluate the estimation capabilities of NDO and RBF approaches when both position and non-position dependent inputs are provided. In order to consistently simulate subject input, an intrinsic disturbance was generated. For the first sixty seconds the disturbance resisted manipulator movement by acting as a virtual spring; since spring force is directly related to manipulator position, this exemplified a position-dependent torque. After sixty seconds had elapsed, non-position dependent sin-waves with 1.5, 3.0 and 4.5 Hz frequencies and 0.05 Nm amplitude were consecutively added at twenty second intervals. The manipulator’s desired trajectory was defined as a sine-wave with 0.25 Hz frequency and 20° amplitude. For the Gaussian
RBF adaptation, seventeen RBFs with 5° function width were defined throughout the trajectory; I attempted to select parameters that provided the best RBF performance.

Fig. 6.4 shows the $L^2$-norm of torque estimation error for both NDO and RBF techniques—as well as the $L^2$-norm of applied non-position dependent disturbance—over twenty second periods. For the first sixty seconds the Gaussian RBFs adapt to position dependent inputs, and hence the estimation improves; during the second sixty seconds, however, that estimation degrades due to the inclusion of non-position dependent disturbances. The NDO approach provides relatively constant performance (change is less than 32% of the maximum error) regardless of whether non-position dependent disturbances are present. The NDO technique converges much faster than the RBF approach when only position dependent inputs are present. These results demonstrate that the force estimation quality of the mAAN controller compares favorably to state-of-the-art Gaussian RBF procedures, both in terms of speed and consistency. I conclude that the proposed mAAN controller is therefore better suited to determine subject capability, since non-position dependent disturbances are expected due to the tone and spasticity of subjects.

6.7.2 Validation of the Error Bound Modification Algorithm

I next sought to experimentally examine how the error bound modification algorithm responded to changes in subject involvement; specifically, I aimed to demonstrate that the proposed algorithm can regulate a subject’s independence from the exoskeleton. This experiment was performed on the RiceWrist-S with ten healthy subjects, all of whom used their dominant arm.

Subjects were instructed to change their involvement strategy during a 180 second series of pointing tasks—“passive” for the first ninety seconds, then “active” for
Figure 6.4: Comparison of mAAN Controller using NDO and RBF approaches for subject input estimation. The bar graph represents the norm of torque estimation error and magnitude of non-position dependent disturbances at twenty second intervals. Parameters for both approaches were selected to provide optimal performance on the FE joint of the RiceWrist-S.

the second ninety seconds. Healthy subjects simulated “passive” inability by keeping their hand relaxed while holding the device handle. When “active,” subjects moved intentionally to match the desired trajectory; in this segment a visual display was shown to indicate actual position, desired trajectory, and randomly assigned target (see Fig. 6.5). The total allocated time to move from center-to-periphery and periphery-to-center was three seconds per task. Initial, minimum, and maximum feedback gains were assigned to be $10^{-2}$, $10^{-5}$, and $0.5 \, Nm \cdot s/rad$, respectively. The feedback gain $K_D$ was updated according to (6.30) at the end of every task.

The user-specified $r^*$ term employed in (6.31) defines a maximum allowable average trajectory error; $K_D$ varies in accordance to the relationship between $r^*$ and subject performance. I verified this correlation by testing three different $r^*$ values,
ranging from $12 \cdot 10^{-3}$ to $36 \cdot 10^{-3} \text{ rad/s}$, in three subject trials. An $r^*$ value was randomly assigned at the start of each 180 second test, and subjects took breaks between trials as necessary.

Fig. 6.6 depicts the average feedback gain and error as functions of task number (time) and $r^*$ across all ten subjects. Tasks 1-30 (i.e., 0-90 seconds) correspond with passive interaction while tasks 31-60 (i.e., 90-180 seconds) reflect active involvement. The experimental results in Fig. 6.6(a) indicate that $K_D$ increased when subjects acted passively; as the allowable average trajectory error decreased, the feedback gain grew to greater magnitudes in a faster manner. This trend likely stems from (6.31), where the rate of change for $K_D$ is determined by comparing average trajectory error to $r^*$. On the other hand, while subjects actively participated, $K_D$ decreased with roughly a first-order decay for all assigned $r^*$ values. When $r^*$ was sufficiently small, however, $K_D$ did not approach zero—this is because users were unable to complete the tasks unassisted with an average error less than $r^*$.

Experimental results shown in Fig. 6.6(b) demonstrate that as $r^*$ decreases, more robotic assistance is required even for healthy, active subjects to maintain the desired error level; but when $r^*$ increases above some physically realizable threshold, less assistance is required and subjects are allowed both greater movement variability and independence. I conclude that the error bound modification algorithm can adjust $K_D$ based on subject performance in order to enforce user-specified allowable error bounds.

6.7.3 Validation of Disturbance Rejection Decay Algorithm

To demonstrate that the proposed decay algorithm can decrease the rejection of “good” disturbances—i.e., subject inputs directed toward the goal while consistently
moving faster than some given trajectory—I conducted an experiment with ten healthy subjects. Subjects were instructed to use their dominant arm and observe the visual feedback presented in Fig. 6.5. Whenever a target was highlighted, the subject attempted to move toward that goal at a comfortable speed. I specified a desired trajectory which allocated three seconds to move from center-to-periphery and periphery-to-center—this trajectory was designed to be slower than typical subject movements.

The mAAN controller was implemented with and without the disturbance rejection decay algorithm in four alternating segments; the decay algorithm was included for segments one and three (shaded gray in Fig. 6.7(a)), while segments two and four exclusively used the mAAN controller. Each segment was 120 seconds long. In the first and third segments the decay term $F$ is modified based on subject performance according to (6.34). So as to maintain consistency during the experiment, I kept $\nu_{\text{dec}}$ and $\nu_{\text{inc}}$ rates constant for all subjects. In practice these rates could be modulated for subjects with different reaction capabilities.

Examining the experimental results reveals that the disturbance rejection decay algorithm decreased resistive controller actions (Fig. 6.7(a)) and allowed subject-defined faster motions (Fig. 6.7(b)). Readers may note that during segment transitions there are rapid fluctuations in the $F$ term; I believe that these stem from a subject familiarization phase. The results demonstrate that including a decay algorithm within
Figure 6.6: Effect of error bound modification algorithm on feedback gain and average error. (a) Adapting bounds to subject performance: feedback gains for passive subjects (task no. 1-30) are higher than for involved subjects (task no. 31-60). As the allowable error decreases, the magnitude of robotic assistance increases. (b) Demonstration of ultimate boundedness: users are constrained to have an average error less than or equal to $r^*$. As the bound radius increases, subjects display more variability and independence from the given trajectory.

the mAAN controller can cater to more able subjects, and increases involvement by enabling these users to exceed given trajectories.
Figure 6.7: Controller and subject performance while varying the rejection of good disturbances. DRDA here indicates the presence of the disturbance rejection decay algorithm. (a) Effect of decay term on controller action: when subjects consistently demonstrate the capability to correctly surpass a given trajectory, $F$ and $\tau_r$ decrease. (b) Sample trajectories with and without the decay algorithm: permitting able movements allows the subject to more quickly attain the target position and therefore increases involvement.

6.7.4 SCI Subject Testing

The main purpose of the proposed subject adaptive algorithms is to maintain the subject engagement throughout the training. In this experiment I aimed to examine
how the inclusion of these algorithms, within the proposed mAAN controller, affect
the variation in subject involvement during wrist flexion/extension movements. For
this purpose a four session robotic training protocol was conducted with a neurolog-
ically impaired subject. The subject was a 47 years old male with incomplete SCI at
the C3-5 level American Spinal Injury Impairment Scale (AIS) C. Each session was
conducted on a different day, and the whole study completed in a two week period.
Each session consisted of two separate training blocks a and b (training blocks are
referred subsequently by using the associated session numbers as (session no)-a and
(session no)-b). A given training block consisted of two ten minute phases, separated
by a short break. In the first phase, the mAAN controller was implemented without
the subject adaptive algorithms. In the second phase, the controller was implemented
with the subject adaptive algorithms.

Throughout the training, visual feedback, which is described in Fig. 6.5, was
presented to the subject. The allocated time to move from center-to-periphery targets
was one second, the targets at the periphery were placed at −20 and 20 degrees, and
Figure 6.9: The subject involvement performances for the cases with and without the inclusion of the subject adaptive algorithms within the mAAN controller shown for every training block separately (1-a indicates session 1 block a). In 6 out of 8 training blocks, average subject involvement was consistently higher for the case with the inclusion of the subject adaptive algorithms, throughout a given training block.

the targets were assigned randomly. The subject was instructed to follow the given desired trajectory as close as possible; however, intentional movements faster than given desired trajectory were not discouraged. For the subject adaptive algorithms, the initial, minimum, and maximum feedback gains were assigned to be $10^{-2}$, $10^{-5}$, and $0.5 \, Nm \cdot s/rad$, respectively, and the $r^*$ value was set to 0.040 rad/s. For the case where mAAN was implemented without subject adaptive algorithms the feedback gain was assigned as $0.5 \, Nm \cdot s/rad$.

The effect of inclusion of the subject adaptive algorithms on the subject engagement was evaluated by comparing the subject involvement performance, as measured by muscle activity during the first and second ten minute phases for a given training block only, to minimize the effect of fatigue as much as possible. I calculated the sub-
ject involvement performance by using muscle activation data gathered via surface electromyography (sEMG), similar to the methods used by Krisnan et al. [114] in a patient-cooperative robotic gait training protocol. Since the experiment was implemented on the FE Joint of the RiceWrist-S, the muscles of interest were flexor carpi radialis (FCR) and extensor carpi ulnaris (ECU). A Delsys Bagnoli-8 sEMG system was used to collect sEMG data. Skin preparation was conducted according to [115] by implementing fine sand paper, and cleaning with isopropyl alcohol wipes prior to electrode placement. The electrodes were placed approximately over the bellies of the FCR and ECU muscles to get best measurement. To reduce possible electromagnetic interference (EMI) caused mainly by electrical actuators, the conductive parts of the exoskeletal frame were grounded and the subjects’ arm was wrapped in neoprene. Additionally, in order to decrease any possible crosstalk between FCR and ECU muscles, and finger muscles due to grip movement a special handle was used, which can be coupled to the palm of the subject so that subject does not need to grip during the training. A 1000x gain was chosen on the Delsys system to amplify the voltage reading, and the system provided a 20-450 Hz band-pass filter. The data was recorded with the aforementioned QuaRC (Quanser Inc.) data acquisition system at a sampling rate of 1 KHz. Another filtering stage was applied digitally using a 25-450 Hz band-pass filter discrete filter to further remove EMI. As a final step, the magnitude of the band-pass filtered EMG data was smoothed for the analysis by using a 100 ms window running root mean square (RMS) calculation.

Although the aim was to use the data collected from both the FCR and ECU muscles, I was not able to gather reliable data from the ECU muscle. A possible reason for this phenomenon might related to the subject’s inability to actuate the ECU muscle, combined with a thick skin layer on the outer forearm. Hence the
following data analysis is conducted by using FCR muscle data only.

Since the analysis was made only on the FCR muscle, the portion of the data considered for the analysis was when the desired movement was in the flexion direction. The subject involvement was calculated as a percentage of time, using the ratio between involvement time, $t_{inv}$, and the total time, $t_{total}$. The involvement time, $t_{inv}$, was calculated as the amount of time the RMS value of the EMG data was larger than a threshold of the maximum voluntary contraction (MVC) recorded on a particular session. For the purposes of analysis in this study, the threshold was set to 0.20. The total time, $t_{total}$, was calculated as the amount of time for the subject to reach the desired target for a flexion movement. Since the implemented subject adaptive algorithms allowed intentional movement faster than the desired movement, the amount of time for the subject to reach the desired target was used in the calculation of $t_{total}$, rather than the complete allocated time for the desired movement, which was one second as specified previously.

The subject involvement performances, for the cases with and without the inclusion of the subject adaptive algorithms within the mAAN controller, were compared using the data gathered throughout the eight training blocks. Fig. 6.9 shows the average subject involvement values for each 50 second interval of a given training block, labeled, for example, as 1-a (session 1, training block a). The results reveal that for 6 out of 8 training blocks, average subject involvement was consistently higher for training blocks when the subject adaptive algorithms were active. For the training blocks 2-a and 4-b, average subject involvement was similar for both cases. These findings are supported by Fig. 6.10(a), which presents the average percentage of time across trials for each block. Again, it is noted that, with the exception of training blocks 2-a and 4-b, subject’s involvement as measured by sEMG is greater when the
subject adaptive algorithms are active.

An important trend was observed when the presented average subject involvement values in Fig. 6.9 were averaged over all the training blocks. Fig. 6.10(b) presents that, for the case without the inclusion of the subject adaptive algorithms the average subject involvement shows an apparent decreasing trend as the time progresses. This finding supports the claim asserted in [16], which is unless properly challenged, subjects may let the robot take control. On the other hand, for the case with the inclusion of the subject adaptive algorithms, the average subject involvement does not show a decreasing trend, and it is consistently higher than the corresponding cases where the algorithms are not active.

As a further investigation, the average position error and the norm of the control input values are plotted per training block (Fig. 6.11). As expected, the average position error for the case with the inclusion of the subject adaptive algorithms is higher for every training block (while being still smaller than 2 degrees for a movement with 20 degrees amplitude). The finding demonstrates that for the case including the subject adaptive algorithms, the standard deviation of the position error is considerably large. The phenomenon is caused by the fact that the subject adaptive algorithm minimizes the intervention to maintain subject participation. The decrease in the intervention is presented via Fig. 6.11(b), which shows the norm of the control input. The total control action is consistently smaller in the case where subject adaptive algorithms are active. Combined with the findings presented in the Figs. 6.9-6.10, the results in 6.11(b) suggest that the subject adaptive algorithms allow more involvement with minimal intervention.

Though subject engagement during robotic therapy depends on numerous factors, such as motivation, fatigue, and external distractions, the findings of this pilot study
suggest that the inclusion of the subject adaptive algorithms, which challenge the
subject based on his/her performance, maintain subject engagement throughout the
robotic rehabilitation sessions.

6.8 Discussion and Conclusion

This chapter has presented a minimal assist-as-needed (mAAN) controller which uses
model-based sensorless force estimation to determine subject capability. The combi-
nation of a baseline controller with that disturbance estimate, results in a control law
that provides only the required aid to complete a movement. The subsequent inclu-
sion of error bound modification and disturbance rejection decay algorithms adapt
the disturbance rejection paradigm to rehabilitation applications, and help challenge
subjects with various levels of impairment.

Impedance schemes have been frequently employed within the context of AAN
control, where their controller properties are modified based on subject performance.
Although impedance controllers are easy to implement and possess intuitive proper-
ties, these approaches are also oblivious to more complicated subject capabilities and
may therefore intervene sub-optimally across the robot workspace. To address this is-
sue, adaptive controllers that model the subject’s functional capability have been pro-
posed within AAN algorithms. Specifically, Gaussian radial basis networks—which
possess a universal approximation property [95]—have been frequently included in
adaptive controllers for estimating interaction forces. This approach relies upon the
hypothesis that subjects apply forces in a position dependent fashion.

Here I employ model-based estimation methods within the subject adaptive con-
troller context. It is shown that, unlike the Gaussian radial basis network approach,
with model-based estimation methods subject input can be dynamically determined
in time without any assumption of underlying pattern, such as position or time dependency.

Considering the discovery that error is likely a driving signal for motor learning [113], I implemented an error bound modification algorithm which utilizes the ultimate boundedness of the mAAN controller and modifies the allowable trajectory error via varying a feedback gain. Furthermore, I developed a disturbance rejection decay algorithm that decreases resistive forces when able subject movement desirably exceeds some given trajectory.

The sensorless force estimation, error bound modification, and disturbance rejection decay algorithms are all validated experimentally. Results demonstrate that the proposed controller does not require position dependency of subject inputs; furthermore, it is shown that estimation convergence occurs much faster than the Gaussian radial basis network approach. Experiments with healthy subjects verify that the error bound modification is capable of responding to changes in involvement. Inclusion of an upper bound on the average allowable error enables explicit definition of acceptable movement variability and subject-robot independence. Experiments also show that the disturbance rejection decay algorithm encourages voluntary movement by decreasing input rejection when subject forces are (a) consistently directed toward the goal and (b) of greater magnitude than strictly required for trajectory following. In this situation subjects are allowed to define a pace different from the externally-imposed reference path.

Additionally, the effect of the inclusion of subject adaptive algorithms, within the proposed mAAN controller, to the subject involvement performance is examined in a case study with an individual with chronic incomplete SCI. The findings support that the inclusion of the subject adaptive algorithms, which challenge the subject
based on his/her performance, maintain subject engagement throughout the robotic rehabilitation sessions.
Figure 6.10: The subject involvement performances for the cases with and without the inclusion of the subject adaptive algorithms within the mAAN controller averaged for every training block. (a) The averaged subject involvement values for the case with the inclusion of the subject adaptive algorithms resulted consistently higher than the values for the case without the inclusion of the subject adaptive algorithms at every training blocks, except at the training blocks 3 and 8. (b) For the case without the inclusion of the subject adaptive algorithms the average subject involvement shows an apparent decreasing trend as the time progresses.
Figure 6.11: The average position error and the norm of the control input values are plotted per training block. (a) The average position error for the case with the inclusion of the subject adaptive algorithms is higher for every training block with considerably larger standard deviation due to the fact that the subject adaptive algorithms allow the subject to make errors to increase and maintain subject participation. (b) The subject adaptive algorithms minimizes the intervention based on subjects performance.
Chapter 7

Conclusions

The use of robotic devices as part of the rehabilitation of neurologically injured individuals requires advances in both mechanical design and human-robot interaction design. Mechanical design of an exoskeletal device for robot-aided upper-extremity rehabilitation must allow ergonomic human-robot interaction by (a) corresponding the complete functional workspace of the related human limb, (b) activating joint by joint, and (c) not causing discomfort or safety hazards for the user. Additionally, the device has to possess specific properties, such as structural transparency, isotropic dynamic characteristics, and high torque output to support various interaction modes.

One of the main foci of this thesis is the development of a novel forearm wrist exoskeleton for robot-aided rehabilitation. Based on the limitations of the MAHI Exo-II parallel mechanism design for the wrist, introduced in Chapter 2 and employed in the study explained in Chapter 4, a novel forearm-wrist exoskeleton the RiceWrist-S, is developed. Mechanical design of the device allows coverage of the full workspace of the human joints. The cable drive mechanisms exhibit low friction and zero backlash, and special cable routing mechanisms allow positioning of the actuators for low apparent inertia. The detailed system characterization and clinical validation of the RiceWrist-S are provided.

Assistive robot-aided control strategies aim to induce neural plasticity, and they target a wide range of severely to mildly impaired subjects. The rehabilitation literature suggests that there is strong evidence that, active participation of the subject is
required to induce neural plasticity. Therefore, assistive controllers should intervene minimally in order to best promote involvement, plasticity, and recovery. This thesis focuses on investigating methods for subject input estimation and incorporating these methods within assistive control strategies in order to minimize intervention. Another important point to consider is that unless properly challenged the subjects might still let the robot take control. The work proposed in this thesis addresses this issue by including challenge algorithms, which further promote active participation of subjects with varying degrees of impairment, within assistive controllers. These algorithms are designed such that the controllers satisfy a uniformly ultimately bounded trajectory error condition.

Chapter 3 presents a subject adaptive controller, which employs an adaptive controller in conjunction with a Gaussian network for subject input modeling. A novel feedback controller is introduced to actively change the allowable error bound based on subject performance. The assumption in the formulation of this controller was that the subject input is position dependent. However, throughout the clinical study described in Chapter 4, it was observed that for the spinal cord injury (SCI) the assumption of position dependency of subject input is not necessarily valid. In Chapter 6, a novel minimal assist-as-needed (mAAN) controller is proposed, which is capable of estimating subject input as a function of time. Two algorithms are introduced to further promote active participation of subjects with varying degrees of impairment. First, a bound modification algorithm, which exploits the ultimate boundedness characteristics of the controller is introduced which alters allowable error. Second, a decayed disturbance rejection algorithm is presented which supports subjects who are capable of leading the desired trajectory. It is explicitly shown that the trajectory errors of the resulting system possess uniformly ultimately bounded characteristics.
Furthermore, the mAAN controller and consistency of the accompanying algorithms are demonstrated experimentally with healthy subjects and with one subject with incomplete spinal cord injury in the RiceWrist-S.
Bibliography


