RICE UNIVERSITY

Neuromuscular Mechanisms of Movement Variability: Implications for Rehabilitation and Augmentation

by

Özkan Çelik

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE

Doctor of Philosophy

APPROVED, THESIS COMMITTEE:

Marcia K. O'Malley, Chair
Associate Professor of Mechanical
Engineering and of Computer Science

Pol D. Spanos
Lewis B. Ryon Professor of Mechanical
Engineering and of Civil Engineering

John W. Clark, Jr.
Professor of Electrical and Computer
Engineering and of Bioengineering

Houston, Texas

April, 2011

ABSTRACT

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Although speed-accuracy trade-offs and planning and execution of rapid goal-directed movements have garnered significant research interest, far fewer studies have reported results on the lower end of the movement speed spectrum. Not only do very interesting observations exist that are unique to slow movements, but an explanation of these observations is highly relevant to motor function recovery and motor skill learning, where movements are typically slow at the initiation of therapy or learning, and movement speed increases through practice, exercise or therapy.

In the first part of this thesis, based on data from nine stroke patients who underwent a month-long hybrid traditional and robotic therapy protocol, a correlation analysis shows that measures of movement quality based on minimum jerk theory for movement planning correlates significantly and strongly with clinical measures of motor impairment. In contrast, measures of movement speed lack statistical significance and show only weak to moderate correlations with clinical measures. These results constitute an important step towards establishing a much-needed bridge between clinical and robotic rehabilitation research communities.

In the second part, the origins of movement intermittency or variability in slow movements are explored. A study with five healthy subjects who completed a manual

circular tracking task shows that movement intermittency increases in distal direction along the arm during multi-joint movements. This result suggests that a neuromuscular noise option is favored against a submovement-based central planning alternative, as the source of variability in slow movements. An additional experimental study with eight healthy subjects who completed slow elbow flexion movements at a constant slow speed target under varying resistive torque levels demonstrates that resistive torques can significantly decrease movement speed variability. The relationship between resistive torque levels and speed variability, however, is not monotonic. This finding may constitute a basis for proper design of novel human skill augmentation methods for delicate tasks and improve motor rehabilitation and learning protocols. Finally, a neuro-musculoskeletal model of the elbow suggests that movement speed variability in slow movements cannot be solely attributed to variability in the mechanics of muscle force generation.

Together, these analyses, simulations, and experiments shed light on variability in slow movements, and will inform the development of novel paradigms for robotic rehabilitation, motor skill learning and augmentation.

To Şule

Acknowledgments

First and foremost, I would like to thank Dr. Marcia K. O'Malley for her continuous guidance, insight, support and encouragement in conducting the research for this thesis. It has been a true privilege for me to pursue my Ph.D. studies with Dr. O'Malley's supervision in the Mechatronics and Haptic Interfaces (MAHI) Lab.

I wish to thank thesis committee members Dr. Pol D. Spanos and Dr. John W. Clark, Jr. for their guidance and support. I feel fortunate for being able to learn from their experience, knowledge and wisdom.

I wish to thank all of my collaborators at various institutions: Dr. N. Yozbatıran, Dr. G. Francisco, Dr. C. Boake, Dr. H. S. Levin, Dr. T. A. Reistetter, and S. Fisher at The Institute for Rehabilitation and Research (TIRR); and Q. Gu and Dr. Z. Deng at University of Houston. I am grateful to all subjects who kindly volunteered for my experiments.

This research was supported by grants from Vivian L. Smith Foundation, Mission Connect, National Science Foundation (IIS–0448341, IIS–0812569), National Institutes of Health (K12–HD055929) and National Academies Keck Futures Initiative.

I am grateful to Dr. Jan Hewitt and Dr. Tracy Volz for their classes on technical writing and presentation skills. I wish to thank many past and present members of the MAHI Lab, for their friendship and for the beautiful and fun working atmosphere they created. I am especially thankful to Dr. Joel C. Huegel, for always kindly helping me on how to deal with simple and not-so-simple matters, especially as I went through the adjustment period following my arrival in the US. I wish to specially thank Vinay Chawda for his friendship and the excitement and insight he brought into the projects we collaborated on. I am grateful to postdoctoral research associates Dr. Zahra

Kadivar and Dr. Ali Israr for guiding me in conducting statistical analyses for my research. Other lab members I wish to thank include Dr. V. Patoğlu, Dr. A. Gupta, Dr. S. Kreml, Dr. Y. Li, K. Bowen, D. Powell, S. N. Purkayastha, Z. Thompson and U. Pehlivan. I was fortunate to have the opportunity to work with and mentor undergraduate students in research projects or teaching labs and wish to thank B. Chalifoux, D. Meyer, C. Krebs and H. B. Gilbert. I also appreciate the assistance of technicians Mr. Joseph Gesenhues and Mr. Carlos Amaro in manufacturing parts for my research projects, and thank them for machine shop and prototyping skills they taught me.

Special thanks go to my Turkish friends in Houston, for making my graduate student life much more fun and enjoyable than what it could have been without them: Dr. Atilla Kılıçarslan; Ömer, Berna and Ela Deniz Özcan; Bayram Aygün; Kerem Y. and Seda B. Toklu; Gizem Keskin and Utku Pehlivan.

I wish to thank Dr. Nihat Berker for inspiring me to pursue an academic career and his mentorship during my undergraduate and masters studies at Istanbul Technical University. I continue finding his advice from those years to be still precisely correct.

I am very grateful to my parents and my sister Özlem, for their endless support and encouragement. Finally, but most importantly, I want to thank my wife Şule for providing me invaluable help, encouragement and inspiration while she too pursued Ph.D. studies, and dedicate this work to her. If it was not together, we would not have embarked on this endeavor. Going through this endeavor together has made us even closer to each other.

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Chapter 1

Introduction

This thesis consists of two parts. First, strong and significant correlations of objective kinematic measures of movement quality with widely used clinical measures of motor impairment for stroke patients are presented. Second, the contribution of neuromuscular dynamics to movement variability in slow movements of healthy persons is proposed and evaluated. Although the two research themes may look distant to each other at first glance, they are in fact inherently and closely related. Section 1.1 underlines the line of research in the field of computational motor control, and explains how the two themes fit into the big picture in this research field. Another goal of this chapter is to highlight the interconnections between the themes and their implications for each other. After these elucidations, Sections 1.2 and 1.3 present the motivation, the problem statement, the objectives and the contributions of each theme separately. Finally the chapter concludes with an overview of the structure of the thesis.

1.1 Computational Motor Control of Arm Movements

The field of computational motor control focuses on the problems involved in planning and execution of; and state estimation and motor learning in voluntary movements [1]. This section will briefly overview the line of research only in planning and execution of movements that are most relevant to the topic of this thesis.

The problem of movement planning arises from the redundant kinematics of the arm, and having been recognized for the first time by Bernstein [2], it is commonly referred to as "Bernstein's degrees-of-freedom problem". The human arm has seven degrees of freedom (DOF), while in three dimensional Cartesian space only six DOF are required to put the end effector (i.e., the hand) in a desired arbitrary pose (translation *and* rotation) [3]. For a given single end effector pose, the redundancy allows infinitely many possible configurations of the arm. For example, one can hold his hand in a specific pose, and without disturbing this pose at all, can rotate his elbow around the axis connecting the wrist and the shoulder, effectively doing the so-called "orbital movement of the elbow." Consequently, even for the simplest task of a point-to-point movement, there are inifinitely many possibilities for the trajectory that the hand can follow, as well as infinitely many possible velocity profiles [1].

As one option to explain how the central nervous system (CNS) resolves the DOF problem in planning, researchers have proposed optimal control theory-based approaches. In these approaches, the preferred end-point trajectory is assumed to be the one that minimizes a certain cost measure. Although there are several variants of this approach [4, 5, 6], the minimum jerk theory (MJT) garnered the highest interest. In their seminal work, Flash and Hogan [5] showed that both position and velocity profiles experimentally observed in unconstrained human reaching (point-to-point) movements can be well approximated by a trajectory that minimizes the squared jerk (time derivative of acceleration) for a movement of equal distance and duration as the actual movement. More specifically, the cost function to be minimized is defined as

$$J = \int_0^T \left[\frac{d^3x}{dt^3}\right]^2 dt, \tag{1.1}$$

where t denotes time, $x(t)$ denotes the position trajectory and T denotes the duration of the movement. The cost function is minimized when $x(t)$ is the solution of Euler-Poisson equation, resulting with the velocity profile given by

$$v_{mj}(t) = \Delta\left(\frac{30t^4}{T^5} - \frac{60t^3}{T^4} + \frac{30t^2}{T^3}\right) \tag{1.2}$$

where Δ is distance traveled. This velocity profile is commonly referred to as the "minimum jerk velocity profile" or "optimally smooth speed profile," and has achieved significant recognition and found applications in many areas including motor control and robotics.

When solved in two or three dimensional space, the minimum jerk model predicts straight line reaching movement trajectories, with a smooth, symmetrical, bell-shaped velocity profile. These predictions are in considerable agreement with experimental observations. Therefore, it is possible to use the minimum jerk position and velocity profiles as a good representation of point-to-point movements expected under normal conditions from healthy subjects.

In the first part of this thesis (Chapter 2), where I explore correlations of kinematic measures of motor function improvement with clinical stroke measures, two of the four kinematic measures, namely trajectory error (TE) and smoothness of movement (SM), are based on the minimum jerk theory. They serve as a basis to quantify how stroke patients' movements deviate from healthy people's movements, hence I use the term "movement quality measures." Indeed, many studies in the literature used movement smoothness measures [7, 8, 9] and trajectory or end-point error measures [8, 10, 11, 12, 13] to quantify motor function improvement in stroke patients. However, the relevance of these measures to clinical measures were left unexplored, which I address in this part of my research. Results of the correlational analyses indicated that movement quality measures showed significant and moderate-to-strong correlations with clinical measures of motor impairment, while the correlations for the "movement speed measures," namely mean tangential speed and number of target hits per minutes, were mostly weak and failed to show statistical significance. Under the examples of SM and TE, the results indicated that it is feasible to arrive at a unified set of robotic measures that will enable objective evaluation and comparison of robotic rehabilitation programs and devices, while maintaining clinical relevance due to their correlation with widely accepted clinical measures.

Although SM and TE proved to be strong candidates to be included into a unified set of robotic measures of motor function recovery, a fundamental shortcoming of them lies in their MJT-based definition. MJT concerns planning of movements that are rapid and can be executed in an open-loop fashion. Because the movements of motor-impaired patients are most commonly characterized to be slow, defining additional or better robotic measures to include into this unified set requires a better understanding of neurophysiological processes underlying planning and execution of slow movements. The search for a satisfactory explanation of motor control in slow movements constitutes the main theme of the second part of this thesis.

Harris and Wolpert's [14] minimum variance theory (MVT) provided a new thrust and direction to the research questions involved in the computational motor control of the arm. In their work [14], Harris and Wolpert note the shortcomings of the MJT as lacking a principled explanation of why jerk would be required to be minimized for a movement, and of how the CNS could estimate and integrate over time quantities such as jerk. They, instead, proposed that principles for minimizing effects of noise present in biological processes and mechanisms underly movement planning. Their model relies on the assumption of a linear relationship between the standard deviation (SD, variability) of the control signals and their mean levels, an assumption called as signal-dependent noise (SDN) in short. SDN assumption is equivalent to assuming a constant coefficient of variation (CV), defined as SD divided by the mean, for control signals. According to this assumption, during the planning of a rapid goal-directed movement, moving as fast as possible should be avoided, otherwise the end point error will be very large due to the large control signals involved in the movement. Hence it places a trade-off between movement duration and end point variability.

Harris and Wolpert's MVT was remarkably successful in predicting well-known and experimentally well-documented Fitts' Law [15], bell-shaped velocity profiles of arm reaching movements, saccadic eye movements and even the two-thirds power law [16], which is another well-documented power relationship between tangential speed and curvature of a path.

More recently, Todorov and Jordan [17] proposed a closed-loop alternative to MVT: optimal feedback control model (OFCM). Todorov [18] pointed out that despite the success of MVT in providing a unified explanation for numerous seemingly unrelated experimental observations in motor control, it is limited to open-loop control scenarios, hence only to rapid goal-directed movements with no disturbances. Saccades of the eye is a very well-suited scenario for MVT to explain, however, tasks during daily life often are slow to allow enough time for feedback to be incorporated in, and involve various disturbances. While MVT provides an off-line calculated movement plan to be executed during movement, possibly by a constant-structure servo-controller, OFCM takes into account noise in both control and sensing (or state estimation), and provides a variable structure feedback controller that is allowed to change its parameters during the movement, based on disturbances or feedback. The noise in motor commands is still assumed to comply with SDN assumption. Unlike MJT and MVT, where motor planning and execution are considered as two separate processes, in the OFCM they take place simultaneously. Todorov and Jordan's [17] results led to the "minimum intervention principle," where variability is allowed in task-irrelevant dimensions in order to minimize variability in task-relevant dimensions. According to the minimum intervention principle, the controller does not act unless the disturbances interfere with the goal of the task, because acting brings costs associated with control dependent noise and energy. This principle, in addition to observations explained by MVT, explains motor synergies and offers an optimal resolution for motor redundancy, or Bernstein's DOF problem.

It is important to highlight that both MVT and OFCM rely on the same essential assumption: SDN. However experimental evidence for SDN has been controversial. Jones et al. [19] and Hamilton et al. [20] provided experimental and motor unit pool-based simulation results showing a constant CV for force throughout the voluntary force spectrum under isometric conditions, except for the low force range (less than 20–30% maximum voluntary contraction). On the other hand, Poston et al. [21] indicated that experimental evidence exists showing that the relationship between isometric force variability and mean force level is not linear or proportional, such as those presented by Taylor et al. [22]. However, there is a consensus on the fact that CV of force increases significantly for low force levels [22]. Also, one of the main results of Hamilton et al. [20] is that larger muscles produce less variable forces, due to increased total number of motor units. Hamilton et al. state that it is likely that a similar relationship is in effect for the number of active motor units during a contraction, within the same muscle, and that this mechanism is responsible for the increased CV at low force levels.

In their study on movement intermittency in slow movements, Doeringer and Hogan [23] showed that voluntary movements become considerably intermittent (or non-smooth) with decreasing movement speed. Subjects were not able to avoid moving intermittently even when they were provided a real-time visual feedback display of their speed profile, and also when visual feedback was occluded. Although increased intermittency in slow movements is such a robust observation of human voluntary movement control, an explanation for the origins of it remained elusive. Despite OFCM can be expected to explain the intermittency or variability in slow movements better than MVT, due to accounting for feedback, it also assumes a SDN based mechanism for introduction of variability into movements. With the SDN assumption, movements involving smaller control signals will always result in less variability. In fact, Jordan and Wolpert [1] state that "longer movements can always be made smoother than short movements," which is in contradiction with Doeringer and Hogan's [23] experimental results. Hence, MVT and OFCM fall short of providing an explanation for variability in slow movements.

Doeringer and Hogan [23] propose two possibilities as the source of intermittency. Their first suggested source is a central movement planner that utilizes submovements to generate plans for complex movements consisting of building-block type simpler movements. Their second suggested source is noise being interjected on top of a continuous (or intermittent) plan along the neuromuscular circuitry. Doeringer and Hogan do not arrive at a final conclusion about the source of intermittency. They do however state that interpreting peaks in tangential speed profiles as incomplete blending of submovements would lead to a conclusion favoring the central planner option for being responsible for intermittency.

Chapter 3 of this thesis presents a systematic characterization of movement intermittency along the arm in natural (unperturbed) multi-joint movements with various speed conditions, through a human subject experiment with five subjects. Results of this experiment indicate that movement intermittency increases significantly in distal direction along the arm and with decreasing movement speed. The orientation of the movement plane failed to show a significant effect on movement intermittency. The results of this experiment are in agreement with those of Hamilton et al. [20], motivating the exploration of whether the increase in muscle force generation variability for small forces due to low number of active motor units can explain the increased variability in slow movements.

Chapter 4 of this thesis presents the results of a human subject experiment and of neuromuscular elbow model simulations, both aimed at answering the question, "can increased muscle force variability in low force levels explain increased variability or intermittency of slow movements?" In the "slow elbow movements experiment," which involved a constant slow speed elbow flexion task at two different target speed levels, force requirement was altered via resistive torque field levels, but the kinematics of the task were kept the same. Results of this experiment demonstrate that resistive torques may be used to significantly decrease movement speed variability. The relationship between resistive torque levels and speed variability, however, is not monotonic. These results are in agreement with the explanation that force requirements of the movement may be responsible for the observed movement variability through muscle force generation variability. In the same chapter, a neuromuscular model of the human elbow, including motor unit pool-based dynamics, Hill-based muscle contraction dynamics and the biomechanics of the elbow provides a modeling-based approach to answer the research question raised above. The model is driven by a simple feedback loop structure with only proportional control and does not allow a source of variability other than muscle force generation. Although the model was qualitatively successful in predicting higher variability for slower movements, simulations of this model predicted a monotonically increasing variability with increasing resistive torques, failing to match the experimentally observed relationship. Based on this mismatch, I conclude that movement speed variability in slow movements cannot be solely attributed to variability in the mechanics of muscle force generation.

The main connection between slow movements of healthy individuals and motor-impaired patients lie in the fact that movements of motor-impaired patients are typically slow. Explaining why people cannot move smoothly (or with small variability) under slow movement constraints can shed light on characteristics of the motor system which can be useful in explaining other relevant phenomena, such as motor skill learning (in which movements are usually very slow at the beginning and get faster with expertise and practice) and motor recovery (similar observations hold). Explaining why moving slowly is an inherently difficult task, can lead to definition of kinematic or dynamic motor recovery measures with a stronger theoretical and experimental basis, help in designing interfaces that can facilitate slow movement tasks and hence can be used for motor rehabilitation and motor skill learning, or design of human-machine interfaces with increased usability, such as exoskeletons and prosthetic devices.

Motivation, problem statement, objectives and contributions of each of the two themes of this thesis are presented in the following sections in detail.

1.2 Correlations of robotic and clinical measures of motor recovery

1.2.1 Motivation

Stroke has a significant social and economic impact on the United States with a $68.9 billion total estimated cost for 2009 [24]. Robotic rehabilitation provides numerous opportunities to improve rehabilitation protocols and to lower therapy expenses [25, 26, 27] and has been an active field of research for the last two decades.

An important advantage of robot assisted therapy is that it makes obtaining objective motor function measures possible. These measures can be directly calculated from the data recorded by the robotic devices' sensors and displayed on-line during the sessions or used for analysis off-line. Such measures are not vulnerable to subjective human interference during evaluation, unlike many clinical measures. The measures can capture the quality of movement, or can ensure independence from factors such as time. They can also be used to provide patients with immediate feedback on their progression after each therapy session, as opposed to the lengthy evaluation procedures conducted by a therapist that typically occur only at the beginning and end of the whole therapy protocol.

1.2.2 Problem Statement

Although robotic measures are objective and can be readily calculated at each robotic therapy session, they do not have the reliability, validity and widely accepted use of clinical measures. More research is needed to reveal the correlation between the two types of measures and establish commonly accepted and reliable robotic measures. Indeed, Hogan et al. [27] state that the challenge is not in the acquisition of kinematic or force data but in extracting clinically useful information.

1.2.3 Objectives

In Chapter 2 of this thesis, I propose to overcome the challenge mentioned in the previous section by identifying robotic measures of movement quality and speed that demonstrate strong correlation with clinical measures. The objectives of this correlational analysis is twofold. The first is to identify key properties for robotic measures of motor function improvement that will increase their correlations with clinical measures and also render them applicable to various rehabilitation protocols and devices. The second is to evaluate which of the two groups of robotic measures commonly used in the robotic rehabilitation literature will give better correlations with clinical measures: measures of movement quality (based on MJT) or measures of movement speed. I meet both objectives by successfully identifying significant and strong correlations between normalized movement quality measures and clinical motor impairment measures, using data from nine chronic stroke patients.

1.2.4 Contributions

This part of the thesis makes two significant contributions to the field of rehabilitation robotics:

The first contribution is recognizing the need for a unified set of robotic motor recovery measures with known correlation to clinical measures, to form a bridge between robotic and clinical rehabilitation research communities. This contribution also includes recognition and highlighting of numerous potential prospects of robotic rehabilitation that would significantly benefit from establishment of a unified set of robotic measures, such as home-based rehabilitation systems, remote supervision by therapists, and automated adaptive rehabilitation programs.

The second contribution is in addressing the recognized needs by a feasibility study that identifies key features for robotic motor function improvement measures that are not protocol or device specific, presents robotic measures with the desired features and reports their correlations to widely used clinical measures.

1.3 Origins of movement variability in slow movements

1.3.1 Motivation

Doeringer and Hogan [23] showed that slow movements are intermittent and that intermittency exhibits itself as submovements in the velocity profile of the movement. Although many studies interpreted the intermittency to be caused by corrective actions [28, 29], Doeringer and Hogan showed that the submovements persisted under no visual feedback, indicating that all submovements cannot be attributed to corrective actions. A satisfactory interpretation of origins of intermittency in slow movements, however, remained elusive.

Although speed-accuracy trade-off and planning and execution of rapid goal-directed movements have garnered significant research interest, far fewer studies have reported results on the lower end of the movement speed spectrum. Not only very interesting observations exist for slow movements, but also an explanation of these observations are highly relevant to motor function recovery and motor skill learning, where movements are typically slow at the initiation of therapy or learning, and movement speed increases through practice, exercise or therapy.

Viewed from a different perspective, movement intermittency can be interpreted as movement variability, defined as within-trial variability rather than trial-to-trial variability. This point of view provides a framework to study movement intermittency as a special case of movement variability observed in slow movements.

Obviously, rapid goal-directed movements closely resemble natural reaching and pointing movements frequently observed in daily life, whereas making slow movements with controlled speed can be considered an unnatural task. However, there are tasks in daily life where control of speed is as important as position and usually slow movements are required including steering while driving, surgical tasks such as suture tying or cutting, making an injection and bowing while playing a violin. Explaining why moving slowly is an inherently difficult task, can help in designing augmentation interfaces that can facilitate the slow movement task and hence can be used for motor rehabilitation and motor skill learning or design of human-machine interfaces with increased usability, such as exoskeletons and prosthetic devices.

1.3.2 Problem Statement

This portion of my research reports results of two human subject experiments and a of neuromuscular model to address problems in identifying the origins of movement variability in slow movements. Existing theories in computational motor control for movement planning and execution, most notably MJM, MVT and OFCM, fall short of offering an explanation for increased intermittency and variability in slow movements. They, on the contrary, predict increasingly smoother movements for decreasing movement speed, a prediction that contradicts experimental observations. Although there has been two propositions for the source of movement variability in slow movements, namely neuromuscular noise or central planning, it remained unclear which mechanism is the dominant cause. Therefore, there is a need for a closer look, via both experiments and modeling, into the neuromuscular mechanisms involved in control of slow movements to shed light on the origins of movement variability.

1.3.3 Objectives

In Chapters 3 and 4 of this thesis, arriving at a satisfactory explanation of the mechanisms behind increased movement variability in slow movements constitutes the main objective. Five objectives complement this main objective.

The first objective is to evaluate which of the two proposed mechanisms is more likely agree with experimental observations. This objective is addressed via a human subject experiment involving completion of manual circular tracking tasks and quantification of movement intermittency along the joints of the arm.

The second objective is to experimentally evaluate the hypothesis that increased variability at low force levels due to the motor unit pool structure can explain increased movement variability in slow movements.

The third objective is to experimentally test whether methods of movement augmentation (via haptic or force-feedback interfaces) can decrease the variability in slow movements. The second and the third objectives are satisfied by an additional human subject experiment that involved completing of slow elbow flexion movements under various speed and resistive torque conditions, implemented via an elbow exoskeleton device.

The fourth objective is to build a neuromuscular model that demonstrates realistic force generation variability in isometric conditions, but also accounts for muscle contraction/extension dynamics to provide a method to explore how force variability propagates into kinematic or movement variability through musculoskelatal biomechanics of the elbow.

The fifth objective is to use the neuromuscular model to evaluate noise in force generation (actuation) as the potential source of intermittency. The fourth and fifth objectives are satisfied by a model that is based on both motor unit pool recruitment and Hill-based muscle contraction.

1.3.4 Contributions

This portion of the thesis makes five significant contributions to the field of computational motor control:

First, it presents a systematic characterization of movement intermittency along joints of the arm during a multi-joint tracking task under varying movement speed levels and tracking plane orientations. It suggests that neuromuscular noise option is favored against submovements-based central planning, as the potential source of intermittency.

Second, it defines a new within-trial measure of movement variability –coefficient of variation for speed– more appropriate for quantifying variability of slow movements than trial-to-trial variability measures commonly used in the literature.

Third, it provides experimental results with this new measure of variability for slow movements, under varying target speed and resistive torque conditions. These experimental results are in agreement with the hypothesis that force requirements of the movement is responsible for the observed movement variability via muscle force generation variability.

Fourth, it experimentally shows that movement variability in slow movements can be significantly decreased by using resistive torque fields that would increase the number of active motor units during the task. Hence, it provides experimental evidence for feasibility of force-feedback interfaces to augment human skill in delicate tasks such as surgery, or to facilitate smoother execution of slow movement tasks in robotic rehabilitation or motor learning protocols.

Fourth, it further explores the validity of the hypothetical explanation for the origins of variability in slow movements via a neuromuscular model of the human elbow. The results of the model indicates that it is not possible to attribute all movement variability to muscle force generation variability alone and that in neuromuscular modeling efforts to address movement variability, dynamics of sensing (proprioception) and feedback need to be included for a more complete understanding of variability dynamics.

1.4 Thesis Structure

The thesis is structured as follows: Chapter 1 provides an overview of computational motor control theories of movement planning and execution, background and motivation for the thesis. Chapter 1 also introduces the motivation, problem statement, objectives and contributions of the thesis, grouped under the two themes of the thesis. Chapter 2 is based on published manuscripts [30, 31] and presents in detail the literature review, methods, results and discussions of the the portion of research on "Correlations of robotic and clinical measures of motor recovery". Chapter 3 is based on the published manuscript [32] and the extended abstract [33]. Chapter 4 is based on an unpublished manuscript. Together, Chapters 3 and 4 present in detail the literature review, methods, results and discussions of my research grouped under the theme "Origins of movement variability in slow movements." Chapters 2, 3 and 4 are in the form of self-contained manuscripts. Chapter 5 summarizes overall findings, conclusions and proposes future research directions.

Chapter 2

Correlations of Robotic and Clinical Measures of Motor Recovery

In this chapter, based on data from nine stroke patients who underwent a month-long hybrid traditional and robotic therapy protocol, a correlation analysis shows that measures of movement quality based on minimum jerk theory for movement planning correlates significantly and strongly with clinical measures of motor impairment. In contrast, measures of movement speed lack statistical significance and show only weak to moderate correlations with clinical measures. These results constitute an important step towards establishing a much-needed bridge between clinical and robotic rehabilitation research communities.

Portions of this chapter were published in the journal IEEE Transactions on Neural Systems and Rehabilitation Engineering [31] and in the Proceedings of the IEEE International Conference on Robotics and Automation (ICRA 2008) [30]. I gratefully acknowledge my collaborators in both publications.

2.1 Introduction

In this chapter, I present the results of a regression analysis correlating four clinical measures and four robotic (calculated from robot recorded data) measures acquired for nine chronic stroke patients who underwent a one-month program consisting of robotic and traditional constraint-induced movement therapy (CIMT) activities. Fugl-Meyer upper extremity scale (FM), Motor Activity Log (MAL), Action Research

Arm Test (ARAT) and Jebsen-Taylor Hand Function Test (JT) clinical scale scores were compared to robotic trajectory error (TE), smoothness of movement (SM), hits per minute (HPM) and mean tangential speed (MTS) measures for a target-hitting task that involved repetitive reaching movements. I show that robotic movement quality measures SM and TE strongly correlate with motor impairment measures FM and ARAT. Obtained results identify key features that robotic measures should exhibit, such as normalization and evaluation of movement quality rather than movement speed. I believe that these key features should be taken into account in design of a unified set of robotic measures for evaluation of motor function recovery in stroke patients. Such measures are highly desirable in the therapeutic robotics community and are important for accurate tracking of patient motor function improvement at every session, realization of accurate patient progress monitoring in home-based or tele-rehabilitation and automatic adaptation of robotic therapy task difficulty based on patient progress. In addition, comparisons of the functional gains of patients who undergo different robotic rehabilitation protocols or use different devices will be more reliable and accurate when based on a unified set of robotic measures than when based on heterogeneous robotic measures or pre- and post-treatment evaluations.

2.2 Literature Review

Robotics provides numerous opportunities to improve rehabilitation protocols and to lower therapy expenses [25, 26, 27]. Stroke has a significant social and economic impact on the United States with a $68.9 billion total estimated cost for 2009 [24]. Because of the potential benefits, robotic rehabilitation has been an active field of research for the last two decades. Although various aspects of robotic rehabilitation have been investigated and presented in the literature, a significant effort has been the design of novel therapeutic robots or devices. Early examples of these robots include the MIT-MANUS [26, 34] and MIME [35, 36], both of which were designed for rehabilitation of the proximal upper extremity joints (shoulder and elbow). Due to the success of these early systems, robotic devices for the rehabilitation of distal joints of the upper extremity have also been developed, such as the MAHI Exoskeleton [37], the wrist module of the MIT-MANUS [38, 39] and wrist rehabilitation devices developed by Hesse et al. [40] and Andreasen et al. [41], to name a few. Most recently, therapeutic robots with more degrees-of-freedom (DOF) such as Rupert [42] and the RiceWrist [43] that are capable of actuating shoulder, elbow and wrist joints simultaneously have also been designed.

Far fewer studies have sought to establish a unified set of measures that will enable objective comparison of the efficiency and clinical success of therapeutic robots [44]. According to Hogan et al. [27], the challenge is not in the acquisition of kinematic or force data but in extracting clinically useful information. I propose to overcome this challenge by identifying key features for robotic measures that demonstrate strong correlation with clinical measures. Hence, the primary focus of this chapter is to identify key features for robotic motor function improvement measures that are not protocol or device specific, to present four robotic measures with the desired features and to report their correlations to widely used clinical measures.

Robotic measures have the benefits of being completely objective, capturing quality of movement, and providing patients and therapists with immediate feedback on patient progress [27]. However, robotic measures lack the wide acceptance of clinical measures because they are often device or task specific. Another factor hampering wide acceptance is that robotic measures have not been extensively tested for correlation to widely accepted clinical measures for stroke. Such lack of acceptance by the clinical community limits realization of the important advantages that robotic measures offer. Clinical measures, while reliable and widely accepted, have several drawbacks including variability due to the methods by which the clinical measures are determined, low resolution, subjectivity due to dependence on patient-reported outcomes, and lengthy evaluation procedures that typically limit measurements to pre-, post-, and follow-up sessions [13, 34, 45]. Various robotic measures have been reported in the literature.

Reported examples in the literature include movement smoothness [7, 8, 9], average movement speed, movement percentage voluntarily achieved by the patient without a robot's assistance [10, 46, 11], amount of force applied by the patient [13, 27] or error values indicating the difference between the desired position or trajectory and that achieved by the patient [8, 10, 11, 12, 13]. Some of these measures are device or task specific [10, 46, 11] while others require administration of special evaluation protocols apart from the actual robotic therapy [13, 27], making them difficult to incorporate in the robotic therapy protocol for simultaneous progress tracking and immediate feedback. Reaching movements are common in many of the rehabilitation protocols, and as such, robotic measures based on kinematic data captured during reaching movements have the potential to be readily applicable to a wide range of devices and protocols. Examples of robotic measures applicable to reaching movements are smoothness measures [7, 8, 9], position or trajectory error measures [8, 10, 11, 12, 13], and average movement velocity measures [10, 11, 9]. With few exceptions, results of the robotic therapy protocols are reported in selected clinical and robotic measures separately, without any correlation analysis between the two.

One study, however, that investigated correlations between robotic and clinical measures was reported by Colombo et al. [10]. Clinical trials were completed with a total of sixteen patients who were assigned to one of the rehabilitation devices developed by the group: a one-DOF wrist rehabilitation device and a two-DOF shoulder-elbow rehabilitation device. Three robotic measures were used in the study, namely mean velocity, robot score and active movement index. Regression analyses revealed a significant and moderate correlation ($r = 0.53 - 0.55$) between pre- and post-treatment Fugl-Meyer scores and the robotic measure scores. Regression analyses for Motor Status Score and Medical Research Council measures with the same set of robotic measures were found to be inconclusive. Results of the study were limited due to only moderate correlation values with just one of the clinical measures used in the study. Another limitation of the study was that two of the three robotic measures, robot score and active movement index, were linearly dependent, thereby reducing the number of independent robotic measures used in the study to two. As an extension of this study, the same group examined the correlations of seven robotic measures with the clinical measures Fugl-Meyer, Motor Status Score and Motor Power Score [11]. Only one robotic measure showed significant correlation with Motor Power Score, while four robotic measures showed significant correlation with Motor Status Score and Fugl-Meyer. In all cases, however, the correlations were only weak to moderate ($r = 0.36 - 0.58$).

Stronger correlations between robotic and clinical measures have been reported in the literature. In [13], Krebs et al. defined two robotic measures: a measure of mean force that patients were able to apply in specific arm configurations and a hold radius measure that quantified the total deviation from a hold position as the patient tried to hold a handle in place while a disturbance force was applied. They reported that a strong correlation ($r = 0.85$) exists between Motor Power Scale, a subset of the Medical Research Council (MRC) measure, and the logarithm of the mean force measure and the hold radius measure. Although the obtained correlation was strong, it was limited to a subset of MRC, and data collection with the robot involved specific configurations, acquisition of force data and tasks for evaluation that are not necessarily a part of the rehabilitation protocol itself.

Chang et al. [9] recorded the movement trajectories during reaching movements of stroke patients using a motion capture system and were able to compute robotic measures from data collected during the rehabilitation protocol. They showed that only weak to moderate ($r = 0.37 - 0.53$), albeit significant, correlations exist between two clinical measures (Fugl-Meyer upper limb component and Modified Ashworth Scale) and four robotic measures (number of movement units –a non-smoothness measure–, movement time, peak velocity and normalized jerk score). I believe that the finding of only moderate correlations could be due to the fact that the number of movement units and peak velocity measures do not have sufficient resolution to report useful information related to the impairment. Also, it is likely that the jerk measure suffers from excessive noise due to being numerically differentiated three times, hence losing almost all useful information content.

In a recent study with similar motivations, Bosecker et al. [47] reported correlation and linear regression models for clinical measures Fugl-Meyer (upper limb component), Motor Status Score (MSS), Motor Power and Modified Ashworth Scale. MSS is a clinical measure proposed by the same group as an alternative to Fugl-Meyer and has better sensitivity characteristics than Fugl-Meyer. Results were reported in terms of both training and validation (prediction) values based on a pool of 111 chronic stroke patients. Robotic measures were composed of 8 kinematic macro-measures (based on movement accuracy, speed and smoothness); 7 kinematic micro-measures (calculated from submovement parameters); and 4 kinetic (force) measures. Linear regression models between all 19 robotic measures and Fugl-Meyer measure led to r values of 0.802 in training and 0.427 in validation while for the MSS measure, r values were 0.788 and 0.696 for training and validation, respectively. Kinematic micro-measures were found to improve correlation coefficients only marginally in training and to weaken them in validation. Correlation coefficients of regression models for Fugl-Meyer and MSS measures and only kinematic macro-measures were also reported, as well as for Motor Power and kinetic measures. In general, MSS was found to yield higher r values in validation compared to Fugl-Meyer, increasing MSS's usability for clinical score predictions.

Similarly, in this chapter, I analyze the correlation between four clinical measures and four robotic measures used to assess motor recovery based on data collected from nine stroke patients. The chapter is structured as follows. Section 4.3 presents the details of the therapy protocol, patient details, clinical measures, robotic measures, and data analysis techniques. Results of the therapy protocol and correlation analyses of clinical measures with robotic measures are presented in Section 4.4. The chapter concludes with a discussion of results, contributions and limitations.

2.3 Methods

2.3.1 Participants

A total of nine chronic stroke patients were involved in the the hybrid therapy protocol. As in standard CIMT, the patients selected were those who exhibited under-utilization of the affected upper extremity. For inclusion in the protocol, patients were required to demonstrate enough wrist range of motion to move the joystick and reach the targets. Characteristics of the patients are summarized in Table 2.1. Clin-

Table 2.1 : Characteristics of the Patients. Abbreviations: BS, Brain Stem; Hem, Hemmorhagic; MCA, Middle Cerebral Artery; BG, Basal Ganglia; IC, Internal Capsule, T, Thalamus; M, male; F, female; R, right; L, left.

Patient number	Gender	Age (years)	Months since stroke	Side affected	Stroke location
1	M	62	24	R	L BS
2	F	63	12	L	R BG
3	M	62	121	R	L MCA
4	M	65	50	R	L BG and T
5	F	48	20	L	R MCA
6	M	67	14	R	L IC
7	M	57	25	L	R BG
8	M	66	77	L	R Pons
9	M	57	13	L	R IC

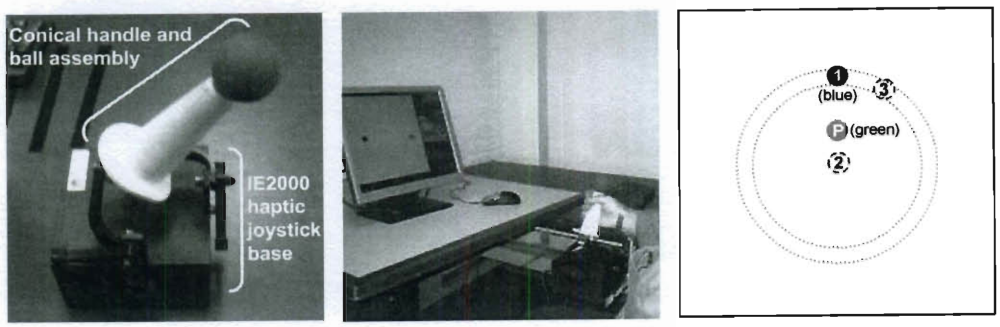
ical scores of the patients (see pre-treatment scores in Table 2.2) indicate that the the inclusion criteria limited the patients included in the protocol to those who were only mildly impaired. The therapy was conducted for four weeks except for Patient 1 who underwent therapy for eighteen days. Therapy sessions were three days per week (Monday, Wednesday, Friday).

2.3.2 Robotic Rehabilitation Device

For the robotic therapy portion of the therapy protocol, the IE2000 haptic joystick by Immersion Inc. was used. The original handle of the joystick was replaced with a conical handle-ball assembly to facilitate patients' grasping as shown in Fig. 2.1(a). The IE2000 is a backdrivable two-DOF device having a workspace of $\pm 45^\circ \times \pm 45^\circ$ which corresponds to a workspace with arc lengths of 152.4 mm $\times$ 152.4 mm at a 100 mm handle height from the pivot. The joystick has high resolution optical encoders for position sensing that provide 0.036° rotational resolution or a minimum measurable displacement value of 0.02 mm at the same handle height. The maximum force value that can be reflected with the device is 4.94 N at the handle. The inertia and dynamics of the joystick are assumed to be negligible; users primarily feel the forces that define a desired virtual environment generated by customized software. The loop rate for haptic feedback based on impedance control was 1 kHz. OpenGL was used to implement a graphical interface for a target-hitting task. To successfully hit the targets visible on the computer screen, the joystick handle had to be deflected ±27° from the vertical position. The testing environment is shown in Fig. 2.1(b). The choice of IE2000 haptic joystick for calculation of robotic measures is supported by the statement by Hogan et al. [27] that backdrivable robotic devices under impedance control provide undistorted measurements of kinematic variables. Additionally, the IE2000 offers the possibility of implementing various operating modes that utilize the device's force-feedback capabilities.

2.3.3 Task Description

The task assigned to the patients was to control the position of a pointer in a 2D workspace to hit targets around a circle. The pointer's position was directly determined by the joystick's position. For patients 1–4, twelve targets were positioned equidistantly on a circle that was centered on the workspace, resembling the positions of numbers on a round clock, as illustrated in Fig. 2.1(c). The number of targets was found to be redundant and was decreased to eight as part of an update to the software after Patient 4. Hence for patients 5–9, the number of targets around the circle was eight. The active target was displayed until it was successfully hit by the pointer, after which the active target became the center point. Once the joystick was



(a) (b) (c)

Figure 2.1 : (a) IE2000 haptic joystick with the replaced handle. The conical shaped handle and ball assembly aimed to provide easier grasping and strapping of the patient to the handle. (b) A patient using the joystick for the target-hitting task (Photo courtesy of kuhf.org). (c) Graphical interface displayed on the monitor during rehabilitation sessions. Marked are active target (1), the pointer (P), and the next two active targets (2 and 3) that will appear upon successful hits.

centered, the active target became the next point on the circle in a clockwise direction. A successful movement from the center to the target and back registered two hits. The defined task resembles the task configuration in [7], and the main purpose of the task is to have patients carry out repetitive point-to-point reaching movements. Position data of the cursor were recorded at a sampling frequency of 20 Hz for further analyses for patients 1–4. The sampling frequency was improved and increased to 100 Hz as part of the software update for patients 5–9.

During the therapy sessions, the patient was seated so that the motion required to move the joystick handle comprised forearm pronation/supination and wrist abduction/adduction, with some wrist flexion/extension due to the imperfect alignment between joystick axes and human wrist axes of rotation. In order to prevent patients from completing the required task by compensating with torso movements, an anterior trunk support with zipper (Stayflex® Anterior Trunk Support, Standard, Large) attached to the back of the chair was used. Note that this arrangement still allowed use of shoulder and elbow joints, but it did not allow use of any unaffected muscle groups or joints, such as body or torso movements, for compensation.

For patients 1–4, four operating modes were implemented, namely *unassisted*, *constrained*, *assisted*, and *resisted*. In addition to these modes, variations of each of the assisted and resisted modes were used for patients 5–9. The purpose of using various modes was to allow the therapist to adjust the difficulty of the robotic task with regard to the needs, capabilities and progress of each patient. This approach resembles the well-developed behavioral therapy method of "shaping" [48]. Indeed, use of various modes constituted the robotic portion of the shaping exercises under the constraint-induced movement therapy (CIMT) protocol (see Section 2.3.4 for further details).

In unassisted mode, no force was generated by the joystick, and the movement of the pointer was solely determined by the movement of the patient. Unassisted mode was suitable for gathering and analyzing data that represented a patient's free movement with no external interference. Therefore, in this chapter, I report robotic measure results recorded in the unassisted mode only. The details of the other modes used in the therapy are not presented here, since they are not relevant to the main focus. Information on the other modes can be found in [30].

2.3.4 Protocol

The protocol consisted of behavioral techniques and shaping exercises to improve motor function and use of the affected upper extremity. Intensity of therapy was 3-hour sessions (including robotic therapy) for 3 days/week for a duration of 4 weeks. The behavioral techniques were written contracts to the patient and caregiver, daily monitoring of amount of use of the affected arm and hand outside of therapy, prescribed home practice tasks, and wearing of a restraint on the unaffected upper extremity. The purpose of the restraint, a protective safety mitt to be worn for six waking hours per day, was to encourage use of the affected upper extremity.

During therapy sessions, patients performed shaping exercises using the affected upper extremity, using robotic tasks as well as tasks presented by the therapist. Shaping is a commonly used operant conditioning technique in which the behavioral objective (movement) is approached in small steps of progressively increasing difficulty [48]. Each patient's shaping program consisted of robotic training and tasks selected by the therapist and tailored to address the motor deficits of that individual patient. Therapist-presented tasks utilized commonly available objects such as clothespins, coins, and cups that were manipulated by the fingers of the affected hand. Each shaping task was performed for ten trials, each with a duration of 30 to 60 seconds. Results were graphed trial by trial and presented to the patient immediately after each trial. The feedback was based on the time and success rate.

In the robotic therapy component of the rehabilitation program, the therapist determined the operating mode to work in for each trial, based on the patient's needs and progress. Patients 1–4 typically completed two or three eight-minute trials (a total of 16–24 minutes) on each therapy day that formed a daily session. For patients 5–9, daily sessions consisted of 25–40 one-minute-long trials and an operating mode was selected by the therapist for each block of 5 trials.

2.3.5 Clinical and Robotic Measures

Four clinical measures were used in the correlational analyses, namely Fugl-Meyer (FM) upper limb component, Motor Activity Log (MAL), Action Research Arm Test

(ARAT) and Jebsen-Taylor Hand Function Test (JT). A total of two therapists participated in the protocol. Clinical measures were administered by one therapist for patients 1–4, and by another therapist for patients 5–9. Although no independent inter-rater reliability of clinical measures was established, both evaluators who performed measuring of upper extremity motor functions had previous experience with the test protocols. In addition both evaluators had a therapist background including extensive experience and knowledge of the nature of stroke impaired arm and hand functions. FM [49] and ARAT [50] have intra- and inter-rater reliability as demonstrated in the literature. JT is a timing based measure and MAL is not administered by the therapist. Hence inter-rater reliability of therapists is not an issue for these two measures.

The 66-point upper limb component of the FM scale was administered by the therapist. The therapist used a 3-point ordinal scale (0: can not perform, 1: can perform partially, 2: can perform fully) to rate each of 32 items completed by the patient in the test. The FM score was the sum of all ratings with score of reflex activity item doubled [51]. The MAL measure had two components: a 6-point scale for amount of use and another 6-point scale for quality of movement. Patient and caregiver independently rated in both components each item in a list of activities of daily living. The result was an average of all ratings [52]. In the ARAT scale, there were a total of 19 items grouped in four components: grasp, grip, pinch and gross movement [53]. Each item was evaluated by the therapist on an integer scale of 0–3. Due to the time-saving design of ARAT scale, if a patient successfully completed the most difficult item in a subscale, it was directly assumed that he succeeded in all less difficult items in that subscale. Similarly, if he failed the easiest item, all items in the corresponding subscale were taken to be failed. Finally, JT was administered with a chronometer. Time in seconds for completing seven different tasks was recorded by the therapist during the test. Total time was the score achieved by the patient [54]. It should be noted that there are fundamental differences among individual clinical measures in this set, with some measuring motor impairment (e.g. FM, ARAT) and others measuring functional use (e.g. MAL, JT). MAL is a structured interview that evaluates by self-report the actual amount and quality of use of the affected upper extremity [52]. In contrast, FM measures the motor recovery of the upper extremity through the assessment of sequential stages of reflexia, synergistic (extension and flexion) patterned movements and finally selective movements [51]. Additionally, some of the measures (like FM) are more widely used and considered to be more reliable and objective compared to others. The motivation in selecting the mentioned clinical measures has been inclusion of both motor impairment and functional use measures. Two measures of each type have been included to widen the range of measures covered in the correlational analyses. Nevertheless, the goal was to seek robotic measures that correlate well with all or at least most of these clinical measures, a goal met by trajectory error and smoothness of movement measures.

Four robotic measures were calculated by postprocessing the data files: trajectory error (TE), smoothness of movement (SM), average number of hits per minute (HPM), and mean tangential speed (MTS).

Trajectory Error (TE)

The TE measure is defined as a normalized difference between the desired trajectory and the patient's trajectory from one point in the workspace to another. Desired trajectory is always a straight line from the last target to the current target. Absolute values of the deviations from this straight line trajectory during the point-to-point movement were summed to obtain the non-normalized TE value. This value was first divided by the total number of data points during the movement under consideration to normalize it with respect to time. Then it was divided by the distance from the initial point to the end point of the movement in order to obtain spatial normalization. This final value, normalized both spatially and temporally, constituted the final TE value for the movement. With this definition, the TE measure is applicable to any point-to-point movement, regardless of the sampling rate of data acquisition and the traveled distance. The TE value can be interpreted as the average deviation from the straight-line trajectory for each position data point, as compared to the total distance traveled. Since it is a dimensionless value, it is reported as a percentage.

Smoothness of Movement (SM)

The SM measure is a correlation coefficient that expresses the correlation between the patient's speed profile and a speed profile utilizing the minimum jerk principle (an optimally smooth speed profile). It was shown in [5] that the speed profiles of healthy subjects' point-to-point movements can be approximated very well with a speed profile that minimizes the squared jerk (time derivative of acceleration) for a movement of equal distance and duration as the actual movement. Emergence and validity of the optimally smooth speed profiles for unconstrained wrist movements was demonstrated in [55]. Also, Huegel et al. [56] recently showed that wrist pronation-supination movement speed profiles during point-to-point manipulation of a simulated multi-mass flexible object were well represented by the minimum jerk profile. Krebs et al. [26] showed that stroke patients' speed profiles converge to single-peaked optimally smooth profiles through the recovery process. SM in the minimum jerk sense was one of the five smoothness measures tested in [7]; however, the formulation in [8] and [57] is used here. The speed profile of the patients is derived from the tangential speed of patients' movements. The minimum jerk speed profile on a straight line for each target hit movement was calculated by the equation*

$$v_{mj}(t) = \Delta\left(\frac{30t^4}{T^5} - \frac{60t^3}{T^4} + \frac{30t^2}{T^3}\right) \tag{2.1}$$

where t is time, Δ is distance traveled and T is the duration of the movement, which was taken to be equal to the time elapsed between two target hits. In order to match the initial points of the actual and the minimum jerk profile, patients' speed profiles were time-shifted. The amount of this shift was determined by the temporal distance between the previous target hit instance and the minimum value in the first half of the actual speed profile. This method is similar to the one mentioned in [8] with some minor differences in calculation of T and data shifting procedure. The correlation coefficient ρ is calculated by

$$\rho = \frac{\Sigma[(V_{pat} - \overline{V}_{pat})(V_{mj} - \overline{V}_{mj})]}{\sqrt{\Sigma(V_{pat} - \overline{V}_{pat})^2 \Sigma(V_{mj} - \overline{V}_{mj})^2}} \tag{2.2}$$

where V_{pat} is the movement speed of the patient, $\overline{V}_{pat}$ is the mean movement speed of the patient, V_{mj} is the minimum jerk speed profile, $\overline{V}_{mj}$ is the mean minimum jerk speed, again following the formulation given in [8]. Since linear scaling of either speed profile does not alter the correlation coefficient, normalization of speeds with

*Note that the equation given for the minimum jerk speed profile here differs from the ones in [8] and [57]. Specifically, there is an extra $1/T$ factor in [8] and [57] which does not appear in Eq. 2.1. I believe that this difference is due to typographical errors in [8] and [57], since the minimum jerk speed profile can be obtained by taking the derivative of the minimum jerk position profile given in [5], which will not have the extra $1/T$ factor. Also notice that this extra factor will not affect the calculated smoothness of movement values, since the measure itself is defined as a correlation coefficient that is invariant to linear transformations on either of its input variables.

respect to peak speed in the profiles were left out, for clarity and simplicity of the definition of the measure. The correlation coefficient takes values between 0 and 1, where 1 indicates perfect correlation with the optimally smooth speed profile and 0 indicates no correlation. During data processing, negative ρ values occasionally calculated for individual movements, which implied negative correlation, were set to zero. Similar to the TE measure, SM can be calculated for any point-to-point movement and is dimensionless since it is a coefficient designating the correlation of the actual speed curve demonstrated by the patients to the optimally smooth speed curve for a movement having the same duration and distance as the actual movement.

Average Number of Hits per Minute (HPM)

An average of the number of hits for a 60-second duration constituted the HPM measure. The HPM measure is more closely related to the task assigned to the patients and was the only robotic measure available to the patients instantly during the robotic rehabilitation since patients were told the number of hits they achieved at the end of a session. Due to its definition, HPM is similar to a mean speed measure and is the only non-normalized robotic measure. I have used a normalized mean tangential speed measure as well, as defined next.

Mean Tangential Speed (MTS)

Several studies in the literature have used mean speed as a robotic motor function improvement measure for stroke patients [9], [10], [11]. Similar to the definitions in these studies, I defined the mean tangential speed measure as the mean movement speed demonstrated for each point-to-point movement trial. Calculating the mean speed in the tangential speed domain gives credit to the patient for moving in any direction, even though the movement may not be towards the target. MTS measure is spatially normalized by dividing the obtained scores by target distance; hence it is reported in the units of [1/sec]. Similar to the HPM measure, the MTS measure demonstrates the overall speed of the patient in the task rather than the quality of the movement.

2.3.6 Robotic Measures in Relation to Activities of Daily Living

The TE and SM measures serve as objective assessments of movement quality. The TE measure evaluates the patients' performance of tracking straight line target trajectories, while the SM measure compares the speed profile of the patients' movements with the speed profiles observed in healthy people's movements. In addition to serving as a scoring method immediately available to the patient and the therapist during therapy, the HPM measure is an indication of how fast a patient is able to move the affected upper extremity, similar to MTS measure. In contrast to TE and SM, HPM and MTS are motor recovery measures in the speed domain based on the fact that stroke patients demonstrate compromised overall movement speed as compared to healthy individuals [58].

A low TE implies the ability of precisely following planned trajectories and adeptness in activities of daily living (ADL) that involve reaching and pointing. Similarly, a high SM implies smooth and non-jerky/non-intermittent movements and would indicate proficiency in ADL that involve carrying an object and handling delicate objects. Both TE and SM measures are closely related to the coordination of movement which is a fundamental component of a skilled, fine movement. A high HPM or MTS score indicates well controlled overall movement speed and would transfer to faster movements in ADL. It should be noted that for the results reported here, the ADL in the preceding discussion would be limited to those that involve mainly wrist movements due to the joystick hardware. However, the highlighted points remain valid for a broader set and range of movements since the measures can be calculated for any point-to-point movement, though validations under additional joint movements (shoulder, elbow, etc.) are not included.

In summary, all four measures can be said to demonstrate how stroke patients' movements deviate from healthy people's movements. Based on sampled data collected from the movements, they provide practical, fast, direct and objective evaluations of movement quality (TE and SM) and speed (HPM and MTS).

2.3.7 Statistical Analyses

I conducted differential significance analyses to determine whether the patients showed a significant motor function improvement with respect to the clinical measures. To be able to make an overall comparison of these results with those recorded in robotic measures, I completed similar analyses using robotic measures. Daily average values of SM, TE and HPM measures were regressed on the number of days to reveal motor function recovery trends of individual patients. The absolute number of days instead of the number of therapy days was preferred by taking the CIMT activities on the off-therapy days into consideration. Significance of the slopes, hence the trend in the motor improvement, was determined. Slope values were also recorded to be able to identify the patient that demonstrated the strongest trend.

Regression analyses were used to investigate the correlation between the clinical and the robotic measures, the main objective of the chapter. The pre-treatment and post-treatment FM, ARAT, JT and MAL scores of the patients were paired with the corresponding robotic measure results that were temporally the closest to the clinical

Table 2.2 : Therapy Results in Fugl-Meyer (FM), Action Research Arm Test (ARAT), Jebsen-Taylor Hand Function Test (JT) and Motor Activity Log (MAL) Measures. Abbreviations: P#, patient number; Pre, Pre-treatment; Post, Post-treatment; p, p value for the mean difference between pre- and post-treatment results

P#	FM		ARAT		JT		MAL	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
1	36	41	21	30	301.0	236.0	0.50	2.52
2	23	39	20	33	334.5	181.7	1.81	3.52
3	36	49	32	36	350.7	198.0	1.12	3.63
4	50	58	49	56	156.1	82.0	1.09	4.05
5	43	48	31	35	623.9	263.6	1.78	3.55
6	49	55	51	55	122.6	65.6	1.14	1.95
7	37	33	13	21	1080.0	1011.0	0.39	2.33
8	52	50	56	57	63.7	48.5	1.91	3.71
9	38	47	49	57	251.2	29.7	0.93	3.74
	$p = 0.0097$		$p = 0.0003$		$p = 0.0032$		$p < 0.0001$	

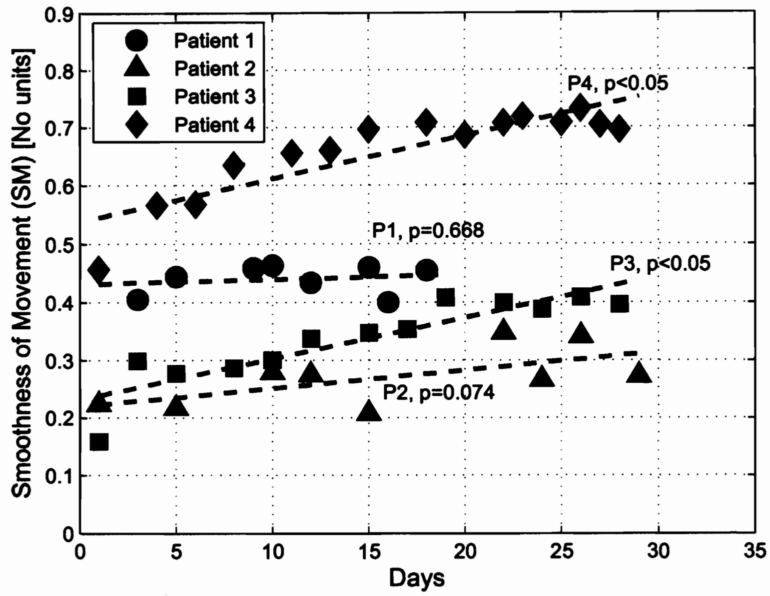
evaluations (the first day and the last day robotic therapy scores in the unassisted mode). Regression analyses were carried out using the paired data sets, and the set of parameters summarized were the correlation coefficient r (Pearson's r) and the p value that represents the significance of the slope of the linear fit line. A significant slope indicates that the correlation coefficient r is also significant; i.e., there is a significant correlation between the two variables. Regressing four clinical measures on four robotic measures resulted in a total of sixteen correlation results.

2.4 Results

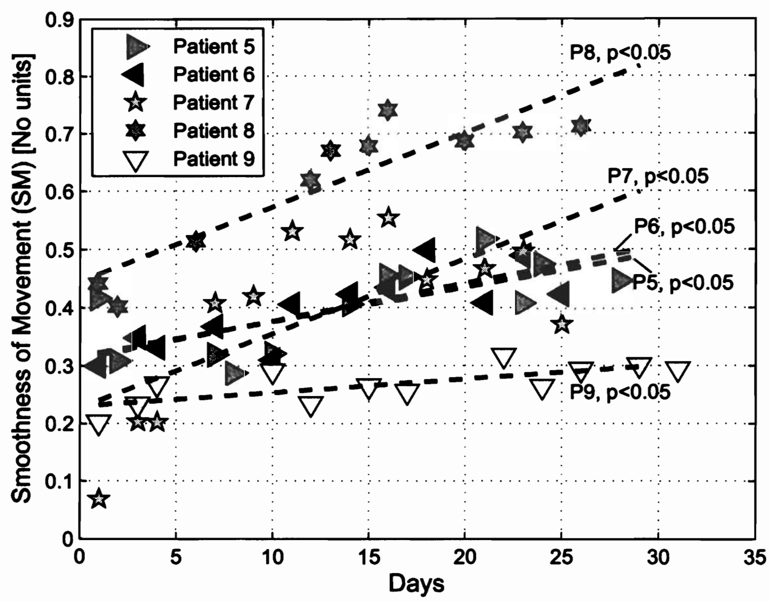
Clinical measure results for the patients are summarized in Table 2.2. The mean difference between post- and pre-treatment scores for all measures is found to be significant ($p < 0.05$) on a one-tailed paired-sample t-test. Based on the p values, it can be said that motor recovery gains were more pronounced in MAL and ARAT scores. Similarly, results of the therapy protocol in robotic measures are summarized in Table 2.3. Again, for all measures, the mean difference between pre- and post-treatment scores are significant. The SM measure indicated a stronger gain in motor function for the group compared to other measures. In the same table, slope values (β) for individual motor recovery trends based on regression of daily average scores on days are reported, and significant slopes are marked with an asterisk (*). The robotic measure results were similar and comparable for both groups of patients (1 through 4 and 5 through 9). The column labeled N lists the number of data points used for the corresponding regression. A general decreasing trend (negative slope) was observed for the TE values (decreasing error) while trends were positive for SM, HPM and MTS (increasing movement smoothness, hit rate and mean tangential speed), except for Patient 9. The strongest trends based on the slope values were observed for Patient 7 with respect to the TE measure, for Patients 7 and 8 with respect to the SM measure, for Patient 4 with respect to the HPM measure and for Patient 1 with respect to the MTS measure. The trends that the robotic measures smoothness of movement (SM), trajectory error (TE), average number of hits per minute (HPM) and mean tangential speed (MTS) followed for all nine patients are depicted in Figs. 2.2, 2.3, 2.4, 2.5

Table 2.3 : Pre- and post-treatment results in robotic measures TE, SM, HPM and MTS and the individual results of the regression analyses of daily average robotic scores vs. days. * denotes significant trends in regression ($p < 0.05$). Abbreviations: P#, patient number; N, number of data points used for regression; β, slope of the regression line; p, p value of the paired-sample one-tailed t-test for difference between pre- and post-treatment scores.

P#	N	TE			SM			HPM			MTS		
		Pre	Post	β	Pre	Post	β	Pre	Post	β	Pre	Post	β
1	8	11.6	10.8	0.034	0.406	0.455	0.001	84.8	111.1	1.177	2.58	3.53	0.057*
2	9	14.8	12.1	-0.056	0.224	0.273	0.003	32.8	45.8	0.627*	1.13	1.26	0.011
3	13	10.3	7.5	-0.099*	0.159	0.396	0.007*	35.7	77.8	1.349*	1.19	1.91	0.022
4	15	5.9	6.6	-0.016	0.457	0.695	0.007*	55.5	116.8	1.931*	1.06	2.50	0.046*
5	12	10.0	10.0	-0.084*	0.417	0.447	0.006*	51.9	75.7	1.532*	1.32	1.96	0.033*
6	12	5.4	6.0	-0.040	0.301	0.425	0.006*	57.1	71.7	0.835*	1.28	1.58	0.012*
7	12	17.6	9.4	-0.336*	0.068	0.371	0.013*	12.5	45.6	1.226*	0.75	1.13	0.011
8	10	9.6	4.7	-0.192*	0.442	0.714	0.013*	63.6	88.5	1.497*	1.78	1.60	0.005
9	12	10.4	5.3	-0.113*	0.202	0.295	0.002*	52.7	39.2	-0.275	1.33	0.76	-0.014*
		$p = 0.0173$			$p = 0.0013$			$p = 0.0033$			$p = 0.0034$		

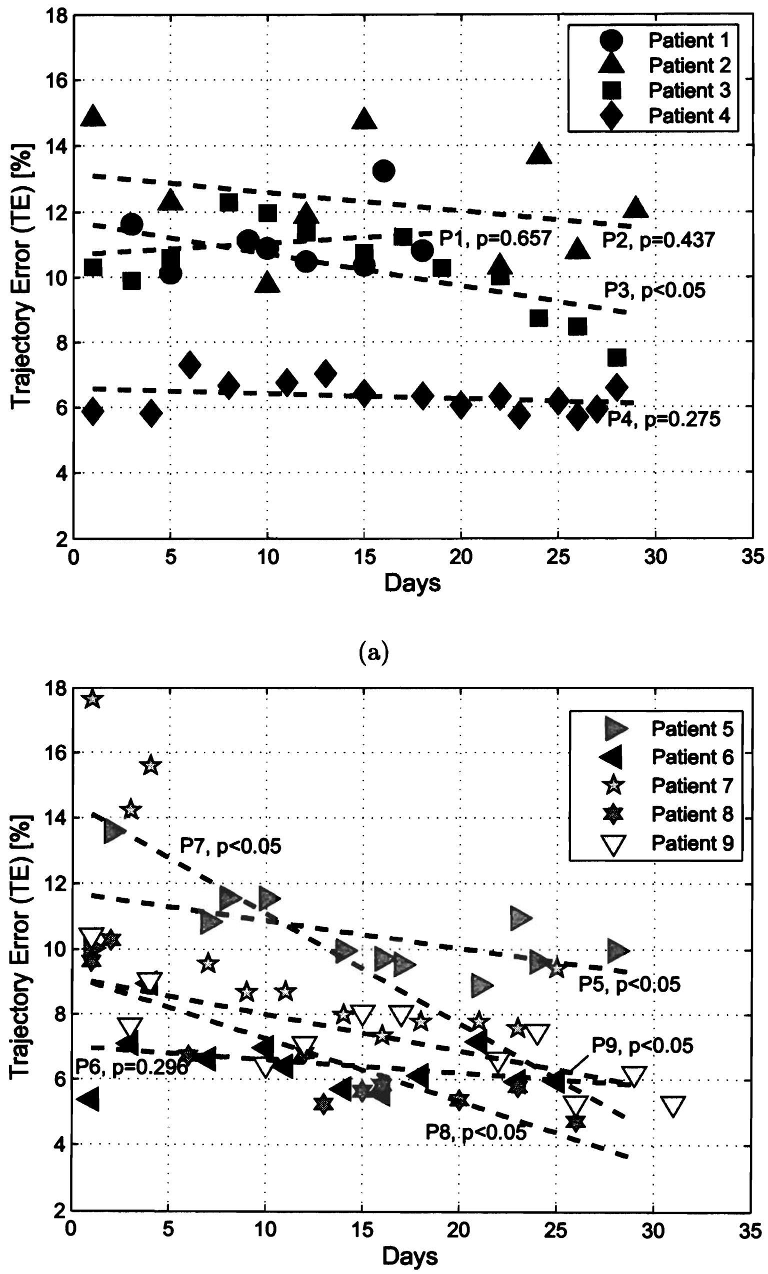


(a)



(b)

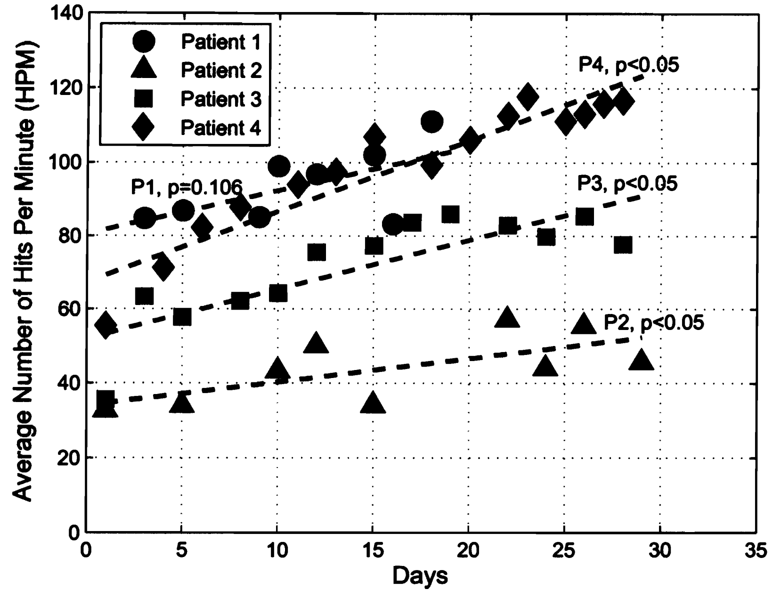
Figure 2.2 : Daily average smoothness of movement (SM) scores of Patients 1–4 (a) and Patients 5–9 (b).



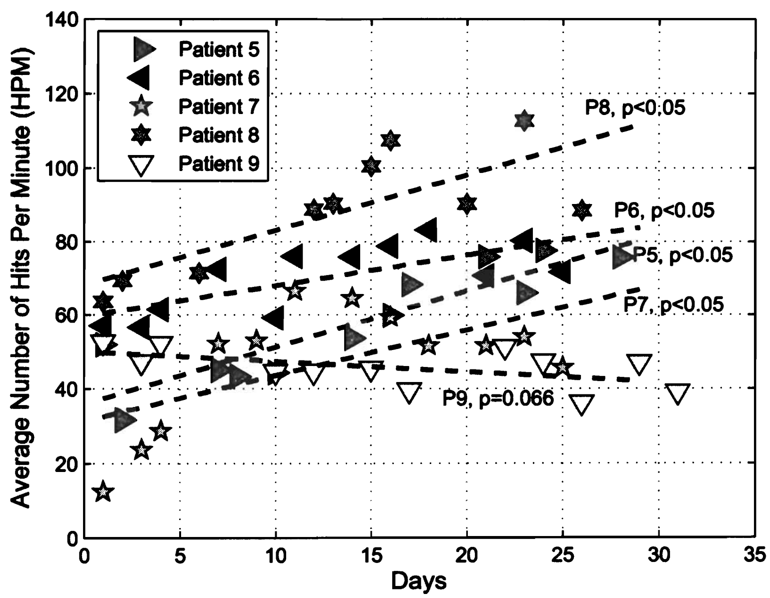
(a)

(b)

Figure 2.3 : Daily average trajectory error (TE) scores of Patients 1–4 (a) and Patients 5–9 (b).

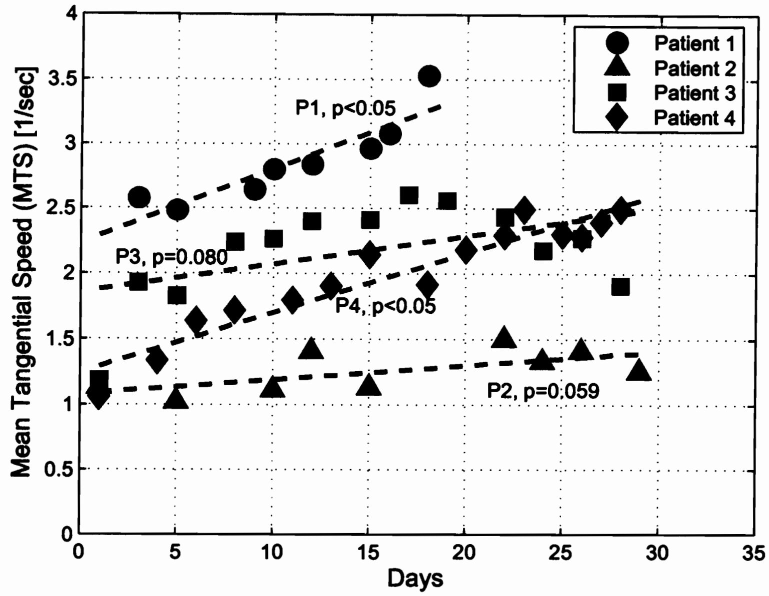


(a)

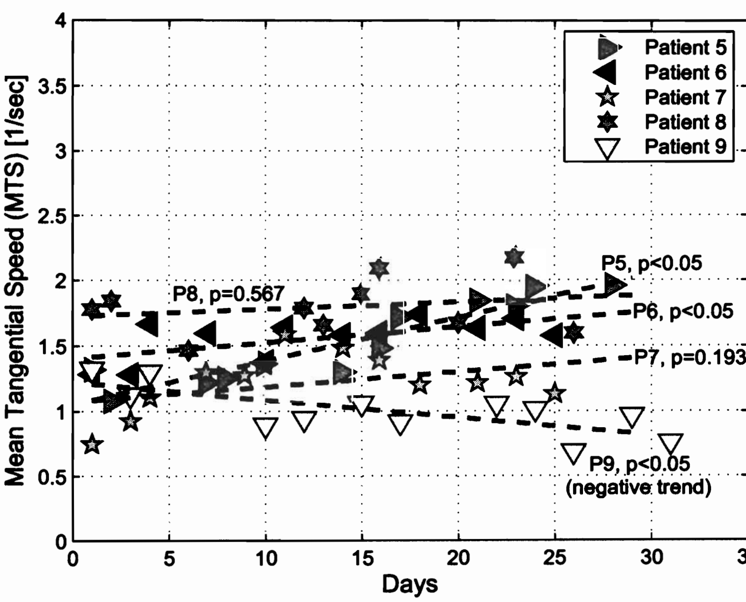


(b)

Figure 2.4 : Daily average number of hits per minute (HPM) scores of Patients 1–4 (a) and Patients 5–9 (b).



(a)



(b)

Figure 2.5 : Daily average number of mean tangential speed (MTS) scores of Patients 1–4 (a) and Patients 5–9 (b).

Correlation coefficients resulting from the correlation analyses of clinical measures with robotic measures are summarized in Table 2.4, with significant correlations marked with an asterisk (*). The TE and SM measures have significant correlation with all four clinical measures, while the HPM measure has significant correlations only with the FM and JT measures. The MTS measure fails to show significant correlation with any of the clinical measures. Regressions of FM-TE, FM-SM and ARAT-TE that have high and statistically significant r values are depicted in Fig. 2.6 together with the regression lines.

2.5 Discussion

Although there have been numerous studies on the design and testing of novel therapeutic robots, an effective method for objective assessment and comparison of such devices is yet to be determined. The potential prospects of robotic rehabilitation include home-based rehabilitation systems, remote supervision by therapists, and automated adaptive rehabilitation programs. For all of these opportunities to be embraced, a unified set of robotic motor recovery measures with known correlation to clinical measures is highly desirable.

This chapter of the thesis identifies key aspects for such unified robotic motor recovery measures by analyzing the motor function improvement scores of nine chronic stroke patients who underwent a hybrid therapy program, utilizing four clinical measures (FM, ARAT, JT and MAL) and four robotic measures (SM, TE, HPM and MTS). It is important to note that the efficiency or the success of the hybrid therapy protocol is not directly explored, and that the proposed measures do not constitute a finalized or complete set of unified measures. Rather, I use the clinical data to compute correlations between robotic and clinical measures and indicate important

Table 2.4 : Results of the correlation analyses of FM, ARAT, JT and MAL measures on TE, SM, HPM and MTS measures (see text for full versions of abbreviations). Correlation coefficient (Pearson's) r is listed. * denotes significant correlation ($p < 0.05$). The correlation plots for the highlighted pairs of measures are presented in Fig. 2.6. Note that improvement is represented by an increase in all measures except TE and JT.

	TE	SM	HPM	MTS
FM	-0.74*	0.64*	0.54*	0.22
ARAT	-0.83*	0.51*	0.37	0.00
JT	0.63*	-0.49*	-0.53*	-0.32
MAL	-0.49*	0.57*	0.46	0.21

properties that such measures should exhibit for strong correlation with clinical measures.

In the following sections, I review the implications due to use of a haptic joystick, summarize the overall outcome of the therapy program, and use the motor recovery gains as a means of identifying the relationships between clinical and robotic measures. I subsequently discuss the main results of this chapter, correlations of clinical and robotic measures and present the limitations. Finally, I highlight the contributions of the work.

2.5.1 Use of a Haptic Joystick for Robotic Rehabilitation

There are a number of examples of force-feedback joysticks being used for rehabilitation applications. The focus in a number of such studies has been to address the need for low-cost and home-based rehabilitation systems. For example, Reinkensmeyer et al. [59] introduced the Java Therapy system that utilized a commercially available low-cost force-feedback joystick and web-based therapy games that provided feedback to the patient on his/her progression. Ellsworth and Winters [12] also used a com-

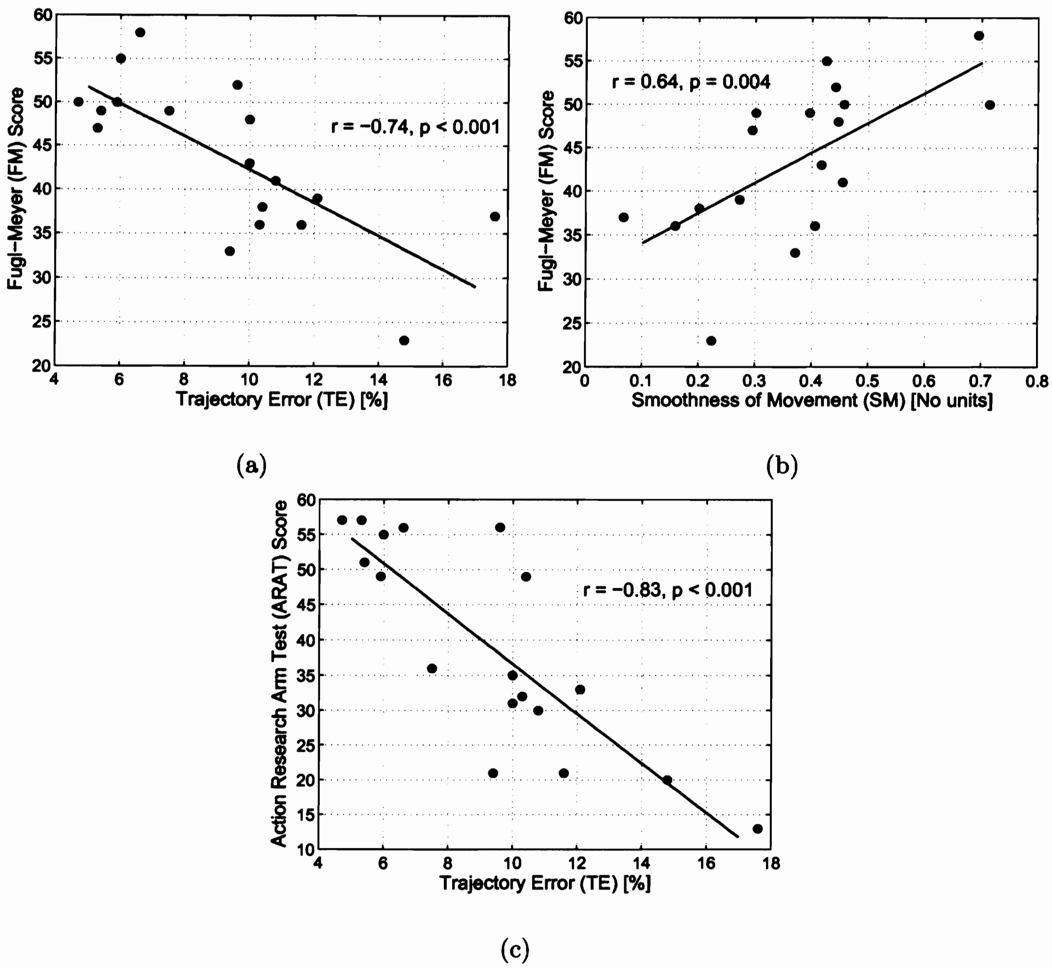


Figure 2.6 : Regression plots for clinical measures Fugl-Meyer (FM), Action Research Arm Test (ARAT) and robotic measures trajectory error (TE), smoothness of movement (SM). Correlation coefficients between two types of measures and the p value of the correlation coefficients are given. Each patient is represented by two points (pre- and post-treatment scores). (a) A strong and significant correlation exists between FM and TE measures. (b) There is a moderate and significant correlation between FM and SM measures. (c) There is a very strong and significant correlation between ARAT and TE measures.

mercial joystick after revising it to improve range of motion and have force-feedback capabilities. A second phase of the study was conducted to create three-DOF movement capabilities [60]. Differing from the previous studies, I selected a commercial haptic joystick for rehabilitation because of its ability to precisely capture position data that are later used to calculate robotic motor improvement measures.

Use of the haptic joystick as the only hardware may cause one to question the extension of results to other devices. The definitions of the normalized robotic measures reported here are formulated in such a way as to be potentially applicable to various hardware and protocols, as long as point-to-point movements are involved. Here I do not explicitly provide proof or validation of the measures under use with different devices, but rather view this as a point for future work. That being said, I do believe that normalization is a crucial feature of any robotic measure.

Another implication of using the joystick for therapy and evaluation is the limitation of the movements mainly to wrist joints. Although it is possible to use the robotic measures defined here for movements involving any number of joints, they were calculated mainly based on wrist movements. Conversely, the clinical measures were not necessarily restricted to certain joints. Rather they involved activities pertaining to most of the joints of the upper extremity. Nevertheless, the results clearly indicate that significant moderate to strong correlations exist between the TE and SM measures and the clinical measures. This result implies that application of the TE and SM measures to tasks that involve the full upper extremity or that more closely resemble the tasks administered in clinical evaluation protocols may lead to even stronger correlations.

2.5.2 Agreement Between Clinical and Robotic Measures

As reported in Table 2.2, patients exhibited a significant motor function improvement, regardless of the clinical measures used for assessment. This finding is in agreement with the significant improvements indicated by all robotic measures, as summarized in Table 2.3. It should be noted that there are several individual insignificant slopes for the regression of the robotic measures on days; however, t-tests for the complete group of patients indicate significant overall improvements for all measures.

Clinical and robotic measure results are found to be mostly in agreement. However, the degree of improvement of any particular participant differs based on the scale used. As a result, significant changes observed in one measure do not always appear as pronounced in other measures. This result is in agreement with the results obtained by Colombo et al. [11]. Colombo et al. reported the difficulty in defining a single measure that would be valid and accurate for all levels of impairment, and said that some robotic measures will always have to be used as complementary to existing objective clinical measures. It should be noted that the majority of the patients included in the therapy protocol were only mildly impaired, and this constitutes a limitation on the generalizability of my results to patients with a broader range of impairment levels. The measures SM and TE both required successful completion of reaching movements, which already requires existence of a certain level of motor function. In this respect, the MTS measure can be used for more compromised cases, although its correlation with clinical measures is poor. Identification of robotic measures that allow objective evaluation of motor function in moderate to high level of impairment is a topic not addressed here and constitutes a potential future direction for work. One possibility is to forego the advantage of real-time evaluation during therapy and instead use special evaluation sessions with robotic devices, examples of which are given in [13, 27], a choice which may be more suitable to severely impaired patients.

2.5.3 Correlation of Clinical and Robotic Measures

In Table 2.4, measures quantifying movement quality, TE and SM, demonstrate significant and moderate to strong correlations with all clinical measures. In contrast, correlations of movement speed based measures, HPM and MTS, with clinical measures mostly fail to show significance, and correlations range from none at all (MTS-ARAT) to moderate (HPM-FM). Therefore, I conclude that one key feature for a robotic measure to have strong correlation with clinical measures is focus on movement quality rather than on speed. It is reported in the literature that the ARAT and FM scales are usually well correlated with each other [53]. My findings are in agreement with the literature; robotic measures that are strongly correlated with the FM measure are also strongly correlated with the ARAT measure.

An important result is the strong correlation between the TE and FM measures ($r = 0.74$) and between the TE and ARAT measures ($r = -0.83$). TE is therefore a stronger candidate as a unified robotic measure of motor impairment than SM is. I consider this to be an interesting result since in my prior analyses the TE measure was defined in a non-normalized fashion. This finding indicates the importance of normalization as a key aspect in defining robotic motor recovery measures. In addition to leading to stronger correlations with clinical measures, normalized robotic measures have the distinct advantage of being applicable to different rehabilitation protocols and devices. This feature is important for objective and effective comparison of outcomes of different therapeutic robots and protocols.

The strongest correlations were observed between the SM and TE robotic measures and the ARAT and FM clinical measures, which are measures of motor impairment. I conclude that the SM and TE measures therefore can capture the degree of motor impairment; though not functional use. I found only weak to moderate correlations between the robotic measures and clinical functional use measures (JT and MAL). Therefore, I conclude that robotic measures based on reaching movement data are not likely to exhibit strong correlation with clinical measures of functional use, and that in order to identify such correlations, one may need to define robotic measures that replicate or approximate administering conditions and methods of functional use measures.

The poor correlation of the MTS measure with the selected set of clinical measures is an important result demonstrating that the definition of robotic measures that will significantly and strongly correlate with clinical measures is not a trivial task. Significant and moderate correlations of mean speed measures with clinical measures were reported in the literature [10], which are comparable to the correlations observed using the HPM measure. However, the normalized MTS measure showed no correlation to weak correlation with the clinical measures, leading me to conclude that mean speed measures are inferior candidates for broadly applicable robotic measures compared to movement quality measures, especially in the context of high correlation with clinical measures. Although mean speed measures are relevant to feedback given to patients in shaping exercises, the fact that movement speed is in general not explicitly part of clinical measures leads to only weak correlations. Nevertheless, robotic devices enable recording of variables that are not explored by the clinical measures.

The significant correlations observed with the SM, TE and HPM measures are in agreement with the results obtained by Colombo et al. [10]. I have observed much higher correlation coefficient values, between $0.49 - 0.83$, with the TE and SM measures defined here, compared to $0.53-0.55$ reported in [10], $0.37-0.58$ reported in [11], and $0.37-0.53$ reported in [9]. I was not able to match the correlation coefficient of $r = 0.85$ reported by Krebs et al. [13], but it should be noted that they applied a specific robotic evaluation protocol that involved non-normalized force measurements. In contrast, the TE and SM measures are normalized kinematic measures (requiring only position data recording) and are applicable to any reaching movement. This approach can be implemented in most existing robotic rehabilitation devices in a straightforward manner. Similar arguments hold for results of Bosecker et al. [47], where they used linear regression models with up to 19 robotic measures, including force and kinematic measurements requiring both reaching and circle drawing tasks. Taking only the movement smoothness measure (best performing measure in their set) into account, they reported r values of 0.62 for Fugl-Meyer and 0.56 for MSS with a training data set.

Based on the moderate to strong correlations reported in Table 2.4 and Fig. 2.6, I believe that it is feasible to identify a set of broadly applicable robotic measures using correlations between robotic and clinical measures. Obviously, high scatter in the data in Fig. 2.6 would indicate diminished correlation coefficients and feasibility. One source of scatter in the data set is pre-treatment scores of Patient 2 (FM score = 23), who is the only more than mildly impaired patient in the group. An additional unavoidable source for scatter is the range of types and locations of stroke for the participant group (see Table 2.1).

2.5.4 Implications and Application Potential of Correlations

Strong correlations suggest that the robotic measures I explored may be used to provide immediate and useful feedback on and continuous monitoring of motor improvement, and to establish a better framework to compare the outcomes of different robotic rehabilitation programs. Strong correlations ensure that if robotic measures are to be provided as feedback to patients during therapy, they must be well grounded in widely accepted clinical assessment techniques. For example, in this chapter, I show that speed-based measures do not correlate strongly with clinical motor impairment measures. Therefore, a participant could be moving very quickly but not improving in their quality of movement, and feedback about their movement speed, intended to be motivational regarding their rate of progress, may not translate to gains in terms of clinical measures such as FM and ARAT over the course of therapy.

I have used an actuated rehabilitation device in the protocol, but have analyzed robotic measures in an unassisted mode. Hence my results are also relevant and important from the perspective of unactuated rehabilitation devices. Because these devices have sensors but no actuators, they cannot provide actively intervening assistive or resistive forces. Despite the absence of actuation, movements of the patients can still be precisely sampled and recorded. An example of these devices was reported by Sanchez et al. [45]. Another possibility is the use of motion capture systems to record marker trajectories during reaching movements to evaluate the extent of motor impairment, as demonstrated by Chang et al. [9]. Since both approaches allow recording of movement data, they can serve as tools for calculating TE and SM robotic measures, which I have shown to be strongly correlated to FM and ARAT scores. Unactuated rehabilitation devices or affordable motion capture systems can provide an inexpensive and practical way of conducting clinically correlated assessments. Actuated backdrivable therapeutic robots can readily be used to take advantage of these findings by simply recording data in an unassisted mode.

I believe that the results discussed here contribute to the efforts of defining robotic motor recovery measures that are well correlated with clinical measures. I have identified two key features for such robotic measures: normalization and focus on movement quality.

I consider the results of my research reported in this chapter to be evidence for the feasibility of the challenging task of identifying reliable robotic measures that may also be used to predict clinical measures such as FM, ARAT or JT. However, larger data sets would be required to accomplish this goal, and obtained regression relations would be required to be validated on additional data sets to ensure reliable estimation capability. Additional data and clinical trials are needed to generate more robust and accurate correlation charts between clinical and robotic measures, which will constitute a focus for future studies. Also of interest for future work is to test how the validity and strength of correlations are affected by external assistive and resistive forces that are usually present in robotic rehabilitation protocols.

Smoothness of movement (SM) and trajectory error (TE) measures defined here are available for use with a wide range of robotic rehabilitation devices and protocols and can be calculated for any point-to-point reaching or pointing movement. I have shown that SM and TE are strong candidates for a unified set of robotic measures that will enable objective evaluation and comparison of robotic rehabilitation programs and devices, while maintaining clinical relevance due to their correlation with widely accepted clinical measures.

Because the movements of motor-impaired patients are most commonly characterized to be slow, defining additional or better robotic measures to include into this unified set requires a better understanding of neurophysiological processes underlying planning and execution of slow movements. The search for origins of intermittency or non-smoothness in slow movements in healthy persons constitutes the main theme of the remaining chapters of this thesis. In Chapter 3, via a human subject experiment involving completion of manual circular tracking tasks and quantification of movement intermittency along the joints of the arm, I evaluate two proposed mechanisms responsible for movement variability in slow movements.

Chapter 3

Intermittency and Variability of Multi-Joint Slow Arm Movements

This chapter presents a systematic characterization of movement intermittency along the arm in natural (unperturbed) multi-joint movements with various speed conditions, through a human subject experiment with five subjects. Results of this experiment indicate that movement intermittency increases significantly in distal direction along the arm and with decreasing movement speed. This result suggests that a neuromuscular noise option is favored against a submovement-based central planning alternative, as the source of variability in slow movements.

Portions of this chapter were published in the Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2009) [32] and in extended abstract form in Understanding the Human Hand for Advancing Robotic Manipulation Workshop, Robotics Science and Systems Conference (RSS 2009) [33]. I gratefully acknowledge my collaborators in both publications.

3.1 Introduction

The human motor control system is able to generate movements with great agility, dexterity, precision and compliance. Furthermore, the motor control system is immensely flexible, allowing humans to adapt to novel environments to regain normal movement patterns [61]. This adaptability also enables humans to become adept at motor skills through training and learning. Because of these attractive properties, the human motor control system has significantly influenced research and design of robotic motor control systems, particularly in the domain of humanoids. Still, there are many aspects of motor control in humans that are not completely understood or even appreciated [62]. I closely examine one such aspect in this chapter, the intermittent or non-smooth nature of movements that become especially evident during considerably slower than normal movements.

3.2 Literature Review

It is well-known that the speed profile of a movement trajectory includes distinct peaks. These peaks are frequently interpreted as an indication for the underlying blended submovements that form up the total movement [63, 26]. These peaks become more pronounced as the average speed of the movement decreases, thereby resulting in decreased movement smoothness. Due to the emergence of almost distinct peaks, the movement appears to be intermittent. Throughout the chapter, I use the term "intermittency" as an equivalent to "non-smoothness," since intermittency is assumed to be quantifiable for all speed profiles, including those where the peaks are not entirely isolated or distinct.

In their study on the origins of movement intermittency, Doeringer and Hogan [23] propose two possibilities as the source of intermittency. Their first suggested source is a central movement planner that utilizes submovements to generate plans for complex movements consisting of building-block type simpler movements. Their second suggested source is noise being interjected on top of a continuous (or intermittent) plan along the neuromuscular circuitry. Doeringer and Hogan do not arrive at a final conclusion about the source of intermittency. They do however state that interpreting peaks in tangential speed profiles as incomplete blending of submovements would lead to a conclusion favoring the central planner option for being responsible for intermittency. Same conclusion was also reached by Dipietro et al. [64].

I show that movement intermittency increases in the distal direction along the human arm. I believe that this trend is an indication that intermittency is due to neuromuscular noise and not due to an originally intermittent movement plan used by the central nervous system. In the experiment, five participants completed manual circular tracking tasks in both vertical and horizontal planes, as the shoulder, elbow, wrist and fingertip trajectories were captured by a Vicon motion capture system that is capable of accurately tracking and reconstructing 3D positions of markers. This motion capture system offers a number of key features. First, one can record completely natural human movements with minimal interference to the participant. Other approaches (e.g. splints or arm rests attached to the arm and equipped with sensors) can add inertial or friction disturbances to the participants' arm movements. Second, it is possible to record multiple joints or points on the limb simultaneously. This feature enables me to compare movement intermittency at various locations on the limb. Sternad and Schaal recognized the importance of acquiring movement data simultaneously from multiple points on the limb. They implemented this technique in their work on segmentation of end point trajectories [65]. They showed that such segmentation was not necessarily due to a segmented control plan, but may be explained by a continuous sinusoidal control of the joints which transform into rhythmic endpoint trajectories that appear to be segmented due to the nonlinear forward kinematics of the system.

Using rhythmic movements only, Nagasaki [66] showed that speed profile of the movements transformed from being asymmetrical to symmetrical as the frequency of the movement increased. Especially over 4.3 Hz, speed profiles became highly symmetrical. He listed changing muscular dynamics (stiffer muscles at higher speeds), as reported by Wann et al. [67], as a potential reason for observed transition to symmetric profiles. It should be noted that, contrary to these two studies considering the effect of muscular dynamics on end point movements, Doeringer and Hogan [23] specifically excluded biomechanics as a source of intermittency in their consideration based on their working definition of intermittency.

To explore the source of intermittency, participants were asked to make circular arm movements at five different speed conditions. Movement intermittency of markers placed along the arm was calculated based on the tangential speed profile of the marker, and movement intermittency was quantified as the number of peaks observed in the speed profile. Results show that intermittency at the fingertip is greater than intermittency at the wrist and the elbow, and intermittency at the wrist is greater than that at the elbow. This trend indicates that noise is a likely source of intermittency, since the intermittency would be amplified due to additional noise being interjected through the limb in the distal direction. In contrast, intermittency in the original movement plan would be expected to produce similar intermittency levels for all joints along the limb.

The chapter is structured as follows: Section 4.3 details the experimental protocol and participants, motion capture system and data preprocessing procedure, intermittency metric calculation and statistical analysis methods. Section 4.4 presents the effects of speed and orientation conditions on intermittency as well as the change observed in intermittency with respect to position of the markers on the arm. Subsequently, results are discussed in comparison to the related findings in the literature and implications for various related research tracks are summarized.

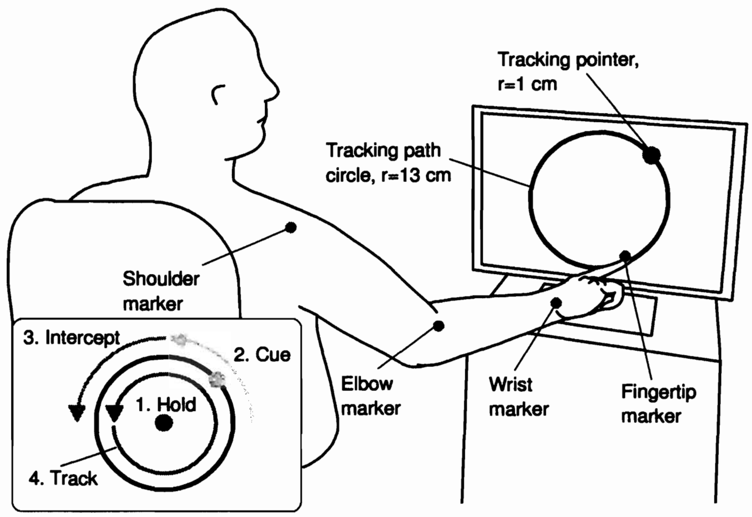


Figure 3.1 : An illustration of a participant in the experimental setting with attached motion capture markers. Inset at bottom left: The trajectory that the tracking pointer follows as a trial progresses through the four phases: (1) pointer at the center during the hold phase, (2-4) pointer changing colors and moving on the tracking path with constant speed during the cue, intercept and track phases.

3.3 Methods

3.3.1 Participants

A total of five participants completed the experiment in the Computer Graphics and Interactive Media Lab of University of Houston. All participants provided informed consent which was approved by the Institutional Review Boards of Rice University and University of Houston. Participant ages were 25–28, one was female, one was left-handed and all completed the experiment with their dominant arm and hand. All participants had normal or corrected-to-normal vision and none had any movement disorders affecting the dominant hand. Three participants completed the horizontal orientation session first (explained in the following section).

3.3.2 Experiment Protocol

Participants were asked to wear a jacket on which motion capture markers were attached on the bony parts of the limb on the shoulder, elbow and wrist joints and a fourth one on the nail of the index finger. A lightweight rod with two markers on its ends was attached on the back side of the hand to capture wrist rotations (pronation/supination), though data from the latter two markers were not used in data analyses. Participants were seated at an LCD computer screen which was in reach of the index finger. An illustration of a participant with attached motion capture markers is given in Fig. 3.1. Participants were informed that once the position of their chair and the position of the screen were adjusted, they should not be moved. Participants were also told to keep their shoulder as fixed as possible throughout the experiment. Shoulder movements that could have still occurred was not a concern for the reported results, for either of the coupled and decoupled data sets (see Section 3.3.4).

The experiment consisted of two sessions of 25 trials each. During one of the sessions the computer screen was in a normal (upright) position (*vertical* tracking plane/orientation). During the other session, it was lying on the table facing up such that participants looked down at the screen from a standing posture (*horizontal* tracking plane/orientation). The order of presentation of these cases to each participant was determined randomly, and all participants experienced each orientation of the screen.

Regardless of the screen's orientation, during the trials, participants were asked to track the pointer that was moving on a white circular path (always visible) on a black background with the tip of the index finger (see Fig. 3.1) as accurately and as smoothly as possible, in order to minimize intermittency. Participants were asked to track the pointer without touching the screen, positioning the tip of their index finger within around 1 cm of the surface. The speed of the pointer to be tracked changed randomly among trials, but it was constant within a single trial. Tracking speed displayed by the pointer formed the second within-subjects factor in the experiment, and I tested five levels: 2.5 cm/s, 3.75 cm/s, 5 cm/s, 12.5 cm/s and 25 cm/s (given as the tangential speed on the perimeter of the 26 cm-diameter tracking circle/path).

Each trial consisted of four phases as schematically shown in the inset on the bottom left on Fig. 3.1. In the *hold* phase, a green pointer with approximately 2 cm diameter (all pointers had the same diameter) at the center of the screen was displayed. Participants were asked to point to the center of the green dot as soon as they saw it and wait there until the next phase. The time period for this phase was 3 seconds. In the *cue* phase, a yellow pointer appeared at the 3 o'clock location on the white circular track. This pointer moved from 3 o'clock to 12 o'clock (counterclockwise-ccw) with a certain constant speed, to give the participant a feeling of the speed that they would need to track by pointing at it with their index fingertip. During this phase, participants were asked to keep their position at the center of the green pointer, and just observe the movement of the yellow pointer. In the *intercept* phase, the yellow pointer changed its color to orange as it passed through 12 o'clock. It maintained its constant speed and moved towards 9 o'clock (again ccw). During this quarter circle movement, participants were required to catch the pointer by pointing with their index finger and to start tracking it. In the *track* phase, as the pointer passed through the 9 o'clock position, its color became red, but its speed remained the same. Participants were asked to track the pointer until it made a full circle in the ccw direction. Data from the tracking phase of each trial were analyzed. The duration of last three phases varied according to the tracking speed for that particular trial. After completing the four phases, the screen went blank for a very short period, and then the next trial began with the hold phase. The visual interface design was adapted from Pasalar et al. [28] where they analyzed the changes in the submovement properties for varying tracking speeds and force fields with a planar manipulandum.

After completing one session with 25 trials, participants were asked to rest for at least 10 minutes before going on to their second session (the other orientation condition). Participants were asked to inform the experimenters as soon as they felt their arm was fatigued, and the experiment was paused between trials until the participant felt comfortable to continue, to exclude potential confounding effects of fatigue on intermittency. There were typically three to four such breaks within one session. After completing the experiment, participants completed a short questionnaire. A total of 250 trials were recorded corresponding to 5 participants $\times$ 5 speed levels $\times$ 5 trials for each speed level $\times$ 2 orientation levels.

3.3.3 Motion Capture and Data Preprocessing

Motion data were acquired with a Vicon motion capture system with ten high resolution MX 40 cameras used for marker motion recording (see Fig. 3.2), two MX Giganet controlling hardware modules for handling the communication, synchronization and control of data flow between cameras and the PC terminal, and Vicon NEXUS 1.3 data processing software for controlling the MX Giganets, enabling real-time capture feedback and data post-processing such as data cleaning and data labeling. The markers used for the experiment were of 5 mm diameter. All three Cartesian coordinates of shoulder, elbow, wrist and fingertip markers were recorded in mm at a sampling rate of 50 Hz.

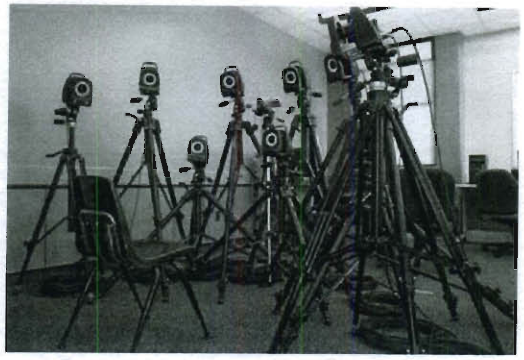


Figure 3.2 : Vicon motion capture system used in the experiments to capture the trajectories of the markers depicted in Fig. 3.1.

Captured data for each trial were first visually checked and manually cleaned in the NEXUS software. Then raw data were converted into ascii format text files with marker coordinates in mm. These files were imported into MATLAB and the extraneous portions of data at the beginning and the end of each trial that did not belong to any phase of the trials were removed. A gap-filling method using cubic splines was applied for the cases where a small portion of data for one or more markers were missing within a trial, primarily due to occlusions. Only 16 trials out of 250 required such interpolation of data and 15 of these trials ended up being included in the data analysis. Among these 15 files, the average ratio of interpolated data points to total data points was 2.6% (2 of them were about 17%, the other 13 were less than 7%). The trials were further truncated to extract only the circular tracking phase of each trial. A total of 12 trials out of 250 were determined to be incomplete due to either the recording or the participant ending the trial before the full circle was completed, and these trials were removed from the data set for analysis. Incomplete trials were not specific to a participant, speed level or orientation.

3.3.4 Coupled/Decoupled Data Sets and Intermittency Metric

I generated two versions of the data set consisting of 238 trials: an original set with no further processing and a decoupled set where the positions of each of the four markers were replaced by the difference in position of two consecutive markers, proximal position subtracted from the distal position. The purpose of the decoupling was to be able to assess intermittency of individual isolated joint movements. Without decoupling, increase of intermittency in distal direction would be a trivial result, since noise or intermittency in the proximal joint movements would cumulatively add to the intermittency in the distal joint movements. After decoupling, I was able to disregard the kinematic accumulation of noise and instead observe any accumulation of noise in transmission of the movement plan or neuromuscular actuation signals. Note that for the original data set, the nomenclature shoulder, elbow, wrist and fingertip actually correspond to the cartesian coordinates of the respective markers, whereas for the decoupled data set, fingertip data now reports (fingertip–wrist), which can be regarded as the movement of the fingertip with respect to the wrist and not to the fixed coordinate system. This effectively becomes information about wrist joint movement as opposed to a tracked single point in the task space. Although after the transformation fingertip data now contains wrist joint information, the same designation of "fingertip" will be used for this data component.

Both the original and the decoupled data sets were filtered with a zero phase-shift second order low-pass Butterworth filter with a cut-off frequency of 5 Hz. Velocity in each axis was calculated using a backward difference Euler algorithm. The Euclidean norm of three components of the velocity vector for each marker was used to obtain the tangential speed profile. As a measure of intermittency, I used the number of peaks in the tangential speed profile. This metric is one of the five smoothness metrics used by Rohrer et al. [7] to quantify and analyze submovement blending observed in stroke patients' movements during the motor function recovery period. Kahn et al. [68] also used the number of peaks metric in a stroke rehabilitation related study. I use a definition for the intermittency metric that is similar to one used by Kahn et al. Specifically, among the local minima and maxima within the tangential speed profile, I use a criterion of having an increase of at least 10% of the global maximum in the profile between a local minimum and the following local maximum to be included into the count of peaks in the profile. The global maximum value was restricted to less than three times the mean speed within the trial. The metric takes integer values since it is a count of peaks, and a higher value corresponds to higher intermittency.

3.3.5 Statistical Analysis

To justify applicability of parametric statistical tests, I first conducted a nonparametric Kolmogorov-Smirnov test and compared each data subset for a specific joint and speed level with a normal distribution of equivalent mean and variance. Among thirty such data sets (five speed levels, three joints and coupled/decoupled data sets), each of which included a minimum of 45 data points, only four data sets had a distribution significantly different from a normal distribution at alpha level of 0.05. Three of these data sets belonged to the fastest speed condition, for which the resolution of the intermittency metric was low due to only a few number of peaks observed in the speed profiles. Nevertheless, I conclude that it is appropriate to use parametric tests for the results, a majority of which failed to show significant differences when compared to an equivalent normal distribution.

Relating to the main question of this chapter, to compare the movement intermittency of elbow to wrist, elbow to fingertip and fingertip to wrist, I used a standard two-tailed paired-sample t-test, where all 238 trials were utilized after pairing the values of intermittency for the two markers of interest within the same trial. I conducted the test on both the original and the decoupled data set.

As for the effects of speed and orientation conditions, the experiment has two within-subjects factors and no between-subjects factors. To increase the robustness of the data and conduct a balanced analysis despite the excluded incomplete trials, I first averaged the intermittency values corresponding to one participant, one speed condition and one orientation condition. This averaging process was checked and verified to include at least four trials and ideally five trials for each case. Then I conducted a multivariate analysis of variance (MANOVA) for determining the main and interaction effects of orientation and speed factors on movement intermittency, as well as for pairwise comparisons of the individual speed levels.

3.4 Results

In section 3.4.1, I show that intermittency in arm movements during a circular manual tracking task significantly increases as the movement propagates along muscles and joints in the distal direction, regardless of the data set being used (coupled or decoupled). In section 3.4.2, I show that the main effect of movement speed on intermittency is statistically significant, while the orientation of the tracking plane does not have a significant main effect on intermittency. The data fails to show significance for interaction effect of speed and orientation, meaning that doing the tracking task in different planes would not significantly effect the intermittency characteristic for varying speed levels differently. I report that the endpoint speed levels used in this experiment induced significantly different intermittency values observed at the endpoint by comparing the mean differences between individual speed levels. This

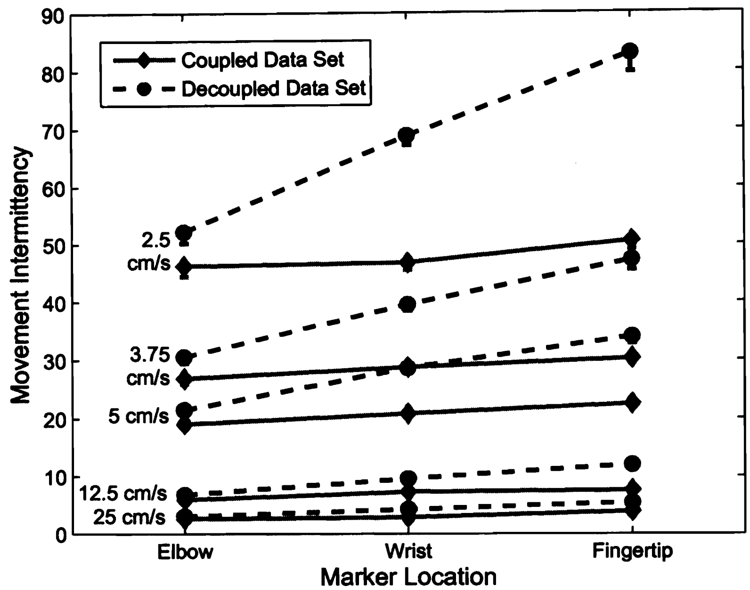


Figure 3.3 : The mean and standard errors of movement intermittency at the corresponding markers for varying speed levels are plotted to illustrate the increasing intermittency trend in distal direction. The trend is more pronounced in the decoupled data set. Based on the results of the paired sample t-test, for all pairs of markers within the same data set, the distal marker intermittency is significantly higher than that of the proximal one ($p < 0.05$). Movement intermittency is quantified as number of peaks in tangential speed profile.

implies that movement intermittency is ever present within a wide range of speeds and varies monotonically yet nonlinearly with increasing or decreasing speed values.

3.4.1 Intermittency Increases in Distal Direction

Results of the paired-sample t-test are given in Fig. 3.3. In this figure, the mean and standard errors of movement intermittency for all trials corresponding to one of the markers (elbow, wrist or fingertip) for varying speed levels are plotted. With respect to the coupled (original) data set results, a significant difference between means exists for elbow vs. wrist $[t(237) = -5.03, p < 0.001]$ and elbow vs. fingertip [$t(237) = -10.04, p < 0.001$], in both cases intermittency for elbow movements is significantly less than intermittency at the wrist and fingertip. Data further indicate significant differences between intermittency at the wrist and fingertip as well [$t(237) = -7.46, p < 0.001$], intermittency at wrist being less than intermittency at fingertip. Similar significant results for the intermittency of elbow vs. wrist [$t(237) = -13.30, p < 0.001$], elbow vs. fingertip [$t(237) = -14.30, p < 0.001$] and wrist vs. fingertip [$t(237) = -9.24, p < 0.001$] are obtained using the decoupled data set, again former point being more intermittent in each pair. In summary, all six pairwise comparisons of movement intermittency at different points on the arm resulted with significantly higher intermittency for the more distal point.

3.4.2 Speed and Orientation Effects on Intermittency

Results of the MANOVA analysis for the fingertip (endpoint) marker using the decoupled data is summarized in Fig. 3.4. As expected, movement intermittency decreases for higher speed levels, and the main effect of speed on intermittency is found to be statistically significant [$F(4, 1) = 2037, p < 0.05$]. Data for the main effect of tracking plane orientation on intermittency failed to show significance [$F(1, 4) = 0.64, p = 0.47$], which is apparent in the very close lines for the different orientation conditions in Fig. 3.4. Data for the interaction effect of speed by orientation on the movement intermittency also failed to show significance [$F(4, 1) = 0.38, p = 0.82$], as depicted by the mostly parallel lines in Fig. 3.4. Results obtained using the coupled data set that are not reported here were mostly similar. Only difference was that the main effect of orientation on intermittency was found out to be significant [$F(1, 4) = 13.71, p < 0.05$] for the coupled data set. These results imply that intermittency characteristics of movements highly depend on the average movement speed but are considerably less sensitive to the orientation of the actual movement plane in the task space.

A pairwise comparison of five speed levels using the decoupled data set with the end point marker showed that the intermittency at fingertip marker was significantly different at the five speed conditions ($p < 0.05$). I obtained similar results for the wrist and elbow markers using either of the data sets. Therefore the speed levels used in the experiment are spaced apart enough to induce significantly different movement intermittency. It can be observed in Fig. 3.4 that although there is a monotonically decreasing trend in movement intermittency for increasing movement speeds, the differential change in intermittency between consecutive speed levels is much higher at the slow end of the speed scale. This is in agreement with the qualitative results and observations reported in the literature [23, 63].

3.5 Discussion

The fact that significant increases in movement intermittency are observed for the speed profiles of points located along the distal direction on the arm supports a neuromuscular noise alternative against a discrete central movement planner hypothesis as an explanation for the movement intermittency observed especially in slow human movements. Although there is strong evidence for the existence of submovements in the literature [63, 7, 28], I report here that submovements as generated by a central planner are not necessarily responsible for the intermittency of movements. My results are in agreement with those reported by Nagasaki [66] and Wann et al. [67], although I do not explicitly propose a change in muscular properties as the source of movement intermittency.

I show that orientation of the plane in which the endpoint movement lies is not

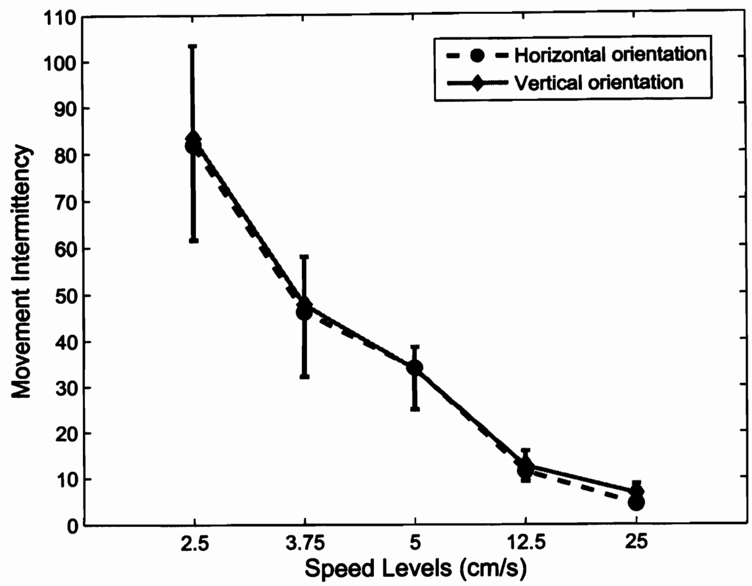


Figure 3.4 : Results of the MANOVA analysis for the fingertip (endpoint) marker using the decoupled data. Plotted are mean values with error bars representing standard deviation. Movement intermittency decreases for higher speed levels, and the main effect of speed on intermittency is found to be statistically significant [$F(4,1) = 2037, p < 0.05$]. The main effect of tracking plane orientation on intermittency failed to show significance [$F(1,4) = 0.64, p = 0.47$], which is apparent in the very close lines for the different orientation conditions. Data for the interaction effect of speed by orientation on the movement intermittency also failed to show significance [$F(4,1) = 0.38, p = 0.82$], as depicted by the mostly parallel lines.

a significant factor in movement intermittency. Orientation does not demonstrate a significant interaction effect by speed conditions on intermittency, either. This result can help researchers simplify their experiment design for movement intermittency or smoothness related work.

My finding that movement intermittency increases significantly with decreasing movement speed is in agreement with work by Dipietro et al. [64]. I present a systematic characterization of movement intermittency at different joints of the arm. Although separate studies in the literature concerning individual joints [23, 69] together implied an increased movement intermittency in distal joints, I provide a comparison of movement intermittency in several joints under simultaneous recording, hence equivalent temporal and task conditions.

I believe that 3D motion tracking offers great opportunities for the study of human motor control, as reported also in [65], especially in identifying and clarifying interesting manifestations of the motor control system which underlies its great flexibility, dexterity and adaptability [62]. The ability to simultaneously track multiple points in 3D was a key feature of the motion tracking system that I used to explore the source of movement intermittency.

One application area for these results would be better design of robotic rehabilitation protocols. Movements of stroke patients are highly intermittent and the intermittency decreases as the patient relearns to move. Due to this fact, movement smoothness is widely used as an objective metric to quantify motor function recovery in stroke patients [7, 30]. In a study that compared benefits of first distal robotic therapy and then proximal therapy vs. the therapy scheme with the alternative order, Krebs et al. [70] reported that although the overall outcomes were very similar for both groups of patients, the skill transfer effect was higher in the group that underwent the more distal therapy first. I believe that this observation can be explained within the light of results reported here. Trying to generate a smooth distal endpoint trajectory, even if the proximal joints were restrained, would imply more intense exercise for the patient than an exercise focusing on a more proximal joint, since intermittency is not due to simple accumulation in kinematic variables, but due to an limitations in the neuromuscular circuitry. Testing of the patient with a proximal joint task after distal joint exercise is then similar to increasing the tolerance band in the task.

The experimental results obtained in this chapter are in agreement with those of Hamilton et al. [20], where they demonstrated that larger muscles produce less variable forces, due to increased total number of motor units. Hamilton et al. state that it is likely that a similar relationship is in effect for the number of active motor units during a contraction, within the same muscle, and that this mechanism is responsible for the increased CV for low force levels, a well-documented observation in several studies in the literature [19, 22, 20].

The agreement between the experimental results in this chapter and the results of Hamilton et al. [20], provided motivation to explore whether the increase in muscle force generation variability for small forces due to low number of active motor units can explain the increased variability in slow movements. Based on this motivation, I conducted an additional experiment with eight healthy subjects who completed slow elbow flexion movements at a constant slow speed target under varying resistive torque levels. I also built a neuro-musculoskeletal model of the elbow to gain a better insight on the contribution of variability in muscle actuation to movement speed variability. Chapter 4 explains the slow elbow movements experiment and the neuromuscular elbow model in detail and presents the results obtained from them.

Chapter 4

Role of Neuromuscular Mechanisms in Variability of Slow Movements

This chapter presents the results of a human subject experiment and of neuromuscular elbow model simulations, both aimed at answering the question, "can increased muscle force variability in low force levels explain increased variability or intermittency of slow movements?" Results of the experiment demonstrate that resistive torques may be used to significantly decrease movement speed variability. The relationship between resistive torque levels and speed variability, however, is not monotonic. These results are in agreement with the explanation that force requirements of the movement may be responsible for the observed movement variability through muscle force generation variability. Although the model was qualitatively successful in predicting higher variability for slower movements, simulations of the model predicted a monotonically increasing variability with increasing resistive torques, failing to replicate the experimentally observed relationship. Based on this disagreement, I conclude that movement speed variability in slow movements cannot be solely attributed to variability in the mechanics of muscle force generation.

4.1 Introduction

To address the research question above, I first conducted an experiment with eight subjects, which involved completion of slow elbow flexion movements at two target speed levels and under five resistive torque fields implemented via an elbow exoskeleton device. Results of this experiment demonstrated that increasing levels of resistive torques decreased movement speed variability, only until hitting a certain torque level, after which variability started increasing. This observation indicated that a motor-unit pool-based muscle force generation variability, which is known to increase at low force levels, can indeed underly increased variability in slow movements, since increasing force demand of the task under equivalent kinematic conditions led to a decrease in variability up to a certain force level. Second, I built a neuromuscular model of the human elbow, based on both motor unit pool recruitment and rate coding dynamics, as well as Hill-based muscle contraction dynamics, to gain a better insight on the contributions of actuation, sensing and feedback dynamics to variability. Although the model provided more accurate prediction of force variability under isometric conditions than other models in the literature, the closed-loop simulations indicated that movement variability in slow movements cannot be attributed solely to variability in muscle force generation.

4.2 Literature Review

In their seminal work, Flash and Hogan [5] proposed the minimum jerk principle (or theory) to explain planning in unconstrained reaching movements. Based on the minimum jerk theory (MJT), the central nervous system chooses the trajectory that minimizes the squared jerk (time derivative of acceleration) among infinitely many possible trajectories, leading to an optimally smooth trajectory. The minimum jerk velocity profile is smooth, symmetric and bell-shaped and accurately predicts the velocity profiles observed in unconstrained reaching experiments [5].

Flash and Hogan anticipated that MJT would not hold for movements that reached limits of the neuromuscular system, such as during very fast movements. A lower limit for speed below which the observation of unimodal smooth velocity profiles would break, however, was not initially anticipated. Doeringer and Hogan [23] showed that movements lose their smoothness and become increasingly intermittent, as demonstrated by distinct peaks in the velocity profile, with decreasing movement speed. Although many studies interpreted the intermittency to be caused by corrective actions [28, 29], which is correct under certain circumstances, Doeringer and Hogan showed that the submovements persisted under no visual feedback, indicating that not all submovements can be attributed to corrective actions. They concluded that increased movement intermittency in slow movements is a very robust characteristic of human motor control system: people cannot avoid moving intermittently during slow movements [62]. It is also important to note that similar highly intermittent behavior is observed in movements of stroke patients, and smoothness of movement is used as a reliable and objective measure of motor function recovery [68, 7, 8, 31].

Doeringer and Hogan [23] proposed two potential sources of movement intermittency: neuromuscular noise and submovements-based central planning. However, they did not arrive at a final conclusion about the source of intermittency and a satisfactory explanation for the origins of intermittency has remained elusive.

An alterative theory of movement planning and control, namely the minimum variance theory (MVT) by Harris and Wolpert [14], has been remarkably successful in predicting well-known and experimentally well-documented Fitts' Law [15], bell-shaped velocity profiles of arm reaching movements, saccadic eye movements and even the two-thirds power law [16]. MVT proposes that principles for minimizing the effects of the noise present in biological processes and mechanisms underly movement planning, rather than cost functions (such as jerk) that are difficult to be sensed or integrated by the CNS. MVT relies on the assumption of a linear relationship between the standard deviation (SD, variability) of the control signals and their mean levels, an assumption shortly called as signal-dependent noise (SDN). According to this assumption, during the planning of a rapid goal-directed movement, moving as fast as possible should be avoided, otherwise the end point error will be very large due to the large control signals involved in the movement. Hence it places a trade-off between movement duration and end point variability.

Todorov and Jordan [17] proposed the optimal feedback control model (OFCM) to overcome the shortcomings of MVT. Specifically, Todorov [18] pointed out that despite the success of MVT in providing a unified explanation for numerous seemingly unrelated experimental observations in motor control, it is limited to open-loop control scenarios, hence to only rapid goal-directed movements with no disturbances. However, tasks in daily life often are slow to allow enough time for feedback to be incorporated in, and involve various disturbances. OFCM takes into account noise in both control and sensing (or state estimation), and provides a variable structure feedback controller that is allowed to change its parameters during the movement, based on disturbances or feedback. The noise in motor commands is still assumed to comply with SDN. Unlike MJT and MVT, where motor planning and execution are considered to be two separate processes, in the OFCM they take place simultaneously [71].

It is important to highlight that both MVT and OFCM rely on one essential assumption: SDN. With the SDN assumption, movements involving smaller control signals will always result in less variability. In fact, Jordan and Wolpert [1] state that "longer movements can always be made smoother than short movements," which is in contradiction with Doeringer and Hogan's experimental results. Hence, MVT and OFCM fall short of providing an explanation for intermittency in slow movements, and are concerned with only rapid movements.

Although speed-accuracy trade-off [15] and planning and execution of rapid goal-directed movements have garnered significant research interest [5, 6, 14, 72, 17], far fewer studies have reported results on the lower end of the movement speed spectrum. Not only very interesting observations exist for slow movements, but also an explanation of these observations are highly relevant to motor function recovery and motor skill learning, where movements are typically slow at the initiation of therapy or learning, and movement speed increases through practice, exercise or therapy.

Newell et al. [73] provided experimental evidence that movements slower than 15 cm/sec became less accurate and more variable in terms of movement timing. They provided insight into the origins of this increased variability, by showing that even movements with a duration as short as 100 msec demonstrated increased variability, hence it cannot be attributed solely to a feedback mechanism. Rather, they pointed out that the source of this variability should be sought in actuation. Although the main variability measure in this study was time and not speed, Newell et al.'s [73] results are considered to be relevant to and indicative of the same type of variability observed in movement speed.

In this chapter, I propose to explore the origins of intermittency problem from a movement variability point of view. I define movement intermittency as within-trial variability rather than trial-to-trial variability, which is a common type of variability measure used for rapid goal-directed movements [14]. This point of view provides a framework to study movement intermittency as a special case of movement variability observed in slow movements. My work reported in Chapter 3 has established the motivation for this framework.

In my earlier work [32], I showed that intermittency of various joints along the arm during a multijoint tracking task increased in the distal direction along the arm. Considering that muscle sizes decrease in the distal direction along the arm, this result is in agreement with the results of Hamilton et al. [20], where they showed that larger muscles are capable of producing force with less variability, compared to small muscles. Hamilton et al. complemented their results with a motor unit pool-based isometric neuromuscular model and suggested that a similar mechanism due to number of active motor units may be responsible for the significant increase in muscle force variability at low force levels. More precisely, this range of low force levels correspond to 20–30% of the maximum voluntary contraction force [19]. This may as well be the region of forces involved in slow movements.

This chapter reports results of a human subject experiment and of a neuromuscular model of the elbow that evaluate whether increased muscle force variability in low force levels can explain increased variability or intermittency in slow movements. The chapter is structured as follows: Section 4.3 describes the experimental setup, protocol, data analysis methods of the human subject experiment, as well as the structure of the neuromuscular elbow model. Section 4.4 summarizes the results of the statistical analyses of experimental data and of the simulations of the model. The chapter concludes with a discussion of results, contributions and limitations of the results.

4.3 Methods

4.3.1 Participants

A total of eight subjects (four male and four female) participated in the experiment. Mean age was 25.5 years (SD 3.1), ranging from 21 to 29. One subject was

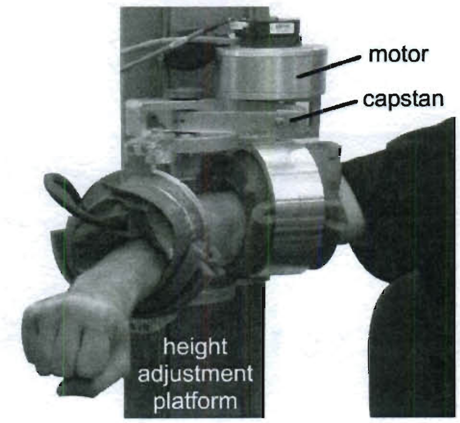


Figure 4.1 : Elbow exoskeleton. Subject's right arm was attached to the device via foam padding and pressure cuffs to provide a comfortable and tight fit. The height of the device was adjusted for each subject so as to have their arm moving in the horizontal plane at shoulder level (shoulder abducted 90 degrees) throughout the experiments.

left-handed. All subjects had normal or corrected-to-normal vision, none had any movement disorders affecting their upper extremities, and all provided their informed consent for the experimental protocol approved by the Rice University Institutional Review Board.

4.3.2 Experimental Setup

Subjects were seated at a 17" LCD computer screen and their right arm was attached to an elbow exoskeleton device via foam padding and pressure cuffs that provided a comfortable and tight fit, as shown in Fig. 4.1. The exoskeleton allowed elbow flexion and extension movements in the horizontal plane and was capable of applying controlled torques on the elbow. The device used a Platinum ServoDisc U9D-E pancake motor from Kollmorgen Motion Technologies with a E3-2048-500-H optical encoder from US Digital with 2048×4 counts per revolution resolution in quadrature mode. Output torque and position sensing resolution were further improved via a 1:11.25 ratio cable drive mechanism, leading to a maximum torque capability of 5.48 Nm and 0.0039 degrees position reading resolution at the elbow joint. The inherent friction of the device was predominantly of Columbic nature and was canceled via a motion-based friction cancelation algorithm [74]. It was verified that the movements of the exoskeleton were essentially frictionless after friction cancelation. A platform allowed adjusting the height of the exoskeleton properly for each subject so as to have the right arm moving in the horizontal plane at shoulder level throughout the experiments. An emergency stop button placed in easy reach of the subjects' left hand and hard stops at the fully extended and at approximately 100 degrees flexed positions of the elbow constituted the safety precautions. Also the maximum elbow torque that the device can apply was limited to 3 Nm in software. MATLAB and SIMULINK by Mathworks Inc. and QUARC by Quanser Inc. were used for the real-time control software and experiment interface. The feedback control loop ran at 1 kHz and data capture rate was 100 Hz.

4.3.3 Experimental Protocol

Subjects were asked to always look at the screen and not at their arms, and to make a fist with their right hands and keep it in this consistent posture throughout the experiment. On the screen, subjects saw a time plot of their elbow movement speed (in deg/sec) and three numerical indicators. The plot was not updated in real time but rather generated after every four-second-long trial, displaying the speed profile of the last trial. This configuration ensured that visual feedback during the trials did not lead to corrective actions. At the end of each trial, the first indicator displayed the mean speed of subjects' movement during the trial. Two additional numerical indicators displayed the current trial number and time in seconds (a chronometer with millisecond precision) during the trial.

The task assigned to the subjects was completing constant speed elbow flexion movements against free or constant resistive torque fields generated by the exoskeleton so as to match a target constant speed profile. There were two target speed levels (5 deg/sec and 10 deg/sec) and five resistive torque levels (0 Nm to 2 Nm, with 0.5 Nm increments). All subjects completed all ten speed and torque level combinations, following a full factorial design. One experiment session took around 45 min, and all subjects completed the experiment in two sessions with different target speed levels on two consecutive days. The presentation order of speed, and an increasing or a decreasing order for resistive torque levels within a speed level were counterbalanced and randomized among subjects. For example, 5 deg/sec target speed on the first session (or day) with an increasing order for torque levels and 10 deg/sec target speed on the second session (or day) with a decreasing order for torque levels constituted one specific presentation order. A total of eight possible combinations for the presentation order of speed and torque levels were randomly assigned to the eight subjects.

Each session consisted of five blocks, each block involving a specific resistive torque level. In each block, subjects completed 40 trials in around 6 min and subjects were required to have a 2 min rest between blocks to avoid fatigue. Each trial started with subject's initiation of movement from a fully extended elbow position (the chronometer started counting to indicate the start of the trial, as subjects passed through 1 degree of flexion). No feedback was available to the subjects during their movement, except proprioception. After the 4 sec trial ended, the subjects observed their speed profile time plot in the trial, superimposed with the target speed level as a horizontal line on the computer screen. The ordinate of the plot was adjusted so that the target speed level always appeared vertically centered. When subjects moved back to the initial fully extended posture, the trial number counter was incremented indicating that they can initiate the next trial when they felt ready.

When subjects arrived for their first session, they were given written instructions about the experiment. The instructions explained the experimental setup, protocol and the interface. The primary goal was defined as always making a constant speed flexion movement to match the target constant speed level as close as possible. Subjects were instructed to always check the mean speed indicator after every trial and adjust their speed in the following trials accordingly. As a secondary goal, they were also instructed to observe the speed profile plots to not only match the mean speed, but also to keep their speed constant throughout the trial and avoid increasing or decreasing trends in this plot. Instructions asked for avoiding slowing down or stopping towards the end of the trial but rather keep a constant speed until the trial ended. After the subjects read the written instructions, example speed profile plots depicting successful and unsuccessful trials (in terms of satisfying target speed levels) were shown and explained by the experimenter.

At the beginning of each session, subjects were allowed to practice as many trials as they wanted until they were convinced that they were being able to successfully and consistently complete the constant speed movement task. Only the last 20 trials out of 40 for each block was included in data analysis. Also, the last 3 seconds of each 4 second trial was used in the analyses, to avoid sudden jerks that occasionally occurred at movement initiation and movements close to the joint limits. Also, the experiment's focus was on sustaining constant speed movements rather than their initiation.

4.3.4 Analysis of Movement Speed Variability

In the literature, various measures are used to quantify movement intermittency or variability. Usually, a number of significant peaks in the speed profile quantifies movement intermittency [68, 7, 32]. Movement variability measures, on the other hand, are most commonly defined as end-point error or variability [14, 8], quantifying only trial-to-trial variability [18]. In contrast, within-trial variability measures are commonly used for force variability, such as standard deviation (SD) of force, and most importantly a normalized version of SD, coefficient of variation (CV) of force. CV facilitates comparison between results of different studies [19] and is defined as SD of force normalized by mean level of force.

Although trial-to-trial variability measures are well-suited to discrete movement tasks, such as reaching, a within-trial variability measure is much better-suited to continuous movement tasks, such as maintaining a constant speed during movement. Hence I use coefficient of variation of speed (CV_{speed}) as the measure of movement variability in this chapter. For each trial in the experimental protocol described in the previous section, CV_{speed} during the last three seconds of the trial quantified the speed variability. Speed was obtained from encoder readings via Euler's forward difference method, and was bidirectionally filtered offline (for zero phase shift) with a second order low-pass Butterworth filter with 20 Hz cutoff frequency.

4.3.5 Statistical Analysis

I used a repeated measures analysis of variance (ANOVA) with no between-subjects factors and with subject, trial, speed and torque within-subjects factors. CV_{speed} constituted the dependent measure. Trial had twenty levels, speed had two levels (5 deg/sec and 10 deg/sec) and torque level had five levels (0–2 Nm with 0.5 Nm increments). Subject (eight levels) is treated as a random factor. Out of 1600 total observations, three data points were not included in statistical analysis. In these three trials, the subject mistakenly thought that the trial did not initiate properly and quit moving at or earlier than the mid-point of the trial. I used Kenward-Rogers adjusted degrees of freedom method to account for Type I error risk. Alpha level was set at 0.05 for all significance tests. Since trial did not lead to any significant results when included as a factor main or interaction effects, I report only the main and interaction effects of speed and torque on CV_{speed}. Tukey-Kramer's post-hoc analysis test was used for pairwise comparisons of main and interaction effects of torque. I used SAS software by SAS Institute Inc. for conducting the statistical analyses. I used a "PROC MIXED" design (due to both random and fixed effects), with trial treated as a repeated measure, and with a compound symmetry structure for the covariance matrix. This design allows incorporation of all available observations excluding only missing individual observations, without having to drop a group or condition of data points [75, 76], and thefore provides higher statistical power for data sets with missing data points.

4.3.6 Neuro-musculoskeletal Elbow Model

There are mainly two types of muscle models in the literature. First is motor unit (MU) pool-based models commonly used to gain insight into isometric force variability. Second is Hill-based muscle contraction models that are commonly used to study numerous types of biomechanical movements and their control.

Fuglevand et al. [77] proposed a MU pool-based model that included both surface electromyogram (sEMG) and force predictions under isometric conditions, in comparison with experimental recordings. This model has become widely accepted and has been adopted by many studies, and later was extended to study effects of synchronization in MU pools [78].

Hill-based models originated from Hill's seminal work on energetics of muscle contraction [79]. Zajac's review of muscle and tendon models [80] is the most comprehensive reference on Hill-based muscle models. These are lumped-parameter models that approximate the force-length and force-velocity properties (or equivalently the dynamic behavior) of the musculotendon complex at a fidelity sufficient to study biomechanics of multi-muscle or multi-joint movements.

Selen et al. [81] proposed a combination of these two types of models in their work where they studied whether co-activation of muscles can be used as a strategy to decrease variability. He showed that Hill-based models alone with Gaussian stimulation noise cannot account for the force variability observed experimentally in the literature [22, 82]. A model combining Hill-based muscle contraction with MU pool recruitment and rate coding dynamics, however, was found to be in agreement with experimental results and used to explain that co-activation indeed can be a valid strategy to reduce movement variability.

Selen et al.'s model [81] provided an attractive starting point since it combined widely accepted MU pool models of force variability with Hill-based contraction dynamics and musculoskeletal dynamics to study kinematic variability. My model most closely resembles that of Selen et al. [81], and the contraction model is described in more detail in the studies by Van Soest and Bobbert [83] and by Ridderikhoff et al. [84]. The motor unit pool model is similar to that of Selen et al. [81], however, I used parameter values from Fuglevand et al. [77] for a portion of the parameters, due to better demonstrated agreement with experimental data for the biceps muscle. For completeness, I explain the elbow model in detail below.

Activation and Contraction Model

Similar to Selen et al. [81], I used an agonist-antagonist pair of muscles to drive the elbow. Schematic representations of the model are illustrated in Fig. 4.2 and functional block diagrams of three levels of the model are given in Fig. 4.3. The activation-contraction model block diagram is given in Fig. 4.3(a). The first order activation dynamics of each motor unit is defined by

$$\dot{\gamma} = \frac{c \times nFR - \gamma}{\tau_\gamma}, \quad \tau_\gamma = \begin{cases} \tau_{act} = 89\text{msec}, & c \times nFR \geq \gamma \\ \tau_{rel} = 178\text{msec}, & c \times nFR < \gamma \end{cases} \tag{4.1}$$

where γ is the intramuscular concentration of Ca^{+2}, $c = 0.1373 \times 10^{-3}$ is a gain coefficient, nFR is normalized firing rate of motoneurons and τ_γ is the time constant, defined differently based on activation and relaxation cases [84]. Active state q is dependent on the Ca^{+2} concentration and the length of the contractile element l_{ce} through the nonlinear relationship

$$q = \frac{q_0 + (\rho\gamma)^3}{1 + (\rho\gamma)^3}, \quad \rho = Gl_{ce}\frac{\lambda - 1}{\lambda l_{ce,opt} - l_{ce}} \tag{4.2}$$

where $q_0 = 0.005$, $G = 52700$, and $\lambda = 2.9$. During simulations q_0 was allowed to take values close to zero, to allow eccentric contractions of the muscles while receiving either zero or very small stimulation. Otherwise, though completely passive, the muscle under eccentric contraction generates significant spurious forces due to the minimum value of q_0 causing l_{ce} to resist lengthening after some saturation value.

The force exerted by each motor unit is calculated by the equation

$$F_{se} = \begin{cases} k_{se}l_{se}^2, & l_{se} \geq 0 \\ 0, & l_{se} < 0 \end{cases} \tag{4.3}$$

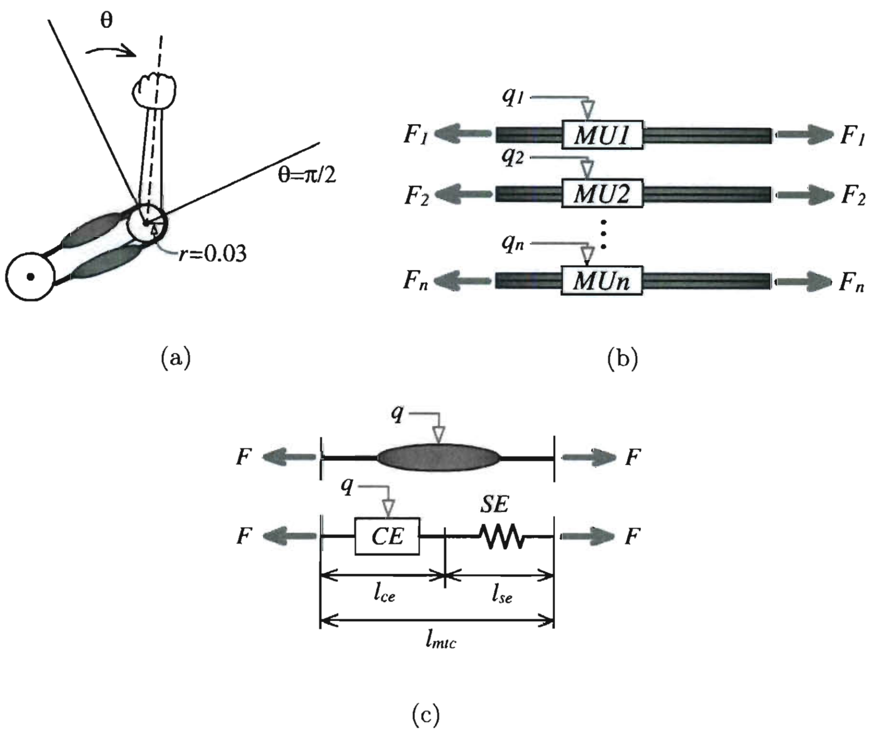


Figure 4.2 : (a) An equivalent agonist-antagonist pair of uniarticular muscles drive the elbow joint in my model. (b) Each muscle consists of $n = 60$ motor units. q denotes the active state for each motor unit. (c) Although Hill-based contraction models are commonly used in explaining lumped-parameter behavior of whole muscles, in my model, each motor unit has a contraction behavior defined by an active contractile element (CE. muscle tissue) and a series elastic element (SE) with nonlinear stiffness (tendon). See text for explanation of all variables. Also see the functional block diagrams corresponding to each level of the model in Fig. 4.3

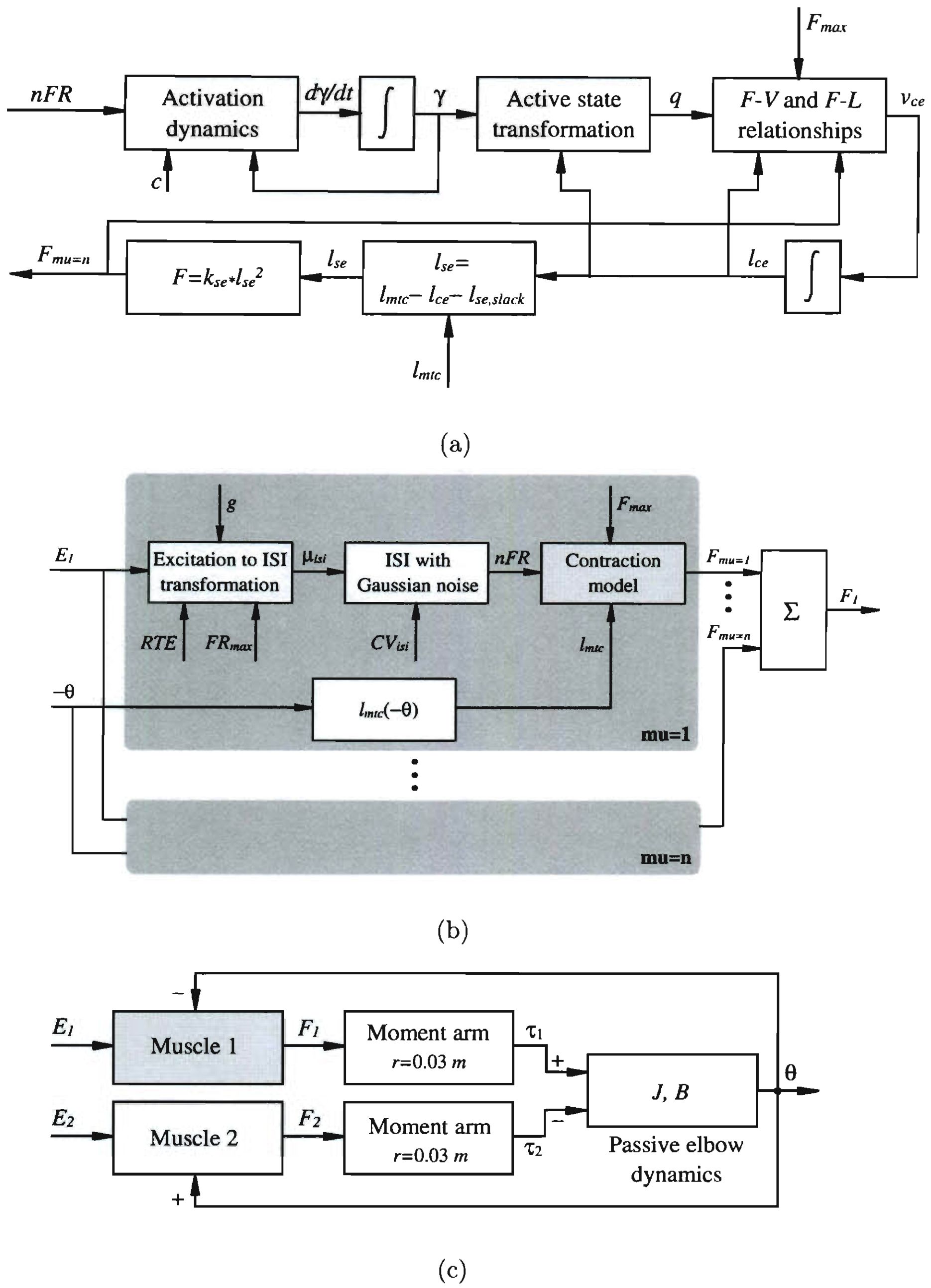


Figure 4.3 : Block diagrams of the neuromuscular elbow model. See text for explanations of the blocks and parameter values. (a) Block diagram of the activation and contraction model. (b) Block diagram of the motor unit pool model. Expanded version of the contraction block (highlighted in yellow) is given in (a). (c) Block diagram of the elbow neuromusculo-skeletal system with an antagonist pair of muscles. Detailed version of the Muscle 1 block (highlighted in yellow) is given in (b).

where $l_{se} = l_{mtc} - l_{ce} - l_{se,slack}$ is the tendon elongation length, $l_{se,slack} = 0.170$ m is tendon slack length, $l_{mtc} = 0.312$ m is musculotendon complex length (it is given by $l_{mtc} = 0.312 \pm r\theta$ for non-isometric simulations) and k_{se} is the stiffness of the tendon. k_{se} values for each motor unit are determined at a tendon elongation of $0.0333 \times l_{se,slack}$ [80, 85] and depend on the maximum force F_{max} each motor unit can generate. F_{max} varies exponentially among motor units and is described in detail later. Note that $F_{ce} = F_{se}$ due to the serial configuration.

The force-length relationship is given by

$$F_{isom} = max\left(1 - \frac{1}{w^2}\left(\frac{l_{ce}}{l_{ce,opt}} - 1\right)^2, 10^{-5}\right) \tag{4.4}$$

where F_{isom} is the normalized maximum isometric force at muscle length l_{ce} and $w = 0.56$ is parameter for the width of the relationship. $l_{ce,opt} = 0.136$ m is the optimum fiber length.

Concentric contractions ($F_{ce} \leq qF_{max}F_{isom}$) are governed by the equation

$$\dot{l_{ce}} = -v_{scale}l_{ce,opt}\left(\frac{F_{isom} + v_{shape}}{\frac{F_{ce}}{qF_{max}} + v_{shape}} - 1\right) \tag{4.5}$$

where

$$v_{scale} = min(1, 3.333q)B_{rel}$$

$$v_{shape} = \begin{cases} A_{rel}F_{isom}, & l_{ce} \geq lce, opt \\ A_{rel}, & l_{ce} < lce, opt \end{cases}$$

$$A_{rel} = 0.41, \quad B_{rel} = 5.2.$$

Eccentric contractions ($F_{ce} > qF_{max}F_{isom}$) are governed by the equation

$$\dot{l_{ce}} = \frac{p_1}{\frac{F_{ce}}{qF_{max}} + p_2} + p_3 \tag{4.6}$$

where

$$p_1 = -\frac{v_{scale}}{\sigma}\frac{((1 - F_{ecc})F_{isom})^2}{F_{isom} + v_{shape}}$$

$$p_2 = -F_{ecc}F_{isom}$$

$$p_3 = -\frac{p_1}{F_{isom} + p_2}$$

In these equations, $F_{ecc} = 1.5$ represents the maximum eccentric force as a fraction of F_{isom} and $\sigma = 2$ is the ratio of eccentric and concentric contraction curves at zero velocity. I implemented a linear eccentric contraction condition to avoid numerical problems in very low active states, similar to the one defined by Ridderikhoff et al. [84], which is not reported here, and the reader is referred to [84] for details.

The activation and contraction model constitutes a sub-component of the motor unit pool model (see Fig. 4.3(b), highlighted yellow block), which is described next.

Motor Unit Pool Model

A schematic representation of the motor unit pool model is illustrated in Fig. 4.2(b). Fig. 4.3(b) provides a block diagram of the model. The formulations below follow closely that of Selen et al. [81], however some parameters are replaced with values in [77].

A MU is recruited when excitatory input (E) exceeds the recruitment threshold (RTE). RTEs of motor units vary exponentially based on the equation

$$RTE(mu) = \exp(mu(\ln RR)/n) \tag{4.7}$$

where mu represents the index of the motor neuron, $RR = 75$ is the recruitment range and $n = 60$ is the total number of MUs. The firing rate of a recruited neuron is given by the equation

$$FR(mu) = g(E - RTE(mu)) + mfr, \quad E \geq RTE(mu) \tag{4.8}$$

where the gain $g = 1.36$ and minimum firing rate $mfr = 8$ pps. FR saturates at 41.6 pps for all motoneurons. The interspike interval ($ISI(mu)$) is calculated from the inverse of $FR(mu)$. A Gaussian noise with CV of 0.2 is added to the $ISI(mu)$, and this constitutes the main source of variability in the whole model. After the noise is added, a normalized firing rate ($nFR(mu)$) is calculated by inverting $ISI(mu)$ with noise, and dividing by maximum FR. In an altered version of the model, to avoid saturation of motor unit activation and hence force variability, I halved the $nFR(mu)$, while all other parameters were kept the same. $nFR(mu)$ provides both the normalized stimulation input to the muscle activation-contraction model, and the duration of this input, which corresponds to the $ISI(mu)$. The maximum force value for each motor unit was calculated from the equation

$$F_{max}(mu) = h \exp(mu(\ln RF)/n) \tag{4.9}$$

where $RF = 108.1$ denotes the range of forces, giving a 1:100 ratio for the ratio of maximum forces of the first and the last MUs. h is a constant used to obtain a total maximum force of 2000 N for the whole muscle. The force outputs of all MUs are summed to obtain the total muscle force following the independent tendon model used by Selen et al. [81].

Elbow Musculo-skeletal Dynamics

An antagonist pair of muscles with described dynamic models in the previous sections, drive the elbow joint. The elbow joint is assumed to have linear damping (B), and inertia (J) and its dynamics is governed by the equation

$$\tau_1 - \tau_2 + \tau_r = J\ddot{\theta} + B\dot{\theta} \tag{4.10}$$

where τ_1 is the torque applied by the extensor muscle, τ_2 is the torque applied by the flexor muscle, τ_r is the resistive torque applied by the exoskeleton and θ is the position of the elbow, as defined with respect to the coordinate system depicted in Fig. 4.2(a). The values of $J = 0.2$ kg-m^2 and $B = 0.2$ Nm/(rad/sec) are obtained from [86]. Value of J accounts for both the inertia of the forearm and hand, and the moving part of the exoskeleton, hence the increased value from the original value of 0.06 kg-m^2 in [86]. Simulations with $J = 0.1$–0.3 kg-m^2 led to similar results in terms of speed variability and are not reported here. A joint stiffness K was not included in the model due to its negligible contribution to total passive torque in configurations away from the joint limit [80].

A time step of 1 msec and Euler's integration method are used for the model. The model is driven via controlling the excitation input (E) of muscle 2 with a proportional (proportional control gain $K_p = 0.05$) position feedback control law. Through this controller, the model is driven to follow a ramp position profile corresponding to either of the target speed levels in the experimental protocol. Excitation input of muscle 1 was always set to zero during the simulations, however this muscles continues to contribute torques to the elbow due to eccentric contractions and to its compliance. CV_{speed} is calculated from the simulations for comparison with experimental results under same experimental (target speed and resistive torque) conditions. Implementation of a controller with no delay and noise-free position feedback aims to create a basis to test the hypothesis whether the relationships between CV_{speed} and movement speed and torque levels can be attributed to variability in muscle force generation alone.

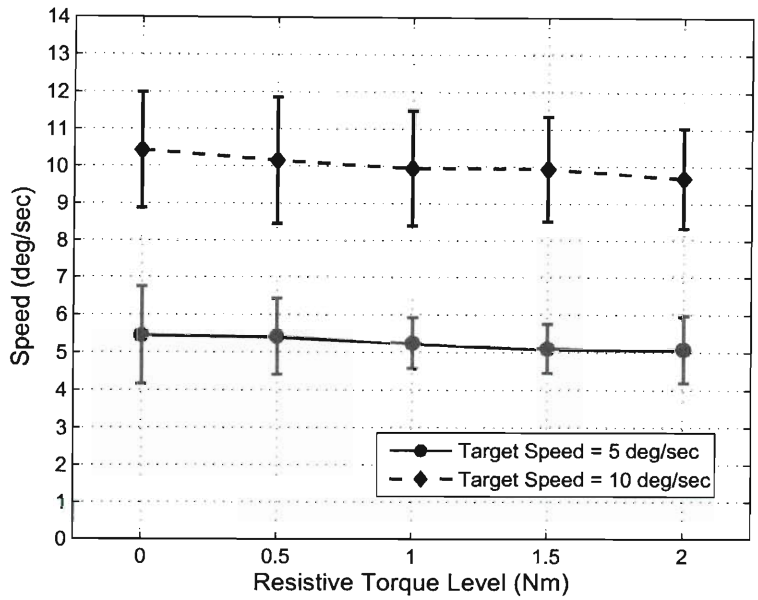


Figure 4.4 : Subjects were successful in matching the target speed level on average. Error bars denote the SD of speed.

4.4 Results and Discussion

4.4.1 Experiment Results and Discussion

Fig. 4.4 shows the mean speed values achieved by the subjects in the experiment, with error bars depicting the SD of speed. Subjects were able to achieve the constant speed flexion task reasonably well, however with high variability, which is an expected observation for slow movements. Increasing resistive torque levels led to a weak and insignificant decreasing speed trend. It can be observed that variability generally decreases as the resistive torque level increases. The variability is lower for the target speed level of 5 deg/sec, however this is simply due to an effect of scaling. A fair comparison of variability of speed for different levels of mean speed necessitates the use of the CV_{speed} measure which normalizes SD of speed by mean speed.

Fig. 4.5 presents raw speed profile data from a representative subject (Subject

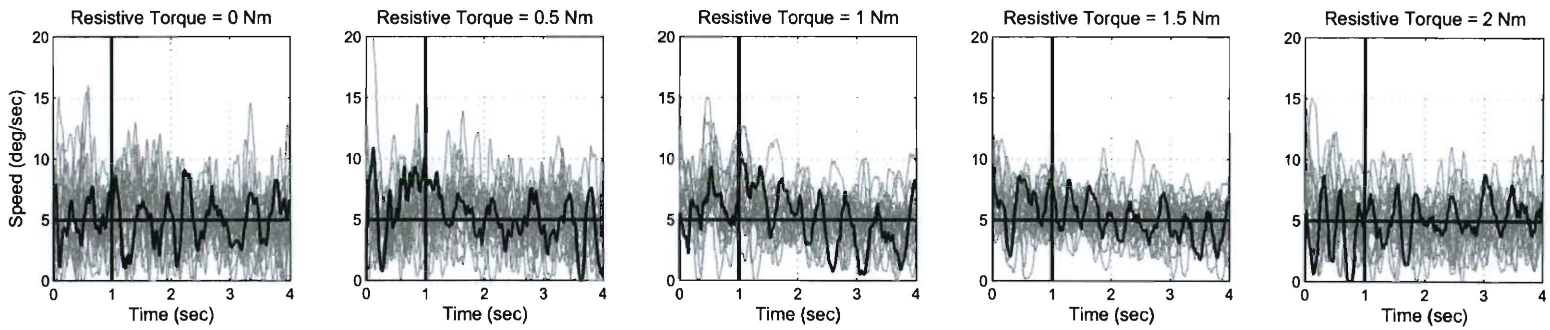
5), from all 10 speed and torque level condition combinations. Only profiles in the last 20 of 40 trials are plotted in gray, with the final trial in black. Horizontal lines correspond to the target speed levels, and vertical lines mark the range (1–4 sec) for which the measure CV_{speed} was calculated.

Results of the ANOVA indicates a significant main effect of Speed [$F(1, 1390) = 465.4, p < 0.05$] and a significant main effect of Torque [$F(4, 1390) = 42.53, p < 0.05$] on CV_{speed}. The interaction effect of Torque by Speed is also significant [$F(4, 1390) = 5.57, p < 0.05$]. The results of the post-hoc Tukey-Kramer test for pairwise comparison of Torque are summarized as a bar plot in Fig. 4.6. Error bars indicate standard errors. This plot indicates that CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels ($p < 0.05$). Although initially there is a decreasing trend for CV_{speed} with increasing resistive torque levels, after 1.5 Nm, the trend reverses direction and CV_{speed} starts to increase. In fact, CV_{speed} for $\tau_r = 2$ Nm is significantly higher than it is for $\tau_r = 1.5$ Nm.

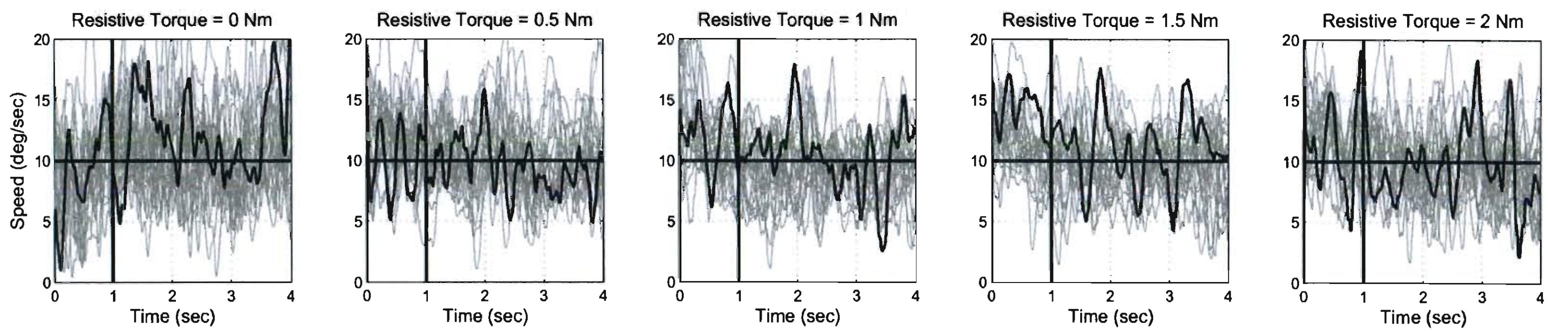
The significant effect of speed on movement speed variability is in agreement with findings using movement intermittency [23, 32] or timing [73] as the measure of variability in the literature. This possibly indicates a single mechanism of variability behind all, as I proposed in Section 2.1.

Fig. 4.7 summarizes the results of pairwise comparison tests for interaction effects of resistive torque level by speed on speed variability, in an interaction plot format. Although the CV_{speed} vs torque level curves under two different target speed level conditions mostly follow a parallel trend, the overall interaction effect is significant because of the non-parallel sub-trends, such as those observed between $\tau_r = 1$ Nm and $\tau_r = 1.5$ Nm.

The non-monotonic relationship between speed variability and resistive torques,



(a)



(b)

Figure 4.5 : Representative speed profiles achieved by Subject 5 under all torque and speed condition combinations. Last 20 of 40 trials are plotted in gray, with the final trial in black. Horizontal lines correspond to the target speed levels, and the vertical lines mark the range (1–4 sec) for which the measure CV_{speed} was calculated. (a) Target speed = 5 deg/sec. (b) Target speed = 10 deg/sec.

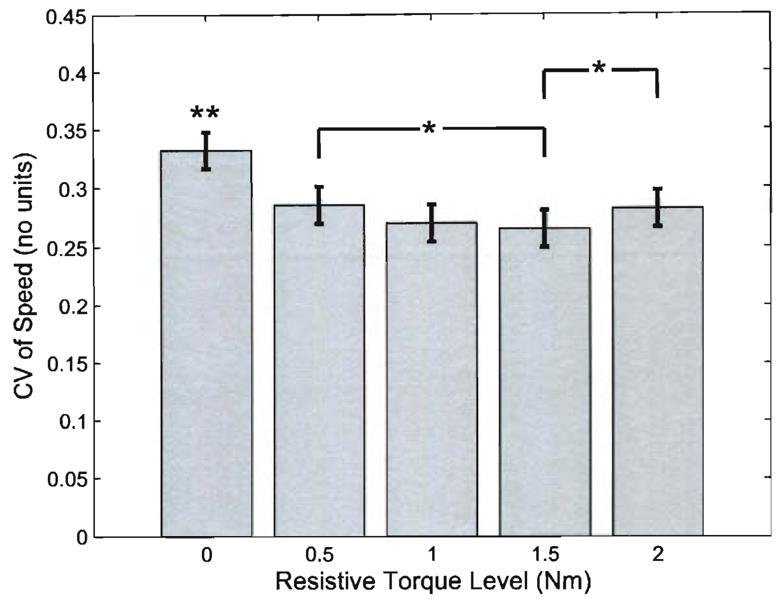


Figure 4.6 : Main effect of resistive torque level on speed variability is significant. Mean and standard error values are displayed. A pairwise comparison of effect of torque levels indicates that, when speed level is not taken into consideration, CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels (denoted by **, $p < 0.05$). Additional pairwise significant differences are denoted by * ($p < 0.05$). Although initially there is a decreasing trend for CV_{speed} with increasing resistive torque levels, after 1.5 Nm, the trend reverses direction and CV_{speed} starts to increase. In fact, CV_{speed} for $\tau_r = 2$ Nm is significantly higher than it is for $\tau_r = 1.5$ Nm. See text for discussion of these results.

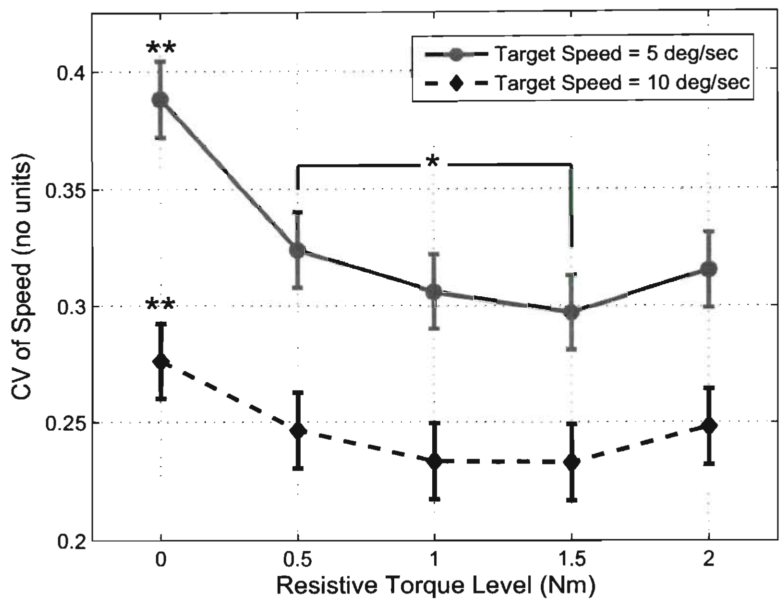


Figure 4.7 : Interaction effect of resistive torque level by speed level on speed variability is significant. Mean and standard error values are displayed. A pairwise comparison of effect of torque levels indicates that, when different speed level results are grouped and analyzes separately, CV_{speed} is significantly higher for the no resistive torque condition in comparison with all other torque levels (denoted by **, $p < 0.05$) in the same speed level. Only other significant difference is between $\tau_r = 0.5$ Nm and $\tau_r = 1.5$ Nm (denoted by *, $p < 0.05$). See text for discussion of these results.

observed in Figs. 4.6 and 4.7 is a novel finding. These experimental results indicate that increased muscle force variability in low force levels can indeed explain increased variability or intermittency in slow movements. Increasing resistive torque levels increase the force requirement of the task, hence may push the muscle forces out of the very low force level with increased force variability [19, 20]. However, the speed variability increases after a certain torque level. This might be due to entering the region where SDN takes hold, with force SD linearly increasing with mean force.

From a dynamics point of view, one can question whether effect of increasing resistive torques is equivalent to applying increased dry friction, and whether decreased variability can be attributed to increased friction. Although resistive torques and dry friction are indeed functionally equivalent, the non-monotonic nature of the relationship helps dismiss this alternative explanation for decreased variability.

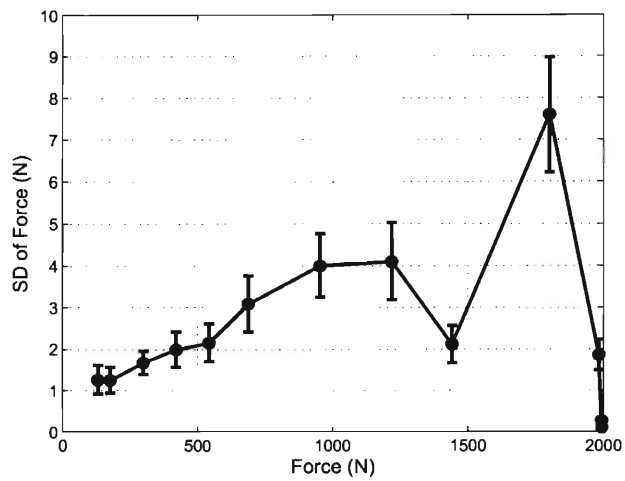
My experimental results indicate potential novel methods of human skill augmentation in delicate or critical tasks such as surgery. Existing technologies such as surgical robots [87] allow filtering of tremors in surgeon's movement within a master-slave teleoperation framework. However, the unilateral nature of the existing teleoperation structures for surgical robots cause a deterioration in dexterity, due to loss of haptic feedback [87]. Skill augmentation algorithms based on resistive torques or forces that will be implemented on the master side can enhance surgeon's ability to generate less variable forces and provide better control over slow and critical tasks. Such an algorithm can be implemented with much lower cost and potential safety hazards compared to bidirectional teleoperation algorithms, although it would not possibly improve the dexterity of the surgeon as much. However, it can potentially provide a mid-point solution. In fact, recent research has focused on increasing surgeon dexterity in robotic surgery via safe mid-point solutions without resorting to bidirectional teleoperation algorithms [88].

Similarly, resistive torques may be used in facilitating or accelerating the learning of a new motor skill. Studies in this area concluded that although task performance can be enhanced during training with various assistance methods, it does not translate to faster or better learning in general [89, 90, 91]. Based on my results, although it may seem counterintuitive, it may be possible to design resistive forces that would make the task easier for a trainee, and potentially lead to faster and more complete learning in comparison with virtual practice without any augmented forces. In fact, research in rehabilitation of motor-impaired patients provided evidence for such counter-intuitive methods to improve rehabilitation outcomes [92]. My results here might provide one potential explanation for the mechanisms behind these counter-intuitive results.

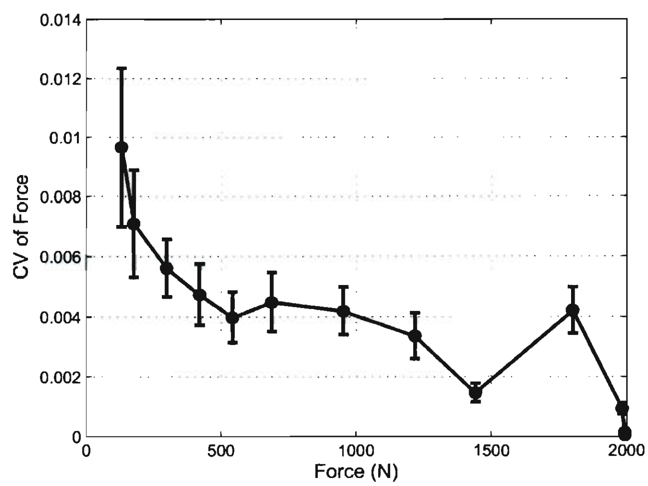
I show that resistive forces can reduce kinematic variability, possibly via moving the task forces into a more favorable region in terms of variability. However, the amount of the resistive forces need to be adjusted carefully, otherwise it may increase rather than decrease variability.

4.4.2 Simulation Results and Discussion

First, to evaluate the accuracy of the model in replicating experimental force variability under isometric conditions, plots of SD of force and CV of force vs mean force level are generated and presented in Fig. 4.8. In these plots, each data point is based on 20 simulations of the isometric model for 3 sec, and only data within the last 2 sec (after force stabilization) is used. Both mean and SD (across 20 simulations) of SD and CV of force are illustrated in these plots. For these plots, maximum normalized firing rate was 1. For comparison, same plots based on experimental measurements from the first dorsal interosseus muscle (index finger abduction) from Taylor et al.

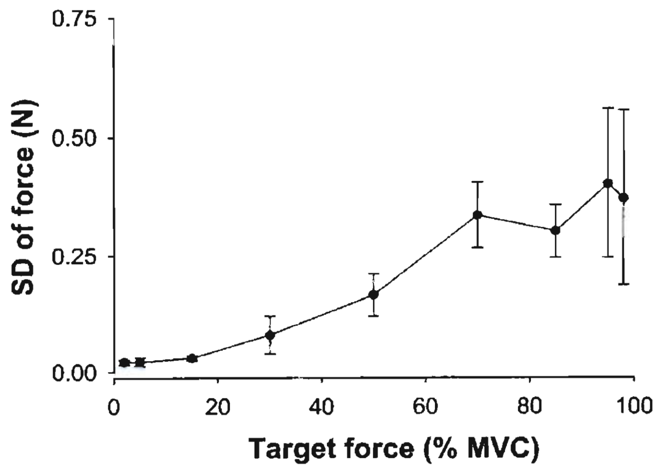


(a)

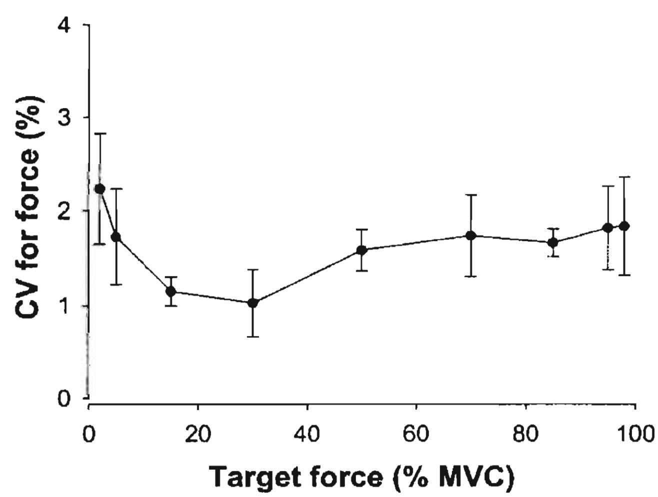


(b)

Figure 4.8 : Standard deviation (a) and coefficient of variation (b) of force, estimated from the isometric muscle model with a maximum normalized firing rate of 1. A comparison with experimental results by Taylor et al. [22] given in Fig. 4.9 shows that this version of the model does not provide an accurate representation of experimental results. CV of force is around 1% for the minimum force level of the model, while it is about 2.5% in the experiments.

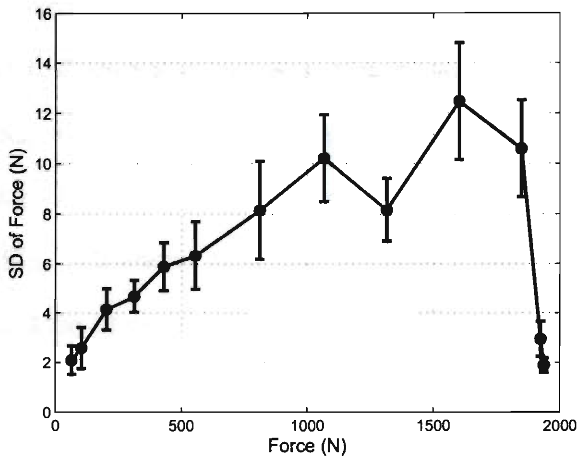


(a)

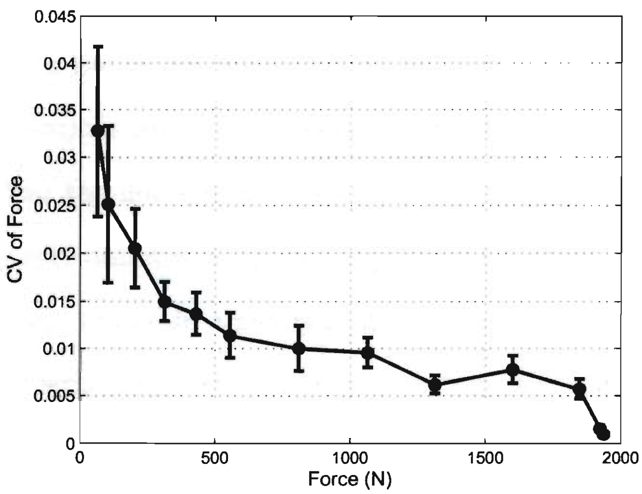


(b)

Figure 4.9 : Standard deviation (a) and coefficient of variation (b) of force in isometric contractions, experimentally recorded from the first dorsal interosseus muscle, as reported by Taylor et al. [22]



(a)



(b)

Figure 4.10 : Standard deviation (a) and coefficient of variation (b) of force, estimated from the isometric muscle model with a maximum normalized firing rate of 0.5. A comparison with experimental results by Taylor et al. [22] given in Fig. 4.9 shows that this version of the model captures a more accurate representation of experimental results. The trends in the SD of force resembles those from experiments much closer than the original model in Fig. 4.8. The CV of force values also match reasonably well in the first quarter of mean force levels.

[22] are given in Fig. 4.9. Although the model is built for the biceps muscle, a reasonable amount of agreement should be expected between experimental results in the literature for the first dorsal interosseus muscle and the model, to validate the accuracy of the model, when compared using normalized measurements such as CV of force. A comparison of the simulation results with experimental results by Taylor et al. [22] given in Fig. 4.9 shows that this version of the model does not provide an accurate representation of experimental results. CV of force is around 1% for the minimum force level of the model, while it is about 2.5% in the experiments. The model predicts mostly a monotonically decreasing CV of force at increasing mean force levels, while the experiments show that CV of force increases after about 30% MVC.

A closer look into the model dynamics led to the conclusion that main discrepancy between simulations and experiments originate from the rapid saturation of motoneurons. When the normalized firing rate approaches its maximum, the variability of its firing rate diminishes significantly, since it cannot take values exceeding the maximum. Hence, to obtain a model that can achieve a better approximation of experimental force variability results in the isometric case, I altered the mean normalized firing rate to take values of only up to 0.5, allowing realistic variability to persist even at high excitation levels. After only this modification, the model is still able to generate forces up to 2000 N, because of the relationship between normalized firing rate and active state q. The range of mean firing rate inputs (0–0.5) still spans the full range for q. Details on this saturation effect of q can be found in [81].

Force variability predictions of the model with the altered normalized maximum firing rate is given in Fig. 4.10. When compared with results by Taylor et al. [22] in Fig. 4.9, it can be observed the altered model captures a more accurate representation of experimental results. The trends in the SD of force resembles those from experiments much closer than the original model in Fig. 4.8. The CV of force values from the model match the experimental values reasonably well in the first quarter of mean force levels. This low range of forces are the most relevant range due to focus on slow movements. Even the muscle forces under the highest resistive torque condition of 2 Nm in the experimental protocol reported in section 4.3.3 fall well within this range, with the maximum torque the muscle can generate being 60 Nm [93]. Having achieved a reasonable match with experimental observations within the low force range, I moved on to evaluate the kinematic variability of the model that contains two muscles with equivalent speed and torque conditions reported in the experimental protocol (section 4.3.3).

Simulation results of the two-muscle elbow system under the equivalent speed and torque conditions reported in the experimental protocol are summarized in Fig. 4.11 as plot of CV_{speed} versus resistive torque level conditions. Each mean and SD of CV_{speed} data point is obtained from 20 runs of the model. This plot is in the same format with Fig. 4.7 to facilitate comparison of experimental results with the predictions of the model. Note, however that in Fig. 4.7 error bars denote standard error, while they denote standard deviation in Fig. 4.11, to improve clarity.

One significant discrepancy between model predictions of CV_{speed} and experimental results is that the model fails to replicate the non-monotonic change in CV_{speed} with respect to increasing resistive torque levels. Although predicted CV_{speed} values are comparable to their experimental counterparts for the torque levels 0.5, 1 and 1.5 Nm, the model predicts a significantly lower variability for speed when there is no resistive torque and it predicts a significantly higher variability for torque level of 2 Nm, in comparison with the experimental results. Predictions of the model for

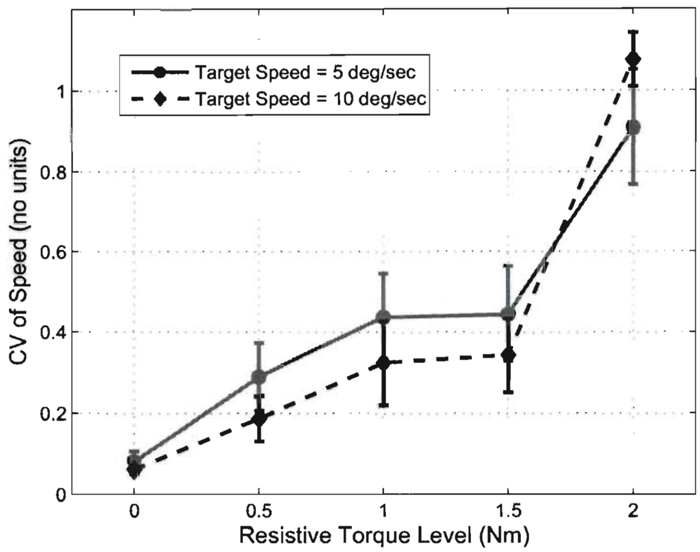


Figure 4.11 : Model predictions of CV_{speed} under equivalent speed and torque conditions with the experiments. Mean and standard deviation values are displayed. The model fails to replicate the non-monotonic change in CV_{speed} with respect to increasing resistive torque levels. Predicted CV_{speed} values are comparable to their experimental counterparts for the torque levels 0.5, 1 and 1.5 Nm. Predictions of the model for CV_{speed} are in qualitative agreement with the experimental results in that it predicts that a slower movement under equivalent torque conditions will result in higher speed variability. However this prediction does not hold for 2 Nm torque level. See text for discussion of these results.

CV_{speed} are qualitative in agreement with the experimental results in the sense that it also predicts that a slower movement under equivalent torque conditions will result in higher speed variability. However this prediction does not hold for 2 Nm torque level. The variability of CV_{speed} within a single condition is much lower in the model predictions than in the experiments.

Although the model has been qualitatively successful in predicting increased speed variability with decreased movement speed, it fails to predict important features of the relationship between CV_{speed} and torque levels. Therefore I conclude that, from a modeling perspective, force variability inherent in muscle force generation mechanisms can be a significant contributor to increased movement variability in slow movements. However, the increase in muscle force variability within low force levels (see Fig. 4.10) cannot be the sole reason behind the increased movement variability in slow movements, since the model fails to predict the decrease in CV_{speed} while the force requirement of the task increases as the resistive torque level is changed from zero to 0.5 Nm or 1 Nm.

One can question the controller structure I have used in simulations of the elbow. Naturally, a delay-free feedback with noise-free position sensing is not a realistic replication of the neurophysiological control mechanisms in the muscle and CNS. However, my goal was to test effects of *only* muscle force generation mechanisms on variability of slow movements. Hence I chose an "idealized" feedback and controller structure to avoid complications that would arise from including realistic models of sensing and control. Using an open-loop control structure for the same purpose, with inputs manually hard-coded is not only an inefficient method but also would cast doubt on the fair comparison of various conditions, since for each condition the input would need to be redesigned. Similar reasons hold for using a single value for the controller gain K_p for varying torque and speed conditions.

The model presented here can be used in future work to explore impedance control strategies in the elbow. Future work can also focus on including models of proprioceptors and delayed feedback, to arrive at a closed-loop model that is neurophysiologically more realistic. Such a model can be used to seek an answer to the question "how much of the variability observed in slow movements can be attributed to variability in sensing, in actuation and delay in feedback?" Nevertheless, the elbow model presented here has provided a closer look into the neuromuscular mechanisms of muscle actuation and how they relate to the movement speed variability observed at the kinematic level, within a constant speed movement task. It also provided an improved agreement to experimental results on isometric force variability in the literature (see Figs. 4.8, 4.9 and 4.10), as compared to others in the literature [82, 22, 81].

Chapter 5

Conclusions and Future Work

Variability in movements is a well-documented property of the human motor control system: no two actions are exactly the same, including those that are extensively practiced and repeated. Earlier theories of movement planning and execution, such as the minimum jerk theory, ignored trial-to-trial variability of the movements completely and seeked an explanation for the average movement. Variability caused by the neuromuscular system noise has constituted the basis for more recent theories of movement planning and execution, such as the minimum variance theory and the optimal feedback control model with minimum intervention principle. Even these models, however, fail to provide an explanation for increased movement intermittency and variability in slow movements.

This thesis proposes the question "can increased muscle force variability in low force levels explain increased variability or intermittency of slow movements?" Additionally, this thesis seeks an answer via both human subject experiments and a neuromuscular model of the elbow.

Chapter 3 of this thesis presented a systematic characterization of movement intermittency along the arm in natural (unperturbed) multi-joint movements with various speed conditions, through a human subject experiment with five subjects. Results of this research indicate that movement intermittency increases significantly in distal direction along the arm and with decreasing movement speed. The orientation of the movement plane failed to show a significant effect on movement intermittency. The results of this chapter are in agreement with the studies in the literature showing that larger muscles are capable of producing forces with less variability as compared to smaller muscles, due to higher number of total motor units. This result motivated a second experiment to evaluate whether a similar mechanism can be responsible of the increased movement variability in slow movements, due to low number of active motor units during slow movements.

Chapter 4 of this thesis presented results of a human subjects experiment involving a constant slow speed elbow flexion task at two different target speed levels. The experimental conditions were designed so as to alter the force requirement via resistive torque fields, but to keep the kinematics of the task the same. Results of this experiment suggest that resistive torques or forces can constitute a valid strategy and method to significantly decrease movement speed variability. This result opens up opportunities for novel methods of human skill augmentation in delicate or critical tasks such as surgery, of facilitation or accelerating the learning of a new motor skill and of improving motor rehabilitation protocols. The relationship between resistive torque levels and speed variability, however, is not monotonic. This non-monotonic relationship indicates that, in designing augmentation schemes to enhance motor skill in critical tasks or to improve motor learning or rehabilitation protocols, the amount of the resistive torques should be adjusted properly to be successful in reducing movement variability rather than amplifying it. Development and testing of such augmentation or enhancement protocols constitutes a promising direction for future research.

In Chapter 4 , a neuromuscular model of the human elbow, including motor unit pool-based dynamics, Hill-based muscle contraction dynamics and the biomechanics of the elbow provided a modeling-based approach to answer the main research question raised above. The model was driven by a simple feedback control structure with only proportional control and did not allow a source of variability other than muscle force generation. Simulations of this model predicted a monotonically increasing variability with increasing resistive torques, failing to match the experimentally observed relationship. Based on this mismatch, I concluded that movement speed variability in slow movements cannot be solely attributed to variability in the mechanics of muscle force generation. Various future directions for research are possible based on the developed model, including investigation of impedance-control or optimal control strategies in various tasks. The model can be expanded to include proprioceptive dynamics via models of muscle spindle afferents and neurophysiologically more realistic feedback dynamics, such as spinal feedback. These expanded models can be used to seek better insight into how different sources of noise in sensing, actuation or feedback demonstrate their effects in the final observation point, i.e., the movement kinematics.

Chapter 2 focused on objective measures of motor function improvement based on movements of stroke patients. Trajectory error (TE) and smoothness of movement (SM) measures, based on the minimum jerk theory, showed significant and moderate-to-strong correlations with clinical measures of motor impairment, while the correlations for the "movement speed measures", namely mean tangential speed and number of target hits per minutes, were mostly weak and failed to show statistical significance. Under the examples of SM and TE, these results indicated that it is feasible to arrive at a unified set of robotic measures that will enable objective evaluation and comparison of robotic rehabilitation programs and devices, while maintaining clinical relevance due to their correlation with widely accepted clinical measures. These results constitute an important step towards establishing a much-needed bridge between clinical and robotic rehabilitation research communities. The insight gained from this portion of my research together with the results reported in Chapters 3 and 4 can lead to design of new kinematic measures of motor function improvement with a stronger theoretical and experimental basis than existing measures.

To conclude, understanding the origins of movement variability in slow movements has important implications for motor skill learning, where movements are usually very slow at the beginning and get faster with expertise and practice, and motor function recovery, where similar observations hold. Gained insight into the mechanisms behind movement variability in slow movements can lead to methods for skill augmentation and for improved motor learning and rehabilitation protocols to be implemented via force-feedback devices. Together, the analyses, simulations, and experiments in this thesis shed light on variability in slow movements, and will inform the development of novel paradigms for robotic rehabilitation, motor skill learning and augmentation.

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