Study of Human Motor Control and Task Performance with Circular Constraints

by

Brian Wilcox

Submitted to the
Department of Mechanical Engineering
in Partial Fulfillment of the Requirements for the Degree of

Bachelor of Science in Mechanical Engineering

at the

Massachusetts Institute of Technology

June 2016

Signature of Author: ____
Department of Mechanical Engineering
May 6, 2016

Certified by: ____
Neville Hogan
Professor
Thesis Supervisor

Accepted by: ____
Anette Hosoi
Professor of Mechanical Engineering
Undergraduate Officer

Study of Human Motor Control and Task Performance with Circular Constraints

by

Brian Wilcox

Submitted to the Department of Mechanical Engineering
on May 6, 2016 in Partial Fulfillment of the
Requirements for the Degree of

Bachelor of Science in Mechanical Engineering

ABSTRACT

This thesis aims to investigate human motor control strategies. Curved constraints offer a unique opportunity to exploit forces of contact. A circular crank experiment using the MIT MANUS robot was designed in order to test how well subjects can follow a set of simple instructions to rotate the crank at various constant speeds. 10 subjects volunteered to participate in this experiment. Velocity, force, and EMG data were collected during four tasks: turning the crank at the subject's preferred or comfortable speed, turning the crank at a constant preferred speed, turning the crank at a constant preferred speed with a visual feedback display, and rotating the crank at three instructed speeds (slow, medium, and fast) with visual feedback. The coefficient of variation (CV) of the velocity for each trial was computed as a measure of performance. Statistical analysis showed that speed significantly affected CV but the direction of turning the crank, clockwise or counterclockwise, did not. The observation that CV increased as speed decreased, despite visual feedback, confirms previous studies showing that human motor control is more imprecise at slower speeds.

Thesis Supervisor: Neville Hogan
Title: Professor

Acknowledgements

I'd like to first thank my faculty advisor, Neville Hogan, who has encouraged me and helped me grow as a researcher and scientist in engineering. He has been a great influence and I am very proud to have been a part of his lab group. I'd also like to thank my graduate mentor, David Mercado, who has put in a lot of time mentoring me and helping me develop my ideas. Thanks for always being patient and understanding. I'd like to thank all of the subjects who participated in my experiments. They endured me for the time and I'm glad that everyone was in a good mood. Lastly, I'd like to thank my sister, who has been an incredible emotional support for me as I finish my undergraduate degree here at MIT.

Table of Contents

List of Figures

List of Tables

Introduction

The human body could be described as nature's most versatile engineering tool. On a daily basis, humans perform actions which reside on a continuum from significant and effortful physical motion to small and fine precise actions. An Olympic sprinter must run to the goal line with the highest speed he or she can muster. A surgeon must use his hands and operate tools in a small and confined space, taking care not to harm the patient. For the average person, daily we must move our bodies and interact with our environment in a variety of contexts – waving hello, cleaning the kitchen counter, opening a door. Certainly, these tasks have different criteria for success. Underneath "the hood", our bodies must coordinate and control these often complex movements in real time. Yet, most humans perform these tasks without a second thought. How do we manage to perform these tasks with at least some modicum of success? How do we even define success for a given task? How can we measure their performance?

1.1 Human Motor Control

Motor control refers to the process by which humans and animals use their brain/cognition to activate and coordinate the muscles and limbs involved in the performance of a motor skill. In the case of the Olympic sprinter, he coordinates the movement of his legs as well as his arms while his pumping muscles propel him forward to the finish. More accurately, he coordinates all the muscles involved in the process of running, from the flexion and extension of his ankles all the way to the flexion and extension of his shoulder joints. In the case of the surgeon, he must coordinate the motion of his shoulder, elbows, wrist, and fingers as he carefully maneuvers near sensitive tissues of a patient. It is very likely he may also interact with some sort of surgical tool, such as a forceps, in order to complete the surgery. In such cases, he is constrained by the geometry of the forceps in order to perform the task. His body must then coordinate itself in a way that accommodates, not necessarily naturally, the design and use of the tool. A daily action of opening a door presents a simple example of one challenge of movement control. A common doorknob requires that the knob be turned either clockwise or counter-clockwise before the door can be pushed open. Here the control of the muscles required to turn a human's wrist while simultaneously pushing or pulling the handle illustrates the importance of coordinated efforts to perform a task. Only a specific and clearly defined set of motions could complete the task successfully. These examples highlight how essential this motor control is to the performance of many tasks that people encounter.

1.2 Evaluation of Human Performance for Movement Tasks

For any given task, there should be exhibited some evidence of the performance or success of that task. Commonly, the criteria for success is simply completion. However, when answering the question of *how well* did someone perform a task, other factors should be considered. Back to the sprinter, how well did he control his body movement in order to reach his maximum potential speed? How much control was required for the surgeon to conduct small movements in order to precisely sew the stitches and avoid causing harm to the patient's organs? In many instances, these questions of performance are vital to the task at hand. Evidence of this performance typically comes in the form of measurements of explicit signals of the body or interaction with the environment – position, velocity, force, etc. Comparing these physical outputs of human motor control against the desired outcome or criteria offer us a way to evaluate and interpret the success of performing a given task.

1.3 Constrained Motion

Human motor control has been studied to a significant extent for unconstrained conditions. For the rehabilitation of stroke patients, robotic therapy for unconstrained upper body motions has been shown to be successful. Studying human physical interaction with physical constraints, however, may exploit human motor behavior that is distinct from that under unconstrained conditions. Tool use is a common daily activity for many people, and it requires physical interaction with the kinematic constraint imposed by the tool. The study of motor behavior against kinematic constraints could provide insight into an appropriate model for human interaction under these complex movement conditions.

1.4 Thesis Scope

The primary purpose of this thesis is to study and present results on human performance of a set of circularly constrained tasks. This study specifically looked at curved constrained motion of a robotic virtual crank.

This thesis aims first to characterize the limitations and strengths of human motor capabilities interacting with a physical constraint. This evaluation of human performance is important before one aims to understand the mechanisms by which this performance is achieved. In other words, this thesis attempts to answer *what* before answering *how* or *why*. While the motivation, experimental setup, and initial findings will be presented on the investigation of these control strategies, in depth analysis will be deferred for future work.

Section 2 of this thesis presents the motivation behind this thesis and its experiment. An overview of the PhD thesis of Joe Doeringer is also presented and his crank experiment highlighted as a direct motivation for this study.

Section 3 discusses the experimental goals, experimental apparatus (MIT MANUS, EMG), and the procedures of the experiment that were the central study of this thesis.

Section 4 presents the results of the experiments, with particular focus on the primary purpose introduced above. Some initial findings regarding other data collected in the experiment will also be presented. A discussion of the limitations of MIT MANUS and the experimental setup is also presented.

Section 5 summarizes the thesis and draws conclusions.

Motivation

The experiment of this thesis was designed to address multiple facets of human movement control. In this section will be presented the guiding motivations behind the chosen experiment. The focus and analysis of this thesis includes only some, not all, of the goals intended by the original experiment design.

2.1 Hypotheses of Human Control Strategies

A few hypotheses of the strategy used for controlling physical interaction have been proposed. The first hypothesis poses that humans attempt to visualize and execute hand control from the perceived visualization of a movement pattern. Another hypothesis presents the case that humans minimize muscle effort to perform movement along a constraint by taking advantage of workless forces that, paradoxically, reduce the muscle effort required to produce the motion [1]. A third hypothesis states that humans rely on control using dynamic primitives (discrete submovements, rhythmic movements, and mechanical impedance for example) to reduce the required knowledge to perform movement with a kinematic constraint. [2]

2.2 Doeringer Thesis Overview

In 1999, Joseph Doeringer submitted his PhD thesis to the Department of Mechanical Engineering at MIT on an Investigation into the Discrete Nature of Human Arm Movements. In his thesis, explored the topic of movement intermittency. Doeringer explains movement intermittency [3]:

> Movement Intermittency refers to variability of movement kinematics that is not attributable to either the task or the biomechanics of the musculoskeletal system.

This intermittency suggests that humans at times perform discrete movements that are not beneficial to complete a given task. Supposing this is true, one might question the origin of this intermittency. Another question may ask how much can these intermittent movements be reduced. The literature review performed by Doeringer revealed three unanswered questions which he aimed to address in his own research:

1. To what degree can movement intermittency be extinguished?
2. Is movement intermittency visual in origin?
3. Is movement intermittency exploited as a strategy in dealing with curved mechanical constraints?

In a single-joint experiment, he came to an answer for the first two questions. He concluded that movement intermittency could not be completely extinguished and that this intermittency was not exclusively visual in origin. In order to address the third question, Doeringer designed a curved mechanical constraint experiment involving the rotation of a horizontal crank. He concluded that while movement intermittency was still prevalent, subjects exerted some level of control over their movement profile when instructed to perform a specific task. It is this experiment which is the model for the experiment performed in this thesis.

2.3 Doeringer Crank Experiments

Doeringer wanted to address the issue of movement control in the context of curved constraints. A curved constraint offers a continuous motion that involves coordination of multiple arm joints and muscles. With visual feedback, or lack thereof, he could address the source of this intermittency, and with a constant radius, he could properly create tests of a subject's control of speed without the confound of a non-uniform rotational inertia opposing the subject's movements that might introduce speed fluctuations. Thus, he designed a crank experiment, where he set up a horizontal crank. The crank hardware included a handle, a force transducer on the handle, and an encoder for position measurements.

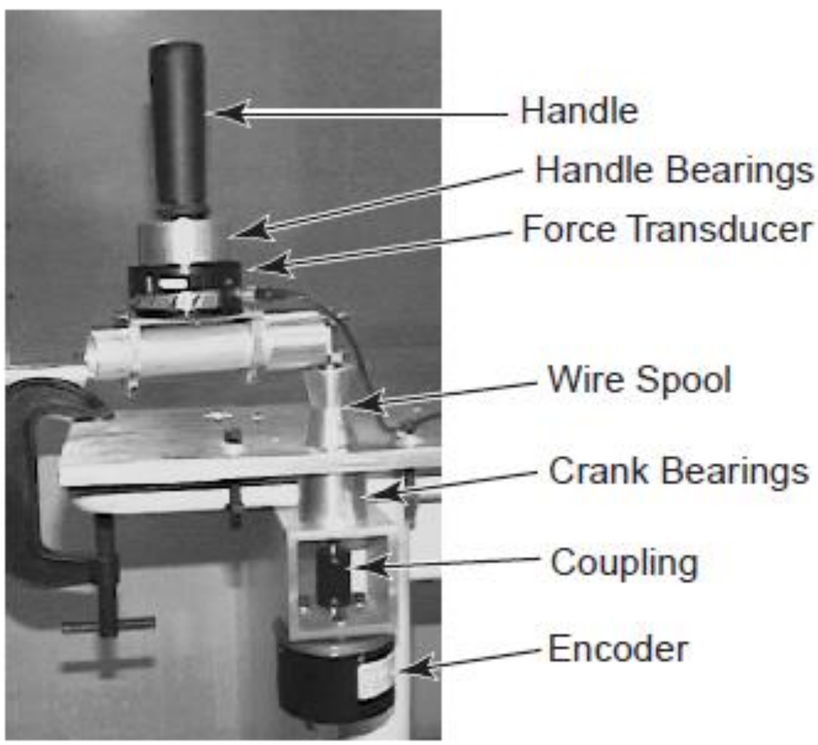

Figure 2-1: Photograph of crank experiment hardware.

All subjects in his experiment were male, right handed, and in good health. Doeringer conducted a series of experiments with these subjects rotating the handle while wearing EMG sensors on the biceps and triceps. A summary of his crank experiment is below:

Subjects were asked to grasp the handle and once instructed, attempt to rotate the crank at a constant speed indicated by a visual display. It showed real time velocity as vertical movement of a cursor. The horizontal axis was time. A horizontal line displayed target velocity. The target velocities for the trials ranged between slow, medium, and fast. The slow velocity was 0.075 revolutions per second, the medium velocity at 0.5 revolutions per second, and a fast speed of 2 revolutions per second. On randomly selected trials, the visual display of the subject's real time velocity vanished on the screen such that the subject no longer received visual feedback of their speed. Subjects were instructed to continue moving at constant speed. These trials were considered "blind".

Extensive qualitative and statistical analysis was performed in order to compare trends between the numerous trials. A further discussion of his relevant results will be presented in the results section of Section 4.

2.4 Focus and Extension of Crank Experiment

This thesis designed a new crank experiment modeled after the crank experiment performed by Joe Doeringer in his PhD thesis. The experiment utilized a robotic simulated crank instead of a physical crank like the one used in Doeringer's tests. Doeringer hypothesized about the benefits of using a robot to simulate the crank. In his future work section, he suggests that a more capable robot than those of his day might offer more flexibility to modify parameters of the experiment. He was, however, very wary of the challenges presented by using a robotic crank as opposed to a real physical one. A major goal of this thesis is to study the merits and limitations of using a robotic simulated crank to perform similar experiments.

2.4.1 Robotic Crank Challenges

Many of the challenges of Doeringer's day to implementing a robotic solution to his crank experiment have largely been addressed by more modern robots. For example, he was concerned about high stiffness exciting modes within the robot without the capacity for enough damping to stop the machine from oscillating. This issue, an important one, is largely resolved by the capabilities of more modern actuators. Similarly, many of his other concerns are resolved by more modern technology.

However, a large challenge that still remains, even for the experiments in this thesis, is the non-uniform inertia of the robot arm. This means that, as Doeringer put it, when moving through particular parts of the workspace, the robot handle tended suddenly to feel heavy, potentially causing the subject to change strategy. This rendered it difficult to identify the source of a subject's movement control strategies.

For this reason of non-uniform inertia, the focus of data analysis in this thesis will be on slower speeds. At slow speeds, inertial effects become negligible, as do all other dynamic effects, including the slow response of muscle.

2.4.2 Velocity Profile and Fluctuations

As mentioned in the scope of this thesis in section 1.5, the primary purpose of this thesis is to evaluate human motor control performance. While the experiment performed and discussed in this thesis provide the data groundwork for more in depth analysis of human motor strategies, this thesis will focus on the accuracy and precision of controlling velocity and any observable trends in the velocity profiles of subjects rotating the robotic crank.

The velocity profiles should provide both quantitative and qualitative information about the pattern of subject performance around the crank. Does the velocity rise or fall at particular locations around the circle? Are there repeatable patterns? Does the speed around the crank affect the velocity profile? Does visual feedback affect the pattern?

Velocity fluctuations inform the precision of human performance. Particularly, the ratio of its standard deviation to its mean, known as the coefficient of variation (CV), gives a strong dependent factor to weigh against independent factors such as direction, speed, or visual feedback.

The analysis, discussed in section 4, serves to lay the foundation for future work that connects the factors that affect performance of human to the underlying control strategies that humans use.

Experiment

Ten subjects (3 female, 7 male, all over 21 years of age) volunteered for a 1.5 hour study on human movement control along a curved constraint. Subjects reported no history of biomechanical or neurological disorders. All subjects gave informed consent following procedures approved by MIT's Committee on the Use of Humans as Experimental Subjects. The experiments were performed individually over the span of two weeks. All subjects performed a series of tasks using MIT MANUS, a robotic platform originally designed for rehabilitation therapy. The experiment tasks were designed to examine hypotheses relevant to human movement control. The content of this thesis focuses on select hypotheses while only briefly touching others that remain for future work.

3.1 Experiment Goals

For the sake of clarity, this section defines the goals and expectations of the experiments in this thesis. Key questions were determined in order to motivate both the design and analysis.

3.1.1 Performance of Velocity around Crank

In order to evaluate the performance of human motor control on a crank, the experiment should set a criterion for success that is conveniently measured and intuitively communicated between both subjects and the researcher. Therefore, the velocity of the crank was chosen as the instructed variable. The experiments aimed to determine what factors affect the precision of the subjects' velocity control when turning a crank. The experiments were designed to address the following questions:

1. How well do subjects maintain an instructed constant speed?
2. Is subject performance affected by visual feedback?
3. Is subject performance affected by direction, clockwise or counterclockwise?
4. Is subject performance affected by the instructed speed, faster or slower?

3.1.2 Investigation of Control Strategies through Force and Muscle Activity

Though this thesis does not focus on analysis of control strategies that humans use to interact with a curved constraint, the experiment was designed to provide data that may be further analyzed for that purpose. Thus, measuring force and muscle activity through EMG may provide insight into the potential strategies humans utilize. The velocity measurements may conclude how well subjects can perform the instructed tasks, but these additional measurements may identify underlying strategies humans use or perhaps fundamental limitation of those strategies.

3.2 MIT MANUS

3.2.1 MANUS History

MIT MANUS is a robotic system originally developed more than 20 years ago at MIT as the Master's thesis of Jain Charnnarong in MIT's Department of Mechanical Engineering [4]. The robot was designed to assist rehabilitation of stroke patients who struggle to regain mobility in their arms. With a joystick-like handle at the end of its arm, the MANUS enables patients to receive robot-assisted therapy with the programs that guide the patient's arm through a variety of movements and tests. A display monitor at the head of the system enables visual feedback for patients as they conduct a series of therapy programs. MIT MANUS achieved much success in robot-assisted therapy [5]. A commercial counterpart was developed by the company Interactive Motion Technologies. Newer models exist today, but the experiment in this thesis was performed using an older model currently housed in in the MIT Newman Laboratory for Biomechanics and Human Rehabilitation.

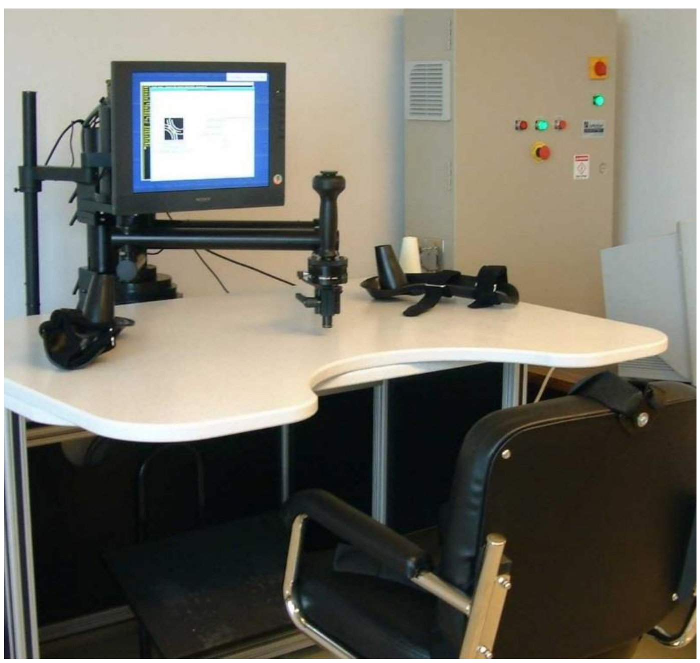

Figure 3-1: The MIT MANUS workbench and monitor display

3.2.2 Description of Robot

MIT MANUS is a two arm planar robot with 2 degrees of freedom in both x and y. The upper arm and lower arm of the robot are 41 cm and 51cm long, respectively. The links are driven by two electromechanical actuators, enabling high performance impedance control. On the end effector is a handle mounted on a force transducer which measures force in x, y, and z directions as well as torques about 3 axes. Encoders at the actuators provide position and velocity measurements. The arms hang over a workbench with a semi-circular space at one end for patients to attend the machine.

MIT MANUS is programmed using a combination of C and Tcl/Tk programming scripts. Commands can be written to the motors for special applications as well as to the visual display of the monitor.

3.2.3 Virtual Crank

The experiments in this thesis are modeled after the crank experiments performed by Doeringer in his PhD thesis. In his experiments, he used a real crank in which subjects rotated. For these experiments, the MANUS robot was programmed to simulate the feel of a real crank – a virtual crank through impedance control [6-8]. This was achieved by setting a fixed radius of a circle such that the subject could only move the handle around that radius. Strong resistance to radial movement of the handle inside or outside of the fixed radius was provided by programming high stiffness and damping in that direction. There was no programmed stiffness or damping to resist motion of the handle tangent to the radius of the circle. The table below summarizes the settings of the virtual crank during the experiments of this thesis.

Table 3-1: Impedance Parameters of the MIT MANUS Virtual Crank

Radius	Stiffness	Damping
0.1 m	3000 N/m	100 Ns/m

3.3 Experimental Setup

3.3.1 Subject Setup

Subjects were asked to sit in a chair in front of the work bench for the MIT MANUS robot as shown in Figure 3-2. EMG surface electrodes were attached to 7 muscles along the right arm. Once the EMG sensors were placed, back straps on the chair were pulled over the subjects' shoulders in order to discourage and reduce torso movement during the trials. The subjects' arm was supported by an arm harness hanging from the ceiling via a long Velcro strap. The subjects were asked to grasp the handle of the MIT MANUS robot while the arm harness was adjusted until the subject felt comfortable. Subjects wore a wrist brace in order to discourage and reduce wrist movements during the experiments. A wooden frame was placed over the virtual crank area with a black cloth sheet draped over the frame in order to block visual view of the subject's arm movements. Its purpose was to prevent the subject from seeing his or her movement and rather focus on the feeling of the constraint and the visual display.

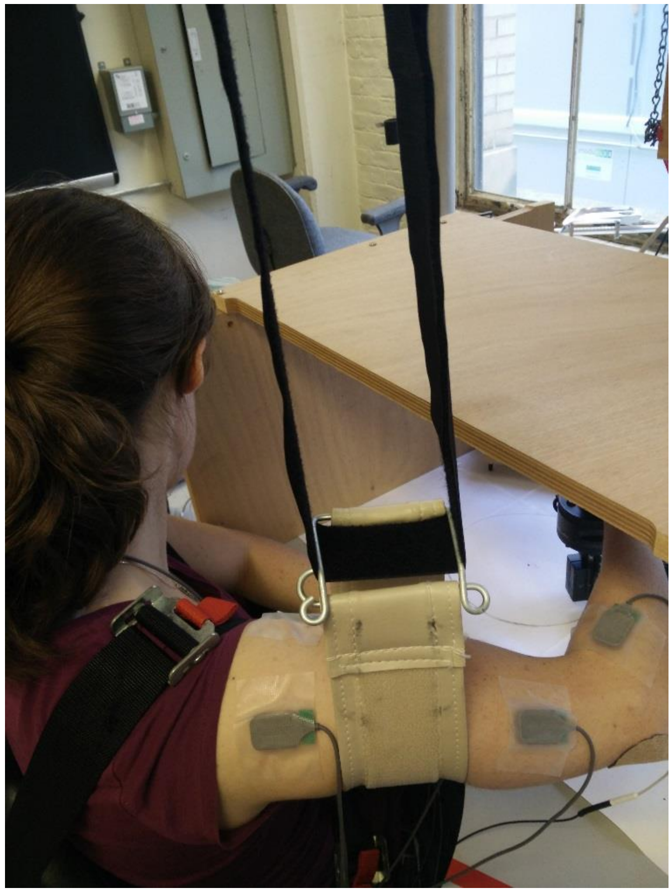

Figure 3-2: Setup of experiment subject. A shoulder harness kept subject's back straight and in contact with the chair back while an arm harness provided shoulder support. A black cloth was draped over the wooden frame to prevent subject from seeing hand motion.

3.3.2 Visual Display

The monitor in front of the patient was used for many (but not all) of the experiments. When in use, the monitor showed a visual display of the subject's real time velocity both numerically and indicated by a red cursor on the screen. Vertical motion of this cursor was proportional to speed; its horizontal motion was proportional to time. A static horizontal green line was also displayed on the screen to represent a target velocity. Subjects could visualize their speed relative to the static green line. A counter on the screen also indicated to the researcher the number of revolutions around the virtual crank.

3.4 EMG

This experiment used an EMG device, the Delsys Myomonitor IV, to monitor and record muscle activity for seven muscles along the subject's right arm and to synchronize data collected between the EMG and data collected form the MIT MANUS.

3.4.1 Measuring Muscle Activity with EMG

Electromyography (EMG) is the study of muscle function and activity through electrical signals produced by the muscles. When muscles contract, muscle fibers generate localized electrical signals. These signals can be picked up by a recording device, which detects the electric potential generated by the muscle cells. Surface electrodes placed on the skin detect these impulses, which can be used to study the level of activity of various muscles in the body.

3.4.2 Arm Muscles and Function

In this experiment, seven electrodes were placed on seven muscles along the subject's right arm. The muscles identified for this experiment were: brachioradialis, biceps, triceps, trapezius, anterior deltoid, posterior deltoid, and pectoralis major. Each muscle contributes differently to different arm movements. In order to complete a planar rotation of the crank, subjects are required to perform elbow flexion/extension and shoulder horizontal abduction/abduction. In order to perform these motions at the joint, particular muscles must contract and extend. As a motivation of this study, the pattern of activity and the coinciding angular position of the crank around the circle may identify how humans coordinate these muscles to perform the desired task. The table below summarizes the muscles measured and their corresponding behavior [9].

Table 3-2: Muscles of the arm and function

Muscle	**Arm movement responsible for ***
Brachioradialis	Elbow flexion, Elbow extension
Biceps	Elbow flexion
Triceps	Elbow extension
Anterior Deltoid	Horizontal adduction
Posterior Deltoid	Horizontal abduction
Pectoralis Major	Horizontal adduction
**Trapezius	Shoulder flexion

*This is not an exhaustive list of every arm movements that each muscle is responsible for. This table only includes arm movements relevant to this experiment
**The trapezius muscle activity was measured as a way to determine whether the subject used extraneous effort to lift the handle (which is not a desired planar motion to rotate the crank). The shoulder harness was provided to discourage this movement.

Because these electrodes are placed on the skin, proper placement is required to record the intended muscle. Careful attention was taken to place each sensor and verify muscle activity on the EMG device before testing began. Figure 3-3 shows the placement of EMG surface electrodes on a subject.

Figure 3-3: Image of EMG placement on a subject's right arm

3.4.3 EMG Synchronization

In order to understand the pattern of muscle activity and how it related to the speed and crank position, the data from the EMG device was synchronized with data from the MIT MANUS robot. Because no interface or direct method to synchronize the EMG data was known to this researcher, an ad hoc solution was built to solve the synchronization problem.

A breadboard was fastened to a wooden plank which stood on four 1.5 inch bolts. A red (infrared) laser was mounted above the circuit such that the intensity of the light was focused on the head of the phototransistor. The leads of an EMG electrode were connected to the circuit such that when light becomes incident on the phototransistor, the EMG device reads "zero", but when the laser is covered (or the phototransistor is covered), the EMG device reads a strong signal.

A wooden cylinder, 1 cm in diameter and 3 inches in height, was attached to the handle of the robot end effector. To synchronize the robot with the EMG, the circuit was placed under the boxed wooden frame and black cloth sheet near the crank. The position of the phototransistor was calibrated using the robot's encoder feedback such that the position at which the wooden cylinder interrupted the laser (and thus caused a spike in electrical activity of the EMG electrode) was known. Later, in data processing, this signal was used to synchronize the first pass of the subject past the calibration position along the crank circle.

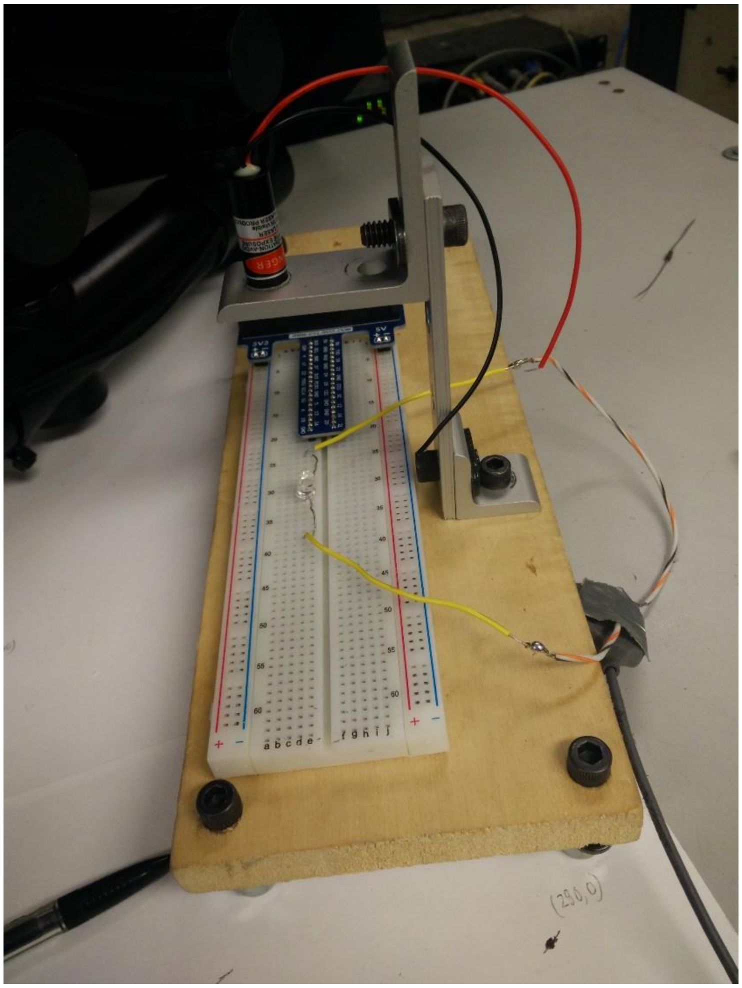

Figure 3-4: Phototransistor circuit for EMG Synchronization

3.5 Tasks

The tasks presented in this section mirror experiments performed by Doeringer in his PhD thesis research. Subjects were asked to perform 4 sets of tasks rotating the robotic virtual crank. These tasks test the questions proposed in section 3.1.1. Each task was performed in both the clockwise and counter-clockwise direction. The table below provides an overview of the tests performed.

Table 3-3: Task order and Instructions for Crank Experiment

Task Order	Task Instruction
1	Turn the crank at preferred rate (but do not explicitly ask for constant speed).
2	Turn the crank at preferred constant speed.
3	Turn the crank at preferred constant speed with visual display of speed
4	Turn the crank at 3 instructed speeds: fast, medium, slow

*Tests were conducted for both CW and CCW
**Direction order of each task was randomized
***Trials lasted for 60 seconds (120 seconds for slow speed instruction)

3.5.1 Preferred Speed Tests

The experiments at a subject's preferred speed aimed to understand the subject's responses to turning the crank at a rate that is comfortable and natural. Performing the tests with and without visual feedback helped identify whether it improved performance or evoked a change of strategy.

3.5.1.1 Preferred Rate Without Visual Feedback (Blind)

In the 1st task, subjects were asked to turn the virtual crank at a preferred or comfortable rate. Caution was taken not to suggest that they should maintain a constant speed. The subjects were asked to choose whichever direction (CW or CCW) they felt most comfortable to begin.

3.5.1.2 Constant Preferred Speed Without Visual Feedback

The 2nd task was also a blind test (i.e. no visual feedback), where subjects were instructed to rotate the crank at their preferred speed AND keep it constant. This instruction differs from the first test in that subjects were told to maintain their speed constant for the entirety of the trial. The order of CW or CCW direction for each subject was selected at random.

3.5.1.3 Constant Preferred Speed With Visual Feedback

The instructions for the third task were to rotate the crank at their preferred speed given visual feedback on the monitor. The monitor was turned on for this task, showing a red line that indicated the subject's real time velocity during the test. Their goal was to match their red line velocity to a green constant horizontal line which represented their target velocity. This target velocity was calculated from the mean of the subject's previous preferred rates in the first two tasks. The screen provided an intuitive interface for subjects to know in real time whether their speed was above, below, or matching the target velocity. The order of CW or CCW direction for each subject was selected at random.

3.5.2 Slow, Medium, Fast Speed Tests

The last set of task instructions for subjects concerned a subject's performance in rotating the crank at three predetermined rates: slow, medium, and fast. Table X provides an overview of these rates.

Table 3-4: Target Speed Rates

Rate	Speed (rev/s)	Speed (mm/s)
Slow	0.075	47
Medium	0.5	314
Fast	2	1257

These rates, also used by Doeringer in his experiments, represented the extremes of speed for this experiment. These tasks were performed to help identify the effect of speed on the velocity performance and control strategy of subjects. All of these tests were performed in both CW and CCW directions in a random order for each subject. The order of slow, medium, or fast was also random across each subject.

3.6 Data Analysis Methods

The experiment performed in this thesis had independent factors of instruction (preferred vs constant), direction (CW or CCW), speed (slow, medium, fast), and visual feedback (on or off). In order to evaluate the performance of subjects asked to rotate the virtual crank at various constant speeds, the coefficient of variation was computed as the dependent factor. The ANOVA test and t-tests were conducted in order to present the statistical significance of these findings.

Matlab was used for all processing and calculations in this analysis.

3.6.1 Coefficient of Variation

The coefficient of variation is a statistical measure of the dispersion or spread of data relative to its mean. In other words, it's a measure of how precisely data points are centered around the mean. The coefficient of variation (CV), c_v , is computed as the ratio of the standard deviation, σ , of a data set to its mean, μ.

$$c_v = \frac{\sigma}{\mu}$$

The CV has no units.

3.6.2 Paired t-test

A paired t-test is a statistical test that compares the means of two data samples which are correlated in some way. This test is called "paired" because it expects that the two data sets are dependent in some way. The result from a paired t-test tells whether the two sample means are significantly statistically different or not. The significance level is determined by the researcher, but a typical default of 5% significance level is common, suggesting that there is up to 5% risk that the means are actually statistically equal. The paired t-test is a function of the mean difference, the sample variance, and the sample size. Matlab provides a function ttest, which shows the results of the paired t-test.

3.6.3 Two-Way Analysis of Variance (ANOVA)

The two-way analysis of variance (ANOVA) is a method which compares the mean difference between data sets which may be influenced by two independent factors. This ANOVA test can inform whether there is interaction between the two independent variables (i.e. how much does the change in one variable affect the contribution by the other variable). Also, the ANOVA test can tell whether either independent variable is statistically significant to the mean difference of the data sets. Matlab provides a function, anova2, which performs a two way analysis of variance on sets of data. The output of the function is the p-values which represent the significance of the comparison. Again, a 5% significance level is common. One null hypothesis of the ANOVA test is that the all variations of an independent variable have an equal mean. The other null hypothesis of the ANOVA test is that the response mean for a variation of one independent factor does not depend on the variation of the other factor.

3.6.4 EMG Data

The EMG activity measured from the Delsys Myomonitor IV was imported into Matlab and normalized by the maximum EMG signal found for each muscle for each subject. A moving window RMS (root mean square), with window size of 5, was computed to average the EMG signals and match the sample rate to that of the data from the MIT MANUS robot. The data was then filtered using a Butterworth filter with an order of 4 and cutoff frequency of 5 Hz and sampling frequency of 1000 Hz. These filter parameters were considered appropriate for measurement of EMG muscle activity [10]. The synchronization signal, discussed in section 3.4.3, was used to determine the start and end frames of data from the robot. EMG data was then averaged over the number of revolutions for each trial and plotted as a function of angular position (or crank position).

Results

4.1 Statistical Results

4.1.1 Preferred Speed Results – Pilot Investigation

The preferred speed tests results are shown below. The graph in Figure 4-2 is presented as an observational study followed by a table of t-tests between the three preferred speed tasks.

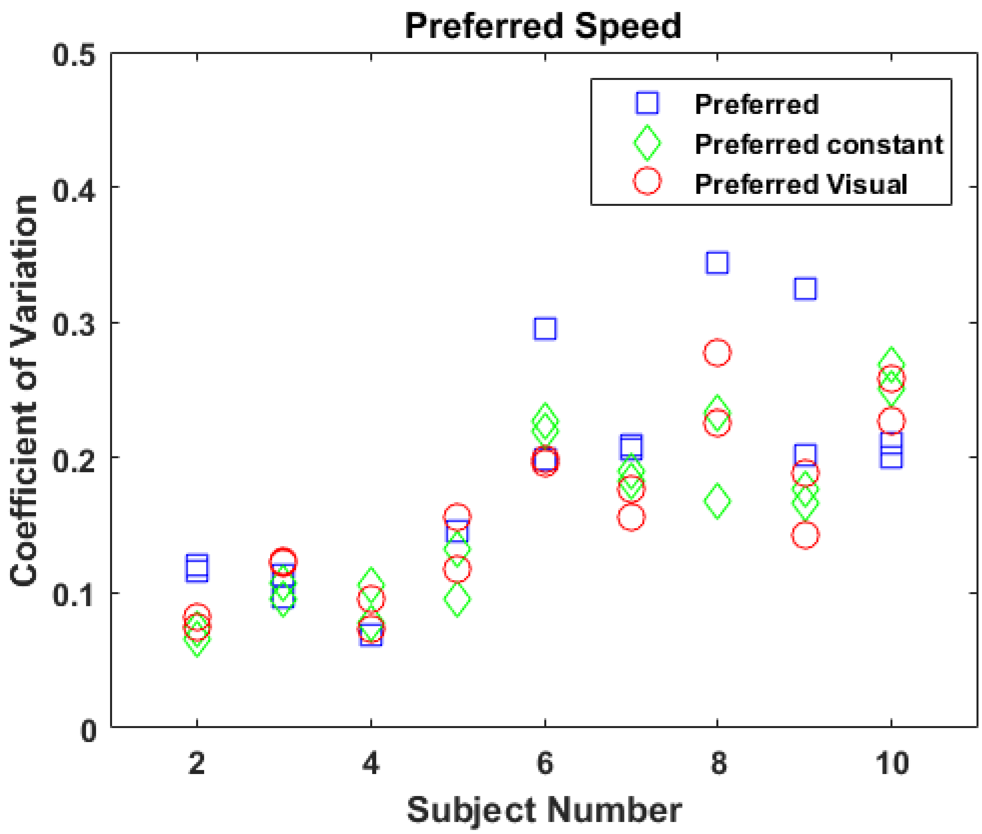

Figure 4-1: Graph showing the preferred, preferred constant, and preferred visual CV by subject number

Table 4-1: Paired t-Tests for Preferred Speed

Paired t-test (p-value)	Preferred	Preferred Constant	Preferred Visual
Preferred	-	0.0800	0.0864
Preferred Constant	0.0800	-	0.7050
Preferred Visual	0.0864	0.7050	-

*Yellow – Does NOT reject null hypothesis (means are equal) i.e. NOT statistically significant
**Significance was evaluated at the 5% significance level for all t-tests.

4.1.2 Slow, Medium, Fast Speed Results

The mean and coefficient of variation (CV) for each trial were computed. Figure 4-1 shows how the CV varies with mean velocity.

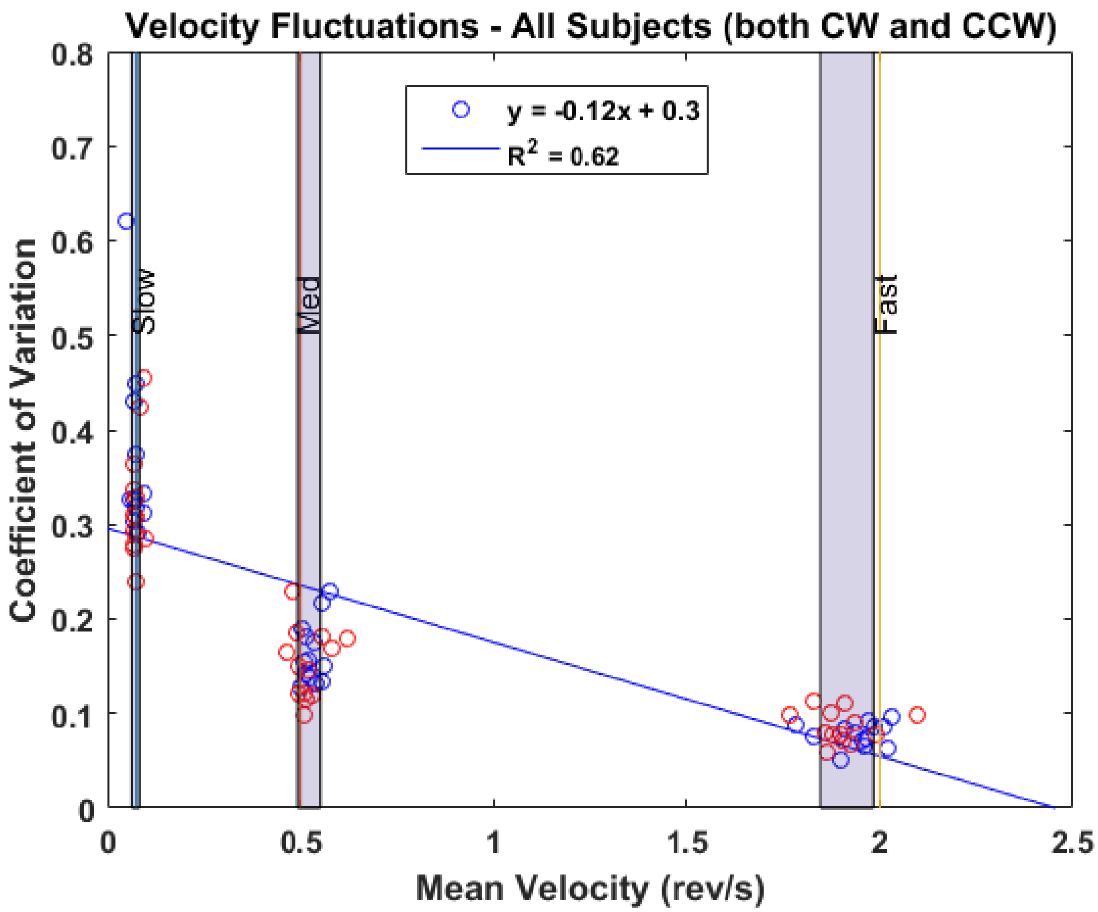

Figure 4-2: Graph of coefficient of variation (CV) vs for mean velocity slow, medium, and fast trials. The vertical lines indicate the instructed speed (slow, medium, fast). The light blue bands at each instructed speed represent plus or minus one standard deviation from mean velocity of the subjects. Each circle represents a separate trial. CW trials are shown with blue circles while CCW trials are shown with red circles.

The results of the two-way ANOVA test and t-tests are shown in the tables below.

Table 4-2: ANOVA Test results for Slow, Medium, Fast Speeds

ANOVA Test Effect	p-value
Direction (CW vs CCW)	0.1811
Speed (Slow, Medium, Fast)	0
Interaction Between Direction and Speed	0.1701

*Yellow – Does NOT reject null hypothesis (means are equal) i.e. NOT statistically significant
**Blue – rejects null hypothesis (means are equal) i.e. statistically significant
***Significance was evaluated at the 5% significance level for ANOVA test.
.

Table 4-3: Paired t-Tests for Slow, Medium, Fast Speeds

Paired t-Test (p-value)	Slow	Medium	Fast
CW v CCW	0.0707	0.3089	0.0780
Slow	-	6.7541e-14	6.5278e-15
Medium	6.7541e-14	-	2.6053e-10
Fast	6.5278e-15	2.6053e-10	-

*Yellow – Does NOT reject null hypothesis (means are equal) i.e. NOT statistically significant
**Blue – rejects null hypothesis (means are equal) i.e. statistically significant

The table and graph below summarize the mean results of the coefficient of variation across the two independent factors.

Table 4-4: Summary table of mean coefficient of variations per condition

Coefficient of Variation	Slow	Medium	Fast
CW	0.3652 ± 0.0898	0.1635 ± 0.0325	0.0760 ± 0.0140
CCW	0.3221 ± 0.0613	0.1524 ± 0.0370	0.0863 ± 0.0168
Both CW and CCW	0.3437 ± 0.0785	0.1580 ± 0.0346	0.0810 ± 0.0160

*Values shown in mean ± one standard deviation

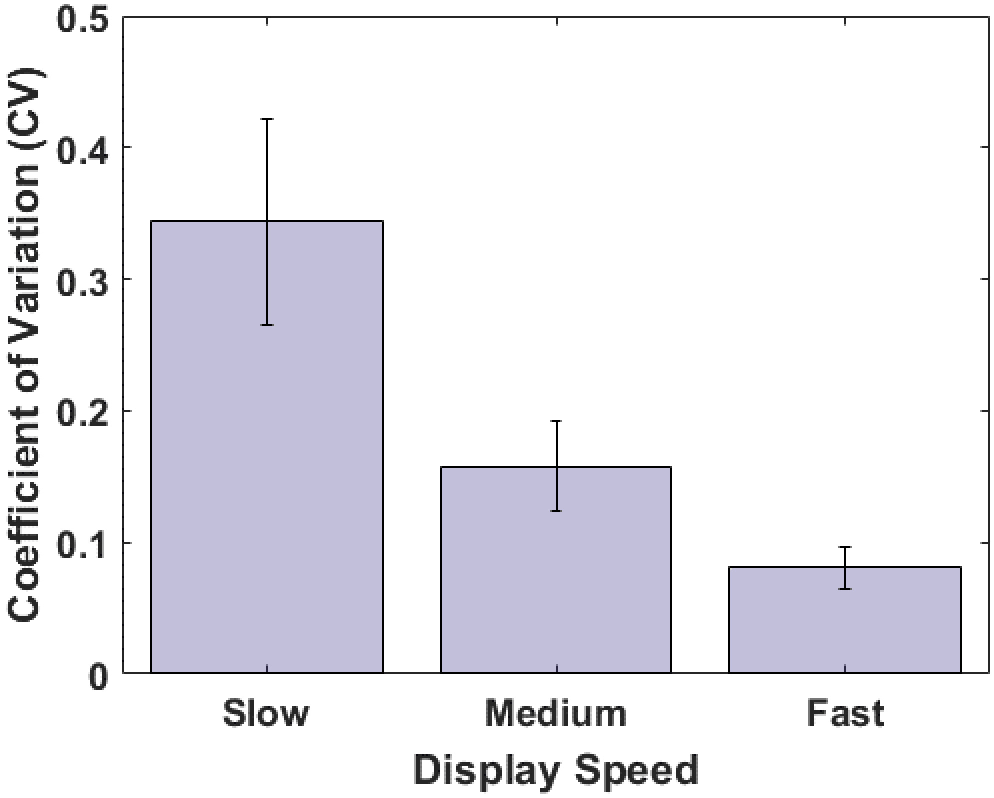

Figure 4-3: Graph of Mean CV for Slow, Medium, and Fast Speeds

4.2 Velocity Profiles

Velocity data was averaged over the number of revolutions performed in each trial and plotted as a function of angular position (or crank position) along the crank. Comparisons to velocity profile data from Doeringer's thesis are provided where relevant.

4.2.1 Preferred Speed Profiles

Sample velocity profiles from two subjects performing task 2 (preferred constant without visual) and task 3 (preferred constant with visual) are shown.

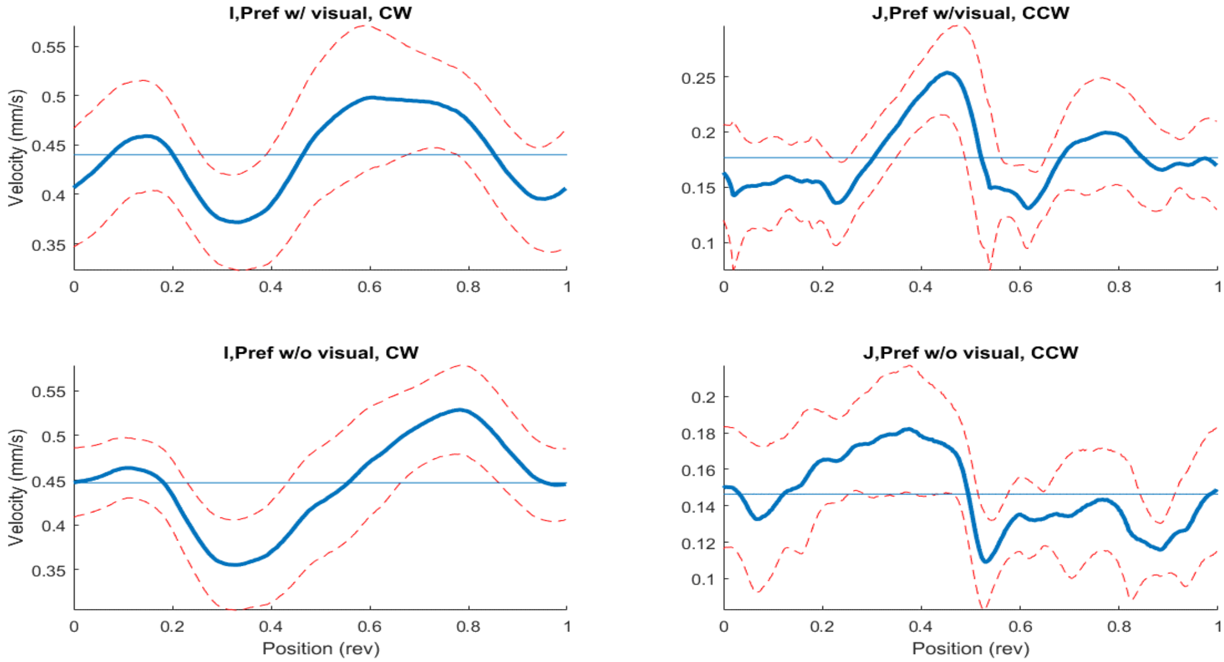

Figure 4-4: Graph of Tangential Speed vs Crank Position for Preferred Speed (with and without visual feedback, CW, and CCW) Data from two subjects, I, and J, are shown.

4.2.2 Slow, Medium, Fast Speed Profiles

Sample plots of three subjects, G, I, and J, are presented for the instructed speed at slow, medium, and fast speeds.. The first plot below shows a representative plot from one subject of how the velocity varied with time for the various instructed speeds. The remaining plots in this section show how the velocity varies with crank position for multiple subjects. The plots always follow the order: CW on top, CCW on bottom.

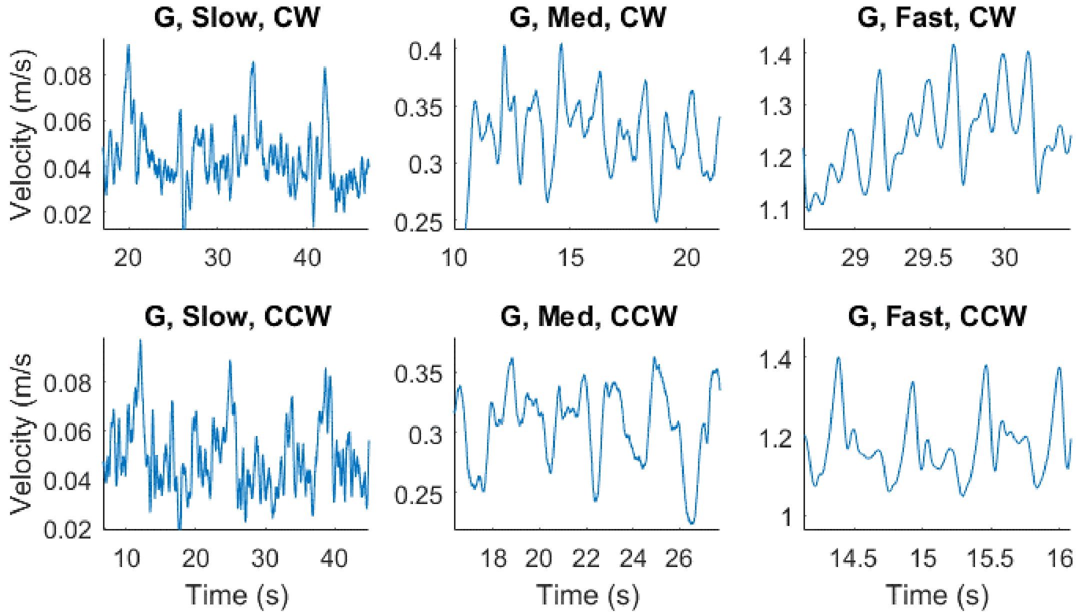

Figure 4-5: Graphs of Tangential Speed vs Time for Slow, Med, and Fast Trials (CW and CCW). The slow instructed speed was 47 mm/s (0.075 rev/s). The medium instructed speed was 314 mm/s (0.5 rev/s). The fast instructed speed was 1257 mm/s (2 rev/s).

The following plots show velocity profiles comparing Doeringer plots and the plots from this experiment. The velocity is plotted against crank position, Note that in the plots from Doeringer, the error bars in the graphs represent the standard error while the error bars in the plots from this experiment show the standard deviation. While the units of the x-axis of both Doeringer's plots and those of this experiment is revolutions, the y-axis are different. The mean velocity in the vertical axis for Doeringer's results is represented in revolutions/second, however, the velocity in this experiment is represented in meters per second.

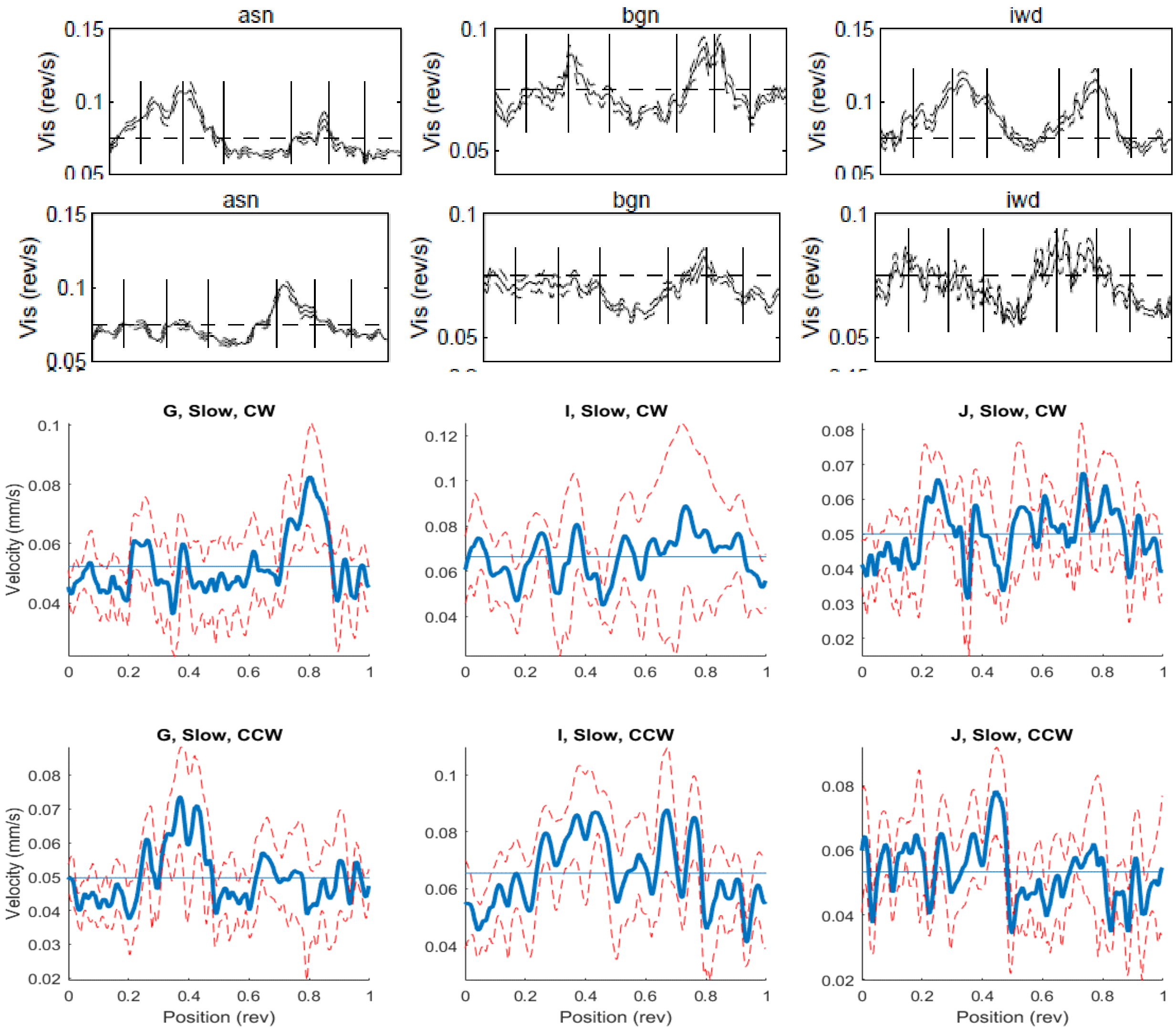

Figure 4-6: Graphs of Tangential Speed vs Crank Position for Slow (CW and CCW) trial. Comparison of results reported by Doeringer (top) and this experiment (bottom).

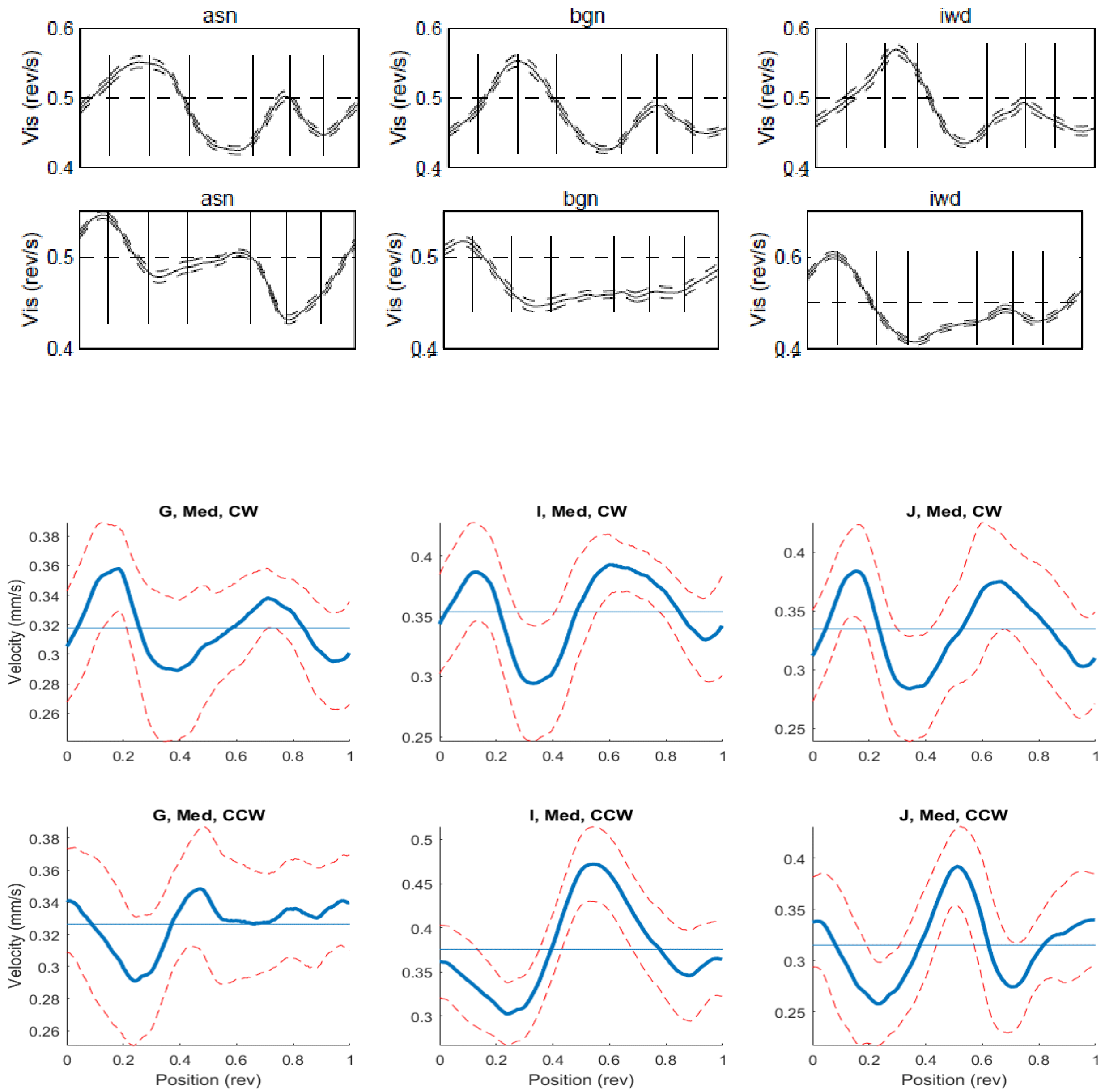

Figure 4-7: Graphs of Tangential Speed vs Crank Position for Medium (CW and CCW) trials. Comparison results reported by Doeringer (top) and this experiment (bottom).

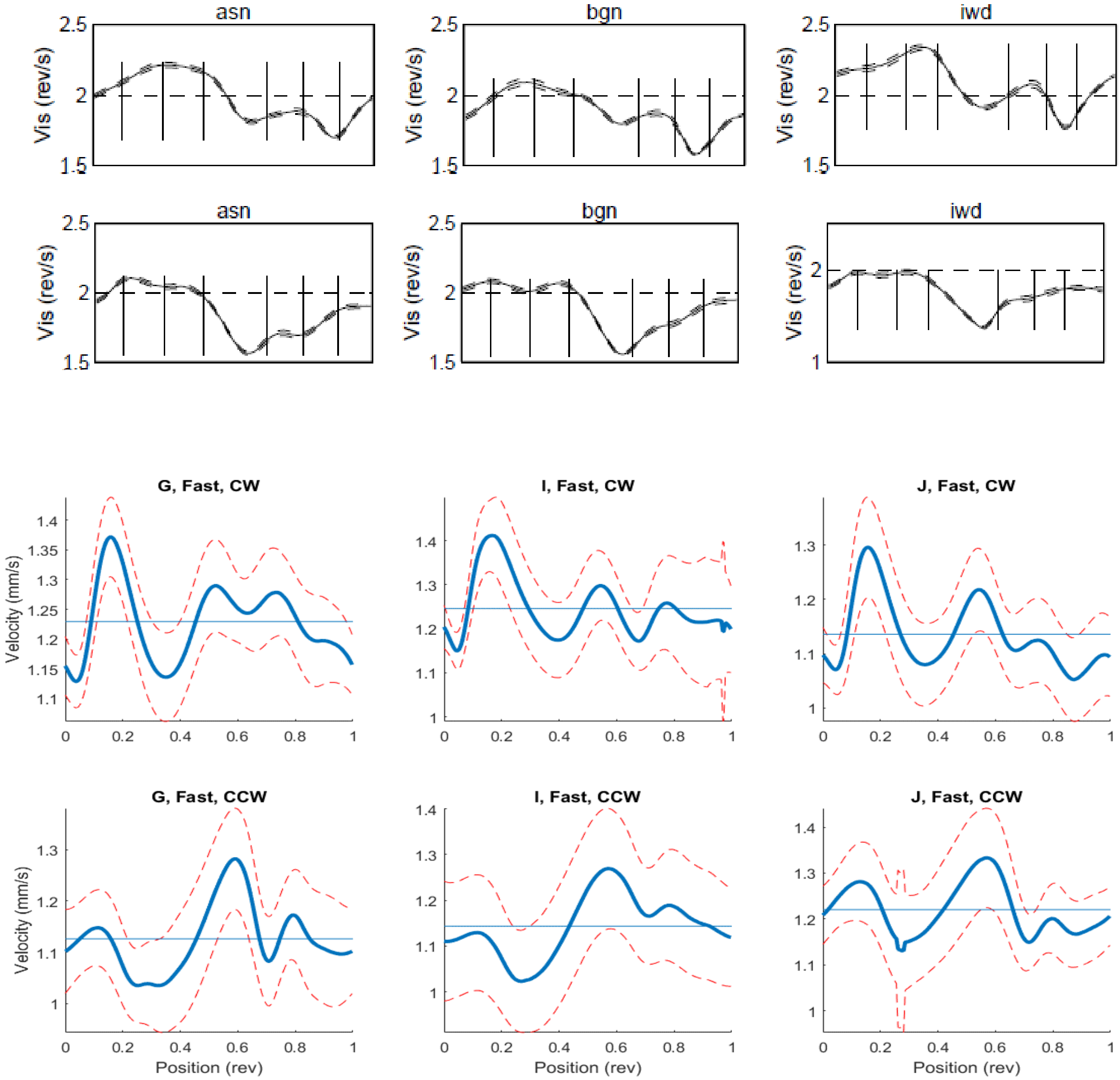

Figure 4-8: Graphs of Tangential Speed vs Crank Position for Fast (CW and CCW) trials. Comparison of results reported by Doeringer (top) and this experiment (bottom).

4.3 Force Profiles

Representative plots show initial findings from a few of the subjects at slow and medium speeds.

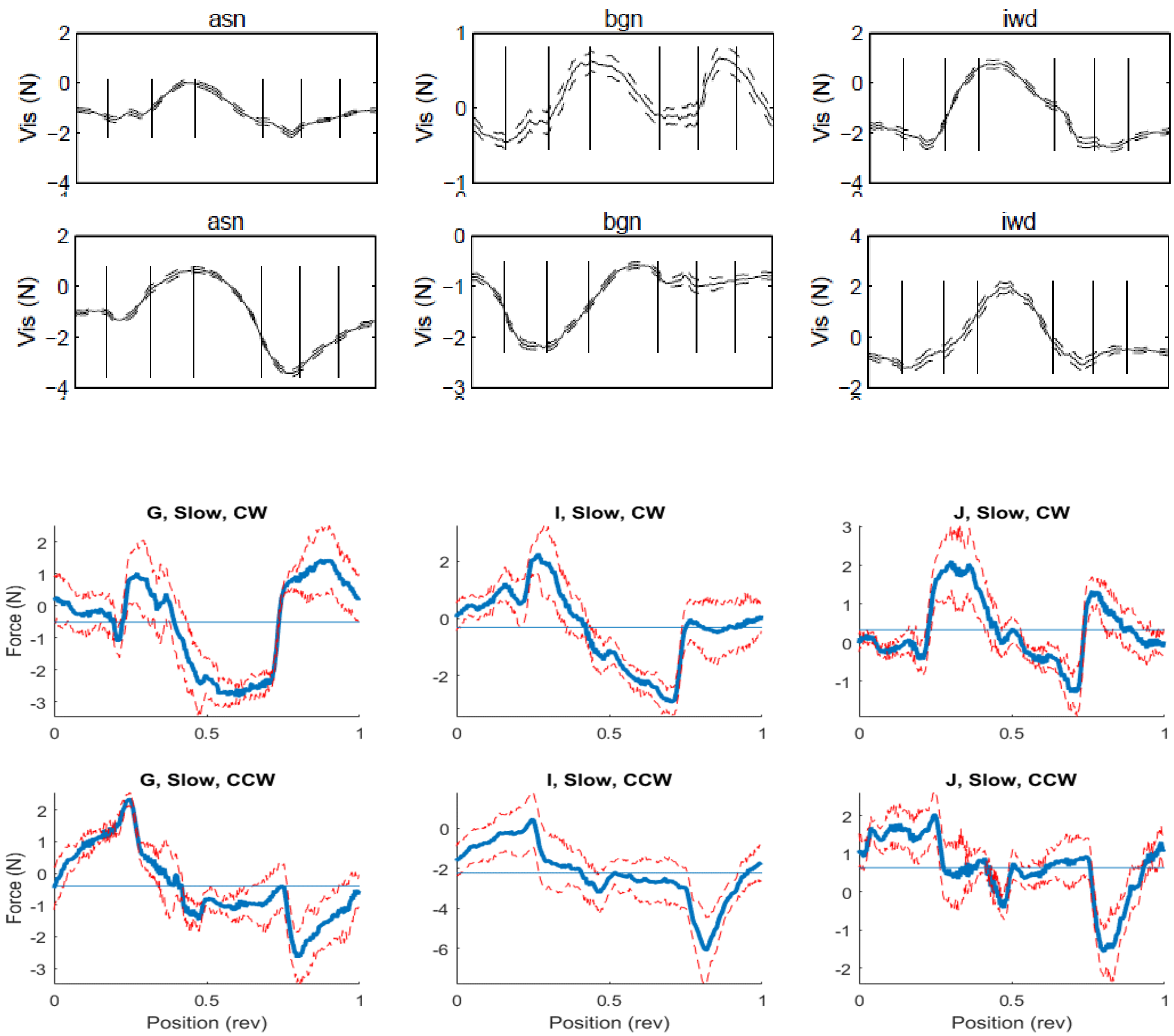

Figure 4-9: Graphs of Radial Force vs Crank Position for Slow (CW and CCW) trials. Comparison of results reported by Doeringer (top) and this experiment (bottom).

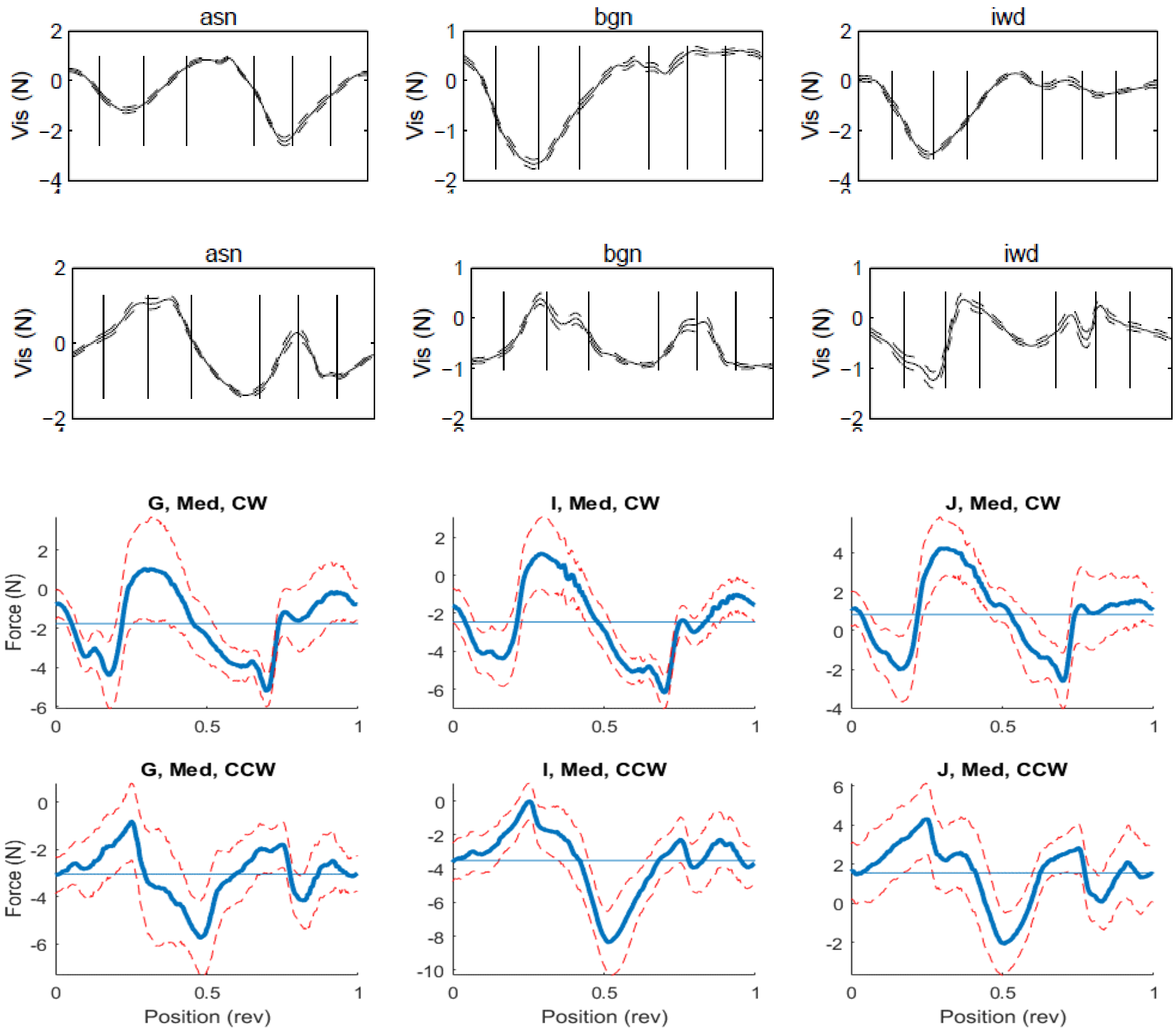

Figure 4-10: Graphs of Radial Force vs Crank Position for Medium (CW and CCW) trials. Comparison of results reported by Doeringer (top) and this experiment (bottom)

4.4 EMG Profiles

A representative plot of the EMG data for a subject's trial performing the preferred constant speed task in the clockwise direction is presented.

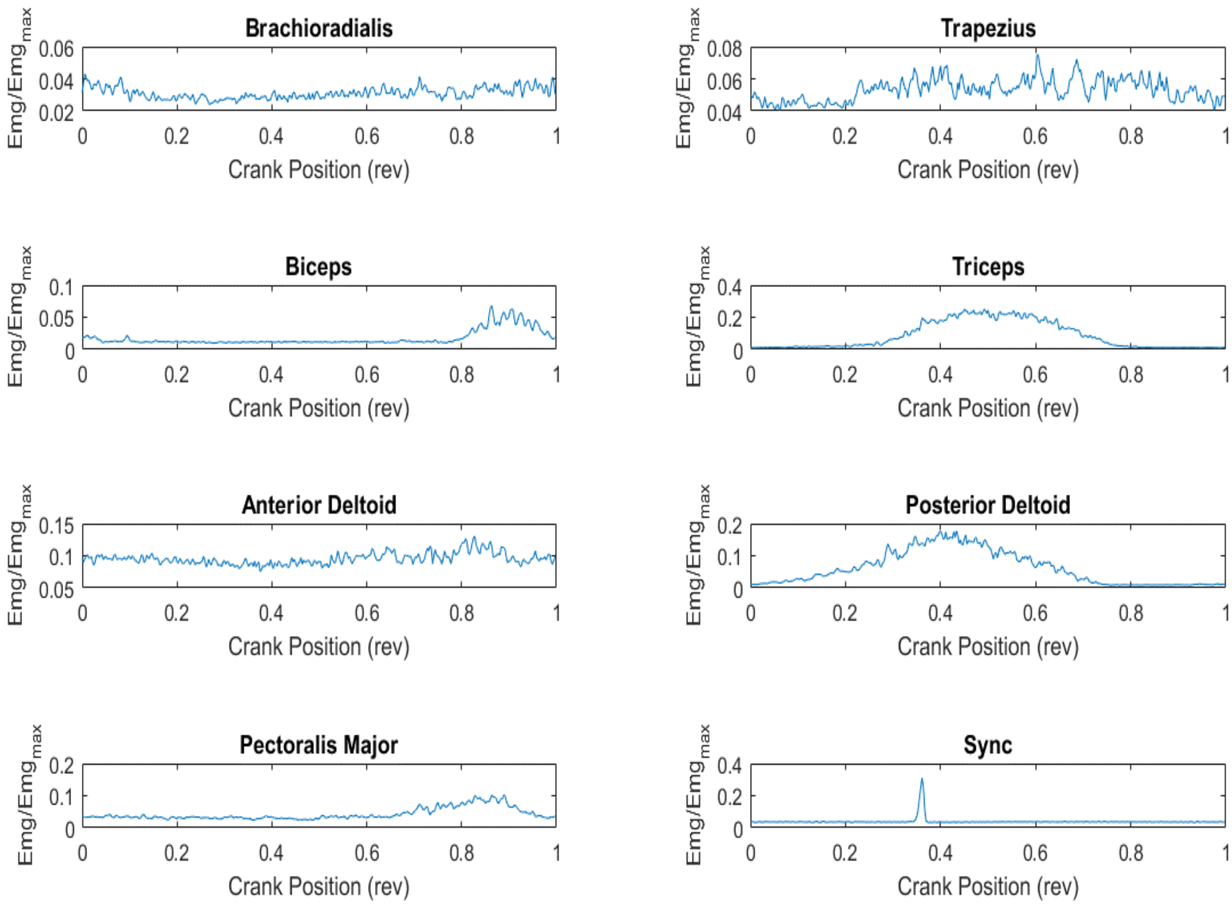

Figure 4-11: Graph of EMG activity for 7 arm muscles during preferred constant speed trial (CW)

Discussion

5.1 Statistical Results Discussion

The discussion of the statistical results presented in section 4.1 are guided by the motivating questions presented in section 3.1.1.

1. *How well do subjects maintain an instructed constant speed?*

Looking at the ratio of the standard deviation to mean velocity, or the coefficient of variation, the trend in Figure 4-2 shows a downward trend with mean velocity. The trend suggests that as the velocity increases, the variability in the data set around the mean (CV), decreases. In other words, as the subject moves at slower speeds, they tend to be more imprecise in their velocity patterns.

Though the graph and data appear to show an obvious trend, the R^2 value of only 0.62 suggests that the trend line is not the most predictive of this trend. Tests of statistical significance explore whether the pattern seen in the data actually tells us anything significant about the effect of the independent factors on the dependent variable CV.

2. *Is subject performance affected by visual feedback?*

The preferred speed tests involved three independent factors: instruction (preferred or constant), direction (CW or CCW), and visual feedback (on or off). Having so many factors makes this test difficult to test statistically. In addition, factors such as the mean velocity being inconsistent between trials (since no target speed was instructed with visual feedback until the 3rd task) make it difficult to interpret the results with confidence. To this end, analysis of the preferred speed tests is only introduced as a pilot investigation into the effect of instruction and visual feedback on performance.

From Figure 4-1, some subjects appeared to have more precise velocity patterns when instructed to go at constant speed and when given visual feedback. Subject 6 appears to be the most obvious example of this, but the pattern is too irregular across all subjects to draw a reliable conclusion.

A Paired t-test between each set of tasks, shown in Table 4-1, highlights their significance. This pilot study data set does not confirm Doeringer's conclusion that blind trials and visual trials are significantly different. P-values of 0.08 show a tendency for preferred to differ from preferred constant and likewise preferred to differ from preferred visual, which almost reaches significance. However, the weakness of the multiple t-tests indicates that no reliable conclusion can be drawn. Perhaps a revised experiment like Doeringer's at a predetermined speed would offer a more fair comparison than attempting to find the subject's preferred speed.

3. *Is subject performance affected by direction, clockwise or counterclockwise?*

To determine the influence of direction, clockwise, or counterclockwise, the results from a two-way ANOVA test and t-tests in Table 4-2 and Table 4-3, respectively, were shown.

From the two-way ANOVA, main effects analysis showed that there were no statistically significant mean differences between clockwise and counterclockwise directions, $p = 0.1811$.

The t-tests agreed with the ANOVA test results which indicate that direction does not have a statistically significant influence on the coefficient of variation. The p-values at slow and high speeds, about 0.07 and 0.08, respectively, however, show a tendency toward significance, yet that cannot be concluded under the significance criteria.

4. *Is subject performance affected by the instructed speed, faster or slower?*

The two-way ANOVA and t-test results determined the statistical significance of the influence of instructed speed on the coefficient of variation. ANOVA main effects analysis showed that there were statistically significant mean differences between slow, medium, and fast speeds, $p \cong 0$. In addition, there was no statistically significant interaction between the effects of speed and direction, $p = .1701$. This concludes that the change in speed does not affect the effect of direction clockwise vs counter-clockwise on the CV. This helps to validate the trend seen in Figure 4-2 since there is a definite statistical difference in the CV as the speed changes.

The t-tests agreed with the ANOVA analysis which indicate that speed has a highly statistically significant mean difference across the variations of slow, medium, and fast.

The graph in Figure 4.3 shows a clear representation of the influence of speed on the CV. With CV as a measure of performance, it is concluded that subject performance is indeed affected by the instructed speed.

5.2 Comments on Velocity Profiles

Representative velocity profile results were presented in section 4.2. Qualitative comparisons to velocity profile data from Doeringer's thesis are provided where relevant.

Comments on the preferred speed trials:

For the preferred speed tasks, Figure 4-4 shows a representative plot of two subjects operating the crank with and without the visual feedback display. In either subject, the pattern with and without visual are about the same which at least qualitatively corroborates the results found by statistical analysis.

Comments on the slow speed trials:

With the slow speed trials shown in figure 4-6, the velocity profiles observed in Doeringer's thesis appear to be more smooth and consistent between subjects. The profiles from this experiment appear to not have any repeatable pattern or consistency.

Comments on the medium speed trials:

Figure 4-7 showed plots of the medium instructed task. The profiles at medium speed are smoother and appear to follow a regular repeatable pattern. The mean velocity speeds of medium trials are closer to most subjects' preferred speed tests, so the velocity patterns are similar to those in the preferred speed tests as in Figure 4-4. The shape of the CW velocity profiles appear to align with those in Doeringer's thesis.

Comments on the fast speed trials:

For the fast instructed speed trials, examples shown in Figure 4-8, the shape of the fast speed velocity profiles in either direction do not appear to align with those from Doeringer. The profiles are quite smooth and repeatable. However, at such high speeds, the non-uniform inertial effects of the MIT MANUS arm are significant which may account for differences.

5.3 Comments on Force Profiles

As mentioned in the introduction, this thesis did not focus on the force data, however, a few comments regarding the representative plots shown in section 4.3 follow.

Comments on the slow speed trials:

From Figure 4-9, the magnitude of the radial force behavior along the circle matches the data Doeringer found, though the profile itself is quite different. Since the radial force is not zero, it implies that subjects apply workless forces while performing the task, even at slow speeds. These workless forces do not help the subject perform the task better, but they could possibly be indicative of an underlying movement control strategy.

Comments on the medium speed trials:

Figure 4-10 showed a sample plot of radial force vs crank position for the medium speed task. The medium speed task profiles of this experiment have a larger negative radial force than those seen from Doeringer. While subject asn from Doeringer has a similar force profile to that of subject G, the other profiles appear very different.

5.4 Comments on EMG Profiles

In future work the EMG data may be analyzed to show the relation of muscle activity to the forces generated and the velocity profile.

Just looking at the EMG activity in Figure 4-11, at the 180 degrees position (0.5 crank position) the triceps are highly activated extending the elbow as the shoulder abducts to move the handle around toward the top of the crank. In the last quartile, the pectoralis major joins the anterior deltoid for horizontal adduction of the shoulder while the biceps activate in flexion to return to 0 degrees (0 crank position).

Future work on the EMG data may reveal more about the control strategy humans use to perform these curved constrained motion tasks.

5.5 Robot & Experimental Limitations

While the experiments yielded hundreds of useful data points, there were certain limitations that may influence the quality of the analysis. As mentioned, the robot’s non-uniform inertia may have influenced the fast speed data since inertial affects were likely significant. Additionally, when some subjects turned the crank at very high velocities in order to match the fast target velocity, one of motors would shut off momentarily and then reengage. A very loud clutching sound alerted the researcher every time this occurred. While the issue did not stop any trials from being completed, most subjects were clearly intimidated by the noise, and thus aimed to turn the crank at a lower speed, undershooting the target velocity. These effects make reliable analysis of the fast speed tests difficult.

A limitation of the preferred speed experiments was the lack of a consistent way to encourage subjects to go at the same “preferred” speed between trials. Since the statistical analysis showed that speed has a significant influence on the coefficient of variation, the inconsistency in the mean preferred speed between tasks or even trials renders data interpretation difficult.

Summary and Conclusions

The coefficient of variation was chosen as the dependent variable used to evaluate the performance of curved constraint tasks that require subjects to maintain a constant speed. The CV is the ratio of standard deviation of velocity in each test to the mean velocity. This serves as a measure of performance precision. Statistical analysis conducted on the CV of slow, medium, and fast speed crank tests showed no statistically significant difference between clockwise and counterclockwise rotation. On the other hand, two statistical tests showed that speed has a significant statistical influence on mean CV. The 2-way ANOVA test also confirmed that there is no significant interaction between direction and speed. Together, these tests show that velocity variability increases as the speed decreases.

A pilot investigation of the preferred speed task indicated no significant effect of visual feedback on velocity CV. This does not support the findings by Doeringer which suggest that there is a significant statistical difference between blind and visual trials.

Little analysis was performed on the EMG and force data. However, the velocity profiles and analysis of velocity performance offer a basis for future work to substantiate the effectiveness of underlying human control strategies used to perform tasks with a curved constraint. Future work may focus on the force and EMG data collected from this experiment and analyze their effect on velocity performance. Also, methods of compensating for the non-uniform inertia of the MIT MANUS robot, or exploring other robotic alternatives, would be valuable future work [11].

References

[1] Hogan, N., 1985 "The Mechanics of Multi-Joint Posture and Movement Control," Biological Cybernetics, vol. 52 (5), pp.315-331

[2] Hogan, N., Sternad, D., 2012, "Dynamic Primitives of motor behavior," Biological Cybernetics, vol. 106 (11), pp.727-739

[3] Doeringer, J. A. 1999, “An Investigation into the Discrete Nature of Human Arm Movements,” Ph.D. thesis, Department of Mechanical Engineering, MIT.

[4] Charnnarong, J., 1988, “The Design of an Intelligent Machine for Upper-Limb Physical Therapy,” M.S. thesis, Department of Mechanical Engineering, MIT.

[5] Krebs, H.I., Palazollo, L.L., Dipietro, L., Ferraro, M., Krol, J., Rannekleiv, K., Volpe, B.T., Hogan, N., 2003, "Rehabilitation Robotics: Performance-Based Progressive Robot-Assisted Therapy," Autonomous Robots, vol. 15. (1), pp. 7-20

[6] Hogan, N., 1985, "Impedance Control: An Approach to Manipulation: Part 1-Theory," Journal of Dynamic Systems, Measurement, and Control, vol. 107.

[7] Hogan, N., 1985, "Impedance Control: An Approach to Manipulation: Part 2-Implementation Theory " Journal of Dynamic Systems, Measurement, and Control, vol. 107.

[8] Hogan, N., 1985, "Impedance Control: An Approach to Manipulation: Part 3-Applications " Journal of Dynamic Systems, Measurement, and Control, vol. 107.

[9] Basmajian, J.V. and De Luca, C.J., 1985, *Muscles Alive*, Williams and Wilkins, Baltimore, MD.

[10] Rose, W., 2014, “Electromyogram Analysis.” KAAP686 Mathematics and Signal Processing for Biomechanics, University of Deleware, from https://www.udel.edu/.../EMG%20analysis.pdf

[11] Foster, C., 1999, “A Performance Characterization of an Interactive Robot,” M.S. thesis, Department of Mechanical Engineering, MIT