

Virginia Commonwealth University [VCU Scholars Compass](https://scholarscompass.vcu.edu/)

[Theses and Dissertations](https://scholarscompass.vcu.edu/etd) [Graduate School](https://scholarscompass.vcu.edu/gradschool) and Dissertations Graduate School and Dissert

2015

Evaluation of a Novel Myoelectric Training Device

Joshua A. Arenas Virginia Commonwealth University

Follow this and additional works at: [https://scholarscompass.vcu.edu/etd](https://scholarscompass.vcu.edu/etd?utm_source=scholarscompass.vcu.edu%2Fetd%2F4050&utm_medium=PDF&utm_campaign=PDFCoverPages) Part of the [Biomedical Engineering and Bioengineering Commons](http://network.bepress.com/hgg/discipline/229?utm_source=scholarscompass.vcu.edu%2Fetd%2F4050&utm_medium=PDF&utm_campaign=PDFCoverPages)

© The Author

Downloaded from

[https://scholarscompass.vcu.edu/etd/4050](https://scholarscompass.vcu.edu/etd/4050?utm_source=scholarscompass.vcu.edu%2Fetd%2F4050&utm_medium=PDF&utm_campaign=PDFCoverPages)

This Thesis is brought to you for free and open access by the Graduate School at VCU Scholars Compass. It has been accepted for inclusion in Theses and Dissertations by an authorized administrator of VCU Scholars Compass. For more information, please contact libcompass@vcu.edu.

EVALUATION OF A NOVEL MYOELECTRIC TRAINING DEVICE

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Biomedical Engineering at Virginia Commonwealth University.

by

JOSHUA ARENAS B.S. in Mechanical Engineering, University of Virginia, May 2012

Director: DR. PETER E. PIDCOE ASSOCIATE PROFESSOR, DEPARTMENT OF PHYSICAL THERAPY

Co-Director: DR. PAUL A. WETZEL ASSOCIATE PROFESSOR, DEPARTMENT OF BIOMEDICAL ENGINEERING

Virginia Commonwealth University Richmond, Virginia November 30, 2015

© Joshua Arenas, 2015

All Rights Reserved

Acknowledgements

I would like to thank my advisor, Dr. Peter Pidcoe, for all the guidance and advice in assisting me throughout the course of my graduate career at Virginia Commonwealth University. I would also like to thank my advising committee members, Dr. Paul Wetzel and Dr. Dianne Pawluk. To my colleagues in the Biomechanics research lab, thank you for your support and input in helping me complete my research project. I would like to extend a heartfelt thank you to my friends and family, both old and new, who have helped me along the way and always made themselves available in times of need. To my dear friend Jehovah and my loving parents, thank you for supporting and providing for me. Without you, none of this would be possible. You're the real MVPs.

List of Abbreviations

- BNC = British Naval Connector
- $D = Digital$
- EMG = Electromyography
- GEE = Generalized Estimated Equations
- MVC = Maximum Voluntary Contraction
- NASA TLX = National Aeronautics and Space Administration Task Load Index
- PL = Proportional Linear
- PNL = Proportional Non-Linear
- PWM = Pulse Width Modulation
- RMS = Root Mean Square

List of Figures

Abstract

EVALUATION OF A NOVEL MYOELECTRIC TRAINING DEVICE

By Joshua Arenas, B.S. Mechanical Engineering

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Biomedical Engineering at Virginia Commonwealth University.

Virginia Commonwealth University, 2015

Director: Peter Pidcoe, PT, DPT, PhD, Associate Professor, Department of Physical Therapy Co-Director: Paul Wetzel, PhD, Associate Professor, Department of Biomedical Engineering

Recent technological developments have implemented the use of proportional control in prosthetic hands, giving rise to the importance of appropriate myoelectric control. EMG models in the past have assumed a linear proportionality to simplify the EMG-force relationships. However, it has been shown that a non-linear EMG-force relationship may be a more effective model. This study focused on evaluating three different control algorithms for a novel myoelectric training device, consisting of a toy car controlled by EMG signals from the distal muscles in the arm. Sixteen healthy adult subjects (5 male and 11 female) with an average age of 23.6 years ($SD = 2.7$) were asked to drive the car through a slalom course. Completion times as well as number of errors (wall hits, cone hits, and reversals) were recorded to evaluate performance. The NASA TLX was administered to evaluate psychometrics such as mental demand, physical demand, frustration, and overall workload. The average total errors per trial on the final day of testing using the linear proportional algorithm was found to be statistically significantly ($p < 0.05$) lower than digital and non-linear proportional. The average course

completion time per trial and overall workload using the non-linear proportional algorithm was found to be statistically significantly ($p < 0.05$) lower than digital and linear proportional. These results suggest that a non-linear algorithm would be most appropriate for myoelectric control in prosthetic hands.

Chapter 1: Introduction

Losing a limb severely changes a person's everyday life and functionality (27). Sadly, thousands each year lose limbs and have to cope with this loss. The majority of limb loss is due to congenital deficiencies. Congenital upper limb deficiency is most common and has been suggested that 75% of all congenital, unilateral upper-extremity amputees will be missing their left arm below the elbow (13). There have also been studies that project there to be 3.6 million amputations by the year 2050 (28). With such an increase in limb loss, the need for functional prostheses to replace these limbs is at an all-time high.

1.1 Prosthetics

The history of prosthetics dates back to the ancient Egyptians. These prostheses didn't hold much value other than cosmetic appearance and were made out of leather and wood. Over the years, different materials were put into use to make the prosthetics more durable. Metals, such as bronze, were used in conjunction with the leather and wood materials of old. In the 1800's, an improvement in functionality was seen as wooden legs were outfitted with catgut tendons to allow the foot to plantar and dorsiflex (26). As technology improved, prostheses became more advanced and more functional than their predecessors. The first powered prostheses appeared in 1915 and were pneumatically controlled. The growth of electronics resulted in the development of the first myoelectric prostheses in the 1940's. As electronic developments continued (such as the creation of the transistor), a Swedish research group created the SVEN hand in the 1960's. This was one of the first myoelectric hand prostheses that was multifunctional and has been used extensively in research (4).

Myoelectric prostheses are advanced prostheses, where movement of the artificial limb is controlled through the measurement of the electrical signal associated with muscle activation. Many of the commercial artificial limbs available today use surface electrodes to sense the electrical activity of the user's muscles. Surgery is sometimes required to bring the muscle nerves closer to the skin which improves the signal strength of the muscle and makes it easier for the prosthesis to sense. Studies have shown that myoelectric prostheses provide a higher grasping force, increased functional performance, and greater range of motion over conventional prostheses (e.g. cable prosthesis system). Users also preferred a myoelectric prosthesis because it looked more natural and it provided them with higher self-esteem (24, 27).

1.2 Control Algorithms

The most commonly used control scheme for myoelectric prostheses is the direct control scheme. Direct myoelectric control schemes map a single EMG control signal to a single control variable, such as motor speed. Several commercial devices, such as the Ottobock System Electric Hand use this type of control scheme. These devices have only one function, which is to open and close the hand. Pattern based control schemes are currently being developed to allow for more functionality of hand prostheses, including multiple grasps and increased articulation (22). Although devices that employ direct myoelectric control schemes are limited, they do increase the functional capability of the user. In the past, these devices implemented digital control (on/off) to operate the opening and closing of the hand. Today, many of these devices use proportional control to vary the speed of the opening and closing of the hand as well as the grasping force, which is more physiologic than digital control and gives users a variety of objects they can handle with their prosthesis (23, 29).

2

It has been suggested since the 1950's, that in order to obtain a graded response from the myoelectric prosthesis, some form of proportional control would need to be implemented (2). Proportional control allows the user to perform small, precise movements as well as rapid, coarse movements. Since proportional control is currently available as a feature from all manufacturers of commercial myoelectric prostheses, appropriate myoelectric control has become increasingly important (3, 11). EMG models in the past have assumed a linear proportionality to simplify the EMG-force relationships. However, it has been shown that a non-linear EMG-force relationship may be a more effective model. Below is an equation that models the non-linear EMG-force relationship of the extrinsic muscles in the finger. EMG_N represents the non-linearly normalized EMG signal, F_m represents max force, EMG_L represents the EMG signal linearly normalized to 100% of maximum, and C is a constant to describe the non-linear curvature. A range of values was found for this constant depending on the type of filter as well as activation condition (flexion or extension) (17).

$$
EMG_N = F_m \frac{e^{(-0.001EMG_LC)} - 1}{e^{(-0.001F_mC)} - 1}
$$

Before an amputee can obtain a myoelectric prosthesis, they need to complete a training phase that allows them to develop the skills necessary for controlling these types of prostheses (25, 9). This includes having to learn how to produce a specific myoelectric signal to control each function of the prosthetic (3). Often times, training systems are used that do not hold the attention of the user. With so many advancements being made to increase the functionality of myoelectric prosthetics, it is important that these training systems not only engage the user, but also be affordable, portable, and adaptable to conventional state of the art control schemes (7). In order to solve this problem, a novel myoelectric training device was developed and evaluated.

The device utilized a toy car controlled by an EMG system, with the goal to keep users better engaged during the necessary training phase. Initial testing showed that users were engaged when using the training system and thought it was "fun to use." However, limitations of the system included that it was not portable and only used a digital control algorithm (5).

1.3 Focus of Study

The overall goal of this research is to evaluate three different man-machine interface algorithms linking EMG to external device control. It is hoped that this understanding may lead to increased usability and an increased prosthesis acceptance rate (11). This study will follow the same concept of the training system mentioned in the previous section and utilize a toy car controlled through an EMG system to hold the user's attention. The system will use a dual site, three-state control scheme, which is

Figure 1: EMG Training System

a direct control scheme that is used in many commercially available myoelectric prostheses (18, 19). However, this version of the training system will be capable of proportional control, unlike the previous version, which was solely controlled digitally. Two separate proportional control algorithms will be implemented: a linear proportional control and a non-linear proportional control based off the exponential equation mentioned previously.

1.4 Specific Aims

With modifications to the previous myoelectric training device, this study will test three hypotheses:

Hypothesis 1: A man-machine control interface that more closely mimics the EMG-muscle force generation relationship will provide more functional control.

Specific aim 1(a): To compare the performance between day 1 and day 2 of EMG controlled steering and direction of a remote controlled car in a predefined course by measuring course completion time and cumulative errors.

Specific aim 1(b): To compare performance metrics with 3 different control algorithms;

(1) digital, (2) proportional linear, and (3) proportional non-linear.

Hypothesis 2: A man-machine control interface that more closely mimics the EMG-muscle force generation relationship will appear more natural, have the quickest acclimation time, result in the least frustration, and have the least overall workload for the user.

Specific aim 2a: To test the user's mental demand level using the NASA TLX.

Specific aim 2b: To test the user's physical demand level using the NASA TLX.

Specific aim 2c: To test the user's frustration level using the NASA TLX.

Specific aim 2d: To test the user's overall workload level using the NASA TLX.

Specific aim 2e: To evaluate the rate of learning for each algorithm by comparing the exponential regression for completion time, total errors, and overall workload of the three control algorithms.

Hypothesis 3: Subject capacity to learn, as elucidated by errors committed per unit time, will impact which control algorithm will produce the best results.

Specific Aim 3a: To see if high-capacity vs. low-capacity learning impacts the rate at which each algorithm can be mastered.

Chapter 2: Materials and Methods

The study included 16 healthy adult subjects (5 male and 11 female), with an average age of 23.6 years ($SD = 2.7$). Data collection took place during two sessions that lasted approximately an hour and a half each. Participants were asked to come back for their second session within 48 hours of their first. This was done to maximize training carryover from the previous session. During each session, subjects were asked to control a remote controlled car through a 40ft long by 4ft wide serpentine course, with 7 turns. Light gates were placed at the beginning and end of the course to measure completion time. Subjects were asked to reach the end of the course as quickly as possible, without hitting any obstacles. Course times as well as the number of obstacle hits were recorded. Control of the car required muscle activation signals from both of the user's forearms. The subject's dominant arm controlled the steering of the car, while the non-dominant arm controlled forward and reverse movement.

2.1 Experimental Design

The subjects were recruited via a sample of convenience from a college age population at Virginia Commonwealth University to participate in this experiment. Before arriving to the lab for the experiment, participants were asked not to wear lotion on their forearms because this could possibly interfere with the EMG signal and to dress in a way that allowed easy access to the muscle in their forearms (14). Following an introduction and consent process, block randomization was used to assign the control algorithm order. In the block randomization, there were six possible interface combinations used that included all three control algorithms, while not allowing an algorithm to be repeated on the same day. Subjects had a different combination each day. With the subject seated in a chair positioned at the end of the demarcated slalom

course, four muscle sensing electrode pairs were placed over the muscle bellies of the extrinsic wrist muscle flexors and extensors on both arms (16). These muscles were chosen because they are normally used in the control of myoelectric prosthetic arms (12). Electrode placement was standardized with electrodes placed approximately 5cm distal to the elbow. Subjects were asked to flex and extend their wrist against resistance and the electrode pair was placed in the center of the muscle mass that emerged in line with muscle fiber orientation (6). Figure 2 shows the relative placement of the electrodes. A reference electrode was also placed on the bony part of the subject's left wrist for the ground lead.

Figure 2: Relative placement of EMG electrodes

After all electrodes were connected to the EMG leads, participants were asked to put their forearms in wooden braces mounted to a table top in front of them (Figure 3), making sure the only electrode located inside the brace was the ground electrode. This position minimized the potential of introducing a motion artifact in the EMG signal. The braces were then adjusted to the arm size of the individual to minimize muscle movement so that isometric contractions could be used to control the vehicle (12, 15). This also allowed a healthy subject to mimic the

Figure 3: Wooden braces used to obtain isometric contractions

type of contractions that an amputee would produce. In addition, participants were given instructions to flex with their fingertips and extend using their fingernails, but avoid curling their fingers in order to keep their hands as straight as possible (17). Again, this was to ensure that the subjects were giving the strongest EMG signal possible from the desired muscle groups by avoiding co-contraction and by activating muscles that crossed the most distal joints in the hand (12). Subjects then practiced producing maximum voluntary contractions (MVC) while watching an EMG signal magnitude on an oscilloscope screen. Calibration was performed by asking the subject to rest for two seconds and then perform a maximum contraction for two seconds with each muscle group independently. These values were used to normalize subsequent data by setting them equal to 0 and 100 percent respectively (resting and maximum) (20). This allowed the system controller to be scaled equally across users.

Subjects were trained to a standardized level of control of the car by completing what was called a "square test". Participants' dominant arm controlled steering and their non-dominant arm controlled forward and backward movement of the car (9). The car was placed in a 3ft by 3ft square wooden box (Figure 4) and participants were allowed to briefly practice the aforementioned controls. After they had successfully moved the wheels left and right as well as moved the car forward and backwards, they were given two minutes to drive the car through a full 360°

Figure 4: Square test

of rotation in one direction to return to the original position. If they did not complete the task in less than two minutes, they were required to start over. Participants could not advance to the slalom course portion of the experiment until they successfully completed the square test.

After the participant successfully completed the first square test, a modified National Aeronautics and Space Administration Task Load Index (NASA TLX) survey was administered to determine the subject's overall workload for the task. It has been determined that the NASA TLX should be administered if the goal is to predict performance of a particular individual in a task. This is because the NASA TLX produces high correlations between workload and performance and has been applied successfully in different multitask contexts, such as using remote-control vehicles and human machine interfaces (1, 21). The participant was shown the survey and asked to rate their perceived experience on a scale of 1-20 for each of the six

categories: mental demand, physical demand, temporal demand, performance, effort, and frustration level* . The endpoint descriptors described the scale as very low (rating of 1) to very high (rating of 20), except for performance, which was described as perfect (rating of 1) to failure (rating of 20). For the second part of the survey, participants were randomly presented with 15 pairs of rating scale titles (e.g. Effort vs. Mental Demand) and asked which category was more important to their experience of workload in the task. This provided a weight for each category, which was used to find weighted ratings that were averaged to find the overall workload. The survey was taken after the first square test so participants could familiarize themselves with the rating scales and make sure they had developed a standard technique for dealing with the scales. After the first square test of the day, the NASA TLX was only administered after participants completed all trials of the slalom course for each control algorithm.

Following success in the square-test, participants were asked to drive the car through a slalom course as quickly as possible (Figure 5). The car was placed at the start line. The subjects were instructed to cross the start line (triggering the first light gate and automatically starting a course timer), pass through the slalom gates marked by white tape, avoid hitting the cones and the walls, and

Figure 5: Slalom Course

 $\overline{}$

^{*} For a full description of the six categories, see Appendix.

to pass through the finish line at the end of the course (triggering the second light gate and stopping the course timer). They were informed that three seconds would be added to their total time if they hit a cone. Completion time, number of wall and cone hits, and direction reversals were recorded as they completed the task. A wall hit was defined as any contact with the wall that prohibited or slowed forward progress of the course. Reversals were defined as any motion that didn't result in forward progress. There were instances where the car would be oriented in a position that resulted in no change of position in the course whether the car itself moved forward or backward. No errors were counted when this occurred. In addition, some subjects completed part of the course by driving backwards. This meant that errors were counted when the car drove forward because it no longer resulted in forward progress in the course.

All three control algorithms were tested in one session: digital, linear proportional, and nonlinear proportional. After they completed six trials with one algorithm, participants were given a break and taken out of the wooden braces. During this time, the NASA TLX survey was administered to determine the overall workload of the task with the control algorithm they just used. Once the survey was completed, subjects were placed back into the wooden braces, the system was recalibrated, and the algorithm was switched. Participants were re-trained using the square test and, after successful completion, moved on to the slalom course. Again, the NASA TLX was only administered after the first square test and after all six trials of the slalom course were completed with one algorithm. This procedure was followed until the participant had tested all three algorithms, resulting in a total of 18 trials per day. The total time per session was about 2 hours and the subjects were asked to repeat the performance for 2 total sessions over 48 hours. Both sessions followed the same procedure.

2.2 Experimental Details

Toy Car

A remote control car with proportional control capabilities was purchased for this experiment. Unfortunately, the car was only capable of proportional control when sent voltages between 5.7 and 7.2 V. The speed at this control voltage was too fast for the course, so the stock control electronics were removed and replaced with an Arduino microcontroller. With the Arduino, the voltage supplied to the car could be varied, giving it full range of proportional control. This was done by using the pulse width modulation (PWM) feature of the digital outputs on the microcontroller. The Arduino alone was enough to power the servo motor used for steering, but was not enough to supply the DC brush motor used to control forward and reverse motion. In order to supply the necessary current for the DC motor, a Pololu motor driver (Pololu High-Power Motor Driver 18v15) was added. Brackets were designed using Solidworks and printed using a Makerbot Replicator 2x 3D printer. These were used to hold the new servo motor in place to steer the car. A housing stand was also printed to hold the Arduino microcontroller on top of the car. The stock battery that came with the car did not provide a long enough run time for one subject to complete the entire experiment. It was rated at 7.2V and 1000mAh. Batteries rated at 7.2V and 2200mAh were used, which provided more run time. The wiring of the car was modified for the new batteries and industrial strength Velcro was used to hold them in place (Figure 6).

Figure 6: Toy Car

Data Processing: EMG Control Box

Since a new circuit was created for the toy car, the stock remote control was discarded and a new remote control was created. A multipurpose plastic enclosure was modified to serve as the new control box. It housed all of the necessary circuitry to process the EMG signal, calibrate the system to each individual user, and wirelessly control the car. The EMG amplification board from the previous study was modified to process integrated EMG signals instead of raw signals. The AD 524 precision instrumentation amplifiers were modified to create non-inverting amplifiers instead of inverting amplifiers. This was done because the integrated EMG signal from the Noraxon Myosystem 1200 is already rectified by using a 100ms root mean square (RMS) filter, which converts the negative voltage into positive voltage, so there was no need to invert the signal (15). The signal was then smoothed with a low pass filter RC filter having a cutoff frequency of 0.7875Hz. The time constant was set to 200ms because it has been shown

that large time constants produce significant controller delays (10). This resulted in smooth control of the car without any noticeable delay. Figure 7 shows the diagram for the EMG amplification board. Since the microcontroller from the previous study was not being used, the gain on the amplification board needed to be adjusted to the specifications of the current microcontroller. This adjustment maximized the sensitivity of the system.

Figure 7: EMG Amplification Board Diagram

The power supply for the control box needed to power the amplification board, as well as the Arduino microcontroller. The amplification board was powered with \pm 9V and the Arduino was powered with +5V. A +10V step down transformer along with a series of voltage regulators were used to obtain the necessary voltages. In order to achieve the +9V needed for the EMG board, an LM2940T voltage regulator in combination with a 22 μ F tantalum capacitor was used. The -9V for the EMG board used a 7909A voltage regulator with a 1 µF tantalum capacitor. An LM7805C voltage regulator was used for the +5V needed to power the Arduino microcontroller. Figure 8 illustrates the layout of the controller box.

Figure 8: EMG Box. Amplification board is below Arduino microcontroller.

Switches and LEDs were needed to both serve as a guide for participants as well as control aspects of the written code in order to tailor the system to each individual. Holes were drilled in the plastic enclosure to house the LEDs, switches, power supply cord, and BNC connections for use with an oscilloscope (Figure 8). A push-button switch was used to initiate the calibration phase of the program, which calibrated the system to each individual user to customize the controls for each person. The LEDs were used to guide the user through the calibration sequence. Two LEDs labeled Left and Right showed which arm was being calibrated. A yellow LED indicated the rest phase of the calibration, while green and red LEDs signaled the flexion and extension portion respectively. A toggle switch was used to differentiate between right and left hand dominance because the user's dominant hand controlled steering of the car. A push-button switch was also used as an emergency stop switch. In case the car wasn't responding correctly,

or the user needed to move their arms without a response from the car, the signal would not be sent as long as this button remained pushed down. A rotary-dial switch was used to move between the different algorithms to control the car. BNC connections were used to externalize the EMG data and were connected to an oscilloscope so the EMG signal could be seen (Figure 9). This allowed the user to see their max flexion during calibration and also showed any possible discrepancies that would require a re-calibration.

Figure 9: EMG setup

Following low pass filtering of the EMG signal in hardware, the signal was sampled via the analog inputs of the Arduino at 2500 Hz. The signal was normalized via software based on the previously obtained calibration limits. The user's resting voltage was normalized to zero and their max flexion/extension voltages were normalized to 100. This ensured that the EMG controller sent only values to which the car could respond. Regardless of which algorithm was being used (digital, proportional linear, or proportional non-linear), the car initiated motion when the user performed an isometric contraction of 10% of their maximum value. Once this threshold was reached, the actions of the car depended on which control algorithm the system was set to. In the digital control mode, the car would move at full speed in the forward and reverse directions and reach the full left and right turn values for steering once the 10% threshold was met. With the proportional linear algorithm, the car would be proportionally controlled for both steering and speed. The proportionality followed a linear EMG-muscle force relationship. The proportional non-linear algorithm was also proportionally controlled, but it followed an exponential curve based on an equation found in literature known to relate EMG signal to muscle force production (17). The maximum exponential constant (C) of 46 was chosen, so the nonlinear curve would be as different from the proportional linear control algorithm as possible. The linearized EMG values were adjusted to the activation threshold and the max force variable was empirically found to fit the limits of the DC and servo motors. This resulted in the following equations for speed and steering:

$$
Steering = \pm 29.50 \frac{e^{(-0.001*(x-10)*46)} - 1}{e^{(-0.02950*46)} - 1} + 81
$$

$$
Speed = 61.02 \frac{e^{(-0.001*(x-10)*46)} - 1}{e^{(-0.06102*46)} - 1}
$$

The differences in these control algorithms can be seen in Figures 10 and 11 below. The control value sent to the car computed for both speed and steering. The control box communicated with the car by using a pair of Xbee wireless communication chips. This communication stream was unidirectional, from the control box to the car only. The communication speed was set to a baud rate of 9600bps.

Figure 10: Digital, linear, and non-linear equations used for the speed of the car.

 Figure 11: Digital, linear, and non-linear equations used for the steering of the car.

Chapter 3: Results

A Generalized Estimated Equations (GEE) test was run using IBM SPSS Statistics v23 to compare the means of time, total errors, and overall workload of each control algorithm across day 1 and day 2. The GEE test was also used to compare the means of time, total errors, and overall workload between the three algorithms on day 2. Tables 1-3 below show a summary of the data. A significance value ($p<0.05$) indicates that there is statistical significance between the data. The full set of data can be found in Appendices A, B, and C.

3.1 Time and Error Data: Day 1 vs. Day 2

Figure 12 below shows the average time per trial for each of the three algorithms (Digital (D), Proportional Linear (PL) and Proportional Non-Linear (PNL)) across both days. Trial number seven was the beginning of day 2, which is represented by the vertical dashed line. A GEE test showed that the mean time difference between day 1 and day 2 for each algorithm was statistically significant ($p < 0.05$). The times for all three algorithms showed a progressive decrease from the first trial on day 1 to the last trial on day 2. Note that D started out with the highest average start time and PNL was the lowest. Although the average times by trial 12 were relatively close to each other, D and PL remained with the highest and lowest average time, respectively. The improvement from the end of day 1 to the start of day 2 is due to memory consolidation, which is defined as "the progressive post acquisition stabilization of long-term memory" (8). This means that there won't be a decrease in performance from the last trial in day 1 to the first trial in day 2 because subjects retained the strategy of operating the toy car.

21

Figure 12: Graph of average course completion time per trial for all three equations on day 1 and day 2. Day 2 begins at trial number 7 and is represented by the red, vertical, dashed line.

Figure 13 below represents the average total errors (reversals, wall hits, cone hits) per trial for each of the three algorithms across both days. Average total errors per trial also steadily decreased like average time per trial. D again started with the highest average total errors, similar to average time per trial. However, PL began with the lowest average total errors. By trial 12, the average total errors decreased significantly for all three algorithms, and although PNL was not much different from PL, the original ranking remained the same. Statistical significance ($p <$ 0.05) between both days was again seen by the GEE test that was performed.

Figure 13: Graph of average total errors per trial for all three algorithms on day 1 and day 2. Day 2 begins at trial number 7 and is represented by the red, vertical, dashed line.

The average time and error difference per day for each algorithm is represented by the bar graph in Figure 14 below. D shows the highest differences for both time and error with 39.30% and 43.61% decreases, respectively. PL has a 22.83% decrease in time and PNL has a 40.32% decrease in errors, both of which are the lowest in their respective categories.

Figure 14: Average time and error differences between day 1 and day 2 for each algorithm. Percentages represent a percent decrease in time and error.

3.2 NASA TLX: Day 1 vs. Day 2

Figures 15-17 below show the results from the NASA TLX survey for the three algorithms on both days. As with the average time and total errors per trial, the majority of the averages for day 2 were lower than day 1, with temporal demand and effort for PL being the only two exceptions. The variances for all three algorithms also decreased. Categories that had a statistical significant $(p < 0.05)$ difference between day 1 and day 2 are marked with an asterisk. The only categories that were statistically significant between day 1 and day 2 for all three algorithms were mental demand and overall workload.

Figure 15: Average weighted ratings of NASA TLX for the digital algorithm on day 1 and day 2. Asterisk denotes statistical significance ($p < 0.05$).

Figure 16: Average weighted ratings of NASA TLX for the linear algorithm on day 1 and day 2. Asterisk denotes statistical significance ($p < 0.05$).

Figure 17: Average weighted ratings of NASA TLX for the non-linear algorithm on day 1 and day 2. Asterisk denotes statistical significance ($p < 0.05$).

3.3 Time and Error: Day 2 only

Since there was a significant difference for each algorithm between day 1 and day 2, only data from day 2 was analyzed to determine if there was a difference between the three algorithms. Figure 18 below shows the average course completion time per trial for day 2. The PNL time seems to have reached a plateau, but the PL and D times are still decreasing. There is a statistical significance ($p < 0.05$) between PNL and both PL and D, which is marked by an asterisk on the graph.

Figure 18: Average course completion time per trial on day 2 for all three algorithms. Asterisk denotes statistical significance ($p < 0.05$).

Figure 19 below shows the average total errors per trial for all three algorithms on day 2. None of these metrics appear to plateau within this timeframe. There is statistical significance ($p <$ 0.05) between D and both PNL and PL, which is marked by an asterisk.

Figure 19: Average total errors per trial on day 2 for all three algorithms. Asterisk denotes statistical significance (p < 0.05).

3.4 NASA TLX: Day 2 only

Figure 20 shows the average weighted ratings on the NASA TLX for day 2. There is statistical significance ($p < 0.05$) between D and PNL for mental demand. The difference in physical demand was statistically significant ($p < 0.05$) between PL and both D and PNL. Performance showed statistical significance ($p < 0.05$) between D and PL. There was statistical significance (p < 0.05) between D and PNL when looking at frustration, with PNL having the lowest value. Overall workload showed a statistical significance (p < 0.05) between PNL and both D and PL.

Figure 20: Average NASA TLX weighted ratings for all three algorithms on day 2. Asterisk denotes statistical significance (p < 0.05).

3.5 Regression Equations

A graphical regression analysis was done to determine how many days it would take a given measurement metric reach a stable value. Figure 21 shows the course completion time regression for each of the three algorithms. The red dashed line represents the fastest theoretical time the car could complete the course if it were to go in a straight line at its fastest speed. The purple, vertical dashed lines represent the beginning of a new day, which are spaced every seven trials. Note that PNL has the fastest completion time on day 1. D and PNL are the first algorithms to reach the fastest time possible for the course by the end of day 4. L reaches the fastest time possible about a day after D and PNL.

Figure 21: Regression graphs for completion time. The horizontal, red, dashed line represents the fastest theoretical completion time if the car were to travel in a straight line down the course. The purple, vertical dashed lines represent the beginning of a new day (every 7 trials).

Figure 22 shows the total errors regression for each of the three algorithms. Note that both PL and PNL start out around the same value on day 1 and D starts at a much higher value. All three algorithms eventually converge to no errors, but PL is the first to reach it by the end of day 6. However, the pattern stays consistent throughout the plot, with PL improving slightly faster than PNL and D trailing behind both of them.

Figure 22: Regression graphs for total errors. The purple, vertical dashed lines represent the beginning of a new day (every 7 trials).

Figure 23 below shows the overall workload regression for each of the three algorithms. Note that the x-axis is labeled represented as days and not trials. Since a modified NASA TLX survey was used, 1 was the lowest possible number that could be obtained for overall workload. This is represented by the horizontal, red, dashed line and will be referred to as "zero overall workload." Although PNL starts out with the highest overall workload on day 1, it dramatically decreases and is the first algorithm to reach zero overall workload. D and PL do not reach zero overall workload until much later than PNL.

Figure 23: Regression graphs for overall workload. Note the x-axis is in days and not trials.

3.6 Learning: Time vs. Total Errors Correlation

To further evaluate the performance of each subject, it was assumed that if the subject truly learned the full capabilities of each control algorithm, they would commit the least amount of errors during their fastest completion times and commit the largest number of errors during their slowest completion times (3). Regression lines were calculated for each subject based on the correlation of time and total errors for each control algorithm on day 2. Based on the average slope of the regression lines, subjects were split into two groups. If a subject had an above average slope for all three control algorithms, they were classified as a high-capacity learner. If a subject had a below average slope for all three control algorithms, they were classified as a lowcapacity learner (3). Figure 24 illustrates a hypothetical example of both a high-capacity and low-capacity learner using the same control algorithm.

Figure 24: High-capacity learner vs. low-capacity learner. Note that the high-capacity learner has a steeper slope than the low-capacity learner.

High Learners

Figures 25-27 show the time vs. total error correlation graphs of high capacity learners performing with all three control algorithms. Note that D has the steepest slope of the three algorithms. However, of the two proportional control algorithms, PNL has the steepest slope.

Figure 25: Time vs. Total Errors correlation for high-capacity learners with the digital control algorithm.

Figure 26: Time vs. Total Errors correlation for high capacity learners with the linear control algorithm.

Figure 27: Time vs. Total Errors correlation for high capacity learners with the non-linear control algorithm.

Low Learners

Figures 28-30 show the time vs. total error correlation graphs of high capacity learners in all three control algorithms. Note that PL has the steepest slope and PNL has the flattest slope out of the three algorithms.

Figure 28: Time vs. Total Errors correlation for low capacity learners with the digital control algorithm.

Figure 29: Time vs. Total Errors correlation for low capacity learners with the linear control algorithm.

Figure 30: Time vs. Total Errors correlation for low capacity learners with the non-linear control algorithm.

Chapter 4: Discussion

The overall goal of this research was to investigate the performance of three different manmachine interface algorithms linking EMG to external device control. These algorithms range from the simple on/off control strategy (D) to a more complex non-linear proportional (PNL) control that mimics the physiological relationship that exists between muscle electrical potential and muscle force generation. Each algorithm was introduced to subjects over the course of two days in a randomized fashion. Subjects were given adequate time to train and then tested by measuring time to task completion and errors during task performance. Psychometrics were also assessed using the NASA TLX to assess perceptions of mental demand, physical demand, frustration level, and overall workload. Three hypotheses were tested. Each is listed and discussed below.

4.1 Hypothesis 1

"Hypothesis 1: A man-machine control interface that more closely mimics the EMG-muscle force generation relationship will provide more robust control."

Course completion time and total errors for all three algorithms had statistically significant differences when comparing day 1 results with day 2 results (Figures 12 and 13). This demonstrates subject learning. The smaller variances from day 1 to day 2 showed that the subjects were becoming more consistent with how long it took them to finish and the amount of errors they made, which is also indicative learning. Further evidence of learning is demonstrated by the large average time and error differences per day (Figure 14). D had the largest percent decrease for both time and errors, while PL had the lowest percent decrease in time and PNL the lowest percent decrease in errors. Therefore, day 1 was considered training and it was assumed that subjects were fully trained on day 2. All subsequent analysis was performed on day 2 data only.

On day 2, PNL had a significantly faster time than D and PL (Figure 18) demonstrating that subjects were able to complete the course fastest using PNL. When looking at total errors, PL and PNL had a significantly lower amount of errors than D (Figure 19). This demonstrates that subjects were able to complete the course more accurately with PL and PNL. Although PL has a fewer amount of errors than PNL, the result is not statistically significant. The oscillatory shape that can be seen by PNL and PL in both time and errors can be attributed to overconfidence. Subjects performed well in the beginning and then stated they became overconfident, resulting in a spike of time and errors before continuing the decreasing trend. This artifact has been documented in similar research (3). The hypothesis was proven correct by the results, which demonstrated that D performed the worst compared to PL and PNL.

4.2 Hypothesis 2

"Hypothesis 2: A man-machine control interface that more closely mimics the EMG-muscle force generation relationship will appear more natural, have the quickest acclimation time, result in the least frustration, and have the least overall workload for the user."

Evidence of learning was supported when comparing the NASA TLX data between day 1 and day 2 (Figures 15-17). The test elements assessing Overall Workload and Mental Demand showed a statistically significant difference between all three algorithms when comparing results from day 1 to day 2. This suggests that on day 2, all three algorithms were easier to use overall

and required lower cognitive demand. PL showed a significant difference in performance from day 1 to day 2, demonstrating subjects felt they performed better on day 2 than on day 1. PNL had a significant difference in temporal demand and frustration, meaning subjects felt less rushed and less irritated/annoyed on day 2 than on day 1.

Day 2 NASA TLX data (Figure 20) revealed subjects felt the D algorithm was the most mentally demanding and frustrating out of the three. These results were also shown to be significantly higher than PNL. This meant they felt D required the most thinking. PL demonstrated a significantly higher physical demand than both D and PNL, indicating subjects felt PL required them to flex and extend their hardest, when compared to D and PNL. PNL had a significantly lower overall workload than D and PL. Subjects felt PNL required the least amount of work to control.

When looking at the average times and total errors per trial for both days (Figures 12 and 13), it can be seen that there is no clear plateau for any of the algorithms. All still show decreasing trends towards the end of day 2, indicating that the subjects were still learning and suggesting that they were not yet fully trained. If the subjects were to continue for multiple days, the average time and total errors per trial would be expected to eventually level out for each algorithm. This would likely affect overall workload for each algorithm and cause it to decrease over time as well. Learning is defined as an exponential improvement in metrics. A regression analysis was performed to determine how many days it would take for the subjects to reach the minimum value possible using each algorithm for average course completion time, average total

41

errors, and average overall workload (Figures 21-23). By definition, the steepness of the negative slope indicates how fast the subjects were learning with that algorithm.

D had the largest negative slope out of all three algorithms, indicating subjects learned fastest with this algorithm. However, this assessment may be biased since D also began with the highest values out of the three algorithms in all categories. The regression graphs demonstrated that multiple days were required for all three algorithms to reach the minimum values possible in each category. A minimum of five days would be required for all three algorithms to reach the fastest completion time possible for the course, six to seven days for total errors to reach zero, and about 14 days for overall workload to reach the absolute minimum.

Although it appears that it would take multiple days for the three algorithms to converge to the same minimum value, the rank order of the algorithms does not change from the day 1 assessment to the final plateau day when looking at performance. PNL begins with the lowest average course completion time and, along with D, is the first to reach the fastest time to complete the course, with PL finishing about a day later. PL begins with the lowest value on day 1, with PNL beginning at about the same value. PL is the first equation to reach zero total errors, with PNL and D reaching the same value 1-2 days later. When looking at overall workload, PNL is the first equation to reach the minimum value. Although the data obtained did not reach a plateau, the regression analysis validates the primary objective of determining if there's a difference between the three equations. From this, it was concluded that the hypothesis was confirmed. PNL, which more closely matches the EMG-muscle force generation relationship, had the least amount of frustration and overall workload compared to D and PL. It also had the

42

quickest acclimation time in terms of average course completion time as well as overall workload.

4.3 Hypothesis 3

"Hypothesis 3: Subject capacity to learn, as elucidated by errors committed per unit time, will impact which control algorithm will produce the best results."

When looking at learning capacity (Figures 25-30), all three control algorithms had steeper regression slopes for high-capacity learners than low-capacity learners, indicating that highcapacity learners were able to learn faster than low-capacity learners. The steeper regression slope of D for high-capacity learners (Figures 25-27), demonstrated they were able to learn this control algorithm fastest out of the three. This is likely due to the fact they were able to realize this was an on/off type control algorithm and had no further capabilities. Out of the two proportional algorithms, PNL had the steepest regression slope indicating they learned how to take full advantage of the proportional capabilities of this control algorithm.

Low-capacity learners (Figures 28-30) had a faster learning rate with PL than the other two algorithms. It seems that low-capacity learners weren't able to fully learn how to operate the D and PNL control algorithms, unlike the high-capacity learners. One explanation for low-capacity learners being unable to operate D despite its relatively simple control activation is that D is not as physiologic as PL or PNL. PNL may model the EMG-muscle force relationship so well that low-capacity learners weren't challenged enough and weren't as actively engaged in the learning process. However, this doesn't mean that low-capacity can't learn the D and PNL algorithms, or that it was more difficult. Over time, subjects could indeed learn how to operate the D and PNL

algorithms, but it would take longer than the two days used in this study. This proves hypothesis 3 correct since high-capacity learners and low-capacity learned faster with different control algorithms.

A training study found that some subjects were not able to fully "use the available options of the proportional control." The study went on to explain that if differences in learning capacity actually exist, this should be taken into account when determining the most appropriate control algorithm for a patient to increase the chances of acceptance. Their findings showed that a digital control algorithm may be more appropriate for those less proficient in myoelectric control (lowcapacity learner) and a proportional algorithm would be more appropriate for high-capacity learners (3). Although the results in Figures 25-27 are in agreement with differences in learning capacity, the specific control algorithms suitable for each group are inconsistent with previous research.

4.4 Summary

Although subjects learned quickest with the D and PL algorithms, as seen by the steeper slopes in the correlation between time and errors (Figures 32-37), the NASA TLX data (Figure 27) shows that these two equations had significantly ($p < 0.05$) higher overall workloads than PNL. D was also significantly ($p < 0.05$) more frustrating and mentally demanding than PNL. PL was significantly ($p < 0.05$) more physically demanding than PNL. In context of application, despite the difference in learning capacity, PNL would be more suitable than D or PL because of the lower overall workload. It would be inappropriate to assign a control algorithm to a patient that would require a high physical demand, workload, or frustration level. This would likely deter the patient from using the prosthesis and cause them to reject it altogether.

4.5 Future Work

A potential application of this study is to test the algorithms using a prosthetic hand. It is clear that D had the poorest overall performance out of the three. However, the results showed that subjects perform better using a proportional algorithm. The next steps in this line of research could be to develop a prosthetic hand that is controlled by the PL and PNL algorithms and have subjects perform tasks, such as object manipulation, to further evaluate differences between the two proportional algorithms in a more real-world setting.

Chapter 5: Conclusion

The primary objective of this experiment was to evaluate differences between D, PL, and PNL control during the performance of a novel task. A training device was modified to have proportional control capabilities. Hypotheses were constructed and tested revealing that a manmachine control interface that more closely mimics the EMG-muscle force relationship provides more robust control and appears more natural despite a longer rate of learning. There was statistical difference between the two days of trials, indicating that subjects learned over time with all of the algorithms. Analysis of day 2 data demonstrated PNL to be significantly different in course completion time, being faster than D and PL. D was shown to be significantly different in terms of total errors, having the most out of the three. PNL showed lower values that were statistically significant in physical demand, frustration, and overall workload. A regression analysis showed that even though subjects would be able to eventually achieve the same performance for all three algorithms, they would reach peak performance faster with PNL. Although there may be differences in learning capacity, the lower cognitive load gives evidence that a PNL algorithm is most appropriate for myoelectric control in prosthetic hands. Further work needs to be done in order to determine the efficacy of both the proportional algorithms when it comes to functional tasks using a prosthetic limb. In conclusion, there were differences found between the three control algorithms. A D equation does not match the EMG-force relationship of muscle and results in a higher mental demand and frustration for the user. Although PNL requires more time to fully learn, it has a significantly lower physical demand and overall workload than PL. Therefore, a PNL algorithm is more suitable for myoelectric control.

46

Literature Cited

1. Akyeampong, Joseph, Udoka, Silvanus, Caruso, Giandomenico, & Bordegoni, Monica. (2014). Evaluation of hydraulic excavator Human–Machine Interface concepts using NASA TLX. *International Journal of Industrial Ergonomics, 44*(3), 374-382.

2. Battye CK, Nightingale A, Whillis J. (1955). The use of myo-electric currents in the operation of prostheses. *J Bone Joint Surg Br*, 37–B(3), 506–10.

3. Bouwsema, H., Sluis, C. K., & Bongers, R. M. (2010). Learning to control opening and closing a myoelectric hand. *Arch Phys Med Rehabil*, 91, 1442-1446.

4. Childress, D.S. (1985). Historical aspects of powered limb prostheses. Clinical Prosthetics and Orthotics, 9 (1), 2-13

5. Clingman, R., & Pidcoe, P. (2014). A Novel Myoelectric Training Device for Upper Limb Prostheses. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 22*(4), 879- 885.

6. Cram, J., Kasman, Glenn S, & Holtz, Jonathan. (1998). *Introduction to surface electromyography*. Gaithersburg, Md.: Aspen.

7. Dawson, M., Fahimi, F., & Carey, J. (2012). The development of a myoelectric training tool for above-elbow amputees. *The Open Biomedical Engineering Journal, 6*, 5-15.

8. Dudai, Y. (2004). The Neurobiology of Consolidations, Or, How Stable is the Engram? 55, 51-86.

9. Dupont, A. C., & Morin, E. L. (1994). A myoelectric control evaluation and trainer system. *IEEE T Rehabil Eng*, 2 (2), 100-107.

10. Farrell, T., & Weir, R. (2007). The Optimal Controller Delay for Myoelectric Prostheses. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 15*(1), 111-118.

11. Fougner, A., Stavdahl, O., & Kyberd, P. (2014). System training and assessment in simultaneous proportional myoelectric prosthesis control. *Journal of Neuroengineering and Rehabilitation, 11*, 75.

12. Gordon, K.E., & Ferris, D.P. (2004). Proportional myoelectric control of a virtual object to investigate human efferent control. *Exp Brain Res*. 159, 478–486.

13. Hubbard, S., Montgomery, G., Stocker, D. (2004). *Powered Upper Limb Prostheses.*New York. Springer.

14. Kamen, G., & Gabriel, David A. (2010). *Essentials of electromyography*. Champaign, IL: Human Kinetics.

15. Konrad, P. (2005). The ABC of EMG: A Practical Introduction to Kinesiological Electromyography. *Noraxon*

16. Knutson, J.S., Hoyen, H.A., Kilgore, K.L., & Peckham, P.H. (2004). Simulated neuroprosthesis state activation and hand position control using myoelectric signals from wrist muscles. *J Rehab Res Dev*, 41, 461–472

17. Mcdonald, A., Sanei, K., & Keir, P. (2013). The effect of high pass filtering and non-linear normalization on the EMG-force relationship during sub-maximal finger exertions. *Journal of Electromyography and Kinesiology : Official Journal of the International Society of Electrophysiological Kinesiology, 23*(3), 564-71.

18. Merrill, D., Lockhart, J., Troyk, P., Weir, R., & Hankin, D. (2011). Development of an implantable myoelectric sensor for advanced prosthesis control. *Artificial Organs, 35*(3), 249-52.

19. Philipson, L., & Sörbye, R. (1987). Control accuracy and response time in multiple-state myoelectric control of upper-limb prostheses. *Med & Biol Eng & Comput*, 25, 289-293.

20. Radhakrishnan, S.M., Baker, S.N., & Jackson, A. (2008). Learning a novel myoelectriccontrolled interface task. *J Neurophys*. 100, 2397–2408.

21. Rubio, S., Díaz, E., Martín, J., & Puente, J. (2004). Evaluation of Subjective Mental Workload: A Comparison of SWAT, NASA‐TLX, and Workload Profile Methods. *Applied Psychology, 53*(1), 61-86.

22. Segil, J., & Weir, R. (2015). Novel postural control algorithm for control of multifunctional myoelectric prosthetic hands. *Journal of Rehabilitation Research and Development, 52*(4), Journal of rehabilitation research and development, 2015, Vol.52(4).

23. Smurr, L. M., Gulick, K., Yancosek, K., & Ganz, O. (2008). Managing the upper extremity amputee: A protocol for success. *J Hand Ther*, 21 (2), 160-175

24. Stein, R.B., & Walley, M. (1983). Functional comparison of upper extremity amputees using myoelectric and conventional prostheses. *Arch Phys Med Rehabil*. 64, 243-248

25. Takeuchi, T., Wada, T., Mukobaru, M., & Doi, S. A training system for myoelectric prosthetic hand in virtual environment. Proceedings of: *IEEE/ICME International Conference on Complex Medical Engineering*. Beijing, China, 23-27 May 2007, p1351-1356.

26. Thurston, A.J. (2007). Pare and prosthetics: the early history of artificial limbs. ANZ J Surg, 77, 1114 –1119

27. Weaver, S.A., Lange, L.R., & Vogts, V.M. (1988). Comparison of myoelectric & conventional prosthesis in adolescent amputees. *Am J Occup Ther*, 42, 87-91

28. Ziegler-Graham, K., MacKenzie, E.J., Ephraim, P.L., Travison, T.G., & Brookmeyer, R. (2008). Estimating the prevalence of limb loss in the United States: 2005 to 2050. *Arch Phys Med Rehabil*. 89 (3), 422-429.

29. System Electric Hands. (n.d.). Retrieved November 23, 2015, from http://professionals.ottobockus.com/cps/rde/xchg/ob_us_en/hs.xsl/6901.html

Appendices

Appendix A

Individual Subject Time and Error Data

Appendix B

Individual Subject NASA TLX Data

Appendix C: Generalized Estimating Equations Analysis

Time

Model: (Intercept), day, condition, day * condition

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable time

a. The mean difference is significant at the .05 level.

The Wald chi-square tests the effect of day*condition. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Error

Dependent Variable: total errors

Model: (Intercept), day, condition, day *

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable total errors

a. The mean difference is significant at the .05 level.

The Wald chi-square tests the effect of day*condition. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Overall Workload

Dependent Variable: NASA

Model: (Intercept), day, condition, day *

Dependent Variable: NASA

Model: (Intercept), day, condition, day * condition

a. Set to zero because this parameter is redundant.

Pairwise Comparisons

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable NASA

a. The mean difference is significant at the .05 level.

a. The mean difference is significant at the .05 level.

comparisons among the estimated marginal means.

Appendix D

Consent Form and Script

RESEARCH SUBJECT INFORMATION AND CONSENT FORM

TITLE: Evaluation of a Novel Myoelectric Training Device

PROTOCOL NO: HM20004508

INVESTIGATOR: Peter Pidcoe, PhD, DPT, PT

If any information contained in this consent form is not clear, please ask the study staff to explain any information that you do not fully understand. You may take home an unsigned copy of this consent form to think about or discuss with family or friends before making your decision.

In this consent form, "you" always refers to the research participant.

PURPOSE OF THE STUDY:

The purpose of this research study is to find an equation that matches the natural behavior of muscles in the forearm during rest and activity.

PROCEDURES

If you decide to be in this research study, you will be asked to sign this consent form after you have had all your questions answered.

At your first study visit (Visit 1), you will begin the study for data collection. This visit is considered training, so you can become familiar with the system. You will be asked to wear braces on your forearms during the study to make sure the data being collected is from the correct muscles. Then you will push the ends of your fingers against the braces to control a toy car and move it through an obstacle course. The total time for you to finish the course as well as the number of mistakes you make will be recorded. Mistakes include backing up, hitting a wall, or hitting a cone.

For your second visit (Visit 2), which should be scheduled within 48 hours of Visit 1, you will go through the procedure again for comparison purposes.

Your participation in this study will last up to 120 minutes for each visit. Approximately 10 individuals will participate in this study.

RISKS AND DISCOMFORTS

You may feel tired or uncomfortable during the study due to the braces, but the risk is small and you can take a break at any time. There is also a small chance of skin irritation from the electrode gel.

BENEFITS

The information gathered during the study may lead to a better understanding of the behavior of muscle activation, which has the potential to make advanced hand replacements feel more natural.

COSTS

There are no charges for the study visits. You will not be paid to participate.

ALTERNATIVE TREATMENT

Your alternative is not to participate in this study.

CONFIDENTIALITY

Data is being collected only for research purposes. Your data will be identified by ID numbers, not names, and stored separately from other records in a locked research area. All personal identifying information will be kept in password protected files and these files will be deleted five (5) years after the completion of the study. Other physical records will be kept in a locked file cabinet for five (5) years after the study ends and will be destroyed at that time. Access to all data will be limited to study personnel.

You should know that research data about you may be reviewed or copied by Virginia Commonwealth University.

Although results of this research may be presented at meetings or in publications, identifiable personal information pertaining to participants will not be disclosed.

VOLUNTARY PARTICIPATION AND WITHDRAWAL

Your participation in this study is voluntary. You may decide to not participate in this study. Your decision not to take part will involve no penalty or loss of benefits to which you are otherwise entitled. If you do participate, you may freely withdraw from the study at any time.

Your decision to withdraw will involve no penalty or loss of benefits to which you are otherwise entitled.

Your participation in this study may be stopped at any time by the researcher without your consent. The reasons might include:

- the researcher thinks it necessary for your health or safety;
- you have not followed study instructions; or
- administrative reasons require your withdrawal.

QUESTIONS

If you have any questions, complaints, or concerns about your participation in this research, contact:

Peter Pidcoe, 804-628-3655, pepidcoe@vcu.edu

West Hospital, Basement, Room 100 1200 E Broad St, West Hospital P.O. Box 980224 Richmond, VA 23298-0224 or **Joshua Arenas, 757-567-3827, arenasja2@vcu.edu**

The researcher/study staff named above is the best person(s) to call for questions about your participation in this study.

If you have general questions about your rights as a participant in this or any other research, you may contact:

Office of Research Virginia Commonwealth University 800 East Leigh Street, Suite 3000 P.O. Box 980568 Richmond, VA 23298 Telephone: (804) 827-2157

Contact this number for general questions, concerns, or complaints about research. You may also call this number if you cannot reach the research team or if you wish to talk to someone else. General information about participation in research studies can also be found at [http://www.research.vcu.edu/irb/volunteers.htm.](http://www.research.vcu.edu/irb/volunteers.htm)

Do not sign this consent form unless you have had a chance to ask questions and have received satisfactory answers to all of your questions.

CONSENT

I have been provided with an opportunity to read this consent form carefully. All of the questions that I wish to raise concerning this study have been answered.

By signing this consent form, I have not waived any of the legal rights or benefits, to which I otherwise would be entitled. My signature indicates that I freely consent to participate in this research study. I will receive a copy of the consent form once I have agreed to participate.

Script

1. Introduction

In this experiment I am going to use an EMG, which senses the electrical activity of your muscles, to allow you to drive a remote control car. I will place pairs of electrodes over muscles in your lower arm and then brace your arms so that the muscles will be in a constant position while we conduct the trial. Then, I will ask you to contract those muscles in order to control the toy car and drive it through a course I have prepared. If you are ready now, I will begin placing the electrodes on your arm.

2. Calibration

With the electrodes now in place, we are going to calibrate the system. I am going to ask you to rest and then contract each of the braced muscles as hard as you can in order to get a baseline reading for the system. It is best that you flex using your fingertips and extend using your fingernails in order to get the most accurate reading for the maximum activation of the muscle.

3. Control Training

Your dominant arm will be used to control the steering of the car, while your other arm will be used to control the forward and backward motion of the car. You may now try moving your arms to move the wheels left and right, as well as move the car forward and back.

I am now going to place the car inside the box. In order to learn to drive the car using this specific algorithm, I am going to ask you to drive the car through a full 360° of rotation from one full turn in one direction. Please let me know if you feel that any adjustments should be made to the sensitivity of the controls. When you have completed this, I will have you take the NASA TLX survey to rate how difficult you felt this task was. After that we will move on to the driving course.

Before you begin, I will read the rating scale definitions of the survey so you can keep them in mind as you complete the task.

4. Functional Training/Testing

When I tell you to begin, I want you to navigate through the course and cross the blue tape at the end. You should pass through each of the gates marked by the white tape and avoid hitting the cones and the walls. If you hit a cone, three seconds will be added to your total time.

5. NASA TLX

Now that you have completed the course using this algorithm, I am going to have you take the NASA TLX survey to rate how difficult you felt this task was.

Appendix E

NASA TLX Survey

Figure 8.6

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low
estimates for each point result in 21 gradations on the scales.

Total count $=$ $-$

Date:

(NOTE - The total count is included as a check. If the total count is not equal to 15, then something has been miscounted. Also, no weight can have a value greater than 5.)

Subject ID:

Task ID: __________

Sum of "Adjusted Rating" Column =

WEIGHTED RATING $=$ [i.e., (Sum of Adjusted Ratings)/15]

Appendix F: Schematics

EMG Amplifying Board

EMG Filters

Switch Circuit

Dial Switch

Remote Control Car Arduino Circuit

Appendix G: Arduino Code

Code used to process EMG data and transmit to car.

#include <EasyTransfer.h> EasyTransfer ET;

SEND_DATA_STRUCTURE txdata;

/*--- variables for LEDs and push button ---*/ const int ledFlex = 13; const int ledRest = 12; const int ledExtend = 11; const int ledLeft = 10; const int ledRight = 9; const int ArmPin = 8; const int CalibratePin = 7; const int EmergencyPin = 6; const int LinearPin = 5; const int DigitalPin = 4; const int NonlinearPin = 3; int buttonState = 0; int emergencyState = 0; int armState = 0; int linearState = 0; int digitalState = 0; int nonlinearState = 0; int ledActive;
/*---

pins for EMG channels

---*/

const int Channel1 = A2; const int Channel2 = A3;

const int Channel3 = A4;

const int Channel4 = A5;

/*--

variables for the original and mapped values of the sensor pins

--*/

int C1sensorval; int C2sensorval; int C3sensorval; int C4sensorval; int C1mapval; int C2mapval; int C3mapval;

int C4mapval;

/*--

variables for calibration method and calculation of channel averages

--*/

const int calib array size = 200; float sumRest; float sumActive; float C1Rest; float C1Active; float C2Rest; float C2Active; float C3Rest; float C3Active; float C4Rest; float C4Active; int C1LinMax; int C2LinMax; int C3LinMax;

int C4LinMax; const float gain = 1.00;

```
/*-----------------------------------------------------------------------------
  variables to determine position for servo and stepper motors
-----------------------------------------------------------------------------*/
int steerdiff;
int speeddiff;
int leftmap;
int rightmap;
int forwardmap;
int backmap;
const int thresh = 10;
const float leftslope = 0.4333;
const float rightslope = -0.4333;
const float forwardslope = 0.7111;
const float backslope = 0.7111;
int straight = 81;
float degreeconv;
int degree;
float spdconv;
int spd;
int direc;
float degree1;
int degree2;
int debug = 0;
void setup() {
 Serial.begin(9600);
  analogReference(INTERNAL);
  setupCalibration();
  /* code below reads data from each sensor pin for 2 seconds to prevent erroneous
   data due to analog Reference being changed*/
  int C1test = analogRead(Channel1);
  int C2test = analogRead(Channel2);
  int C3test = analogRead(Channel3);
  int C4test = analogRead(Channel4);
  delay(2000);
```

```
 ET.begin(details(txdata), &Serial);
}
```

```
void loop() {
  emergencyState = digitalRead(EmergencyPin);
  if (emergencyState == HIGH) {
   digitalWrite(ledExtend, HIGH);
  spd = 0; degree = straight;
   txdata.angle = degree;
   txdata.carspeed = spd;
   ET.sendData();
  }
```

```
 if (emergencyState == LOW) {
 digitalWrite(ledExtend, LOW);
 buttonState = digitalRead(CalibratePin);
```

```
 if (buttonState == HIGH) {
  armState = digitalRead(ArmPin);
 C1Rest = 0;C1Active = 0;
 C2Rest = 0;C2Active = 0;
 C3Rest = 0;
 C3Active = 0;
 C4Rest = 0;C4Active = 0;
```

```
 digitalWrite(ledRight, HIGH);
 ledActive = ledExtend;
 calibration(Channel1);
 C1Rest = sumRest / calib_array_size;
 C1Active = sumActive / calib_array_size;
 C1LinMax = round(C1Active * gain);
 delay(1000);
```

```
 ledActive = ledFlex;
 calibration(Channel2);
 C2Rest = sumRest / calib_array_size;
C2Active = sumActive / calib array size;
C2LinMax = round(C2Active * gain);
 delay(1000);
 digitalWrite(ledRight, LOW);
```

```
 digitalWrite(ledLeft, HIGH);
 ledActive = ledFlex;
 calibration(Channel3);
 C3Rest = sumRest / calib_array_size;
 C3Active = sumActive / calib_array_size;
 C3LinMax = round(C3Active * gain);
 delay(1000);
```

```
 ledActive = ledExtend;
  calibration(Channel4);
  C4Rest = sumRest / calib_array_size;
  C4Active = sumActive / calib_array_size;
  C4LinMax = round(C4Active * gain);
  delay(1000);
  digitalWrite(ledLeft, LOW);
 }
```

```
 if (buttonState == LOW) {
  linearState = digitalRead(LinearPin);
  digitalState = digitalRead(DigitalPin);
  nonlinearState = digitalRead(NonlinearPin);
```

```
if (armState == LOW) {
  leftmap = C4mapval;
  rightmap = C3mapval;
  forwardmap = C2mapval;
  backmap = C1mapval;
  steerdiff = C4mapval - C3mapval;
  speeddiff = C2mapval - C1mapval;
```

```
 else {
  leftmap = C2mapval;
  rightmap = C1mapval;
  forwardmap = C3mapval;
  backmap = C4mapval;
  steerdiff = C2mapval - C1mapval; 
  speeddiff = C3mapval - C4mapval;
 }
```
}

```
 C1sensorval = analogRead(Channel1);
 C1mapval = constrain(map(C1sensorval, C1Rest, C1LinMax, 0, 100), 0, 100);
 C2sensorval = analogRead(Channel2);
 C2mapval = constrain(map(C2sensorval, C2Rest, C2LinMax, 0, 100), 0, 100);
 C3sensorval = analogRead(Channel3);
 C3mapval = constrain(map(C3sensorval, C3Rest, C3LinMax, 0, 100), 0, 100);
 C4sensorval = analogRead(Channel4);
 C4mapval = constrain(map(C4sensorval, C4Rest, C4LinMax, 0, 100), 0, 100);
```

```
 if (linearState == HIGH) {
  digitalWrite(ledFlex, HIGH);
  digitalWrite(ledRest, LOW);
  if (steerdiff > thresh) {
   degreeconv = ((leftslope * leftmap) + 76.6667);
   degree = constrain(degreeconv, straight, 120);
  }
  else if (steerdiff < -thresh) {
   degreeconv = ((rightslope * rightmap) + 85.3333);
   degree = constrain(degreeconv, 42, straight);
  }
  else {
   degree = straight;
  }
  if (speeddiff > thresh) {
   spdconv = ((forwardslope * forwardmap) - 7.1111);
   spd = constrain(spdconv, 0, 64);
  direc = 1;
```

```
 }
  else if (speeddiff < -thresh) {
   spdconv = ((backslope * backmap) - 7.1111);
   spd = constrain(spdconv, 0, 64);
  direc = 0; } 
  else {
  spd = 0;direc = 0;
  }
 }
 if (digitalState == HIGH) {
  digitalWrite(ledRest, HIGH);
  digitalWrite(ledFlex, LOW);
  if (steerdiff > thresh) {
   degree = 120;
  }
  else if (steerdiff < -thresh) {
  degree = 42; }
  else {
   degree = straight;
  }
  if (speeddiff > thresh) {
  spd = 64;direc = 1;
  }
  else if (speeddiff < -thresh) {
  spd = 64;direc = 0;
  }
  else {
  spd = 0;direc = 0; }
 }
```

```
 if (nonlinearState == HIGH) {
     digitalWrite(ledFlex, HIGH);
     digitalWrite(ledRest, HIGH);
     if (steerdiff > thresh) {
      degree1 = ((pow(2.71828, ((-46*(leftmap-10))*0.001))) - 1) / ((pow(2.71828, (-
0.02950*46)) - 1);
     degree2 = round((\text{degree1} * 29.50) + 81);
      degree = constrain(degree2, straight, 120);
     }
     else if (steerdiff < - thresh) {
      degree1 = ((pow(2.71828, ((-46*(rightmap-10))*0.001))) - 1) / ((pow(2.71828, (-
(0.02950*46)) - 1;
     degree2 = round((\text{degree1} * -29.50) + 81);
      degree = constrain(degree2, 42, straight);
     }
     else {
      degree = straight;
     }
     if (speeddiff > thresh) {
      spdconv = ((pow(2.71828, ((-46*(forwardmap-10))*0.001))) - 1) / ((pow(2.71828, (-
(0.06102*46)) - 1;
     spd = round(spdconv * 61.02);spd = constant(spd, 0, 64);direc = 1;
     }
     else if (speeddiff < -thresh) {
      spdconv = ((pow(2.71828, ((-46*(backmap-10))*0.001))) - 1) / ((pow(2.71828, (-
(0.06102*46)) - 1;
     spd = round(spdconv * 61.02);spd = constant(spd, 0, 64);direc = 0;
     }
     else {
     spd = 0;direc = 0; }
    }
```

```
 if (linearState == LOW && digitalState == LOW && nonlinearState == LOW) {
     digitalWrite(ledFlex, LOW);
     digitalWrite(ledRest, LOW);
    spd = 0; degree = straight;
    direc = 0; }
    constrain(degree, 42, 120);
    constrain(spd, 0 , 64);
    txdata.angle = degree;
    txdata.carspeed = spd;
    txdata.cardirec = direc;
    ET.sendData();
   }
 }
}
/*--------------------------------------------------------------------------
  method used to find the sum of resting and flexion/extension values for
  the specified EMG channel (sensorPin); the average is then calculated in
  the loop code
--------------------------------------------------------------------------*/
void calibration(int sensorPin) {
int calibrationArray[calib_array_size];
int i = 0;
  int sensorval;
  sumRest = 0;
  sumActive = 0;
  blinkLED(ledRest);
 while (i < calib array size) {
   sensorval = analogRead(sensorPin);
   calibrationArray[i] = sensorval;
   sumRest = sumRest + calibrationArray[i];
   delay(15);
  i = i + 1; }
```

```
if (i == calib \arctan x size) {
   digitalWrite(ledRest, LOW);
  }
i = 0; delay(1000);
  blinkLED(ledActive);
 while(i < calib array size) {
   sensorval = analogRead(sensorPin);
   calibrationArray[i] = sensorval;
   sumActive = sumActive + calibrationArray[i];
   delay(15);
  i = i + 1;
  }
 if (i == calib array size) {
   digitalWrite(ledActive, LOW);
 }
}
/*------------------------------------------------------------------------
  initializes the pins for LEDs and the button of the calibration system
------------------------------------------------------------------------*/ 
void setupCalibration() {
  pinMode(ledLeft, OUTPUT);
  pinMode(ledRight, OUTPUT);
  pinMode(ledRest, OUTPUT);
  pinMode(ledFlex, OUTPUT);
  pinMode(ledExtend, OUTPUT);
  pinMode(ArmPin, INPUT);
  pinMode(CalibratePin, INPUT);
  pinMode(EmergencyPin, INPUT);
  pinMode(LinearPin, INPUT);
  pinMode(DigitalPin, INPUT);
  pinMode(NonlinearPin, INPUT);
```

```
 digitalWrite(ledLeft, LOW);
  digitalWrite(ledRight, LOW);
  digitalWrite(ledRest, LOW);
  digitalWrite(ledFlex, LOW);
  digitalWrite(ledExtend, LOW);
}
```

```
/*-----------------------------------------------------------------------
  method used to blink the LEDs, signaling to the user which channel
  is being calibrated
-----------------------------------------------------------------------*/ 
void blinkLED(int led) {
  digitalWrite(led, HIGH);
  delay(500);
  digitalWrite(led, LOW);
  delay(500);
  digitalWrite(led, HIGH);
  delay(500);
  digitalWrite(led, LOW);
  delay(500);
  digitalWrite(led, HIGH);
```
}

Code downloaded to car to receive transmission and control car.

```
#include <Servo.h>
Servo Steer;
#include <EasyTransfer.h>
EasyTransfer ET;
const int speedpin = 11;
const int dirpin = 13;
int servo;
int spd;
int dir;
struct RECEIVE_DATA_STRUCTURE {
 int angle;
 int carspeed;
  int cardirec;
};
RECEIVE_DATA_STRUCTURE txdata;
void setup() {
  Serial.begin(9600);
  setupMotor();
  ET.begin(details(txdata), &Serial);
  Steer.attach(9);
}
void loop() {
  if(ET.receiveData()){
   servo = constrain(txdata.angle, 42, 120);
   spd = constrain(txdata.carspeed, 0, 127);
   dir = constrain(txdata.cardirec, 0, 1);
   Steer.write(servo);
   Drive(dir, spd);
```

```
 }
}
```

```
void Drive(int dir, int spd) {
  digitalWrite(dirpin, dir);
  analogWrite(speedpin, spd);
```
}

void setupMotor() { pinMode(speedpin, OUTPUT); pinMode(dirpin, OUTPUT); digitalWrite(speedpin, LOW); digitalWrite(dirpin, LOW);

}