Effects of Training Methods on Classification on Surface Electromyographic Signals for Myoelectric Control

by

Hugh C. Day-Williams

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Signature of Author: Signature redacted

Department of Mechanical Engineering

May 25, 2018

Certified by: Signature redacted

Leia Stirling

Charles Stark Draper Professor of Aeronautics and Astronautics

Thesis Supervisor

Accepted by: Signature redacted

Rohit Karnik

Professor of Mechanical Engineering

Undergraduate Officer

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Abstract

Myoelectric devices, devices which use the electric signals from human muscles as a control scheme, have shown promise in their potential to aid in human movement augmentation and assistance for those that have suffered injury. Previous studies involving myoelectric devices and the classification of surface electromyographic (sEMG) signals, electrical impulses obtained from muscles from sensors on the skin, have sought to use various types of machine learning models for sEMG pattern recognition. This technique shows promise in being able to accurately classify human sEMG signals and map them to certain movements, which can then be used as a method of myoelectric control. In this study we explored how two methods of training a K-Nearest Neighbor (KNN) classifier, used to control a MyoPro arm orthosis, affect two subjects' performance on various experimental tasks and their measured sEMG activation throughout the tasks. It was found that for subject 1, the assisted training method, where another individual helps move the orthosis while training the KNN, resulted in a lower variance in the measured mean sEMG values, and reduced the cross validation accuracy of the controller, but did not reduce subjects' performance of the experimental trials, as compared to the KNN controller trained without assistance. For subject 2, the assisted controller reduced the performance on three out of the four tests performed compared to the unassisted controller.

Thesis Supervisor: Leia Stirling

Title: Charles Stark Draper Professor of Aeronautics and Astronautics

1. Background

1.1 Motivation

Myoelectric orthoses have a variety of applications, primarily in augmenting existing human movement, or the rehabilitation of functionality in patients that may have existing neuromuscular disorders [1] [2]. For example, in a study on the effects of a myoelectric assistive device for stroke patients, the assistive torque on the patient's elbow was found to improve their ability to extend their arm beyond the range they would be able to without assistance [2]. Similar technology was used at the University of Michigan Human Neuromechanics Lab in the development of a pneumatic lower-body exoskeleton designed to augment or assist in human lower-body movement [3]. The integration of machine learning into myoelectric controllers may allow for more accurate control over devices that augment or assist human movement.

1.2 Surface Electromyography

Electromyography is the measuring of electrical signals from muscle tissue. Surface Electromyography (sEMG) is the process of non-invasively measuring these signals in order to gain information on muscle activation in the human body. In sEMG, electrodes are positioned around specific muscle groups. The electrical signals obtained from these electrodes can then be used, most commonly, for the control of external devices [1]. sEMG signals used for control purposes are filtered in order to obtain a variety of signal features that inform on the muscle activation in the user. An example device that uses sEMG is the MyoPro orthosis, which is the assistive arm exoskeleton used in this paper. While sEMG provides a non-invasive way of measuring muscle activation, there are a variety of challenges associated with controlling an external device using sEMG. Because sEMG signal are measured using external electrodes, the signal is impacted by the positioning of the electrodes on the human body, donning and doffing of the electrodes, the conductivity of the skin, cross talk with other muscle groups and fatigue [1]. Each of these factors affects the clarity or strength of the signal and therefore affects the accuracy of the implemented control scheme.

1.3 Surface Electromyography Control Schemes and Machine Learning

There are a variety of common control schemes used with sEMG in order to control external devices. Two common control schemes for myoelectric devices, device controlled by the electrical signal of muscles, are 'ON-OFF' control and proportional control. In 'ON-OFF' control, sEMG signals are measured and control the actuation of a device if the EMG signals surpass a certain pre-set threshold. In proportional control, one or more input signals is/are used to determine the current, state of the device, which is not necessarily binary [1].

Recently, machine learning has begun to be incorporated into myoelectric control schemes as a method of sEMG pattern recognition. Learning through demonstration is one type of machine learning which has been used with myoelectric devices to map a variety of features in the sEMG signal to real-world states of the device[4][5]. In learning from demonstration, the system is provided with training data, which consists of a set of examples from the teacher (the user of the device) completing a task. The device then 'learns' to abstract certain features into a potential state for the device [6]. Previous studies have utilized machine learning models such as Support Vector Machines (SVM), Gaussian Mixture Models (GMM), Hidden Markov models (HMM) and K-Nearest Neighbor Classifiers, in order to classify sEMG signals as a control scheme for an external device [4][5][7][8].

Previous studies have explored the use of machine learning in order to classify muscle movement patterns. Khokhar, Xiao and Menon [7] explored the relationship between sEMG forearm signals and wrist torque. Using a Support Vector Machine, they were able to classify wrist movements by the differing levels of wrist torque with 96% accuracy. The classification was done using four sEMG sensors on the forearm, and used to actuate a two-degree-of-freedom wrist exoskeleton prototype. A study by Siu, Shah and Stirling [4] investigated the ability of a machine learning model to classify grasp and release movements of the human hand. A Gaussian Mixture Model and a hidden Markov Model were used to classify the sEMG signals received from seven sensors on the forearm. The study was able to achieve a 75.96% accuracy rate on classifying sEMG signals from the forearm as an open or close hand signal [4]. This study was expanded to investigate the ability of a myoelectric control system to anticipate human movements. In a follow-on study by Siu, Arenas, Sun, and Stirling [5], forearm sEMG signals were classified in order to serve a control system for a thumb exoskeleton with two discrete states, open and close. During the study, a KNN was used to classify human forearm sEMG signals as either grasp or release. The study found that the system, by measuring and classifying 84 sEMG features (14 distinct features over six sEMG sensors) could actuate the thumb exoskeleton before the user had begun to open or close their hand, thereby anticipating the user's movements [5].

1.4 Thesis Aims

This thesis serves as a follow-on to the study by Siu, Arenas, Sun, and Stirling [5]. In this study a similar machine learning algorithm, K-Nearest Neighbor Classifier, was utilized to classify bicep and tricep sEMG signals which were then used to control a myoelectric arm exoskeleton, the MyoPro. In this study the two state controller used in the study by Siu, Arenas, Sun, and Stirling [5], has been expanded to three distinct states, flex, extend and hold in place/static. Furthermore, while the previous study used a device built for the given experiment, in this study, the exoskeleton used is a commercially available medical orthosis and the machine learning control algorithm has been designed to work with the existing features and control schemes of the exoskeleton. The machine learning controller is not integrated with the software of the device, but instead communicates with it via Bluetooth, classifying sEMG features from the device and relaying commands back to the device to control the movement of the elbow joint servomotor.

The purpose of this paper is to examine how two methods of training the machine learning controller affect the performance of a subject over four movement tasks using the MyoPro exoskeleton, and the sEMG signals measured during the movements tasks. It is hypothesized that an assistive training method, where the movement of the subject's arm is aided by another individual, will result in lower mean sEMG activation and lower performance on the movement tasks, compared to an unassisted training method, where the subject trains the device without aid.

2. Methods

2.1 The MyoPro

Figure 1. Myomo MyoPro

The device used for this study was the Myomo MyoPro Electric Elbow orthosis (Fig. 1). The device is intended for use by individuals with neurological disorders or injuries that impede or reduce their ability to actuate their elbow or hand. This version of the device attaches to the arm of the user and contains a battery-powered motor capable of moving the user's elbow joint in order to flex or extend the arm. The MyoPro attaches to the user's arm with straps and the hand, forearm and upper arm. Two sets of sensors, one positioned on the bicep, the other on the user's tricep, detect sEMG signals from the two muscle groups respectively. The sensors are attached to the upper arm strap using Velcro and are movable. The controller built into the MyoPro, then translates these signals into the flexion or extension of the arm depending on the strength of a two signals. A stronger bicep signal, as compared to the signal from the user's tricep will result in the flexion of the arm and vice versa for a stronger tricep signal.

The device has built-in Bluetooth connectivity and a companion demonstration application which allows an individual to interface with the device and give direct commands. By opening a Bluetooth connection to the MyoPro using a computer, commands can be sent in order to adjust device settings, read the position of the elbow joint in degrees, move the device to a specific angle at a given speed and various other functions. The relevant commands (see Appendix) used by the controller were reading the EMG values from the sensors on the MyoPro, reading the position of the elbow joint and moving the elbow joint to a given angle.

2.2 The Controller

The control algorithm, developed in Matlab, was designed to take the EMG values obtained from the device, and store them with a directional value as a label. This information was then used to train a KNN machine learning model which was used to control the device based of certain sEMG input features. As previously stated, a similar model was implemented by Siu, Arenas, Sun, and Stirling [5], in which a KNN was used to classify sEMG outputs from the forearm in order to control a hand exoskeleton with two distinct states, opened and closed. The three states device states in this study – flex, extend, and hold in place/static – allow for greater functionality and precision of movement of the MyoPro in comparison to a controller that only allows for two states. Using three states, the arm can move to and stop at several discrete elbow angles.

The control algorithm is separate from the MyoPro controller, which is embedded in the hardware/software of the device. In this paper, the term controller will refer to the control algorithm developed in Matlab to poll the MyoPro for sEMG data, classify the data and output a command to the device. The machine learning model used in the controller was a weighted 10-Nearest Neighbor Classifier. The model measures the Euclidian distance between points and then takes the squared inverse of the distance in order to determine the weight of a certain data point. While various types of machine learning models could be used, the weighted 10-NN Classifier was chosen due to its relatively high accuracy in comparison to other types of KNN's available in Matlab and because of the relatively small training size that needs to be obtained for the model to work.

The KNN Classifier was generated from the Matlab Classifier Application, and utilizes three features for each of the two muscle groups, in order to determine the proper output. The features used for classification were the mean of the previous ten measured sEMG values, the median of these values, and the variance of these values. The previous ten measurements of the sEMG values are utilized during training, however during use of the controller the previous five sEMG values are used as opposed to ten. This change was made to increase the responsiveness of the device during use in the experimental trials. The five sEMG values were measured over a time of approximately .2 seconds.

As stated, the MyoPro has built in commands that can be used to interact with the device via a Bluetooth connection. The command used to poll the device for EMG values returns two integer values, representing the sEMG signal from the user's bicep and tricep. No units are specified for these returned values. The device filters the raw sEMG signal from the user and therefore a variety of commonly used features in sEMG classification cannot be utilized by the controller. Therefore, all signal features used are based off the EMG integer values obtained from the device and all features are in the time domain. A version of the KNN included Wilson Amplitude [9] as a feature, but the inclusion of the Wilson Amplitude reduced the accuracy of the system and it was therefore removed as a feature.

The MyoPro commands allow an individual to move the arm to a chosen position at a specified motor speed. However, after each command the device will return a confirmation statement. Therefore, the elbow joint cannot continue to move until the current command is completed and the confirmation statement is sent. A true velocity controller could not be implemented as there will always be discrete pauses between each command while the confirmation statement is sent and there is no command that allows the user to control the device movement speed. Therefore, the algorithm controls the position of the elbow joint instead. Had the controller been integrated into the existing controller of the MyoPro rather than communicating with it externally, a true velocity controller may have been feasible, as the MyoPro is controlled with a velocity controller during regular operation.

The angle and speed at which the elbow joint is actuated can be adjusted; for these trials, they were set to a 5-degree movement of the elbow joint at 50% speed. Thus, upon receiving a command to extend the arm from the controller, the elbow joint angle will increase by 5 degrees at a rate which is 50% of an unspecified maximum speed.

2.3 Training the Controller

In order to train the classifier on a dataset, the user initially performs a standardized training routine which involves sub-tasks of flexing their arm, holding the arm in place, extending the arm and then holding the arm in place, with each task done for the same amount of time, approximately three seconds, and then repeated as a cycle. This cycle of the subject flexing their arm, holding it still and the extending the arm etc. is continued for approximately six minutes until 500 data points have been collected at a rate of approximately one data point per .06 seconds. The user was directed by an on-screen text prompt on how to train the arm, and how long to perform each sub-task. This training method allows the controller to obtain a set of sEMG integer values and the associated direction of current movement (flex, extend, hold in place/static). To reduce sEMG signal noise, the sEMG values were windowed so that the mean of every ten values is stored in a matrix, as mentioned previously, along with the associated direction of movement label. These labels were determined by reviewing the current and past position of the elbow joint, in order to determine the direction of motion of the arm. The features were then calculated in post-processing of the EMG data. Upon training the KNN Classifier, Matlab creates an object which is then used to predict which command to output to the arm. The classifier returns both the recommended label for the provided feature-set, as well as a confidence score for each of the three labels. Initially when operating the arm using the controller, the user could flex their arm, but then would not be able to extend the arm afterwards as the controller was misclassifying the measured sEMG values and outputting the command to flex the arm. The errors were due to the change in how the bicep comes into contact with the sEMG sensors on the device as the bicep is contracted. An adjustment was made to the KNN in order compensate for this imbalance. If the user's elbow joint is flexed to an angle greater than 50 degrees than the controller only requires confidence interval of at least 38, that the set of sEMG features should be labeled as an extension, in order to output the extend command. In contrast, at angles less than 50 degrees, the label with the highest confidence interval between flex, extend and static will be output to the device. Therefore, there is a lower threshold of tricep activation needed in order to extend the arm at elbow angles larger than 50 degrees and the command to extend the arm may override the other two labels (flex or hold in place/static) even when they have a higher confidence interval than the extend label.

2.4 Assisted and Unassisted Training Methods

Each subject trained the exoskeleton using the arm on which they had donned the MyoPro (their left) in order to actuate the elbow joint (unassisted) and by having another individual help them in actuating the elbow joint as they attempted to flex or extend their arm in the direction of motion (assisted). Each of the subjects in the study participated in four different tests, each to be completed five times. For each test, windowed EMG values were recorded along with test-specific metrics. The tests are as follows:

Box Movement Test ***(Box Test)***: The participant sits in a chair in the middle of two zones, which are 20 cm wide and positioned 60 cm apart. A light box is initially located in one of the zones. While keeping their back flat against the back of their chair, the participant must reach out, fully extend their arms, pick up the box, bring it to their chest and then fully extend their arms in order to place the box in the next zone (Fig. 2). The participant must the return their arms to their chest before repeating this process. The participant has two minutes in order to move the box between the zones as many times as they can. The number of times the box is moved between zones is recorded for each trial.

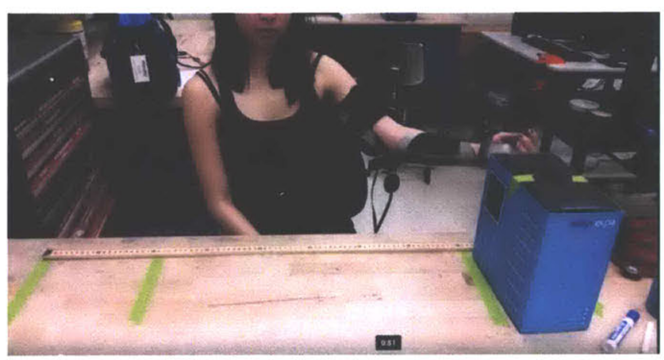

Figure (2): Box Test

Standing Test: The participant begins by sitting in a chair with their feet on the floor and his/her back against the chair. Without leaning forward, the participant must use their arms to push themselves up to a standing position as quickly as possible (Fig. 3). The person is considered standing when their hands are no longer holding onto the arms of the chair. The time from sitting to standing is recorded for each trial.

Figure (3): Standing Test

Angle Matching Test: The participant stands against a chart hung from the wall. The chart is marked with degrees of the MyoPro elbow joint beginning at 0 degrees and ending at 75 degrees in 25-degree increments. The participant begins with his/her elbow joint at the fulcrum of the chart with their elbow joint at 0 degrees (Fig. 4). They must then move their elbow joint through the different degrees, holding for three seconds at each 25-degree increment and finishing again at the 0 degree marker. The total time to move through the circuit is recorded for each trial.

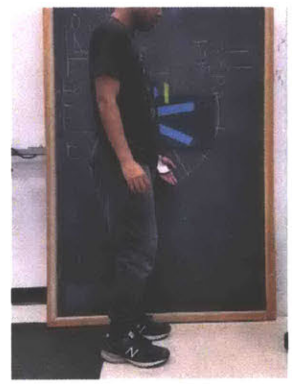

Figure (4): Standing Test

Box and Block Test *(Block Test)*: The participant sits in front of a box with two open-faced sides and a divider between them. The participant must move ~ 1.5' X 1.5' X 1.5' blocks from one side of the box to the other, making sure their fingers cross the ~ 1-foot-high divider each time (Fig. 5). The number of blocks moved across the divider is record for each trial.

Figure (5): Box and Block Test

2.5 Subjects

The two subjects were both age 21, healthy and had no impaired neurological or motor functions. Subject 1 had no experience using the MyoPro with either controller, prior to the study. Subject 2 had experience using the MyoPro and both the assisted and unassisted controllers. Prior to conducting the experiment, the protocol was approved by the MIT COUHES board. Both subjects also provided informed consent and signed MIT COUHES form prior to participating in the study (see Appendix).

3. Results

3.1 Subject 1

3.1.1 Subject 1: Training Data

An analysis of the data set used to train the assisted and unassisted controllers shows that though the two training data sets have a similar mean sEMG activation (Table 1), they have qualitatively different variances (Table 1). This difference in the data sets becomes especially evident in Fig. 6, which shows a 2-D t-distributed stochastic neighbor embedding (t-SNE) projection of the 6-D data set used as features for the KNN. Upon inspection of Fig. 6, it is evident that in the assisted tSNE plot there is less separation between the three labeled groups. Assisted data points of different labels are relatively intermingled, particularly the points labeled for hold in place and extend, in contrast to the unassisted data which has more clear divisions between groups. The differences in the two datasets led to a difference in the cross-validation accuracy of the two controllers (Table 2), as the assisted controller has an accuracy of 75.6% compared to 85.0% for the unassisted controller.

	Bicep	Tricep
Unassisted sEMG Variance	1144.7	6638.2
Assisted sEMG Variance	299.49	3990
Unassisted Mean sEMG	546.76	598.64
Assisted Mean sEMG	546.30	599.15

Table (1): variance of sEMG training data for assisted and unassisted.

	Assisted Trained Controller	Unassisted Trained Controller
Cross-Validation Accuracy (%)	75.6	85.0

Table (6): 5 fold cross-validation accuracy for the assisted and unassisted controllers. The training data is first partitioned into 5 equal parts. Four of these parts are then used to train the model, while the remaining one is used to validate model accuracy.

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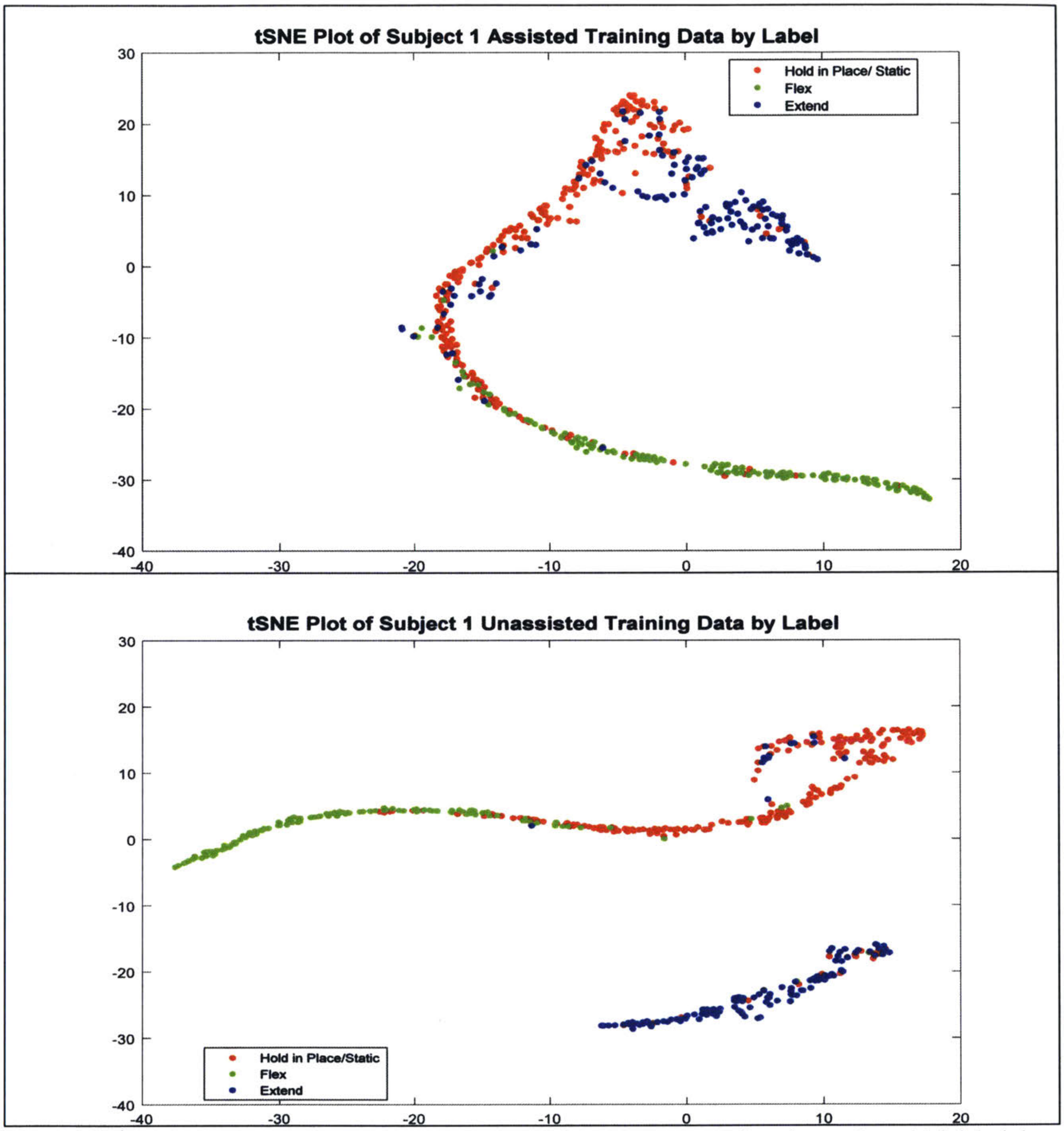

Figure (6): tSNE plots representing the six-dimensional feature space used to determine which label the controller will output, for the assisted and unassisted trained data sets respectively. Each point shown represents a given set of six features, three collected from the bicep and three features from the tricep. The data points are compressed by the tSNE graph from six dimension into two, while attempting to preserve a representation of relative the Euclidian distance between each point. The data is labeled by its classifier group: hold in place/static, flex, or extend.

3.1.2 Subject 1: Test Performance

The differences in the training data did not translate into substantial or consistent differences in performance for subject 1 between assisted and unassisted trails. As shown by the data in Table (3) and Table (4), subject 1 performed similarly on both sets of trials and any differences in performance were not consistent for assisted or unassisted trials. For example, subject 1 performed better on the 3rd through 5th trials for the Box and Block test with the assisted controller, but had almost equivalent performance on the Box Test between the two controllers. It can be concluded, from observation, that the assisted training had no detrimental effect on the overall performance of the subject on the administered tests, in comparison to the unassisted training.

Subject 1 Assisted Data				
Test Number	Box Test	Box and Block	Angle (s)	Standing (s)
1	4	5	71	8
2	4	5	99	13
3	3	6	99	14
4	4	8	105	10
5	3	9	122	11
Mean	3.6	6.6	99.2	11.2

Table (3): Aggregated data for Subject 1 assisted tests.

Subject 1 Unassisted Data				
Test Number	Box Test	Box and Block	Angle (s)	Standing (s)
1	4	5	87	11
2	4	5	103	13
3	3	4	67	13
4	4	5	86	15
5	2	6	94	13
Mean	3.4	5	87.4	13

Table (4): Aggregated data for Subject 1 unassisted tests.

3.1.3 Subject 1: sEMG Data

As was observed in the training data set, there was little difference observed in the mean sEMG values recorded for each test. sEMG values were recorded and then every five recorded values were averaged or 'windowed', to represent the mean sEMG values being passed into the classifier during operation of the MyoPro. There is an observed difference between bicep and tricep sEMG values that appears relatively consistent across all trials. There does not observationally appear to be a difference in windowed mean bicep sEMG or windowed mean tricep sEMG respectively, across different test and training methods. Similar to the training data, the windowed mean sEMG values recorded during the assisted tests generally have a lower variance compared to the unassisted windowed mean sEMG values of the same test as shown in Figure (7). Such differences are consistent across each of the four tests and for both muscle groups Figure (7), with the exception of Figure (7) Box and Block Test (column 4), where from visual inspection it can be seen that the variance of assisted trained sEMG values is larger than of the unassisted.

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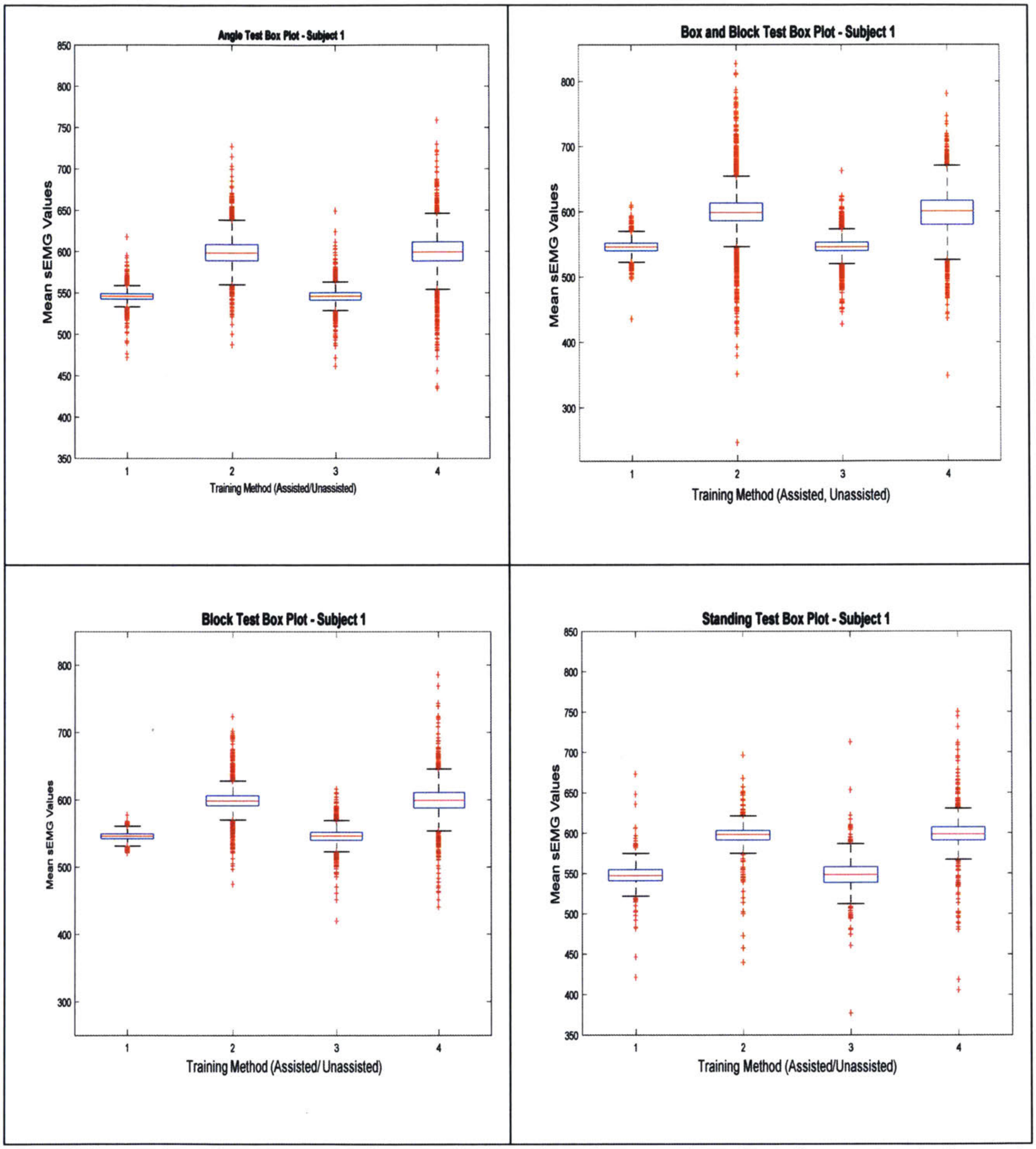

Figure (7): Four box plots comparing the recorded windowed sEMG values from the MyoPro during each test. sEMG values were recorded and then average over every five values to represent the sEMG values passed into the classifier. The values recorded are therefore the mean of every five measured sEMG value. The values are separated by muscle group (bicep and tricep) and by training method (assisted and unassisted). Groups 1 and 2 represent assisted trained, bicep and tricep respectively. Groups 3 and 4 represent unassisted trained, bicep and tricep respectively, for each graph.

3.2 Subject 2

Due to an error in the data collection during subject 2's trials, the following sections for subject 2 only analyze the training data and experimental trial performance, not the sEMG values collected during the trials.

3.2.1 Subject 2: Training Data

In the case of subject 2, an analysis of the training data collected shows that there is very little difference in the mean sEMG activation for the assisted and unassisted controllers (Table 4). However, the variance of the two data sets does appear to vary based on the muscle group in questions. The variance of the assisted controller sEMG values, measured from the subject's bicep, was less than that of the unassisted controller. For the tricep sEMG values, the variance was lower for the unassisted controller compared to the assisted (Table 5). As shown in Table (6), the difference in the two training set led to a difference in controller accuracy. The assisted controller had a lower classification accuracy, 58.8% in contrast to the 70.6% accuracy of the unassisted controller.

	Bicep	Tricep
Unassisted sEMG Variance	495.47	6828.50
Assisted sEMG Variance	355.18	15087.00
Unassisted Mean sEMG	546.30	599.60
Assisted Mean sEMG	546.29	599.59

Table (5): variance of sEMG training data for assisted and unassisted.

	Assisted Trained Controller	Unassisted Trained Controller
Cross-Validation Accuracy (%)	58.8	70.6

Table (6): 5 fold cross-validation accuracy for the assisted and unassisted controllers. The training data is first partitioned into 5 equal parts. Four of these parts are then used to train the model, while the remaining one is used to validate model accuracy.

As shown in the two tSNE plots in Figure (8), both the assisted and unassisted training sets lack clear spatial distinctions between the three groups. It is particularly evident in the assisted sEMG tSNE plot that the majority of the data points of a given label are intermixed or in close proximity to a data point with a different label. This intermingling is particularly true for the extend and hold signals which overlap substantially. Similar overlap of data points with different labels is evident in the unassisted training data as well. However, by observation, it occurs more frequently in the assisted data tSNE plot.

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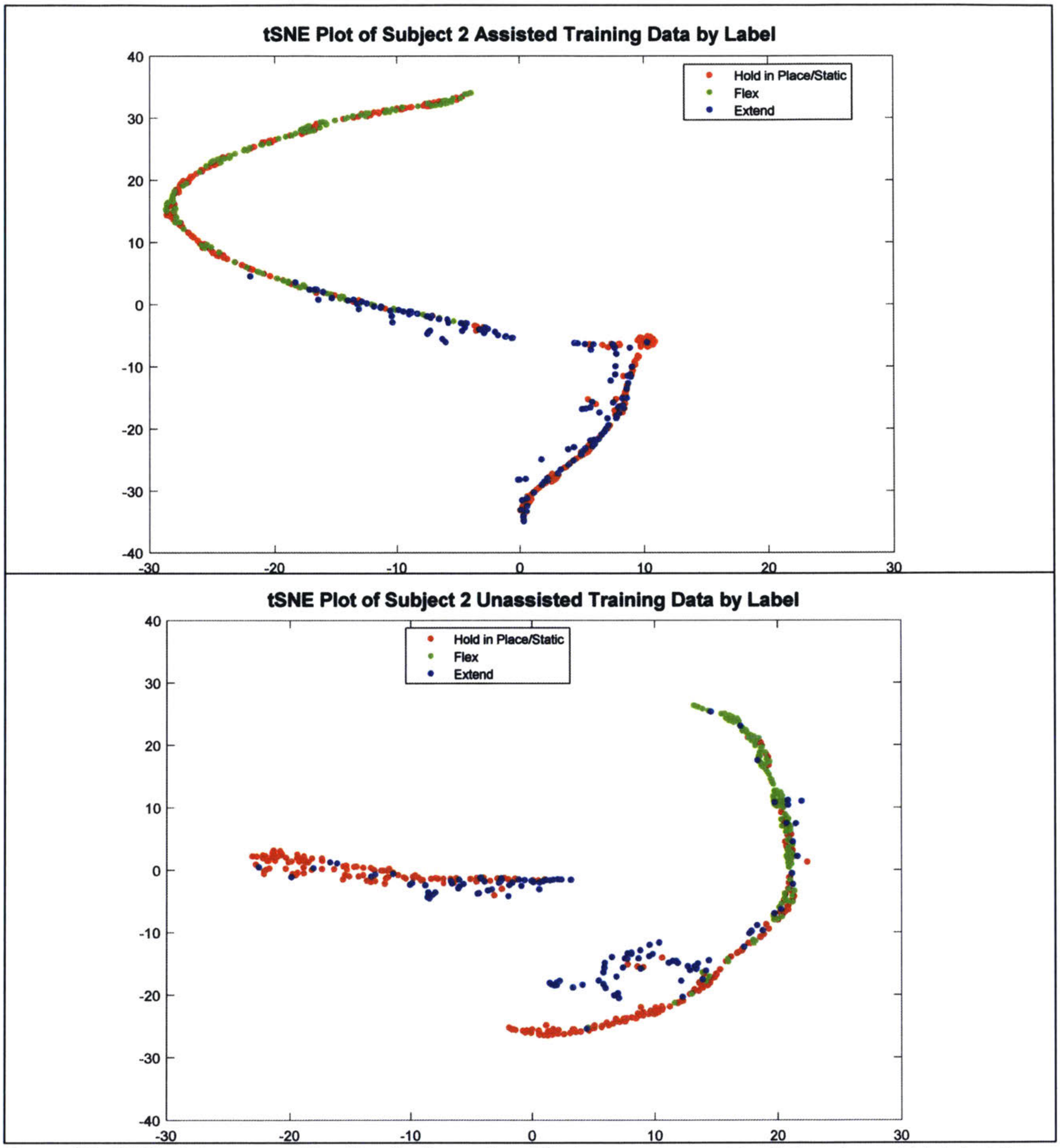

Figure (8): tSNE plot representing the six dimensional feature space used to determine which label the controller will output, for the assisted and unassisted trained data sets respectively. Each point shown represents a given set of six features, three collect from the bicep and three features from the tricep. The data points are compressed by the tSNE plot from six dimension into two, while attempting to preserve a representation of relative the Euclidian distance between each point. The data is labeled by its classifier group either Hold in Place/static, flex the arm or extend the arm.

3.2.2 Subject 2: Test Performance

The assisted and unassisted controllers had a substantial impact on subject 2's performance on the experimental trials. The results from the four tests are displayed in Table (6) below. In all tests expect the standing test, the subject performed better using the MyoPro with the unassisted trained controller. A two-tailed t-test was used to compare the performance of each controller on a given test. A statistically significant difference was found between the performance on the box test ($p = .0085$), the box and block test ($p = .0007$), and the angle test ($p = .0014$). A t-test of the standing test data was not found to reject the null hypothesis at a 5% significance level.

Subject 2 Assisted Data				
Test Number	Box Test	Box and Block	Angle (s)	Standing (s)
1	1	2	112	7
2	2	3	157	7
3	1	2	138	6
4	1	3	136	16
5	2	3	94	15
Mean	1.4	2.6	127.4	10.2

Table (6): Aggregated data for Subject 2 assisted tests.

Subject 2 Unassisted Data				
Test Number	Box Test	Box and Block	Angle (s)	Standing (s)
1	3	6	84	41
2	3	6	80	11
3	2	5	60	27
4	2	4	52	5
5	3	7	60	23
Mean	2.6	5.6	67.2	21.4

Table (7): Aggregated data for Subject 2 unassisted tests.

4. Discussion

4.1 Subject 1

It was initially hypothesized that the assisted training method would reduce the measured sEMG values of the participant while using the device and reduce the subject performance in each test. However, Table (1) and Fig (7) show that the mean sEMG values were similar for assisted and unassisted during training. As previously stated, there was a difference in the accuracy of the controller between the two training methods, 75.4% for assisted and 85.0% for unassisted (Table 2). The reduction in accuracy of the assisted controller compared to the unassisted can most likely be attributed to the difference in the variance of the two training datasets. As shown in Fig (6), the intermixed population of data points for the assisted controller leads to each point having a higher number of neighbors with a variety of different label in close proximity, which can lead to incorrectly labeling a given feature set.

The difference in the accuracy of the assisted and unassisted controller did not impact the subject's performance on the tests as hypothesized. Any differences in performance caused by the differing accuracy of the two controllers was most likely mitigated by the occasional errors in the classification of sEMG features, which reduced the performance of both controllers. The accuracy of both controllers can also vary as the device moves relative to the user's arm and as the arm becomes fatigued. An incorrectly-labeled sEMG input causes the device to move counter to the user or not move at all, which results in lost time on the trials. Although the unassisted trained controller was 9.6% more accurate during cross-validation of the KNN, the subject reported similar difficulties controlling the MyoPro with the unassisted controller and the assisted controller. In particular, it was observed that the subjects had difficulty fully extending or flexing their elbow joint. As the subject moves the device, the biceps and triceps contact the sEMG sensors on the device with varying amounts of pressure. For example, as the participant flexes their arm, the bicep muscle fibers contract resulting in a change in shape of the bicep. The position of the arm may also activate certain muscle groups by the bicep or tricep, such as the shoulder if the arm is not resting on an object. Peripheral muscle activation can result in crosstalk or activate the bicep and tricep without the user consciously contracting them, leading to incorrect outputs from the controller. The performance of the controller, assisted or unassisted, therefore varies based on the position of the elbow joint. However, despite the similarities in subject 1's performance quantitatively, subject 1 stated that in general the MyoPro using the unassisted controller was easier to control and would result in misclassified outputs less frequently.

The performance of the systems was also limited by the use of Matlab to implement the sEMG classification. The use of Matlab to communicate with the MyoPro led to limitations on the speed at which the MyoPro sent sEMG signals and received commands, which impacted both controllers. The system takes approximately .2 seconds to record sEMG signals, output the command to the device and return a confirmation that the device has executed the command. This delay restricts the speed at which the user can actuate the device, irrespective of the training method of the controller.

4.2 Subject 2

As originally hypothesized, subject 2 had significantly lower performance on the experimental trials when using the MyoPro with the assisted control. The mean sEMG values were not recorded during the trials and therefore this case study cannot address whether the assisted training had any effect on the mean sEMG values for the experimental trials.

The difference in trial performance is most likely due to the accuracy of the controllers (Table 5). The assisted trained controller had 11.8% lower accuracy than the unassisted trained controller. This difference can be explained by the data sets on which the two controllers were trained. From Figure (8), it is evident that the close proximity of data points with different labels led to a decrease in the accuracy of the KNN, which takes into account the 10 nearest neighboring data points when classifying a feature set. Subject 2 also reported that the MyoPro, when used with the assisted trained controller, frequently misclassified sEMG signals. The subject also perceived that the unassisted controller misclassified sEMG signals less frequently, than the assisted controller.

Both controllers also have similar limitations as those discussed for subject 1. Movement of the sensors across the arm and muscle fatigue can impact the sEMG signals measured and therefore reduce the accuracy of the machine learning controller. The use of Matlab further limits the speed at which the user can input commands to the MyoPro, due to the approximately .2 second delay between sending sEMG signals to the classifier and completing the outputted command.

4.3 Future work

Moving forward there are several improvements that could be made to the experimental procedures and the controller. In terms of the experimental procedure, a more consistent method of minimizing muscle activation during assisted training may result in a change in the mean sEMG activation. This could be accomplished by using force sensors to monitor and regulate the amount of force the subject is applying to the arm while training so as to minimize muscle activation. A consistent amount of weight could also be used in order to assure that the same level of assistance is given with each round of training the device. For the controller, the addition of elbow position to the features set of the KNN could potentially reduce the variation of the accuracy of the controller with elbow angle. Furthermore, obtaining a pre-processed signal from the device would allow for more features to be extracted and most likely increase the accuracy of the controller regardless of the training method. Finally, increasing the number of neighbors used by the KNN to determine the output label could also lead to an increase in controller accuracy.

5. Conclusion

The results of the subject 1 case study showed that assisting the movement of the subject's arm during the training of the K-Nearest Neighbor classifier, resulted in the sEMG data, obtained during trials, having a similar mean value but a lower variance compared to the unassisted trials. The assisted training method did not reduce mean sEMG activation for subject 1, nor did it impact the performance of subject 1 on the experimental trials as was originally hypothesized in this study. However, it did reduce the overall cross-validation accuracy of the assisted controller during training, with the unassisted and assisted controllers having an accuracy of 85% and 75.4% respectively. The effect of the lower accuracy using the assisted controller did not reduce performance on the experimental trials. The differences in accuracy of the controllers were mitigated by occasional errors in their classification of sEMG features and system limitations caused by the use of Matlab, which reduced the performance of both controllers.

In contrast, the difference in the controller accuracy for subject 2, 58.8% for the assisted controller and 70.6% accuracy for the unassisted controller significantly impacted their performance on the experimental test. Subject 2 performed significantly better on the tests when using the MyoPro with unassisted controller for the box test ($p = .0085$), the box and block test ($p = .0007$), and the angle test ($p = .0014$). The assisted controller performed better in the standing test, however the differences in performance of the standing test for assisted and unassisted controllers were not found to be statistically significant. The effect of the controllers on sEMG activation during the trials could not be measured due to equipment errors during testing of the unassisted controller.

Future works may seek to investigate how, for a device such as the MyoPro, limb position may impact sEMG signals and how such information can be incorporated into machine learning control algorithms to improve system accuracy and performance.

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7. References

1. D. Farina *et al.*, "The Extraction of Neural Information from the Surface EMG for the Control of Upper-Limb Prostheses: Emerging Avenues and Challenges," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 797-809, July 2014. doi: 10.1109/TNSRE.2014.2305111
2. R. Song, K. y. Tong, X. Hu and L. Li, "Assistive Control System Using Continuous Myoelectric Signal in Robot-Aided Arm Training for Patients After Stroke," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 4, pp. 371-379, Aug. 2008. doi: 10.1109/TNSRE.2008.926707
3. D. P. Ferris and C. L. Lewis, "Robotic lower limb exoskeletons using proportional myoelectric control," *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Minneapolis, MN, 2009, pp. 2119-2124. doi: 10.1109/IEMBS.2009.5333984
4. Siu HC, Shah JA, Stirling LA. Classification of Anticipatory Signals for Grasp and Release from Surface Electromyography. Leonhardt S, Teichmann D, eds. *Sensors (Basel, Switzerland)*. 2016;16(11):1782. doi:10.3390/s16111782.
5. Siu HC, Arenas AM, Sun T, Stirling LA. Implementation of a Surface Electromyography-Based Upper Extremity Exoskeleton Controller Using Learning from Demonstration. *Sensors (Basel, Switzerland)*. 2018;18(2):467. doi:10.3390/s18020467.
6. Argall, Brenna D.; Chernova, Sonia; Veloso, Manuela; Browning, Brett (May 2009). "A survey of robot learning from demonstration". Robotics and Autonomous Systems. 57 (5): 469–483. doi:10.1016/j.robot.2008.10.024.
7. Khokhar ZO, Xiao ZG, Menon C. Surface EMG pattern recognition for real-time control of a wrist exoskeleton. *BioMedical Engineering OnLine*. 2010;9:41. doi:10.1186/1475-925X-9-41.
8. A. D. C. Chan and K. B. Englehart, "Continuous myoelectric control for powered prostheses using hidden Markov models," in *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 1, pp. 121-124, Jan. 2005. doi: 10.1109/TBME.2004.836492
9. R. Boostani, M. H. Moradi, "Evaluation of the forearm EMG signal features for the control of a prosthetic hand", *Physiol Meas.*, vol. 24, no. 2, pp. 309-319, May 2003.

Appendix

Relevant Commands Used in Controller Algorithm

- Poll Device for sEMG values: returns two positive integer values corresponding to the sEMG values measured from the bicep and tricep sensors, respectively. Then returns an '$OK' once command is confirmed sent from the device. No units are specified for the values output by the device in its documentation.
- Poll Device for Position: returns a positive integer value corresponding to the angle of the elbow joint with ~0 degrees as full extension of the arm and ~100 degrees as full flexion of the arm. The maximal range of motion is adjustable and was changed slightly for the two subjects. Then returns an '$OK' once command is confirmed sent from the device.
- Move Device to Specific Angle: actuates servomotor on the elbow joint in order to move the elbow to a given angle, at a speed specified by the user who inputs the command. Then returns an '$OK' once command is confirmed sent from the device.

Subject COUHES Forms: Subsequent Pages