IMPROVING THE ROBUSTNESS OF PATTERN RECOGNITION-BASED MYOELECTRIC PROSTHESES

by

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Abstract

An upper-limb amputation is a life-changing procedure severely impacting the individual's ability to perform every-day tasks. Prosthetic devices have been designed to provide some relief to these individuals. Myoelectric prostheses have received significant attention in recent years as they have been designed to look more natural and provide the user with enhanced degrees of freedom (DoF) over the traditional body-powered prostheses. Myoelectric prostheses rely on the acquisition and processing of signals attributable to muscle activity within the residual limb. This signal is known as the electromyogram (EMG), representing the surface recording of electrical activity of muscle fibers. EMG signals recorded from an array of electrodes on forearm are used as signals to decode patterns of dexterous hand movement. Specifically among the myoelectric-based control schemes, pattern recognition-based approaches provide the user with immediate access to multiple DoFs. This functionality promotes a more intuitive experience over those schemes which provide the user with access to only one DoF at a time. In the case of pattern recognition-based prostheses, a set of features are extracted from the EMG signal recorded from the user's residual limb from one or more sites and patterns of muscle activity are "learned". Subsequently, when a known pattern of muscle activity is observed, the prosthetic device is actuated and moved appropriately.

Despite the advantages of pattern recognition-based prostheses over other prosthetic control methods, the robustness of the control scheme in real-world use remains an issue. Many factors experienced during real-world use have been shown to negatively impact the ability of the system to correctly predict the intended action of the user. This work is dedicated to enhancing the robustness of pattern recognition-based myoelectric prostheses thereby making the devices more reliable, useful, and accepted by those using the devices. The specific focus of the work is to improve the robustness of the devices pertaining to variations in limb position. In the introduction, background information regarding myoelectric prostheses and previous work to improve their robustness is presented. Following this introductory information and having established the need to address the robustness of myoelectric prostheses, an analysis of the effect limb position has on extracted features of EMG from able-bodied subjects is discussed. Subsequently, a thorough investigation of this effect is presented through an experiment conducted with able-bodied subjects and amputee subjects both wearing and not wearing their prostheses. It is found that a particular strategy of training in multiple positions should be employed to optimally reduce the negative effects of the limb's position on EMG features. Specifically, it is concluded that when using Linear Discriminant Analysis to classify time-domain features of EMG during discrete hand and wrist actions, a two-stage position specific classification method does not outperform a system in which data from multiple positions are aggregated to form a single classifier. After a discussion of the impact of this research, directions of future research are suggested with supporting preliminary experimentation.

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Dedication

This thesis is dedicated to members of the United States Armed Forces who have been injured serving our country. I recognize and appreciate the sacrifices made in my behalf.

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Chapter 1

Introduction

Controlling myoelectric prosthesis by way of pattern recognition has attracted significant attention for decades. Since 1967, myoelectric signal patterns have been recorded and employed in aiding prosthetic arm movements [1]. Pattern-recognition based myoelectric systems are intended to provide the user immediate access to more than two degrees of freedom (DoF), or movements, at any moment. This is beneficial over the standard system of myoelectric control (direct two-site control) in which prosthetic users only have access to one DoF at a time. For devices using direct two-site control, signals from the users flexor and extensor muscle groups are used to control the currently active DoF. To close one's prosthetic hand for example, the user would contract their flexor muscles in their residual limb and to open their hand they would contract their extensor muscles. Access to other movements or "modes" such as pronation and supination is achieved by contracting the flexor and extensor muscles simultaneously in what is termed a 'co-contraction.' In doing so, the user can navigate to a desired mode [4]. A subsequent contraction of the flexor or extensor muscles in the residual limb would produce a movement of the selected mode. Systems that employ co-contraction for mode selection are non-intuitive and time-consuming.

In contrast, pattern recognition-based prostheses provide the user with immediate access to multiple degrees of freedom. This functionality makes controlling the prosthesis more intuitive [5]. The user activates the muscles of their residual limb as if they were performing the intended action. Additionally, many pattern recognition-based myoelectric prostheses have been reported as having extremely high classification accuracy and thus they illustrate the potential for highly reliable control of a prosthetic device [6]. Another advantage of pattern recognition systems is that they account for individual patient anatomy. In regards to the EMG recorded from the residual limb of an amputee, Herberts et al. reported that "the myoelectric patterns from various electrodes in the stump region show considerable individual variations due to, for instance, the methods used in surgery" [1]. Where the unique anatomy of amputees may be detrimental to other control methods, individual anatomic variations do not significantly negatively impact pattern recognition systems.

Despite the advantages of pattern recognition-based prostheses over other prosthetic control methods, the robustness of the control scheme in real-world use remains an issue. Many claims of high accuracy were drawn from the results of controlled experiments including those in which the limb was held in static positions or stick-on electrodes were used. It has since been shown, however, that many factors experienced in real-world use negatively impact the robustness of the system. For example, training and evaluating a system with the limb in a single static position may yield excellent classification accuracy when tested or used in that position, yet when the limb is moved to a position other than where the system was trained, classification accuracy significantly degrades [7]. This fact typifies an important discrepancy between research and real-world use. Many other factors influence the robustness of myoelectric prostheses in real-world use including changes in the condition of the electrode-skin interface and changes in the load placed on the limb. These and other inciting factors will be discussed and elaborated upon throughout this work. It is necessary that the upper-limb prosthetic device maintain its functionality in a wide range of positions and environments for it to be a useful rehabilitative device.

This thesis is devoted to addressing and presenting solutions for improving the robustness of these prostheses in real-world use. Specifically, this thesis will present the fundamentals of pattern recognition theory and myoelectric prosthesis control, elucidate the current state of upper-limb pattern recognition prosthesis, discuss avenues for improving the robustness of these systems, present previous work by others in this area, and fully address my work to improve the reliability of the prosthesis throughout the user's entire physical working space. I will conclude by discussing the major findings of my work and propose directions forward.

1.1 Components of a Pattern Recognition System

The process of controlling myoelectric prostheses via pattern recognition consists of multiple components. In the initial training phase, EMG data are collected while the subject performs specific grasping tasks. Following training, parameters of the classifier are "learned" or estimated from the data collected during training. Finally a test phase is conducted to determine the ability of the classifier to generalize, or correctly label data that it was not exposed to during training. Each of these components has been a focus of dedicated research intended to maximize the performance of the system. For example, significant work has been conducted to determine the optimal number of electrodes to use, the optimal electrode spacing, and the optimal features to extract from the recorded EMG. As for the classification component of a pattern recognition system, work has been conducted to determine the optimal method to employ. Finally, others have analyzed particular metrics to determine the accuracy and robustness of their system during the testing phase. The following sections will explore the details of the training, classification, and testing phases of myoelectric pattern recognition-based prostheses. A brief introduction to virtual environment use is also provided.

1.1.1 Training

The first process of a pattern recognition system is the collection of training data. During training, the individual performs prompted actions while EMG signals are collected and associated with the prompt. The data to be collected are dependent on the type of classification to be subsequently performed. Thus, a thorough understanding of the chosen classification method is required before collecting training data. The data collected during training must be representative of the data observed during testing. Significant efforts have been reported to collect or process the data received during training to improve subsequent classification accuracy [8–12].

1.1.2 The Classifier

Pattern recognition, as its name implies, involves learning the pattern or structure of a given set of data and subsequently using that learned knowledge to predict the group to which incoming data most likely belong [13, 14]. The method is a form of supervised learning in which a mapping is learned from one or many inputs to a single output variable or class. The input variables are known as features. When classifying a person as being either male or female, for example, informative input features could be the person's height and weight. In the case of myoelectric prostheses, the features are attributes of the recorded EMG such as its mean absolute value (MAV) and variance. The ability of a classifier to predict the class of a previously unseen data sample is known as generalization. A metric of a classifier's ability to generalize is given by its classification accuracy or error and will be a metric reported throughout this work. The ability of a classifier to generalize well and correctly classify incoming data is critical in the case of myoelectric prostheses. Following training, the user should be able to use the device throughout the day to perform tasks of daily living.

Within the field of machine learning and statistics, many classification methods exist for classifying data of this type (continuous input features and discrete output classes). A few examples include: decision trees, K-nearest neighbor (KNN), support vector machine (SVM), artificial neural network (ANN), and linear discriminant analysis (LDA). Interested readers are referred to [13] and [14] for detailed information regarding these and other classification methods. Significant research has been conducted to determine the optimum classifier to use in real-time myoelectric pattern-recognition control. Some of the methods explored include: multilayer perceptron neural networks [15], Gaussian mixture models [16], LDA [12, 17], hidden Markov models [18], dynamic artificial neural networks [19], genetic algorithms [20] and fuzzy logic classifiers [21].

Although reported with slight variability among researching groups, LDA has consistently been shown to yield maximal classification accuracy of the tested methods [12, 17]. In addition to its high accuracy, other benefits of LDA include the minimal storage required to run the classifier and relatively fast and efficient method of prediction. Its high accuracy, low storage requirement, and minimal processing time all contribute to the method being widely used for real-time myoelectric pattern-recognition control.

LDA classification involves using a set of training data to determine linear boundaries between classes. In other words, it is a method for finding a linear combination of features which best separates two or more classes. Once these boundaries have been learned from the training data, a novel data point can be classified according to the side of the boundary on which it lies. If each class is associated with two features, the separating boundary is a line; for classes with three features, the separating boundary is a plane; if the classes are defined by more than three features the separation boundary is a hyperplane. The majority of classification presented in this work is performed using 27 features of surface-recorded EMG. See section 3.3 for more information regarding this feature set.

In the case of LDA, the linear combination of features to separate the classes is found by maximizing the ratio of the variance between the classes to the variance within the classes. An illustration of this idea is given in Fig. 1.1. A line is found separating two classes of data which maximizes this ratio.

In their paper published in 1973, Herberts et al. laid the foundation for pattern recognition myoelectric prostheses [1]. The basic process by which current pattern recognition systems function rely on this established framework. Amputee subjects were instructed to contract muscles in their residual limb in attempt to generate in their phantom limb one of seven particular positions. The data from six EMG

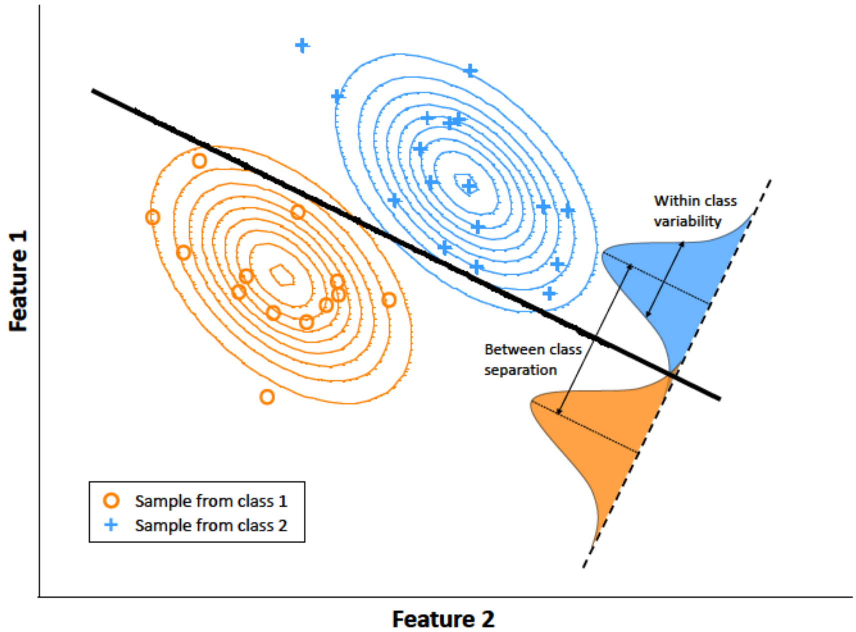

Figure 1.1: Illustration of a linear boundary between two classes of data generated using LDA. The boundary is computed by maximizing the between class separation while minimizing the within class variability.

channels were recorded and used to create a classifier which separated the multi-channel input signal into bins corresponding to the desired output. After creation of the classifier, the test phase was conducted by suggesting positions to the amputee which they would attempt to achieve in their phantom limb. The six-channel input signal was mapped to each position using the classifier and labeled or classified as that position to which it most closely matched. Upon classification of an input signal, the mechanical arm was moved accordingly. Although this is a very significant work, multiple claims have since been refuted including the assertion that classification accuracy was not significantly impacted by changing the load placed on the prosthesis, by having the user move their limb to positions outside of the training position, or by re-donning the prosthesis.

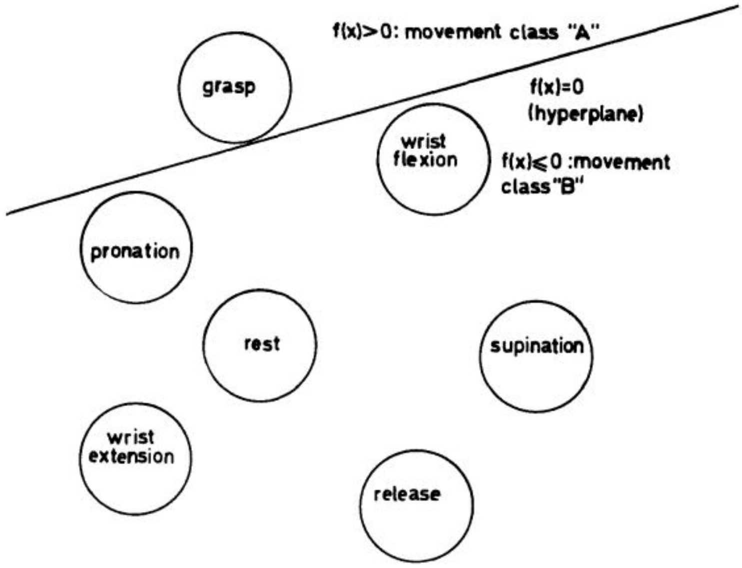

Figure 1.2: Figure shown in 1976 publication by Herberts et al. demonstrating the classification process using a linear classifier. The original caption states, "Schematic illustration showing the separation process. In this example, a hyperplane $f(x) = O$ separates grasp, belonging to class "A", from the remaining five movements, lumped in class "B"." [1].

Fig. 1.2 is the diagram created by Herberts et al. to demonstrate this process. The representation of each motion being contained in its own hyper-dimensional sphere is highly idealistic. In actuality, these spheres are not so distinguishable resulting in a difficult classification process. With overlapping spheres, any generated hyperplane will not perfectly separate one motion from the others. This, along with many other factors, caused their system to have a less than perfect classification accuracy. Improving classification accuracy remains today a significant issue with pattern recognition based myoelectric prosthesis. The group did show however, "that control of a below-elbow multifunctional prosthesis is indeed possible using myoelectric signal patterns from the stump itself" [1].

Foundational to pattern recognitions usability is the accuracy of the classifier. A decade ago, Englehart and Hudgins reported that using time domain features including mean absolute value (MAV), wave length (WL), zero crossing (ZC), and slope sign change (SSC) with LDA classification, a prosthesis can effectively be controlled using pattern recognition in a static environment [22]. Practical use however, requires accurate classification with the prosthetic and the users residual limb in a wide variety of positions, orientations, and under different loading conditions. Addressing these conditions, it has been shown that the classifier is less accurate in a non-static environment [23].

A recent study by Ashkan et al. demonstrated that by adding the Willison amplitude (WAMP) feature to the "commonly used [time domain] feature set combined with [an] LDA classifier reduces the averaged absolute classification error by 1.4%" [12]. An even more recent publication introduces an extension to LDA classification that "generates bounded confidence scores" and compares those scores with each classs unique rejection threshold. Scheme et al. named this technique LDAR with the 'R' for 'rejection' [24]. Evidenced by the high volume of recent publications directed towards finding an optimal classification scheme, a single, accurate, and accepted classifier has yet to be found.

1.1.3 Evaluating a Classifier's Performance

Central to the goal of the myoelectric system is its ability to correctly predict the intended action, or inaction, of the user. Quantifying a particular method's ability to correctly predict the intended action of the user using classification accuracy is simple and, if performed properly using methods such as cross validation, is generally accepted as being representative of the classifier's strength. Classification accuracy is given by equation 1.1.

$$\frac{\text{Number of samples correctly classified}}{\text{Total number of testing samples}} \tag{1.1}$$

Other metrics of a pattern-recognition system, such as throughput, efficiency, and task completion time, claiming to either support or undermine a pattern-recognition system are useful as well. Throughput is a valuable metric in many studies as "summarizes usability through the tradeoff of speed accuracy" [25]. Task completion time, the time required for a subject to perform a given task, is useful again to directly compare two methods within a particular study [26].

Because of the variability of each study however, comparing metrics such as classification accuracy or task completion time of one study with another holds little value. The classification accuracy reported by one group may vary considerably depending on the specific task or experimental procedure. Some efforts have been made to facilitate the comparison of methods among researching groups. Ortiz et al. in an effort to "provide a common research platform for the development and evaluation of algorithms in prosthetic control," released BioPatRec as open source software [27]. The software is released with three fundamentally different classifiers including Regulatory Feedback Networks (RFN), Multi-Layer Perceptron, and LDA. The group states the transparent implementation aims to facilitate collaboration and speed up utilization.

Groups pursuing research in this field have yet to adopt one particular method for evaluating the performance of their system. Arguably, this frustrates the advancement of the field, making collaboration and meaningful comparisons between individual investigations difficult. Other fields of research, such as arrhythmia detection using electrocardiography (ECG), have had great success adopting standard test material for evaluation of arrhythmia detectors [28]. With this factor in mind, it is suggested that the metrics reported within a particular study best be used to compare the methods or parameters varied within that particular study, rather than be strictly compared to metrics reported within other works.

1.2 Virtual Environment Testing and Training

Many groups working to progress the state of the art of myoelectric prostheses are utilizing virtual environments to move quickly through the development of their pattern recognition systems. The virtual environment provides researchers the ability to test various control schemes efficiently using both able-bodied (both arms healthy and fully functional) and amputee subjects [29–32]. Novel methods are most commonly evaluated with able-bodied subjects before expanding the patient population to amputee subjects. Additionally, virtual environment systems benefit the research community by decentralizing the work to groups without access to expensive physical prostheses or amputee subjects.

Not only is the virtual environment system useful for research groups, but also it has been shown to assist in patient training as well. Fig. 1.3 shows a virtual environment simulating a prosthetic hand being controlled by pattern recognition in real-time.

Figure 1.3: Images showing the testing of a pattern recognition system in a virtual environment where (A) shows a hand close grasp, (B) shows a hand open grasp, and (C) shows a wrist supinate grasp. The hand is controlled in the virtual environment by means of EMG pattern recognition. The arm is controlled in the virtual environment by means of the inertial measurement units (IMUs) worn by the subject as described in Appendix A.

There are multiple benefits to having a virtual environment for testing and evaluating a person's ability to control a pattern recognition device. It is possible to evaluate a person's ability to control a pattern recognition system before money and time is spent buying and making a device specific for that person. It would be evident if the person's anatomy is conducive to a pattern recognition system if tested using the virtual environment. By training on a virtual system as soon as possible after amputation, perhaps more users would accept the new limb once they received it and, therefore, learn to use it more naturally.

An additional benefit of a virtual environment is had by amputees seeking Targeted Muscle Reinnervation (TMR). TMR is a surgery in which the nerves of an amputees residual limb are reassigned to alternative muscles. EMG activity from the reinnervated muscles can then be recorded and used to control a myoelectric device [26, 33]. The motivation then for such a surgery, is to enable the patient to be successful with a myoelectric prosthetic system. By evaluating a potential TMR candidate with a virtual pattern recognition system, it could be shown that TMR either remains a potential useful surgery or that it is unnecessary. If the person exhibits satisfactory control of the virtual prosthesis, perhaps the need for the surgery is diminished.

Although a virtual environment for prosthesis control has many benefits to both researchers and amputees, in some critical ways the virtual environment does not represent or simulate the environment encountered during actual use of a prosthesis. For example, analysis performed with electrodes mounted to a person's arm may not be representative of actual use when the electrodes are mounted to the inside of a rigid prosthesis. By distancing the environment during testing from that encountered during actual physical use of the prosthesis, the system may be optimized for an environment different from that for which it was intended. Geng et al. found for example that "EMG signals acquired from an intact limb are more affected by limb position variation [than the amputated limb]" [34]. Thus optimizing a system for an intact limb may not be optimized for use with an amputated limb. Novel work presented in chapter 4 reinforces this idea with a presentation of how for amputees, wearing a prosthesis dramatically effects classification accuracy compared to when no prosthesis is worn.

Chapter 2

Previous Efforts to Improve the Robustness of Pattern Recognition-based Prostheses

The many aspects of a myoelectric prosthetic system illustrate the need to address its many facets when looking to enhance the robustness of the system. In this case, robustness refers to the ability of the pattern recognition system to provide accurate commands to the terminal device in a wide variety of real-world, environments. Not only can advancements be made by producing a more sophisticated control scheme or finding features more robust to environmental changes, but work can and should continue in all aspects of the myoelectric prosthetic system including patient training and education, prosthesis fitting, hand design, etc. Addressing these various components of the system is the responsibility of multiple populations; namely: prosthetic users, occupational therapists, prosthetists, engineers and researchers. The following sections will discuss efforts made by these various groups primarily in regards to subject training and engineering efforts. The responsibilities of occupational therapists and prosthetists is not the focus of this work, yet should not be excluded from a discussion regarding the robustness of the system.

The following items contain brief descriptions of the sections of this chapter.

Section 2.1: Focused subject training can significantly improve the robustness of pattern recognition-based myoelectric prostheses. Subjects can learn to create consistent and reliable contractions optimal for pattern recognition systems.

Section 2.2: Users of pattern recognition-based prostheses need to understand and apply correct working principles of their system. Not doing so will unnecessarily lead to significant degradation of performance.

Section 2.3: Electrode pairs ought to be placed longitudinally to muscle fibers, yet the optimal spacing between electrode pairs remains unclear. Most recently, it was found that increasing inter-electrode distance from 2 cm to 4 cm made a pattern recognition system less sensitive to electrode shift [35].

Section 2.4: Accepting that misclassification of intended hand or wrist actions will occur, many groups have worked to assuage its effects. Limiting the movement speed of the prosthetic hand when there is a change in classifier decision, imposing majority vote methods or confidence thresholds, or rejecting unknown data patterns are all methods explored to limit the impact of incorrectly predicted active grasps. A tradeoff exists between accuracy and responsiveness in the application of these methods.

Section 2.5: Rather than deal with errors after they have occurred it is logical to work to improve the classifiability of the incoming data before classification. Efforts in this direction include applying filtering methods to the raw EMG, extracting new features, using high-definition EMG arrays, or by recording intramuscular EMG as opposed to recording from the skin's surface.

Section 2.6: Increasingly, researchers have sought to more specifically address one of the major factors influencing their robustness: limb position variation. Addressing this source of variability is the focus of all subsequent chapters of this work.

2.1 Subject Training

Users of myoelectric prostheses, the amputees, have the ability to improve the robustness of their system through training and by applying correct usage principles. It has been shown that focused subject training can significantly enhance a subject's ability to control a pattern recognition device [2, 36]. A subject can learn to improve their ability to create consistent muscle contractions by applying feedback received following practice sessions. The ability to do this is essential for control of a pattern recognition device. The effect of training on a subject's ability to create consistent muscle contractions is illustrated in Fig. 2.1. Over the course of a 10-day period, an amputee subject learned to generate more consistent muscle contractions. This ability resulted in an increase in classification accuracy when the device was used. Powell et al. state, "the training focus for this subject was primarily to generate more consistent muscle patterns. The denser class clusters in the final evaluation session illustrate the accomplishment of this first goal of pattern recognition training: developing consistent muscle patterns" [2].

Figure 2.1: Illustrations of the data collected during initial and final evaluation sessions from a transradial amputee who completed 10 training sessions with a pattern recognition training system. Individual movement classes are depicted in unique colors with a superimposed confidence ellipse for cluster identification and visual contrast. The axes' ranges and units have no significance. Used with permission from [2]

2.2 Subject Application of Correct Working Principles

Along with training to produce consistent and reliable muscle patterns, it is critical for a user of a myoelectric system to be educated and understand the working principles of the system. Such an understanding will allow the user to correctly control the device and achieve maximum functionality. Although not a complete discussion of the topic, one such example is the importance of understanding the time course of the electrode-skin interface. The impedance between the user's skin and the electrodes within the prosthesis decreases significantly in the time following the donning of the prosthesis. Because of this change, data collected immediately after donning a prosthesis are not representative of the data collected a short time later. Thus, a classifier trained on data collected immediately after donning will do poorly in classifying data collected even a short time later. Because the interface reaches a steady state after only a few minutes ([37,38]), a classifier trained on data collected just a few minutes after donning however, will generalize well to future data assuming the other conditions at the time of training are kept constant. Preliminary research in this area is shown in Fig. 2.2, demonstrating the negative impact of training a classifier immediately after donning a prosthesis.

This example illustrates the need for the user to be educated and understand the working principles of the system to maximize functional use. Training immediately

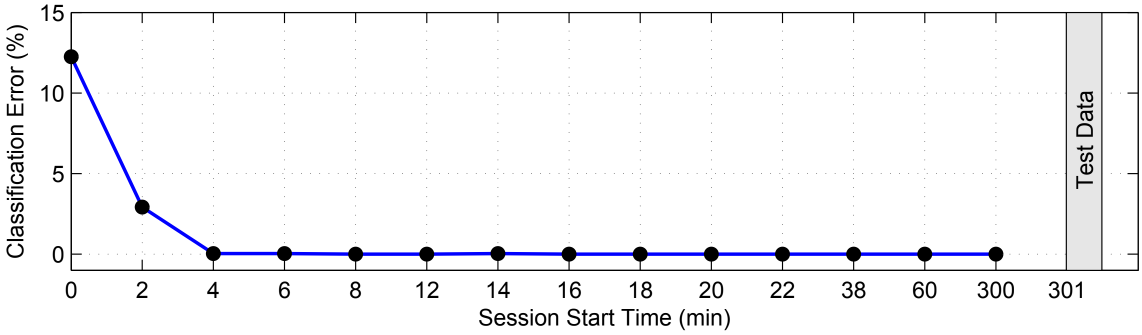

Figure 2.2: This figure illustrates the negative impact of training a classifier immediately after donning a prosthesis. In this preliminary experiment I conducted, an electrode cuff was applied to an able-bodied subject at time $t = 0$. Unique classifiers were created with data obtained at each marked point in time. Test data were gathered 301 minutes after donning the cuff. It is evident that the classifiers trained with data obtained directly after donning and two minutes after donning yielded higher classification error than classifiers trained with data obtained after this time.

after donning is devastating to classifier performance during use. Knowing this fact and simply waiting a few minutes after donning a prosthesis however, can mitigate the issue. Although not discussed further here, how the amputee receives this information illustrates one of the responsibilities of prosthetists and occupational therapists.

2.3 Optimize Electrode Placement

As mentioned previously, a significant issue in a pattern recognition-based prosthetic system is the initial acquisition of EMG signals. From the initial work of Herberts et al. in 1973, electrode placement has been a concern [1]. They chose particular locations "by careful clinical examination, based on anatomical landmarks." Many pattern recognition systems today employ a greater number of signals (6-10) spread around the residual limb in attempt to measure all electrical activity in the area. In an effort to gather even more data from the contracting muscles, some research groups have employed the use of high-density surface EMG arrays [39]. These arrays consisted of up to 120 electrodes. In a currently available prosthesis however, such a configuration is not ideal as the setup requires meticulous placement and preparation.

Another concern regarding the electrodes used in pattern recognition systems is electrode movement. Because the system must be trained upon first use to generate classifier parameters for future classification, keeping the electrodes fixed to their initial positions is paramount. It has been shown that “a shift of 1 cm of four electrodes placed circumferentially about the forearm [increases] classification error in a 10-class experiment from roughly 5% to 20% (if shifted distally) and to 40% (if rotated about the forearm)” [40].

Work by Young et al. continued this investigation of electrode shift. They concluded that electrodes placed longitudinally to muscle fibers were less sensitive to electrode shift [35]. They also found that increasing inter-electrode distance from 2 cm to 4 cm made the system less sensitive to electrode shift [41].

2.4 Limit the Effect of Misclassification

Another approach to improving the robustness of pattern recognition systems is to limit the effect of misclassification. Conceding that misclassification will occur, multiple groups have worked to assuage its effects. One such method involves limiting the movement speed of the prosthetic hand when there is a change in classifier decision [26]. During the use of a prosthetic limb, the "true" class label of incoming data is unknown. Because of this, it is not possible to determine if the predicted class was correctly or incorrectly classified. By limiting the movement speed of the prosthesis when a particular grasp is predicted filters the responsiveness of the hand making small glitches of misclassification less influential. Such a method also however reduces the responsiveness of the device for desired actions. This tradeoff between accuracy and responsiveness arises in multiple efforts to improve the robustness of the prostheses.

A clear demonstration of this tradeoff is when imposing majority vote techniques to limit the impact of incorrectly predicted grasps [42, 43]. Rather than filter the mechanical system's response as previously mentioned, imposing a majority vote to the classification stream filters the input to that mechanical system. The class which is predicted most prevalently over a defined window of time is selected and is relayed to the actuators of the device. If the window is long, glitches of incorrectly classified grasps will be ignored as desired, but the time for the system to initiate a newly-desired grasp is lengthened. Such a delay may be frustrating for the user.

Similar efforts to limit the effect of misclassification involve imposing confidence thresholds or rejecting unknown data patterns in such a way as to limit the impact of incorrectly predicted active grasps. Scheme et al. imposed confidence thresholds utilizing the assumption in LDA that the conditional probability density for all classes is Gaussian [25, 44]. In the case of highly dimensional data, this is a multi-variate normal distribution. The threshold was set independently for each class as a specified distance from the class-specific mean according to the class-specific covariance. If a particular class was predicted but the threshold was exceeded, regardless of the prediction, the data were classified as belonging to the "no action" or "rest" class. Thus, for any threshold level, the active motion classification accuracy was shown to outperform the unmodified LDA [25].

2.5 Improve Classifiability

Rather than deal with errors after they have occurred as was described in the previous section, it is logical to work to improve the classifiability of the incoming data before it is classified. Efforts in this direction include applying filtering methods to the raw EMG, extracting new features, using high-definition EMG arrays, or by recording EMG activity from within the muscle as opposed to recording from the skin's surface.

Rehbaum et al. proposed applying a filter based on the common average reference (CAR), which is often used in EEG processing [9]. By imposing this filter, the group reports in improved performance of "both pattern recognition and regression methods for myoelectric control." A different filtering method has been proposed by Hargrove et al. aimed to minimize crosstalk between neighboring electrodes by applying class-specific principal component matrices to the raw EMG to "spatially decorrelate the measured data prior to feature extraction" [45]. The group reported a significant reduction in classification error when this method was applied for both able-bodied and transradial amputee subjects. Another approach involves removing channels determined to be faulty. Zhang et al. have shown that by incorporating a "sensor fault detector," classification accuracy was less affected by disturbances to those channels [46].

Another approach to improve the classifiability of EMG data is to extract features of the signal which are more informative of the grasp being performed and robust to variability in factors experienced during daily use. Initial work presenting the real-time performance and high accuracy of pattern recognition systems by Hudgins et al. proposed the extraction of time domain (TD) features [15]. Subsequent work with continuous classification of myoelectric signals suggested the extraction of a wavelet-based feature set with dimensionality reduction by principal components analysis (PCA) [47]. It has since been shown that "the performance of classifiers degrades with PCA transformed time domain features compared to non-transformed time domain features" [48]. Following the suggestion of extracting wavelet-based features, the extraction of a new set of TD features was proposed by Englehart et al. which set continues to be commonly used by those working with myoelectric pattern recognition systems today [22]. Researchers continue to look for features of EMG that further improve classification accuracy and are less influenced by environment variations experienced by a prosthetic user. As will be discussed in great detail hereafter, the limb's position significantly influences these commonly extracted features. Not specifically addressing the system's robustness, Ashkan et al. suggest the addition of the Willison amplitude feature in conjunction with the commonly used time domain features to improve classification accuracy [12]. Others have suggested that Auto-regressive coefficients be included with the traditional time domain features for maximal classification accuracy [8].

An additional area of research involves adapting the classifier over time. Incoming data may more accurately be classified for example, if the classifier is able to recognize variations in the incoming data from that seen during training and "re-center" or calibrate itself to the current situation. In a recent publication, Liu presented an implementation of an adaptive classifier based on support vector machine in which it is argued that such a method can account for changes in "electrode [movement], fatigue, impedance changes and physiological factors" [49].

Next, addressing the classifiability of the raw EMG signal, multiple groups have reported success using high-definition (HD) EMG arrays [10, 11]. Rojas-Martinez et al. show that the signal power obtained from single bipolar electrodes were significantly different from that obtained using an HD-EMG setup [11]. They report increased accuracy with the HD-EMG configuration over the standard single-bipolar setup. With the unique data set, they also suggest that intensity and spatial distribution of HD-EMG maps could be useful features in identifying movement intention and strength. This point highlights their work to utilize unique aspects of the new signal. Stango et al. similarly extracted unique features of HD-EMG to achieve enhanced robustness [10]. They included a measure of the spatial correlation between electrodes as a feature. The performance of their approach was "comparable to the classic methods based on time-domain and autoregressive features," and improved the system's robustness to the number of electrodes used and electrode shift.

Finally, a promising method of improving the classifiability of the EMG signal is to record the signal from within the muscle as opposed to recording from the skin's surface. There are many potential benefits to using intramuscular EMG recordings over surface EMG recordings for prosthesis control. A few examples of these benefits include: increasing the signal-to-noise ratio of the signal, bypassing electrode slippage effects, bypassing electrode-skin impedance variability, and minimizing crosstalk between channels. Ortiz-Catalan et al. have provided an in-depth presentation of intramuscular EMG recording and its application in prosthesis control [50].

Initial work by Hargrove et al. did not suggest that using intramuscular EMG enhanced prosthesis control over the use of surface EMG [51]. Recording simultaneously from intramuscular and surface electrodes and comparing classification accuracy achieved through each signal, they concluded “that there was no significant difference in classification accuracy as a result of using the intramuscular [myoelectric signal] measurement technique when compared to the surface [myoelectric signal] measurement technique.” Others have continued work with fine-wire intramuscular EMG recording testing new control schemes [52–54]. Smith et al. demonstrated that a “parallel dual-site” control scheme yielded enhanced throughput over pattern recognition control. It is therefore suggested that control schemes optimized for use with surface EMG may differ from control schemes utilizing intramuscular EMG.

Weir et al. demonstrated the functionality of a multichannel EMG sensor system “capable of receiving and processing signals from up to 32 implanted myoelectric sensors” (IMES) [55]. They present the many benefits of IMES over fine wire intramuscular recording methods arguing that “wireless telemetry of EMG signals from sensors implanted in the residual musculature eliminates the problems associated with percutaneous wires, such as infection, breakage, and marsupialization.” Tested initially in cats, the IMES system has since received FDA approval for human use. Promising preliminary results have been presented demonstrating their use in amputee subjects [56]. The use of intramuscular electrodes remains a promising potential way forward. This thesis however, will continue to focus on EMG recordings from the skin's surface.

2.6 Reduce the Limb Position Effect

The previous sections presented work intended to improve the general robustness of myoelectric pattern-recognition systems. Increasingly, researchers have sought to more specifically address one of the major factors influencing their robustness: limb position variation. Addressing this source of variability is the focus of all subsequent chapters of this work.

In 2010, Scheme et al. published an article illustrating the dependence of grasp classification accuracy on limb position [57]. To address the issue, they integrate accelerometers to support a dual stage classification process in which position is first classified followed by a classification of the intended hand action using a position-specific classifier. With data from eight able-bodied subjects they show this method reduces classification error.

A subsequent study by the same group with 17 able-bodied subjects reported again that "variations in limb position associated with normal use can have a substantial impact on the robustness of EMG pattern recognition, as illustrated by an increase in average classification error from 3.8% to 18%" [23]. The effect the limb's position has on classification accuracy they named the "limb position effect." Using only time domain features of EMG in grasp classification, average classification error was reported as 5.2%. Applying a two-stage classification process as previously described yielded an error of 3.7%. This error was further reduced to 3.4% by incorporating the accelerometer data in grasp classification. The group proposes multiple causes of the limb position effect including: variations in muscle recruitment, electrode shift, the force-length relationship of the muscle, and changes in the musculotendon lever arm [23].

Geng et al. addressed the limb position effect by integrating a mechanomyogram (MMG) signal with EMG. Their study was performed with five transradial amputees [34]. They found that MMG was in fact more strongly influenced by limb position than EMG and including its signals degraded classification accuracy. Interestingly, using MMG to classify intended hand actions was equally as accurate as when using EMG when trained and tested in the same location. An important, unintended finding from this work however, is that their results suggested for the first time that the limb position effect was more prominent for an intact limb than an amputated limb. Throughout the experiment, the amputee subjects elicited the contractions with their intact and amputated limb simultaneously. Although statistically insignificant, the group reported that average classification error for the amputated limb was lower than that for intact limb.

In a subsequent publication, the same group confirmed that the limb position effect was more substantial for an intact limb than an amputated limb [3]. Thus, they suggest that "investigations associated with practical use of a myoelectric prosthesis should use [amputee] subjects instead of using able-body subjects." They also suggest a two-stage cascade classifier to address the issue. As seen in Fig. 2.3, accelerometer and MMG signals are used to classifying the current position of the hand following which a position-specific grasp classifier is applied to the EMG data.

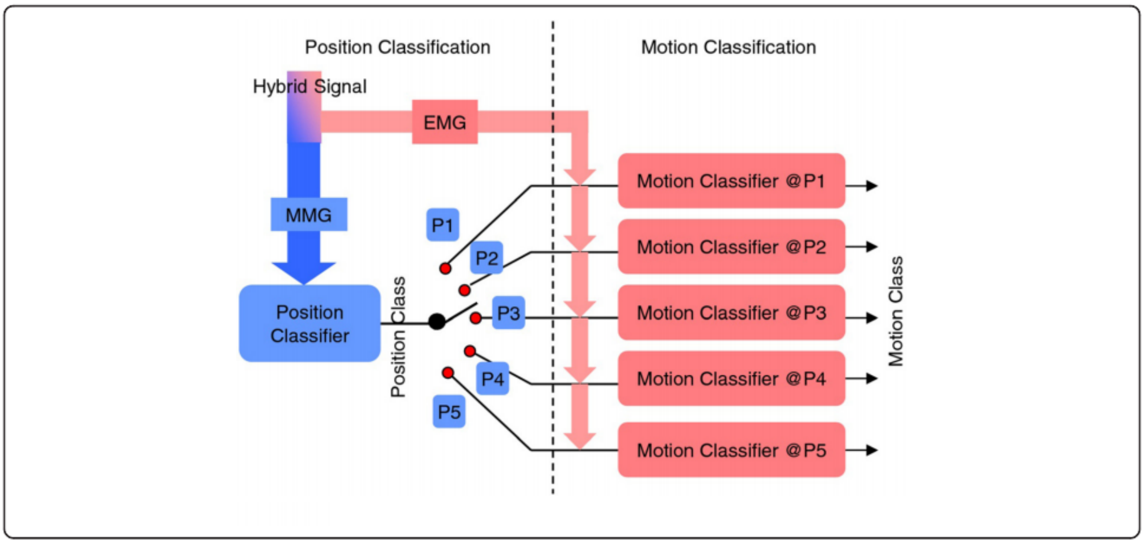

Figure 2.3: Illustration of a two-stage classification method in which first the limb's position is classified using accelerometer and MMG signals following which a position-specific grasp classifier is applied to the EMG data to predict the intended hand/wrist action [3]. BioMed Central was the original publisher of this figure.

Other groups have addressed the limb position effect by increasing the number of EMG channels with an HD-EMG array or by extracting different features of the EMG. With one able-bodied subject, Boschmann et al. showed that by using an HD-EMG array and training in multiple positions, they could minimize this effect [58]. With 11 able-bodied subjects, Khushaba et al. found that time dependent spectral features were less dependent on limb position and thus resulted in a more robust system to limb position variation [59].

Another report claiming enhanced robustness to positional variation suggested a hybrid approach in which dual-stage classification is performed with the position specific classifiers having been trained on data from multiple neighboring positions [60].

With data from 10 able-bodied subjects, they showed this method outperformed having a single classifier trained on data from all positions and applying location specific classifiers trained on data from only its respective position.

2.6.1 Limitations of Previous Work Aimed at Reducing the Limb Position Effect

Although these promising solutions have been suggested, multiple critical factors suggest weaknesses in the arguments aimed at reducing the limb position effect. First, most studies were performed with able-bodied subjects. The limb position effect however, has been shown to be different between able-bodied and amputee subjects. Furthermore, the limb position effect was not observed or analyzed in its actual use-case: when the amputees were wearing their prostheses. The potential causes of the effect may vary for an amputee wearing a prosthesis compared to an able-bodied subject. Electrode movement, for example, may be of much larger concern for an amputee wearing a prosthesis than an able-bodied subject or amputee wearing stick-on electrodes or a cuff with embedded electrodes. All groups referenced in this section utilized one of these two methods for collecting EMG. A second critical weakness in the presented works is the small number of discrete positions in which the system was tested. For the device to be a useful rehabilitative tool, it need be applied to a wide range of positions encompassing the user's entire working space. Finally, recent work by Radmand et al. has suggested that the dual-stage classification method proposed by multiple groups as being a potential solution to the limb position effect, may not optimize classification accuracy [61]. The group reported that when not every position explored during testing is explored during training, dual-stage classification performs significantly worse than training in multiple positions and aggregating the training data to form a single classifier.

These weaknesses in the aforementioned studies and the desire for the prosthesis to be robust to limb position variation validate and support the continued research of this phenomenon.

Chapter 3

The Limb Position Effect

Adapted from the author's publication:

M. R. Masters, R. J. Smith, A. B. Soares, and N. V. Thakor, "Towards better understanding and reducing the effect of limb position on myoelectric upper-limb prostheses," in Conf Proc IEEE Eng Med Biol Soc, 2014, pp. 2577-2580.

3.1 Chapter Abstract

Myoelectric control of prosthetic devices tend to rely on classification schemes of extracted features of EMG data. Those features however, may be sensitive to arm position resulting in decreased performance in real-world applications. The effect of varying limb position in a pattern recognition system have been illustrated by documenting the change in classification accuracy as the user achieves particular limb

configurations. We continue to investigate this limb position effect by observing its impact on classification accuracy as well as through an analysis of how each extracted feature of the raw EMG varies in each position. Finally, LDA classification schemes are applied both to demonstrate the effect varying limb position has on classification accuracy and to increase classification accuracy without the use of additional hardware or sensors such as accelerometers as has been done in the past. It is shown that high classification accuracy can be achieved by (1) training an LDA classifier with data from many positions, as well as (2) by utilizing an extra position LDA classifier which can weigh the grasp classifiers appropriately. The classification accuracies achieved by these methods approached that of a model relying on a perfect knowledge of arm position.

3.2 Introduction

Although pattern recognition based prostheses have been given significant credit for bringing the user increased degrees of freedom, a significant limitation to pattern recognition prostheses has yet to be overcome. Its accuracy significantly degrades as the user moves from the location in which the system was trained. Many myoelelectric control schemes have been reported as having high classification accuracies [26, 62]. These results however, were achieved in experimental paradigms that largely did not consider the impact of changes in limb position and orientation. These are significant factors as it has been shown that the accuracy of a pattern recognition-based upper-limb myoelectric prostheses is significantly influenced by the position of the limb [3, 23, 40, 58, 59]. It is desirable that the upper-limb prosthetic device maintain its functionality in a wide range of positions so that its usability can be expanded towards a greater number of daily tasks.

The disparity between classification accuracy at the training position and the accuracy of the system when the limb is in a different location has heretofore been referenced as the "limb position effect" [23]. Previously, the effect of varying limb position in pattern recognition systems has been illustrated by documenting the change in classification accuracy as the user achieves a particular limb configuration. The problem has been ameliorated by groups incorporating sensors to discriminate between positions [3, 23], or find features which are not as susceptible to change across limb positions [59]. This paper continues to investigate the limb position effect by observing not only the degradation of classification accuracy, but also, more fundamentally, through analysis of how each extracted feature of the raw EMG varies in each position. Additionally, potential solutions are presented by generating classifiers using Linear Discriminant Analysis (LDA) each having varying degrees of positional awareness. Through a more comprehensive understanding of the issue, one can gain a greater insight into not only why a solution to this issue is necessary but also where the solutions fall short and how future work may advance the field. Finding a solution to the issue is paramount to improve the usability of such a device in day-to-day use.

3.3 Methods

3.3.1 Population and Data Acquisition

For this pilot study, EMG data were collected from two able-bodied individuals: Subject 1 - male, age 24, with extensive exposure to pattern-recognition based myoelectric prostheses control; Subject 2 - female, age 25, with no prior exposure to myoelectric control. The first having trained according the model established by [2] in which principles were learned to create “consistent and distinguishable movements through interaction with a visual biofeedback training system” [2].

Eight channels of raw EMG were obtained through differentially amplifying electrode pairs placed approximately equidistant around the circumference of the forearm, approximately three inches distal to the medial epicondyle of the humerus. The electrode pairs were numbered one through eight with the first placed above the extensor carpi ulnaris muscle and the others continuing clockwise around the forearm if viewing a cross section of the forearm looking up the arm. The stainless-steel dome electrodes were inserted into a non-conductive elastic band with options for sizing according to the diameter of the user’s forearm. The ground electrode was a Norotrode 20 bipolar Ag/AgCl EMG electrode (Myotronics, Kent, WA) and was placed approximately one inch proximal to the olecranon. The cables connecting the electrodes to the amplifiers and to the data acquisition system were well maintained eliminating extraneous factors and potential artifacts due to pulling forces on the electrodes or rotation of the clips attached to the electrodes. The raw data were amplified after approximately one foot of shielded cable by 13E200 MYOBOCK electrodes (Ottobock, Plymouth, MN) such that saturation did not occur. Following amplification, the signal was sampled using the NI USB-6009 (National Instruments, Austin, TX) at 1000Hz per channel. A subsequent 30-300Hz bandpass and a 60Hz notch filter were applied to the signal as indicated by [2]. Although standard surface EMG signal conditioning usually utilizes a 20-500Hz bandpass filter, the authors decided to narrow that band in order to avoid as much as possible low frequency instabilities due to fast twitching of the stump muscles in a real application (amputees) and noise outside the main band of the power spectrum (below 300Hz). Additionally, the features extracted in this work are not strongly affected by frequencies outside this range.

Each subject performed five unique hand or wrist configurations including rest (R), hand open (O), hand close (C), wrist pronate (P), and wrist supinate (S). These hand and wrist configurations will hereafter be referenced as “grasps.” The subjects performed five repetitions of each grasp maintaining the contraction for a duration of four seconds for each repetition. They performed this routine while standing with their arm in seven locations relative to their body, namely: (1) in the neutral (N) position (from anatomical neutral, 90^o elbow flexion and 90^o wrist pronation), (2) in the “upper right” (U-R) location with 135^o shoulder abduction in the sagittal plane, (3) in the “down right” (D-R) location with 45^o shoulder abduction in the sagittal plane, (4) in the “down” (D) location with the shoulder in its anatomical neutral position, (5) in the "down left" (D-L) location with 45° shoulder flexion and 45° shoulder adduction, (6) in the "upper left" (U-L) location with 135° shoulder flexion and 45° shoulder adduction, and finally (7) in the "upper" (U) location with 135° shoulder flexion.

3.3.2 Data Processing

Time domain (TD) features of the amplified and filtered EMG signals were obtained by imposing a 200ms moving window with 175ms overlap (25ms delay plus processing time). The TD features extracted were mean absolute value (MAV), waveform length (WL), and signal variance (VAR). These features were extracted over others because of prior work suggesting they are sufficient for high classification accuracy in real-time myoelectric control environments [12, 22].

Subsequent LDA classification of the acquired features and the associated grasp was performed. The method in which LDA classification was applied was unique to each of the four scenarios described hereafter. It is shown how the resulting classifiers were utilized in various ways to both demonstrate the effect of varying limb position on classification accuracy and work towards achieving higher classification accuracy. In each case, five fold cross validation is used to estimate classification accuracy. This is performed by using data from four of the five trials of each grasp to train the system and evaluating the resulting classifier on the remaining trial. A classification accuracy percentage is computed for each of the five folds as given by equation 3.1.

$$\frac{\text{Number of samples correctly classified}}{\text{Total number of testing samples}} \tag{3.1}$$

The average of these five individual classification accuracies is reported along with the standard error of the mean.

3.3.2.1 Method 1

Seven unique grasp classifiers are created using the data obtained from each respective location. By applying the classifier corresponding to the current position of the arm, the system has perfect positional awareness and the classifier that was created in the current position of the arm can be applied to incoming data. In so doing, an upper bound for classification accuracy is found given the model parameters (window, extracted features etc.).

3.3.2.2 Method 2

A single grasp classifier was created from training data collected in the neutral position. This classifier is applied to new data obtained in the neutral position as well as to data from the remaining six positions.

3.3.2.3 Method 3

A single grasp classifier was created using training data from all seven locations. In this way, the resulting classifier can be described as an "aggregate" classifier over the seven training locations.

3.3.2.4 Method 4

A position classifier is created whose output weighs each individual grasp classifier accordingly. Thus, if the position classifier is confident that the user's arm is in a particular position, the upper-right position for example, the grasp classifier created from data collected in the upper-right position will have a larger influence on the predicted grasp being performed. In this way, an estimate of arm position influences the degree to which the output of each grasp classifier is considered when making the final estimate of the grasp being performed.

3.4 Results

3.4.1 Illustrations of the Limb Position Effect

The limb position effect is clarified and depicted in this section by providing the results of various analysis methods in the form of (1) confusion matrices, (2) depictions of EMG activity around the circumference of the arm, and (3) through

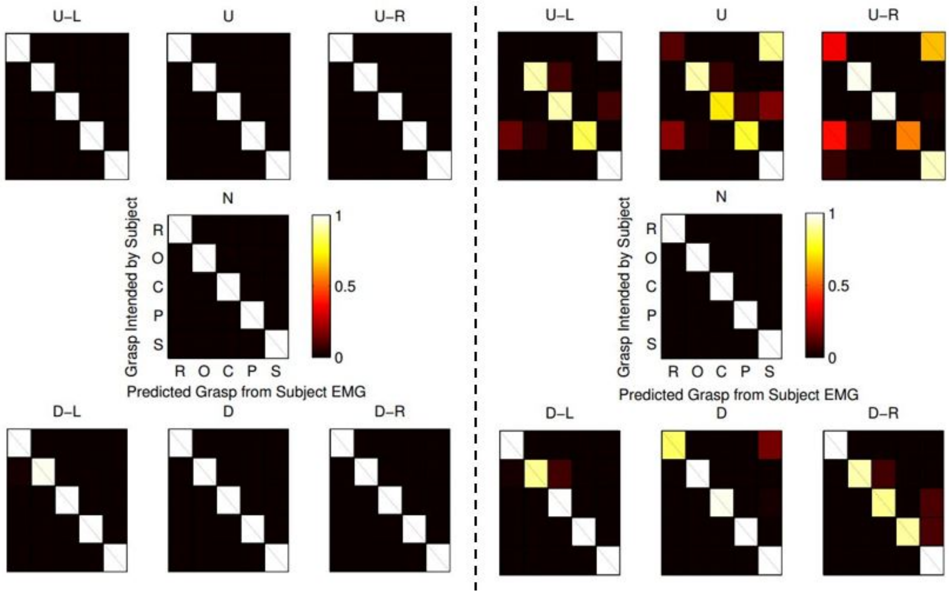

Figure 3.1: The seven confusion matrices on each half of the figure represent the seven positions from which training data were obtained from Subject 1. To the left of the dashed line are confusion matrices for the provided cue matching the predicted cue when the classifier is created and applied in the same location. To the right are confusion matrices for the provided cue matching the predicted cue when the classifier is created in the "neutral" position and applied in all locations.

plots of extracted feature behavior during each grasp performed in each position as detected by a single electrode.

Fig. 3.1 gives a visual representation of the effect limb position variation has on classification accuracy. When the classifier is created and evaluated in the same position, classification accuracy of 98.5±0.2% is achieved. When the classifier is created in the neutral position and evaluated in all positions, classification accuracy decreases to 83.5±0.8%.

The effect of varying limb position in a pattern recognition system have been documented by reporting the change in classification accuracy as the user achieves a particular limb configuration. Although Fig. 3.1 goes beyond reporting a single value for classification accuracy, it similarly reports classification accuracy as a means for demonstrating the effect. Fig. 3.2 and Fig. 3.3 however, shed more light into why classification accuracy degrades as the subject moves from the position in which the classifier was trained.

Fig. 3.2 shows how MAV recorded by each electrode varies according to arm position while performing the hand-close grasp. Similar results were obtained for the other four grasp types. It can be seen that the MAV values change considerably depending on arm position.

Fig. 3.3 also shows that extracted feature means vary considerably from position to position. It illustrates that not only MAV means, but the mean of each extracted feature (MAV, WL, and VAR) varies. A one-way ANOVA was used to test this obser-

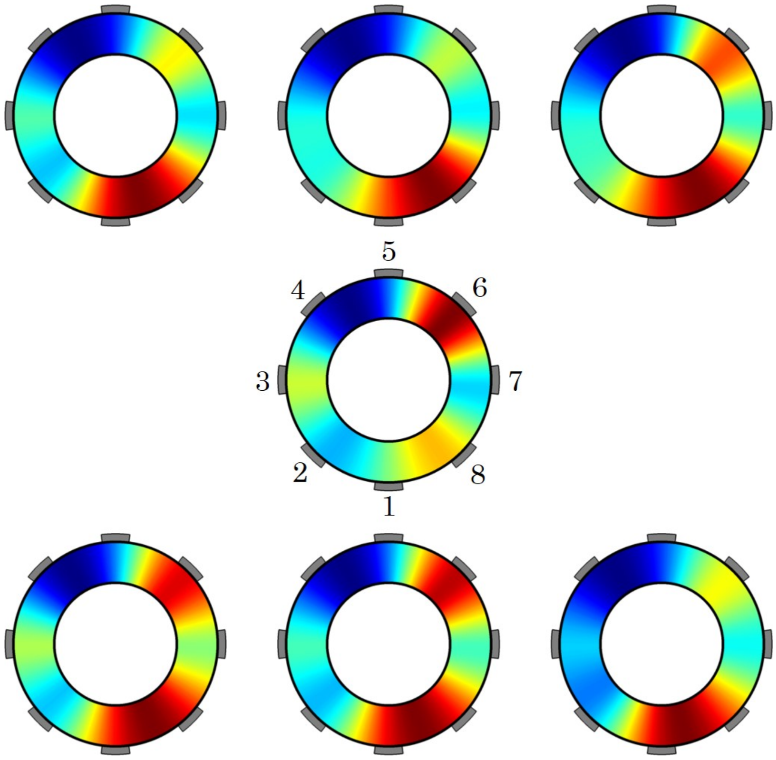

Figure 3.2: Periodic cubic spline interpolation of average MAV over the entire grasp period for the "close" grasp in each of the seven locations for Subject 1. The electrode pair numbers are shown around the center ring. Red denotes large MAV values while blue denotes low.

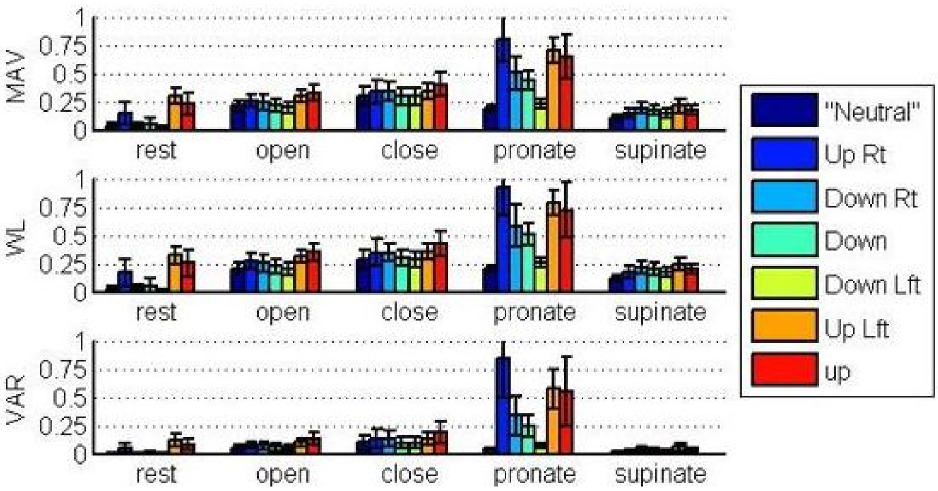

Figure 3.3: Normalized mean of the respective feature with error bars representing one standard deviation above and below the mean for each grasp in each position as measured by electrode pair 8 from Subject 1.

vation that the extracted features differ according to position. With $p<.001$ for each feature and grasp combination, it can be concluded that the features are significantly different across positions. Although the figure only shows the data obtained by one electrode pair, similar results were observed for all electrode pairs. Such a depiction of the limb position effect shows the issue at a more fundamental level.

3.4.2 LDA Classifiers

3.4.2.1 Method 1

For Subject 1, average classification accuracy when the classifier was created and applied in the same location was 98.5±0.2%. For Subject 2, average classification accuracy in this scenario was 87.4±1.2%.

3.4.2.2 Method 2

For Subject 1, average classification accuracy when the classifier was created in the neutral position and applied in all positions was 83.5±0.8%. For Subject 2, classification accuracy for this scenario was 77.9±0.4%.

3.4.2.3 Method 3

When a single grasp classifier was created using training data from all locations, the classification accuracy for Subject 1 was 96.5±0.3%. Implementing this method for Subject 2 yielded an average classification accuracy of 86.9±0.9%.

3.4.2.4 Method 4

By creating a position classifier whose output applies a weight to the individual grasp classifiers, grasp classification accuracy for Subject 1 was 96.5±0.7% (with position classification accuracy of 43.4±3.3%), while for Subject 2, classification accuracy was 83.8±1.4% (with position classification accuracy of 38.7±2.3%). The result of the position classifier for Subject 2 can be seen in Fig. 3.4.

The results of the four classification schemes are summarized in Table 3.1.

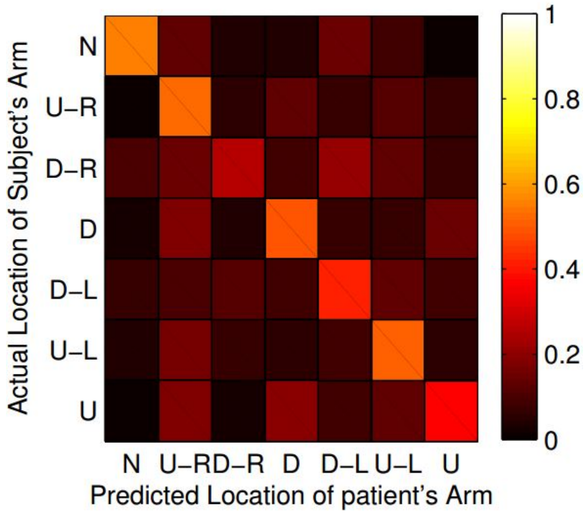

Figure 3.4: Confusion matrix of actual position vs predicted position for Subject 2 applied in classification Method 4.

Table 3.1: Results of Classification Schemes

Method	Classification Accuracy (%)	
	Subject 1	Subject 2
1	98.5±0.2	87.4±1.2
2	83.5±0.8	77.9±0.4
3	96.5±0.3	86.9±0.9
4	96.5±0.7	83.8±1.4

3.5 Discussion

Fig. 3.1 illustrates that classification accuracy deteriorates when the model receives data from positions different than that where it was trained. In other words, classification accuracy degrades as the user moves their arm from the location in which the classifier was trained. Thus the claim from previous research is made stronger that the limb position effect is an issue requiring serious attention in order to improve usability to myoelectric pattern-recognition prostheses.

Fig. 3.2 and Fig. 3.3 address the issue at a more fundamental level. It is observed that the signals received by each electrode during each grasp type vary significantly across position. Ultimately, it is the changing extracted EMG features that explain the degrading classification accuracy in positions other than where the classifier was trained. Hence, if a classier is trained in the neutral position and is applied to data acquired at different arm positions, one can expect a higher degree of miss-classification.

In an effort to create a more robust system to these variations, four classification methods were explored. The results show that classification accuracy can be increased from the "worst case" scenario (no account for limb position after having created a classifier in one position) without integrating additional sensors such as accelerometers or other inertial measurement units (IMUs). This can be done by either creating an aggregate classifier combining the training data from all locations into one classifier (Method 3), or by incorporating some information about arm position to weigh the individual grasp classifiers appropriately (Method 4). It is worth mentioning that the classification accuracy achieved by these aforementioned methods approached that of the best case scenario given the model parameters in which a perfect knowledge of position was utilized.

Although methods 3 and 4 provided satisfactory improvements in accuracy, the authors argue that Method 4 has a greater potential for further improvement, as it can benefit from real world position information provided by kinematic sensors.

3.6 Conclusion

The results of this pilot study clearly illustrate the variation in extracted EMG features across limb position and the effect these changes have on classification accuracy. Classification methods 3 and 4 serve to create a more robust myoelectric control scheme of an upper limb prostheses allowing for greater utility of the device.

Having a perfect knowledge of position, classification accuracy of 98.5% and 87.4%

is achieved by subjects 1 and 2 respectively. By creating an aggregate classifier created over all space, classification accuracy is 96.5% and 86.9% for each subject respectively. Finally, by weighing each grasp classifier by an estimate of position, accuracies of 96.5% and 83.8% are achieved.

Chapter 4

Aggregate vs. Position Specific Classification

Adapted from the author's work:

M. R. Masters, R. J. Beaulieu, R. J. Smith, A. B. Soares, R. R . Kaliki and N. V. Thakor, "Aggregate Training Outperforms Location-Specific Training of a Pattern Recognition-Based Myoelectric Prosthesis," *Pursuing publication.*

4.1 Chapter Abstract

Many control schemes of multiple degrees of freedom (multi-DoF) myoelectric prostheses rely on the classification of a set of features extracted from the user's surface-recorded electromyogram (EMG). Pertaining to upper-limb myoelectric pros-

theses, these features are sensitive to limb position. This sensitivity has been shown to impact performance in real-world applications as users move their limb and encounter conditions not explored during training. This work investigates whether or not limb position information from the user can be incorporated along with recorded EMG to decrease classification error of the intended hand or wrist action across the user's entire working space. Using Linear Discriminant Analysis (LDA), multiple variations on the availability of training data were evaluated including: single-position, random-position, and position-specific models. With data from ten able-bodied subjects and two amputee subjects with and without prostheses, we find that applying a classifier trained with data from multiple random positions outperforms any of the tested location-specific methods. This finding helps to focus the work aimed at creating robust myoelectric prostheses.

4.2 Introduction

Pattern recognition-based prosthesis control using time-domain features extracted from EMG can achieve high levels of classification accuracy [6, 63]. The success of pattern recognition techniques in myoelectric prostheses has provided users with a more intuitive control scheme for multi-DoF prostheses from the traditional two-site controlled prostheses [22]. With a pattern recognition system, the user has immediate access to multiple DoFs unlike the two-site system which requires switching between modes to access a particular DoF. Despite the significant benefits of pattern recognition systems, they are susceptible to many factors which impact their robustness [6]. One such influencing factor is the position or orientation of the user's limb. Classification accuracy can dramatically degrade when the limb is moved to a position different from that in which it was trained [3,23,58,59,63]. This phenomenon has been referred to as the "limb position effect" and can significantly impact the functionality of an upper extremity myoelectric prosthesis. Overcoming this hurdle represents an important step in improving the usability of multi-DoF upper extremity prostheses.

Many strategies have been explored to improve the robustness of myoelectric prosthetic control without special attention to the effect of limb position. Approaches within this category include: limiting the movement speed of the prosthetic hand when there is a change in classifier decision [26] and imposing confidence thresholds or majority vote methods to limit the impact of incorrectly predicted active grasps [25, 42–44]. Others have attempted to improve the classifiability of incoming data through different filtering methods of the raw EMG [9], introducing new features [10], or through the use of high-definition EMG arrays [11, 12]. Finally, work has been conducted to enhance robustness to other parameters such as changes in electrode position [35, 41].

Increasingly, researchers have sought to more specifically address robustness to limb position variation [3, 23, 58, 59, 61]. These groups have worked to augment recorded EMG data with information about the position of the limb to more accurately classify intended actions. Data from sensors, such as accelerometers or other inertial sensors, can be used as another feature in the classifier or for use in a multi-stage classification method in which position is first estimated then a position-specific classifier is applied to the recorded EMG [3, 23, 57]. There have been contrasting results as well, showing that incorporating accelerometer data can degrade performance compared with using EMG alone [61].

The purpose of this study is to investigate whether or not limb position information from the user can be incorporated with recorded EMG to decrease classification error of the intended hand or wrist action across the user's entire working space. Building on work presented in chapter 3 and published in [7] that demonstrated the limb position effect by training in a few discrete positions, in this study a training database is created of 50-80 repetitions per subject each performed in a random position to train and evaluate multiple classifiers. We observe and analyze the limb position effect in multiple patient populations including: able bodied subjects, amputees while wearing their prostheses and amputees without their prostheses.

A significant consideration when comparing classification methods is that each method utilizes the same amount of training data. This essential factor is left vague and even unmentioned in many previously reported works. Classification methods should be compared having been trained with equal amounts of training data *available* to them; in the end, not all need be trained on the same amount of data. It is in this way that the classification methods are compared in this study.

To illustrate, if 20 repetitions of each grasp are available for training, with each repetition having been collected from a unique position, it may seem valid when comparing an aggregate and a position-specific classifier to train both methods on an equal number of repetitions; say five. So the aggregate classifier is trained with five random repetitions and the location-specific is trained with the five repetitions obtained nearest the test position. This reasoning however, is flawed. In this example, the position-specific method had access to the full 20 repetitions and intelligently down-sampled to five for use in training, whereas the random position method had access to only five. A more accurate comparison of the methods is done by training both *having access to* the same number of repetitions. Thus, if the location-specific method down-samples from the 20 to some lower number of repetitions more local to the test position, the classifier for the random position method should be trained on all 20 repetitions.

4.3 Methods

4.3.1 Population and Data Acquisition

All procedures of this study were conducted in accordance with protocol approved by Johns Hopkins University's Institutional Review Board (IRB).

Ten able-bodied subjects (two female, eight male) with no known neurological disorders, ages 22-34, along with two transradial amputees, participated in the study.

The first amputee subject (Amp1) is a 63 year old male who is seven years status post right upper extremity amputation due to a work-related trauma. The second amputee subject (Amp2) is a 68 year old female who is three years status post bilateral upper and lower extremity amputations secondary to overwhelming sepsis. Both amputee subjects have been using a myoelectric pattern recognition-based prosthesis for over one year.

For all able-bodied subjects and amputees tested without their prostheses, eight channels of raw EMG were obtained through differentially amplifying electrode pairs placed equidistant around the circumference of the forearm. For able-bodied subjects, the electrodes were placed around the area of greatest mass. For the amputees, the electrodes were situated over the area of their residual limb that made contact with the electrodes in their prostheses.

The raw data were amplified after approximately one foot of shielded cable by 13E200 MYOBOCK amplifiers (Ottobock, Plymouth, MN) which were modified for remote application. Following conditioning, the signal was sampled using the NI USB-6009 (National Instruments, Austin, TX) at 1 kHz. A subsequent 20-500 Hz digital bandpass filter and a 60 Hz digital notch filter were applied to the signal.

For the sessions in which the amputees wore their prostheses, eight channels of raw EMG were obtained through differentially amplifying electrode pairs mounted within the rigid socket of their personally-owned, custom-fitted prostheses. The signals were amplified using LTI amplifiers (Liberating Technologies Inc, Holliston, MA) and acquired and filtered in the same manner as previously stated. Each amputee conducted the experiment with a bebionic3 hand (RSLsteeper, Leeds) attached yet unactuated to simulate the weight of real-world use.

Limb posture information was recorded concurrently with EMG during all acquisition sessions using a custom network of three 9-axis inertial measurement units (IMUs) (MPU-9150 Nine-Axis MEMS MotionTracking Device). This system is described more fully in Appendix A. One sensor was placed on the subject's back, the second on the upper arm, and the third on the forearm. Each sensor was programmed to output a quaternion representing the rotation from an initial vector common to all sensors. A direction vector for each sensor was found by applying the direction cosine matrix (DCM) from each quaternion to the common vector. A virtual representation of the subject's body and limb configuration was generated using this data. This representation was updated and displayed to the subject in real-time as part of the experiment's graphical interface (GUI) and can be seen on the left hand side of Fig. 4.1.

Each subject performed five unique hand/wrist configurations: rest (Rest), hand open (HO), hand close (HC), wrist pronate (WP), and wrist supinate (WS). The hand and wrist postures will hereafter be referenced as "grasps."

Each experimental session began by performing nine repetitions of each grasp presented in random order with the arm in the neutral position (elbow flexed 90°and the wrist pronated 90°from the anatomical neutral position). Before performing subse-

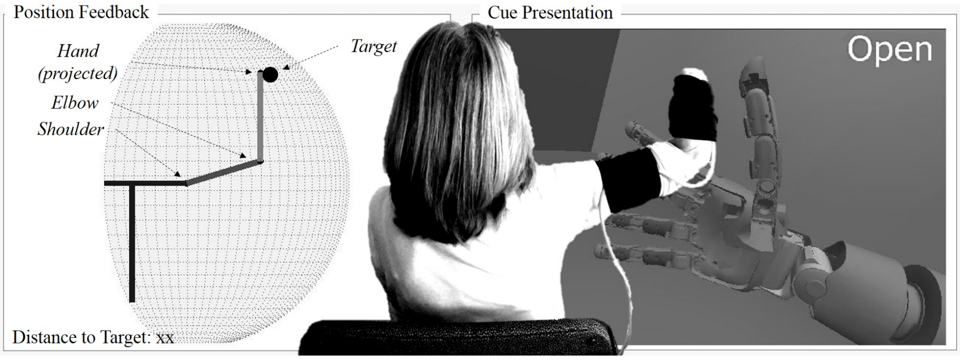

Figure 4.1: An illustration of the experimental procedure with the subject viewing the large GUI in front of them. The framework on the left represents the subject's body and is shown to the subject in real-time. Once the subject's hand or projected hand (amputee) is within 3 cm of the randomly-prompted target position, the subject performs the cued grasps shown to them on the right.

quent repetitions, the subject was prompted to reach a target point in space as shown to them in the GUI. The depth of the target was encoded by its size and color in the GUI. Once a minimum distance from the target point had been achieved (less than 3 cm) the five grasps were prompted in random order. A new target point was presented to subjects after completing one repetition of each of the five grasps. This process continued until all the grasps had been performed at 81 randomly distributed target locations for all subjects except for Amp2 while wearing her prosthesis. In this case, the grasps were performed in 54 target locations. Fig. 4.1 illustrates this experimental setup.

The target points were generated by randomly selecting points within a 3-dimensional volume centered around the subject's shoulder. The volume is bounded in spherical coordinates by r values equal to the subject's total arm length and the subject's upper arm length, $15° \leq \theta \leq 165°$ and $10° \leq \phi \leq 120°$, where θ is defined as the polar angle and ϕ is the azimuthal angle with 0° being the position at which the shoulder is abducted 90° from the anatomical neutral position.

4.3.2 Data Processing

All data processing and analysis were performed offline using MATLAB (MathWorks, Inc., Natick, MA). Time domain (TD) features of the amplified and filtered EMG signals were extracted by imposing a 200 ms moving window with a 175 ms overlap.

The TD features extracted were: mean absolute value (MAV), waveform length (WL), and signal variance (VAR). The slope sign change (SSC) and zero-crossings (ZC) features suggested in [22] were not used due to the need to determine the threshold value when extracting these features. Initial work found the threshold which yielded highest classification accuracy varied across subjects. Thus, to remove a potential source of performance variation across subjects, these features were not included.

This study was concerned with accounting for the limb position effect while statically holding a grasp. For this reason, it was determined to analyze the data from only this portion of the grasp. Thus, the first 1.5 seconds were removed following each cue presentation due to the subjects' delayed response to the grasp cue and the initial EMG activation not being representative of the static portion of the grasp. For all subjects, the prompted grasp was initiated prior to the beginning of this interval and maintained throughout its duration.

4.3.2.1 Analysis of the Limb Position Effect

Analysis of the limb position effect began with quantifying the impact particular covariates had on extracted EMG features. We anticipated finding a parameter that most strongly influenced EMG features and could subsequently be incorporated into classification to improve robustness to positional variation. Covariates included in the investigation were: elbow angle, the angle between the axis of the forearm and the ground, the height of the hand or distal end of the forearm relative to the subject's shoulder, and repetition count. The position related parameters were calculated from data obtained from the body-mounted IMU network as explained previously. Repetition count, or time, was included as a covariate to determine if subjects fatigued over the course of the experiment. The analysis was limited to investigating the impact of these covariates only on MAV because of the strong correlation between MAV and the other extracted features obviating the need to perform the analysis on each feature.

The average MAV over the duration of each grasp was computed for each of the eight channels and each repetition. The relationship between MAV and each covariate was quantified by the slope of a fitted univariate linear regression model where the input variable was one of the position-related covariates and the output variable was the average MAV. A distribution of slopes of the linear regression model for each covariate was obtained. The distributions were tested for a mean of zero using one sample t-tests. Additionally, we tested for equal variance among the distributions using the Brown-Forsythe test. Statistical testing was performed on the combined data from all ten able-bodied subjects and for each amputee individually. A threshold of $p = 0.05$ was used when reporting significance.

4.3.2.2 Classification

The hand/wrist grasps were classified using Linear Discriminant Analysis (LDA). Six variations on the availability of training data were explored. For accurate comparison of the methods, each was given access to the same number of training repetitions. In the end, not all were trained on the same amount of data.

The variations on the availability of training data were analyzed across an increasing number of training repetitions available (from 1 to 50). The following methods describe the variations explored.

1. *Single position* (SP): The classifier is trained using data obtained from the single "neutral" position.

2. *Random position* (RP): Data from randomly selected positions are used in training.

3. *Nearest position* (NP): For each novel grasp repetition to be classified, a local classifier is trained using data from the m nearest locations evaluated during the training session where $m \in \{1, 5, 10\}$.

4. *Nearest elbow angle* (NE): Similar to the previous method, the classifier was trained using m repetitions having been performed at an elbow angle most similar to the elbow angle during the test repetition where $m \in \{1, 5, 10\}$.

5. *Majority vote* (MV): Individual classifiers are trained on the data from each location visited during the training protocol. For a given test sample, that grasp class is selected as the predicted grasp which receives the majority of the predictions from the individual classifiers.

6. *Weighted posterior* (WP): Individual classifiers are trained on the data from each location visited during the training protocol. The posterior estimates resulting from each classifier are weighed inversely proportional to the the distance between the query location and the location from which the training data originates. After weighting the posteriors, the maximum of the sum of the posterior estimates across each of the individual classifiers is selected as the predicted class of the training data. This algorithm is shown in equations 4.1 through 4.4 where N is the number of grasps classes (in this case 5), and M is the number of individual classifiers created. The weights $\mathbf{d}$ are multiplied by the matrix P yielding the weighted posterior estimates of the data belonging to each class $\mathbf{p}^*$. The class with the maximum weighted posterior is selected as the predicted grasp $\hat{g}$.

$$\mathbf{d} = \begin{pmatrix} d_1 & \cdots & d_M \end{pmatrix} \tag{4.1}$$

$$P = \begin{pmatrix} p_{1,1} & \cdots & p_{1,N} \\ \vdots & \ddots & \vdots \\ p_{M,1} & \cdots & p_{M,N} \end{pmatrix} \tag{4.2}$$

$$\mathbf{p}^* = \mathbf{d}P = \begin{pmatrix} p_1^* & \cdots & p_N^* \end{pmatrix} \tag{4.3}$$

$$\hat{g} = arg\, max(\mathbf{p}^*) \tag{4.4}$$

For each number of repetitions available for training, 50 repetitions were randomly selected from all available (81 in most cases, 54 for Amp2 with prosthesis) as test repetitions allowing for cross validation of each method. In each case, classification error was computed by dividing the number of samples misclassified by the total number of testing samples without the application of a sliding majority vote filter or other misclassification rejection methods..

The mean of the classification errors of the 50 trials is reported along with the standard error of the mean. Comparative evaluation of classification methods was conducted using paired-sample t-tests. A threshold of $p = 0.05$ was used when reporting significance and the Bonferroni correction was applied to conservatively counteract the problem of multiple comparisons.

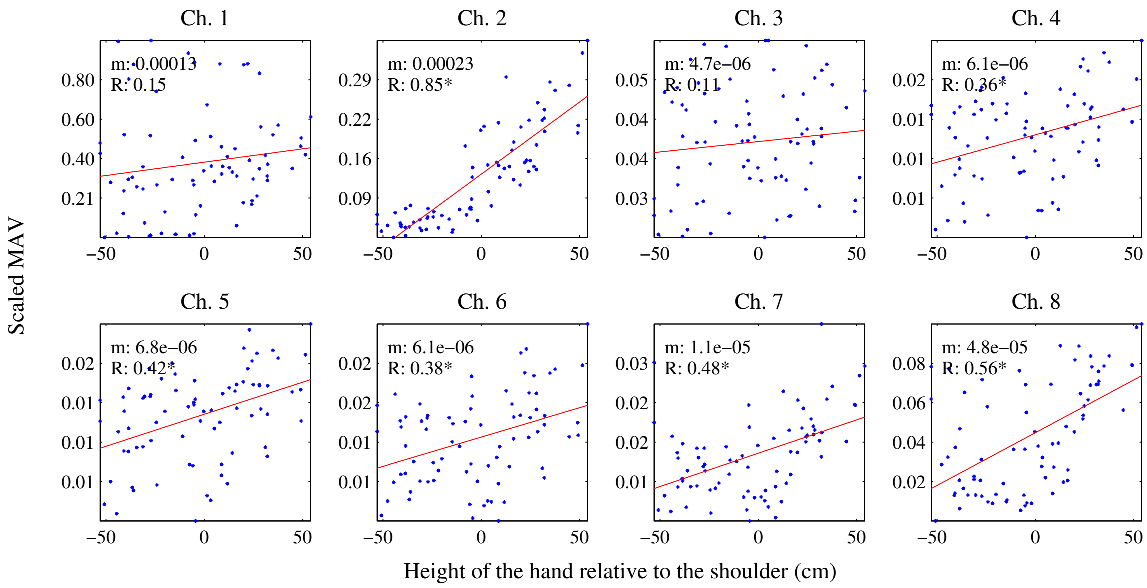

Figure 4.2: A depiction of how MAV recorded during the Rest grasp varies by hand height for an able-bodied subject. Each point represents the average MAV recorded on that particular channel over the duration of a Rest interval. The vertical axis of each plot has been scaled to the maximum and minimum MAV values seen across all channels. The line was obtained through linear regression of the two variables where m is the slope of the line, R is the correlation coefficient of the two variables, and the asterisk signifies significance in the probability that there is a non-zero correlation between the variables.

4.4 Results

4.4.1 Analysis of the Limb Position Effect

The results of the statistical tests analyzing and comparing the distributions of slopes resulting from fitting linear regression models to MAV and multiple covariates are summarized in Table 4.1. Each distribution was tested for a mean of zero using one-sample t-tests and the variance of each was compared to the variance from the distribution resulting from regression with elbow angle because in each case, this distribution had the largest variance.

Table 4.1: Results of Statistical Testing

	All able		Amp1				Amp2			
			W/o prost.		With prost.		W/o prost.		With prost.	
Covariate	Zero mean	Equal var.	Zero mean	Equal var.	Zero mean	Equal var.	Zero mean	Equal var.	Zero mean	Equal var.
Repetition count		*				*		*		*
Elbow angle		--		--	*	--		--		--
Forearm-gnd. angle		*		*	*	*	*	*		*
Hand/arm height	*	*			*	*	*		*	

An asterisk denotes significance ($p < 0.05$), and the dashes denote comparisons that are irrelevant.

For all subjects, statistical testing did not provide sufficient evidence to reject the null hypothesis that the distributions of slopes obtained through fitting linear regression models to MAV and repetition count had means equal to zero for all subjects. Thus, there is not sufficient evidence of fatigue among tested subjects.

For all able-bodied subjects combined, the distribution of slopes resulting from regression with the hand's height relative to the user's shoulder was the only distribution with a statistically significant non-zero mean. Specifically, the distribution of slope values had a positive mean suggesting that across all the channels and grasps, as the hand rises a general increase in MAV is observed. Additionally, of the covariates tested, the distribution of slopes resulting from regression with elbow angle yielded the significantly largest variance. Fig. 4.2 illustrates the average MAV during each repetition on each channel and a fitted linear regression of MAV recorded during Rest with the height of the hand for the eight recorded EMG channels of an able body subject. It is apparent that a strong relationship exists for some channels (2 espe-

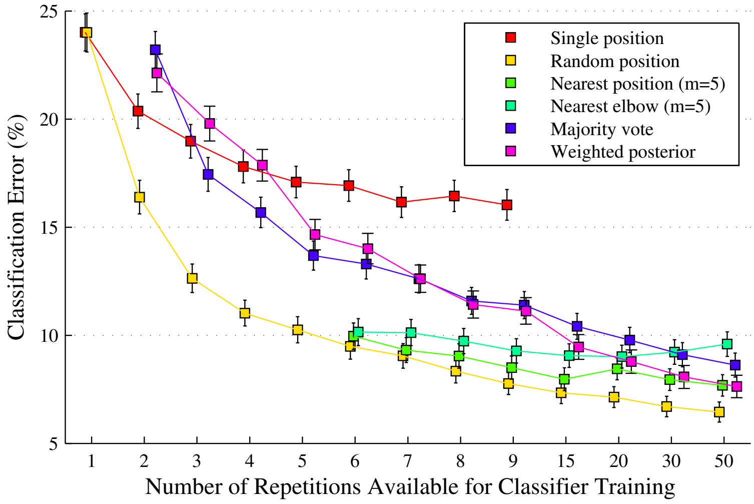

Figure 4.3: Average classification error for all able-bodied subjects resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean.

cially) and not others (1 and 3). Additionally, it is observed that channel 1 accounts for the largest variation in MAV across the many repetitions (note its scale).

For Amp1, regressing MAV onto the forearm's height relative to the shoulder for all grasps yielded a distribution of slopes with a mean significantly non-zero only when the prosthesis was worn. As with the able-bodied subjects, a positive mean was observed in this case suggesting a general increase in MAV as the arm is raised. Regressing MAV onto elbow angle for all grasps yielded a distribution of slopes with a variance larger than the others. This difference reached statistical significance only when the prosthesis was worn. Similarly for Amp2, regressing MAV onto the forearm's height relative to the shoulder for all grasps yielded a distribution of slopes with a mean significantly non-zero (and positive), yet different from Amp1, this was true for with and without the prosthesis. Again both with and without the prosthesis, regressing MAV onto elbow angle for all grasps for Amp2 yielded distributions of slopes with the largest variance.

4.4.2 Classification

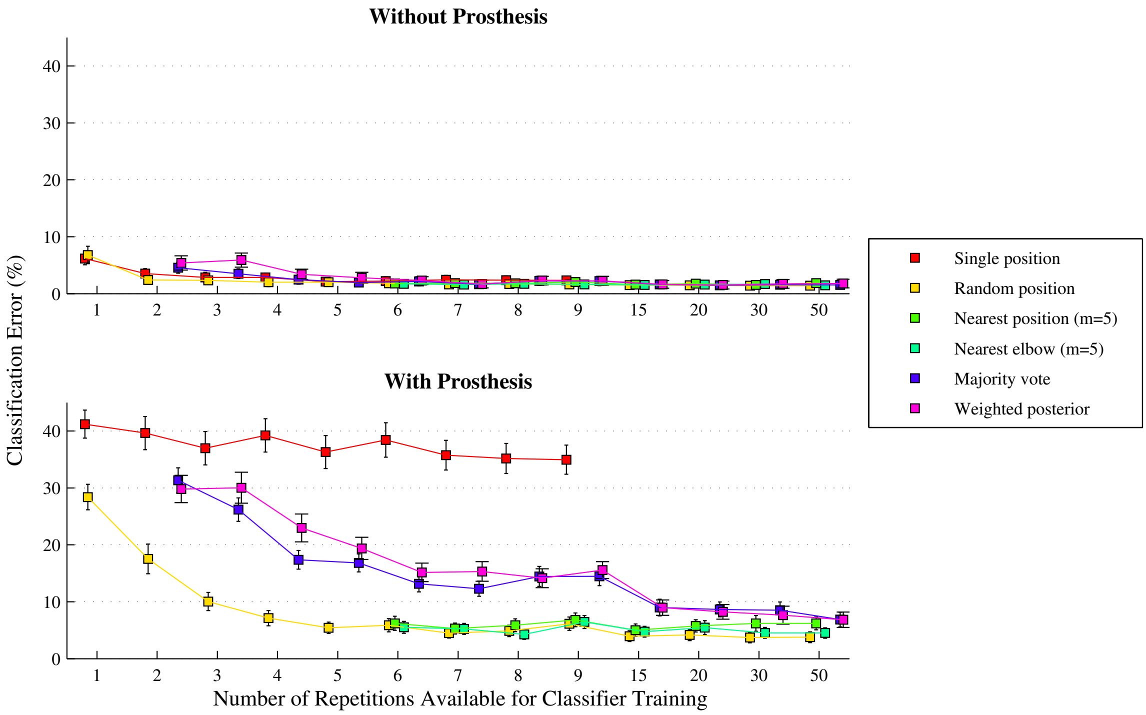

Figure 4.4: Average classification error for Amp1 resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean.

The average classification error of all able-bodied subjects for multiple variations on the availability of training data is depicted in Fig. 4.3. For clarity, only the results for $m = 5$ are shown for the NP and NE methods. It is generally noted that RP outperforms the other methods except in a few instances in which the difference between the classification error resulting from RP is not significantly greater than

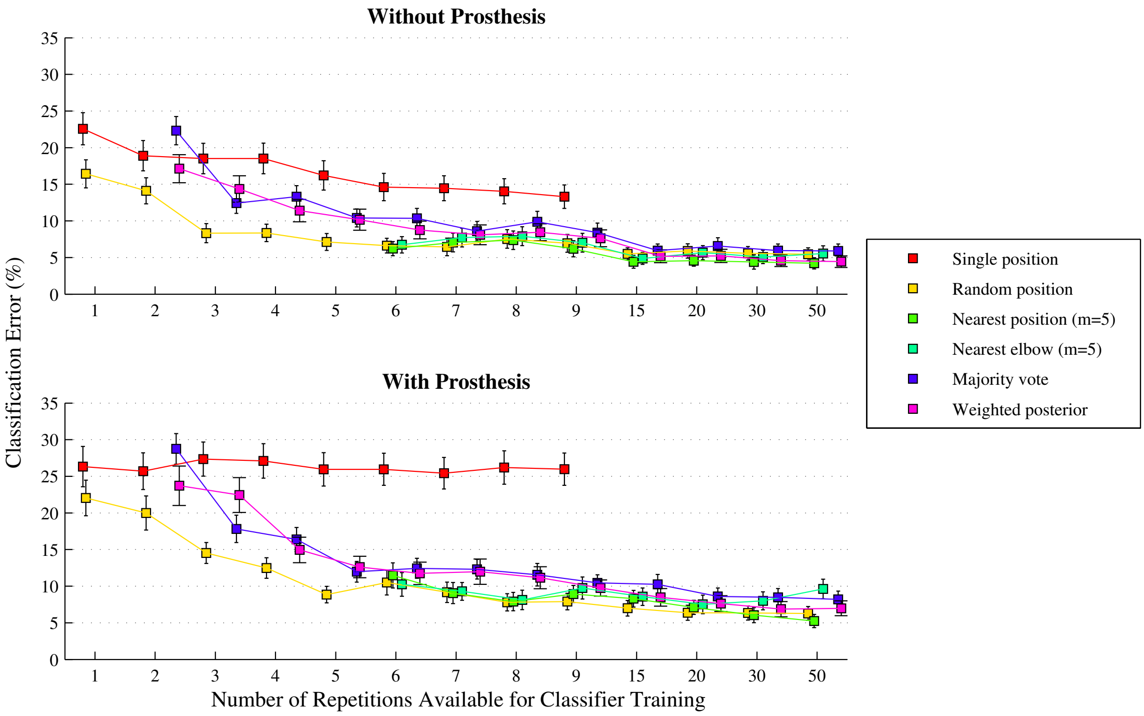

Figure 4.5: Average classification error for Amp2 resulting from multiple variations on the availability of training data. Error bars represent the standard error of the mean.

that from the NP ($m = 10$) method.

Classification error results differed for the amputee subjects depending on whether or not they were wearing their prostheses. This can be seen in Fig. 4.4 and Fig. 4.5 comparing the plots on the left (without prosthesis) with those on the right (with prosthesis).

For Amp1 without his prosthesis, classification resulting from training based on the SP method performed similarly to RP for all number of repetitions available for training. The NP ($m = 1$) and NE ($m = 1$) methods yielded significantly higher classification error than all other methods for all numbers of repetitions available for training. Not for any number of repetitions available or m was classification error significantly different between these methods.

For Amp1 while wearing his prosthesis, the classifier based on the SP method had the significantly highest classification error among all methods and for all numbers of repetitions available for training. The RP method on the other hand, yielded classification error rates lower or insignificantly higher than all other methods.

For Amp2 without her prosthesis, the SP method yielded significantly higher classification error than the RP method for all number of training repetitions available with the exception of when one and two repetitions were included in training in which case the difference was not significant. Without her prosthesis the NP and NE methods for $m = 5$ and $m = 10$ tend to outperform the RP method. Although under the specified criteria, in no instances is the difference significant with that from the RP method. As with Amp 1, the NP and NE methods for $m = 1$ yielded significantly greater classification error than all other methods for all numbers of repetitions available for training. Not for any number of repetitions available or m was classification error significantly different between these methods.

For Amp2 while wearing her prosthesis, the SP method yielded significantly higher classification error than all other methods with the exception of when one and two repetitions were included in training in which case the difference was not significant. With her prosthesis, the performance of the NP and NE methods over the RP method is less significant. Only in a few cases do these methods outperform the RP method and in these cases the difference is not significant.

For both amputee subjects, classification error was greater when the prosthesis was worn for all implemented classification methods. Additionally for both subjects, while wearing their prostheses, 90% of the reduction in error was achieved with five repetitions.

4.5 Discussion

4.5.1 Analysis of the Limb Position Effect

Through univariate linear regression of multiple covariates onto MAV, we found that the variance of the distribution of slopes resulting from regression with elbow angle for able-bodied subjects was the largest, indicating that for able-bodied subjects the angle of the elbow most influences the recorded MAV feature of EMG. The influence of the elbow angle on recorded EMG has not been investigated in previous reports.

On the other hand, we found that the hand's height relative to the shoulder for able-bodied subjects yielded a distribution of slopes with a positive and significantly larger mean than the distributions resulting from regression with the other covariates. This suggests that of the parameters tested, the limb's height most consistently positively impacts the MAV of the recorded EMG. Physiologically, this likely reflects the increased effort required to maintain the position of the arm and hand at higher positions. The small variance of this distribution in relation to the others however, indicates that this covariate does not generally impact (positively and negatively) MAV as significantly as the other covariates.

Similar results were obtained from the amputee subjects as from the able-bodied subjects. Regressing EMG onto the forearm's height relative to the shoulder for all grasps yielded a distribution of slopes with a mean significantly non-zero for both amputees yet only when the prosthesis was worn. This suggests that when the amputees wear their prostheses, MAV generally increases across all channels as the arm is raised. Regressing EMG onto elbow angle again yielded significant results only when the amputees wore their prostheses; in which case the resulting distribution of slopes had a significantly larger variance than the others. As with the able-bodied subjects, this finding indicates that of the covariates tested, the angle of the elbow most significantly impacts the recorded MAV feature of EMG.

This demonstration of the impact of the angle of the elbow on EMG MAV for able-bodied and amputee subjects suggests that accounting for this parameter during classification may be most important in the development of a position-robust myoelectric prosthesis. It was for this reason that the elbow angle-specific classification method (NE) was implemented.

4.5.2 Classification

With an understanding of the parameters influencing extracted features of EMG, the goal of implementing the variations on the availability of training data explored in this paper was to develop a more intelligent classification system robust to the limb's position in space. Method 4 (NE) was specifically tested due to the finding that of the parameters tested, the angle of the elbow had the largest impact on the extracted MAV. Supportive of this finding, it is shown that for all numbers of repetitions available in training, the NP and NE methods resulted in an insignificant difference in classification error. Therefore, changes in EMG features across positions in 3D space appear to be largely captured by changes in the angle of the elbow alone.

Methods 5 (MV) and 6 (WP) were implemented as additional strategies to incorporate positional awareness into the model. Previous work had shown that a model similar to the WP method yielded performance comparable to the RP method [7]. This current analysis, however, has shown that these methods do not outperform the position specific methods (NP, NE) nor the aggregate method (RP).

More generally, noting the difference in classification error between single-position training and the other methods, it is evident that the limb position effect is more prominent in able-bodied subjects and with amputees wearing their prostheses than for amputees without their prostheses. In fact, for Amp1 without his prosthesis, the limb position effect is almost unobserved. Whether he trains in two, or 50 unique positions, the resulting classification error is different by less than 1%. Additionally, not for any number of repetitions available for training do the RP or NP methods significantly outperform the SP method. The finding that the limb position effect is minimal for amputees without their prostheses supports the idea suggested by Geng et al. that "EMG signals acquired from an intact limb are more affected by limb position variation" [34].

In those cases where the limb position effect is manifest, it is shown that training in random positions and aggregating the training data to create a single classifier (RP), yields similar or significantly lower classification error for all number of repetitions available for training compared to the other methods.

Largely unconsidered in related work is the tradeoff between training with less data but having the data be potentially more representative of test data (location-specific methods) and training with more data but it being less representative of the test data (aggregate methods). This work shows that, in general, for a given number of training repetitions, each obtained at a different point in the user's working space, training a single aggregate Linear Discriminant classifier using all of the available data yields lower classification error than intelligently downsampling the training data (NP, NE) or weighing more heavily the data gathered most near the position from which the testing data was obtained (WP). Previous work has also confirmed the improvement in robustness afforded by pooling training data from multiple static positions [64].

We conclude that the benefit of a large, pooled training set from multiple limb positions outweighs the benefit of localized data used in a position-specific classifier. Other work similarly shows that increasing the size of the training data set, even with training data from previous days, aids subsequent classification [65]. With training data obtained from multiple positions, the noise due to positional variations appears to be less influential on the classifiers' ability to distinguish between intended grasp classes. Future work should consider the tradeoff between excluding data from the training set for location-specific training and aggregating the entire training set for a potentially more generalizable classifier.

This finding is supported by the theory of LDA. Under LDA, classification relies on assigning query points to the class with its centroid nearest the query point measured by the Mahalanobis distance. The Mahalanobis distance is a scaled Euclidean distance measure in which the distance is inversely scaled by a covariance matrix. Within the context of LDA, this generally means that distance along dimensions with larger relative variance are discounted compared to dimensions with smaller variance. In LDA, the estimated covariance matrix is a weighted combination of the within-class covariances for each of the classes. Elements of the within-class covariance matrices that are common across multiple classes become larger in the resulting pooled covariance matrix and thus de-emphasized under Mahalanobis distance. Similarly, components of the within-class matrices that are either small or are different across classes will remain small or become "averaged out" relative to other covariance components when the matrices are pooled. This results in euclidean distances along these directions becoming enhanced according to Mahalanobis distance.

If the variation in features of EMG during grasping are due to the sum of a grasping component and a limb position component, by training in multiple limb positions, the variation due to limb position will be much larger than that of the grasping component. If we assume that this variation is common across classes, it is amplified relative to grasping variation when the covariance matrices are pooled. This results in the limb position effect being de-emphasized relative to the grasping effect in the final covariance matrix. This hypothesized effect is reflected in the analysis of this experiment. Sampling from multiple limb positions makes the classifier more resilient to variations in signal due to the limb position effect. Likewise, sampling from fewer positions does not result in adequate estimations of the true variation due to limb position and the classifier is unable to de-emphasize them.

A limitation of this work is that we did not evaluate these methods on dynamic testing data in which the data are gathered while the limb is moving. It has been shown that dynamic training yields lower classification error than pooled static training when testing on data from dynamic movements [64]. The same study also shows, however, that pooled static training yields lower classification error than dynamic training when testing on data from static postures. We suggest that for pattern recognition-based prosthesis control methods, classification accuracy should be optimized for static postures as has been the focus of this work. Changes in grasp type are most often desired while in a static posture. The task of picking up, moving, and setting down an object for example, requires changing grasps in static postures (open/close) while maintaining a desired grasp during the dynamic portion of the action (close). To ensure the appropriate grasp is maintained through the dynamic portion of the action, a simple algorithm could be implemented restricting the class from changing until the limb is once again static as measured by an on-board accelerometer.

4.6 Conclusion

It is concluded that training an aggregate classifier from multiple random positions in most cases yields classification error lower than those achieved through the location-specific methods and significantly lower than those achieved by training in a single position. This finding is the result of appropriately comparing each classification method with each having access to the same amount of training data.

Of the covariates tested, the angle of the elbow was found to most strongly impact the MAV feature of EMG for all grasps. Subsequent classification incorporating information about the angle of the elbow yielded classification error insignificantly different from a method incorporating the limb's exact position in space.

These findings will be useful in progressing the work toward achieving robust myoelectric prostheses.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

This thesis has addressed weaknesses in previous work relating to enhancing the robustness of myoelectric prostheses and has thus advanced the field's state of the art. By applying the principles developed by this work, users of myoelectric pattern recognition prostheses will experience improved robustness of their devices to limb position variation. The amputee subjects who participated in this work have, of their own accord, begun training in multiple positions and have reported in private communication that the simple variation of their usual training protocol has resulted in less perceived unwanted movement of their devices in daily use.

Not only does this work have immediate application for the end users, it also provides evidence for researchers in the field suggesting that when using time-domain features of EMG in LDA to classify intended hand action, a two-stage position specific classification method does not outperform a system in which data from multiple positions are aggregated to form a single classifier. The same amount of training data are best used to train a single classifier responsible for the user's entire working space than to be separated according to the position in which it was obtained and used to train multiple classifiers responsible only for a local region of space. This finding is relevant for future research to improve the robustness of pattern recognition myoelectric prostheses.

In addition to this clarifying contribution, this work also illustrates the need to optimize a system for the scenario in which it will be used. Most previously reported works analyzed and accounted for the limb position effect experienced by able-bodied subjects with very limited analysis of amputee subjects. This thesis has provided a thorough analysis of the limb position effect as experienced by two transradial amputees. Not only did this work analyze this impact while the amputees wore an electrode cuff as has been reported previously, but the study went further to analyze and account for the effect while the amputees wore their prostheses. This condition is that for which the system must be optimized. Working to optimize the system in a condition other than this does not guarantee optimal performance when the device is in use. It is found that the limb position effect is of greater significance when the prosthesis is worn than otherwise. The difference in classification accuracy between training in a single position (nine repetitions) versus training in nine random positions (one repetition in each position) for each amputee without their prosthesis is 0.71% and 6.37% respectively; while when wearing their prostheses, these accuracies differ by 28.80% and 18.06% respectively. This finding suggests further research ought to be conducted to understand and mitigate the effects of the prosthesis itself.

Furthermore, this work continued beyond previous work described in chapters 1 and 2 by observing the limb position effect throughout the entire working space of the user rather than in a few, discrete positions. For each subject, able-bodied and amputee, training was performed in more than 54 target locations across the user's working space. By so doing, an analysis of how the EMG features vary across space (joint angle space and the absolute position of the hand relative to the shoulder) could be conducted. The variability of the features is found not to be consistent across channels or grasps. By training and testing the system in these many positions, a more accurate representation of the effect could be obtained. Efforts were undertaken to observe and account for the effect in a scenario more relevant to actual use.

Pattern recognition-based myoelectric prostheses are bringing added function and utility to their users. Their robustness continues to improve as work continues by researchers around the world. As it was reasoned that such prosthetic devices necessarily retain their functionality throughout the user's entire working space, this thesis presented work specifically targeting the robustness of the systems with regard to limb position variation. By exploring and evaluating previously published work (chapter 2), experimenting to better understanding the limb position effect (chapter 3), and experimenting with able-bodied and amputee subjects using a custom built real-time limb tracking system (chapter 4 and Appendix A), a method for enhancing the device's robustness to limb position variation has been validated.

5.2 Future Work

As research continues and our understanding and knowledge of a system or process grows, so does that boundary between the known and the unknown. Much can yet be done to further improve the robustness of myoelectric pattern recognition systems. The following sections present preliminary work which may yield benefits with continuing experimentation and analysis.

5.2.1 Pressure Accommodation to Minimize Variability

One potential direction of work to enhance the robustness of myoelectric prostheses is to gain a better understanding of and account for pressure variability within the socket. A potential factor contributing to the limb position effect is variability in pressure within the socket as the arm is moved through space. It is hypothesized that as the limb is moved through space or loads are placed on the limb, the pressure between the electrodes and the user's skin changes causing a change in impedance at that interface. This impedance change would cause the recorded EMG to change from the otherwise neutral pressure case. Such changes could impact subsequent classification accuracy. Previous work with electrocardiogram (ECG) electrodes has shown that contact pressure has an effect on signal quality [66, 67]. The impact of a changing electrode-skin interface over time on classification accuracy is illustrated in section 2.2.

Using a prosthetic socket emulator on able-bodied subjects, Cipriani et al. found that "variations in the weight of the prosthesis, [as well as] upper arm movements significantly influence the robustness of a traditional classifier based on [a KNN] algorithm" [68]. They conclude that inertial sensors ought to be incorporated into myoelectric prostheses to monitor these effects.

Rather than incorporating inertial sensors, which would not be informative about loads placed on a prosthesis, a preliminary experiment was conducted to observe the pressure distribution within a prosthesis of a transradial amputee subject to monitor changes in pressure and EMG due to variations in the position of the limb and variations of load placed on the prosthesis.

5.2.1.1 Methods of Preliminary Experiment

Eight low-profile flexible FlexiForce force sensors (Tekscan, South Boston, MA) were mounted to the interior of an amputee's custom-fitted prosthesis. The force sensors were too wide to secure the sensing element between the electrodes already in the subject's prosthesis as was initially desired. The sensors were thus mounted inside the socket proximal to the electrodes as seen in Fig. 5.2.B. Each sensor was connected to a typical amplifier circuit as depicted on the device's product sheet and illustrated in Fig. 5.2.A. Individual potentiometers were used to tune each sensor's sensitivity. The output of each measurement was sampled using a NI USB-6009 (National Instruments, Austin, TX) data acquisition device. EMG was recorded simultaneously with these pressure measurements in the same manner as described in chapters 3 and 4.

Two experiments were conducted, the first involving varying the limb's position, the second varying the load on the device. In the first experiment, the hand/wrist actions of rest, open, close, pronate and supinate were performed in the positions depicted in Fig. 5.1 with a cue duration of five seconds. Each position was repeated three times.

Figure 5.1: The five positions in which hand/wrist actions were performed were: straight down, neutral, straight out front, hand to mouth, and straight up.

In the second experiment, the same five grasps were prompted under varying load conditions while remaining in the neutral limb position. The three load conditions explored were: no weight, 500 g and 1 kg. The weights were applied by hanging them freely from the prosthetic hand as seen in Fig. 5.2.C. Each load condition was repeated four times.

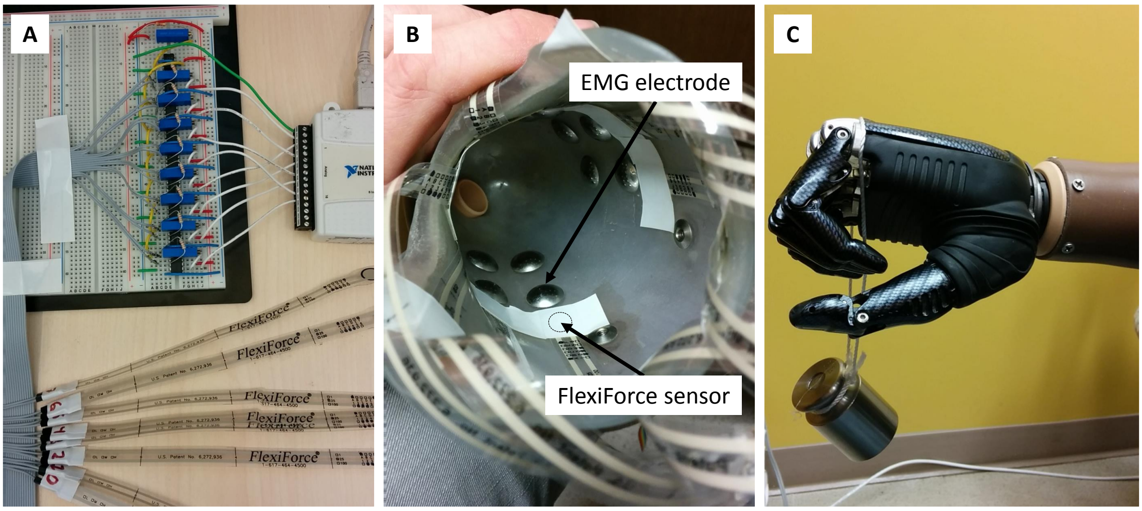

Figure 5.2: (A) Picture of the breadboard used to interface with FlexiForce pressure sensors. (B) Picture of the inside of the prosthesis showing the mounting of each sensor just proximal to the electrodes. (C) A 500 g weight hanging from the prosthesis as used in the second experiment.

The results from each experiment were analyzed similarly. First, changes in pressure as the grasps were performed were observed in the raw data. Second, the pressure distribution around the circumference of the prosthesis was inferred and illustrated by interpolating between sensors using a periodic cubic spline as described in chapter 3 and seen in Fig. 3.2. Finally, classification accuracy of multiple variations of training and test data were explored using LDA. All measurements are reported with respect to baseline values which are those taken during the rest grasp in the neutral position under no load.

5.2.1.2 Results and Analysis of Preliminary Experiment

Fig. 5.3 depicts both the raw EMG as well as the force measurements collected during the first experiment in which the limb's position was varied. The colored sections of time illustrate the intervals during which the subject's limb was in a particular position. It is noted that pressure measurements vary considerably by grasp type as can be seen by five discrete time periods each lasting five seconds within each colored interval.

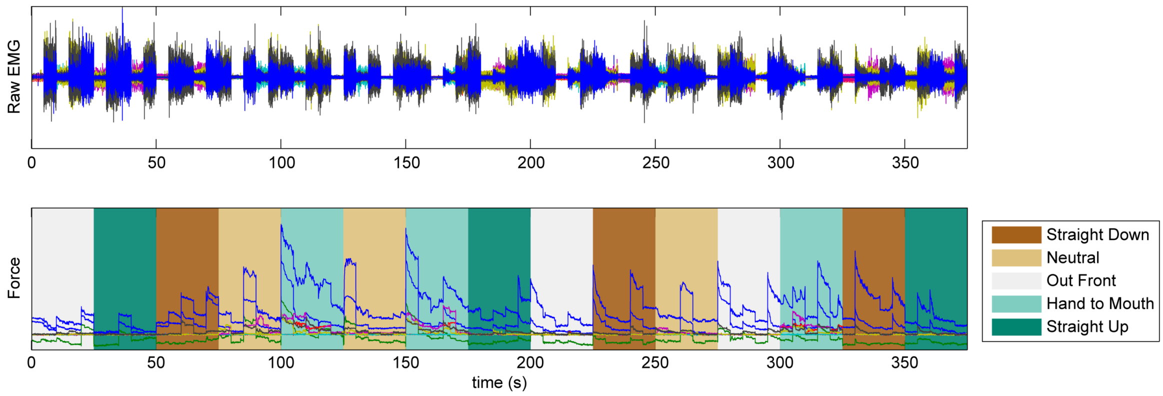

Figure 5.3: Raw data collected from an experiment in which an amputee's arm position was varied. Each line in the lower plot represents data from a single force sensor. Each colored segment of time represents an interval during which the subject's limb was in a particular position. Data was only acquired when the subject was stationary in one of the six positions.

The pressure distribution around the circumference of the prosthesis was then inferred and illustrated by interpolating between sensor measurements using a periodic cubic spline. The resulting illustration can be seen in Fig. 5.4. The figure depicts the average pressure distribution inside the prosthesis during each individual grasp in each position. Fig. 5.5 illustrates the average pressure distribution inside the prosthesis at each position across all grasps. The accompanying bar plot displays the average force at each sensor relative to baseline for each position across all grasps.

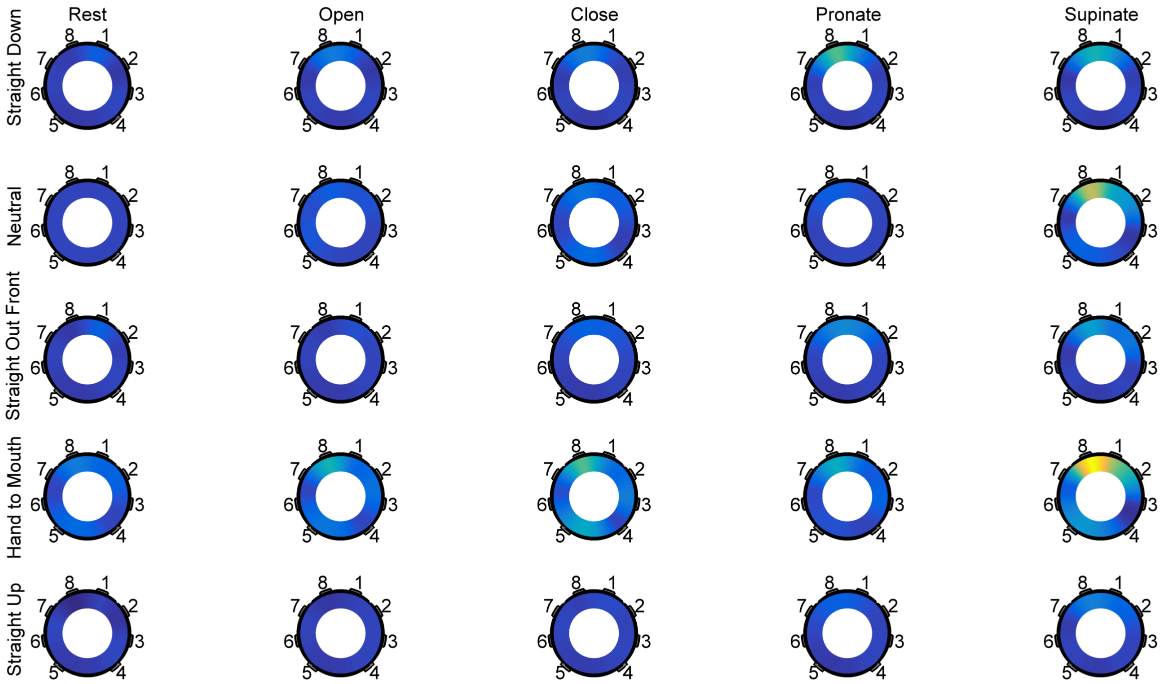

Figure 5.4: Cross sectional view of the pressure distribution within the amputee's prosthesis as viewed from the elbow to the wrist during multiple grasps at multiple positions. All values are depicted with respect to baseline values which are those taken during the rest grasp in the neutral position under no load. Yellow denotes an increase in pressure from this baseline while dark blue denotes a decrease in pressure.

Ultimately, the hypothesis that pressure recordings can be used to enhance classification accuracy was tested. Fig. 5.6 summarizes the information regarding the classification accuracy of multiple training and testing conditions. When training on a single repetition and in each position other than when the arm is left to hang straight down, including pressure measurements along with features of EMG degrades classification accuracy. When training on two repetitions from each position however and testing in all positions, combining features of EMG and force measurements re-

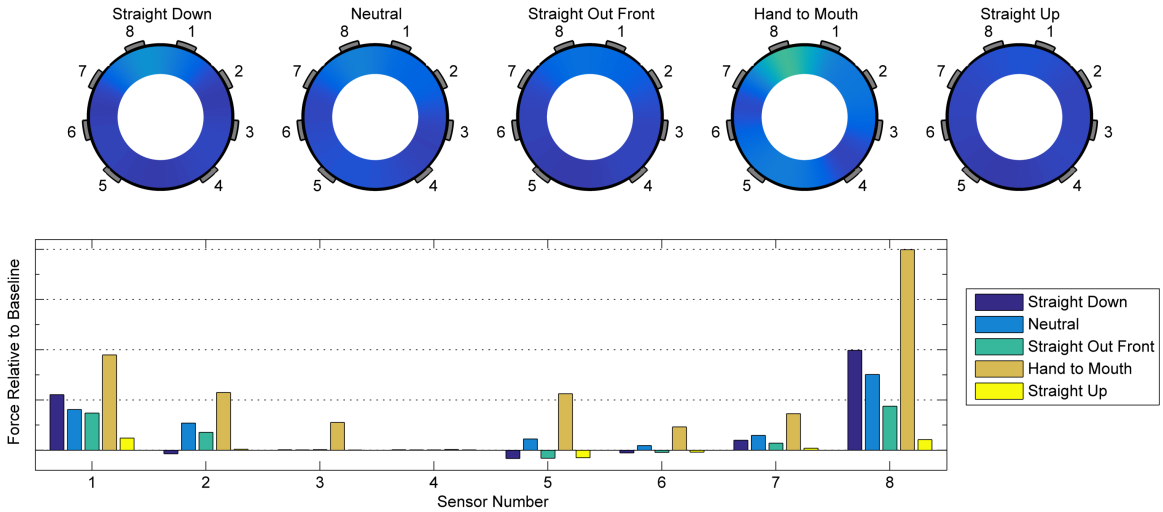

Figure 5.5: Pressure distribution at each position across all grasps with adjoining bar plot displaying the average force at each sensor relative to baseline. It is clear that aggregated across all grasps, the pressure at each sensor is maximum when the arm is in the "hand to mouth" position.

sults in improved classification accuracy above that achieved when using features of EMG alone.

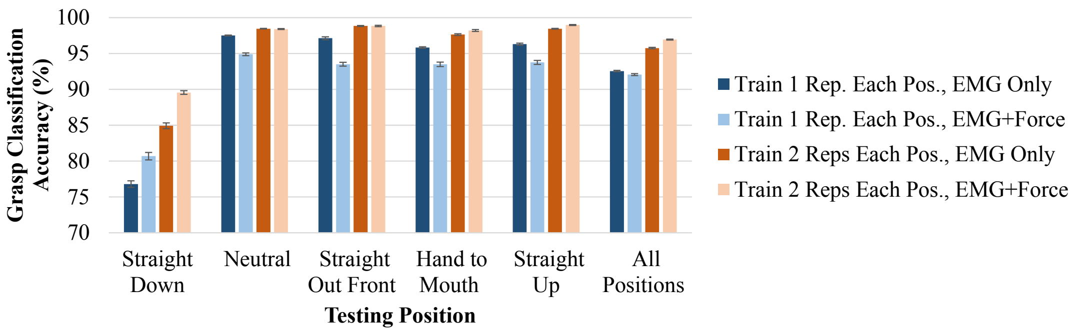

Figure 5.6: Classification accuracy of multiple training and testing conditions.

Results from the second experiment in which the load on the prosthesis was varied are presented in a similar fashion to the previous. Fig. 5.7 shows both the raw EMG and force measurements collected during the experiment. The colored sections of time illustrate the intervals during which the prosthesis was under a particular loading condition.

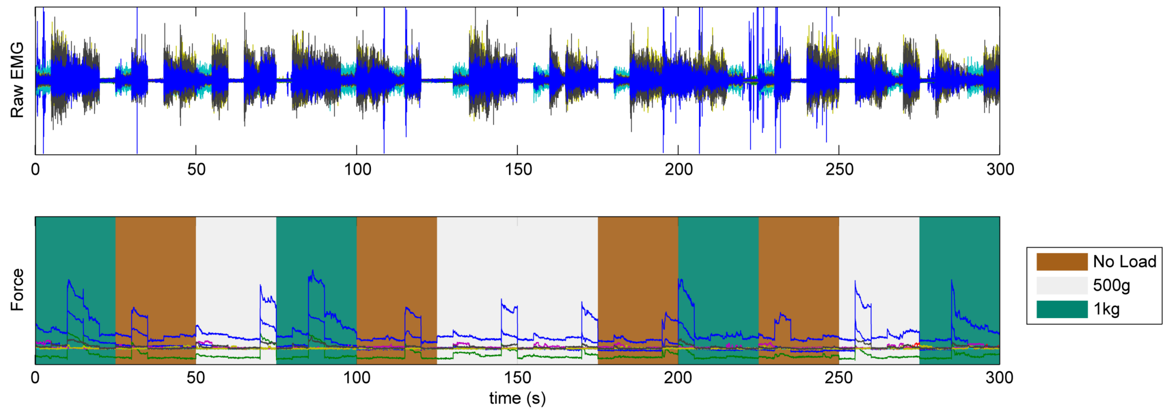

Figure 5.7: Raw data collected from an experiment in which the load placed on an amputee's prosthesis was varied. Each colored segment of time represents an interval during which the subject's limb was under a particular loading condition. Data was only acquired when the load on the prosthesis was constant.

The pressure distribution around the circumference of the prosthesis was again inferred and illustrated by interpolating between sensor measurements using a periodic cubic spline. Fig. 5.8 illustrates the average pressure distribution inside the prosthesis during each individual grasp under each loading condition. It is clear from this representation of the pressure distribution within the prosthesis that the force on sensor #8 is maximum during supinate and when a load of 1 kg is applied to the prosthesis.

Fig. 5.9 illustrates the average pressure distribution inside the prosthesis under each loading condition aggregated across all grasps. The accompanying bar plot displays the average force at each sensor relative to baseline under each loading condition across all grasps. Unexpectedly, the force measured by each sensor under each loading condition was larger than that measured in the baseline condition.

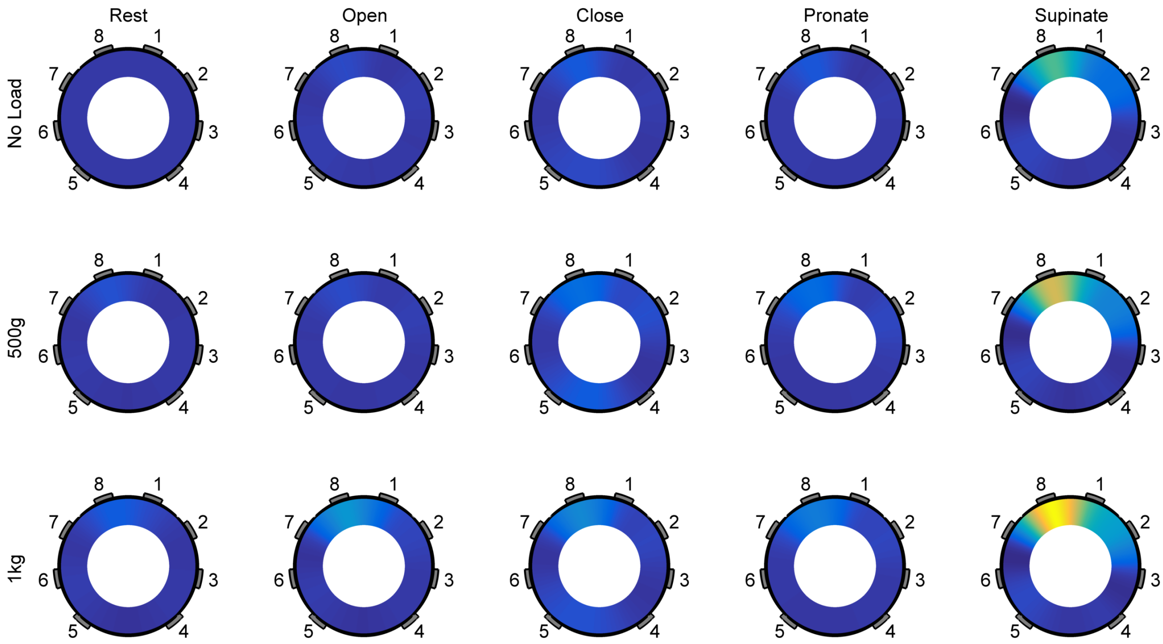

Figure 5.8: Cross sectional view of the pressure distribution as viewed from the elbow to the wrist during each grasp under different loading conditions. All values are depicted with respect to baseline values which are those taken during the rest grasp in the neutral position under no load. Yellow denotes an increase in pressure from this baseline while dark blue denotes a decrease in pressure.

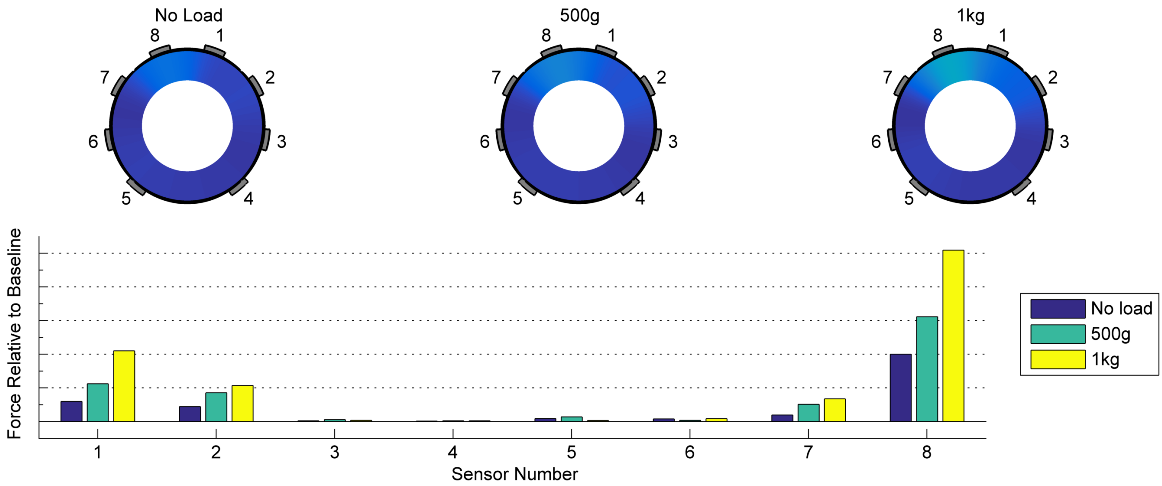

Figure 5.9: Illustration off the average pressure inside the prosthesis over all grasps under different loading conditions. The bar plot further clarifies how the pressure varies by sensor location.

Finally, Fig. 5.10 provides information regarding the classification accuracy of multiple training and testing conditions. It is important to note that when training on three repetitions in a non-loaded condition and including force measurements along with features of EMG to classify intended hand/wrist actions, classification accuracy is significantly degraded when tested in a loaded condition of 1 kg.

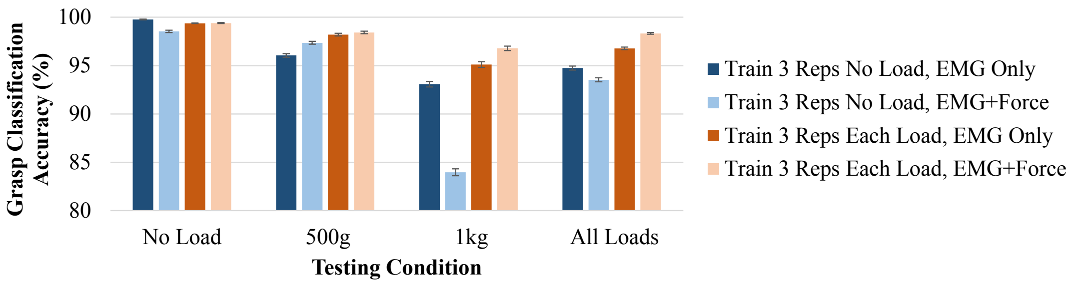

Figure 5.10: Classification accuracy of multiple training and testing conditions resulting from the experiment in which the load condition was varied.

5.2.1.3 Discussion of Preliminary Experiment

As seen in Fig. 5.6, when training on two repetitions from each position and testing in all positions, combining features of EMG and force measurements results in improved classification accuracy above that achieved when using features of EMG alone. Using force measurements alone in classifying grasp yielded an accuracy of 47.41%. Classifying grasp using features of EMG alone yielded an accuracy of 95.11%. Combining the two sources of data yielded a grasp classification accuracy of 96.14%. Although only a marginal improvement, this is a significant finding suggesting that including data from force sensors may improve the robustness of myoelectric pattern recognition prostheses. Future analysis may find that including force sensors aids most in specific situations such as in extreme loading conditions.

More generally, by monitoring the force from multiple sensors when the arm's position is varied, it is observed that the force on each sensor is most increased from baseline when the arm is in the “hand to mouth” position (see Fig. 5.5). This may be due to the high degree of elbow flexion required in this position. Because of this finding, it is suggested that when training a system, a position of high elbow flexion be explored to improve the robustness of the system to such positions during use.

One of the motivating questions promoting this preliminary work was, “how does load effect classification accuracy and how can any negative effects of a changing load be mitigated?” From Fig. 5.10, it is clear that when trained on three repetition under no load and tested under a loaded condition, classification accuracy is less than when tested under no load. This scenario is further clarified in Fig. 5.11 in which the confusion matrices reveal how the individual grasps are impacted by testing in a load condition not seen during training.

From the previous experiment with positional variation described in chapter 4, it may be suggested that to account for various loads, the system ought to be trained in multiple loading conditions. This configuration, in which the classifier is trained using data from multiple loading conditions, is shown in Fig. 5.10 (dark orange) and validates this assumption. Training with three repetitions in each load condition yields higher classification accuracy when tested in each load condition than when

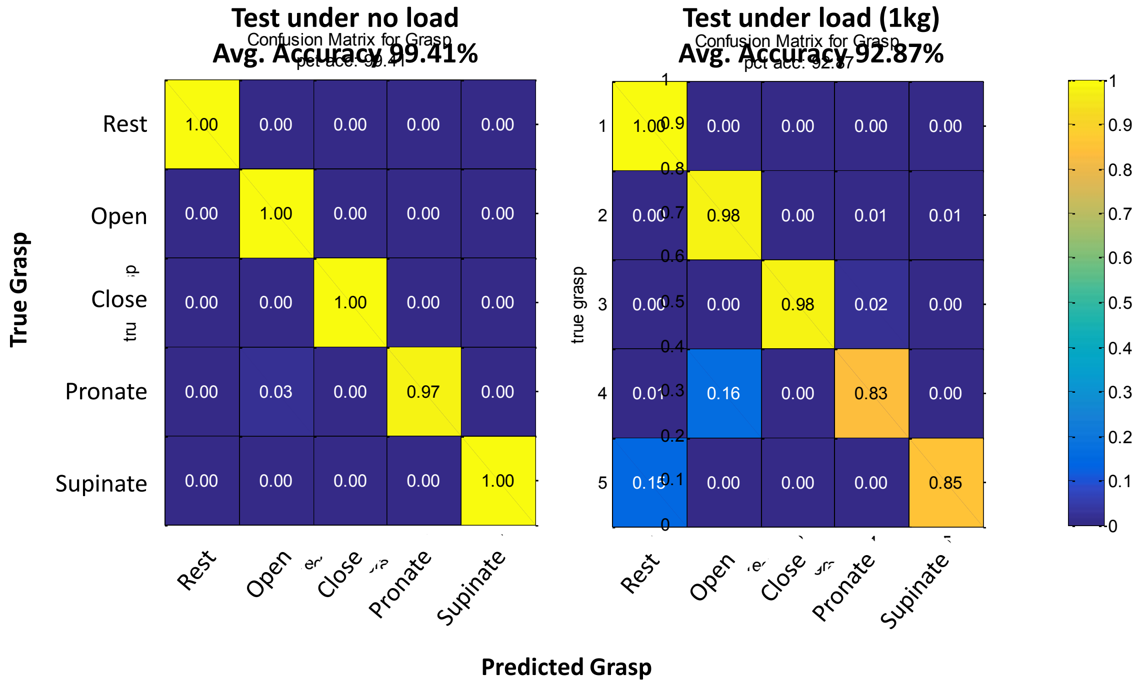

Figure 5.11: Confusion matrices showing the effect of training under no load and testing both under no load (left) and testing under a loaded condition (right). Yellow indicates high classification accuracy while blue indicates low. Comparing the two confusion matrices, it is evident that when testing under a loaded condition not explored during training, classification of the pronate and supinate grasps are most negatively impacted. When testing under a 1 kg load, pronate is classified as open 16% of the time as opposed to only 3% of the time when testing under no load (the training condition). Testing in the loaded condition, supinate is classified as rest 15% of the time as opposed to 0% of the time when testing under no load.

trained in only a non-loaded condition. It may however be unreasonable to train in all loading conditions. Additionally, by training in all loading conditions, subsequent classification accuracy for a particular loading condition is less than if the system were trained only in that condition. Thus, it may degrade the device's utility to train in multiple loading conditions if the system is primarily used in an unloaded condition.

It is observed in Fig. 5.10 that when including the force measurements, training in all load conditions yields high classification accuracy when tested in all loading conditions. This observation however, may be similar to that observed when including accelerometer data with EMG and training in multiple positions [23]. Initially, it was presented as a promising solution, yet Radmand et al. demonstrated that using accelerometers is actually harmful to classification accuracy when testing in multiple limb positions if all the test positions are not explored during training [61]. Such a condition is observed in Fig. 5.10 when including force measurements in training of a classifier in a non-loaded condition. Testing such a system under a loaded condition yields lower accuracy than when the force measurements are not included. This finding reinforces the idea that the data received during training must lie in a "space" representative of the test "space".

A more general finding of this preliminary experiment was that force measurements on a particular sensor varied significantly depending on grasp type. This is seen in figures 5.3 and 5.7 as well as in figures 5.4 and 5.8. In particular, it is noted that during the supinate grasp, the force on sensor 8 is significantly greater than at baseline.

If the hypothesis is correct however, that pressure changes inside the prosthesis are influencing the impedance of the electrode-skin interface and this impedance change is affecting classification accuracy, it may be more beneficial to measure this parameter directly. By so doing, other factors influencing this interface may be accounted for such as sweating or other causes of moisture in the prosthesis. Additionally, measuring impedance directly would obviate the need for the pressure sensors and their associated hardware. Impedance measurements could be taken from the same electrodes as are recording EMG simplifying the incorporation of this signal into existing systems. Bioimpedance has been used in the classificaion of muscle movements in other human machine (HMI) applications [69].

This preliminary work suggests the need to conduct further experimentation to generalize these findings. Future work ought to include a larger number of amputee subjects in the analysis, explore a larger range of positions and loads, and explore whether or not the additional information from force sensors can be used to improve robustness generally or if the information can be used to improve robustness to specific situations or for particular hand/wrist actions.

5.2.2 Restrict Movement When Different or Uncertain

A message reinforced throughout this work has been that to achieve a high level of classification accuracy, the test condition must be similar to the training condition. It is therefore suggested that more work be conducted to restrict movement of the prosthesis when this condition is not met. As an example, if the device is trained in static positions, it may improve robustness to restrict movement of the hand or wrist when the limb is in motion. Such motion could be determined with an on-board accelerometer or other inertial measurement unit. Similarly, hand or wrist movements could be limited when force measurements inside the prosthesis are different from that seen during training. Although such a system is not ideal, it would provide enhanced reliability to users of myoelectric systems. Currently, the reliability of myoelectric prostheses is one of the major hindrances to their full adoption over body-powered prostheses [70, 71].

Not only could movement be restricted when the test condition is different from the training condition, but also if there is uncertainty in the predicted hand or wrist action. Such efforts to impose confidence thresholds have been made by other groups [25, 44]. If a predefined threshold of certainty is not met, “no motion” should be selected thus limiting the effects of incorrectly classified “active” grasps.

Thresholding the posterior values resulting from LDA may be a method of rejecting uncertain predictions. Data from an amputee subject while wearing his prosthesis were used to develop this idea. The data were obtained from the experiment explained in chapter 4. A classifier was trained and evaluated using separate training and test data. Fig 5.12 shows histograms of the four largest posterior values when a correct and incorrect prediction is made. The vertical limit of the top-left plot has been limited to show detail. On that plot, the rightmost bin of the correctly classified samples (blue) contains 8788 counts while the rightmost bin of the incorrectly classified samples (red) contains 436 counts. Because the second, third, and fourth largest posteriors were very small, histograms were created of the exponent of these posteriors in scientific notation.

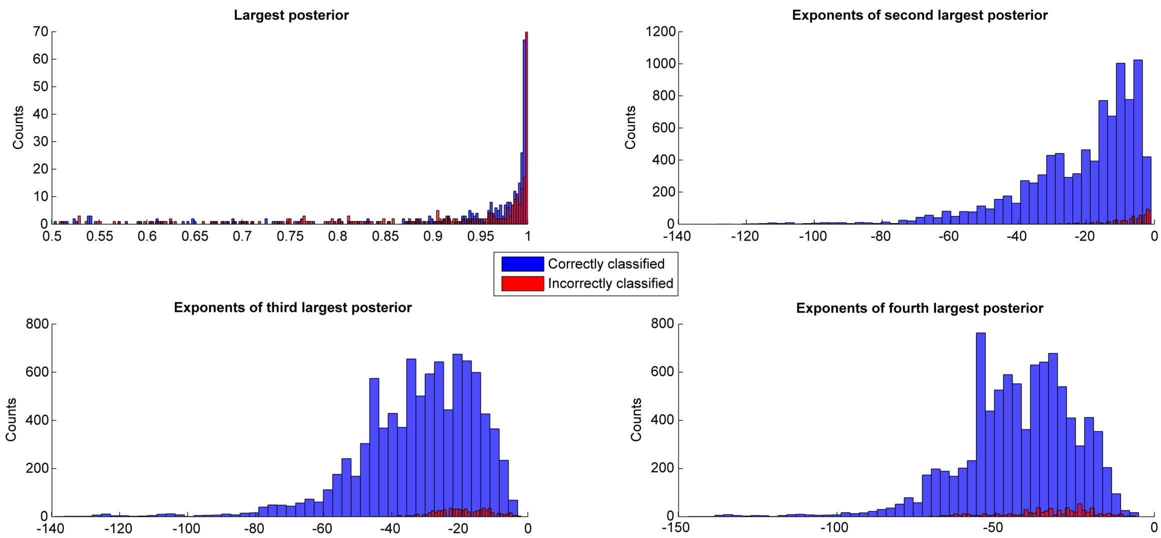

Figure 5.12: Histograms of the four largest posteriors resulting from LDA when a hand/wrist action is correctly and incorrectly classified. In the construct of LDA, a value is assigned to each potential grasp quantifying the degree to which the classifier believes that particular grasp is the intended grasp. This value is the posterior of that grasp. Pure LDA will select that grasp with the largest posterior. Placing a threshold on the posteriors may be a useful method of rejecting uncertain predictions.

Fig 5.13 shows the percent of correctly and incorrectly classified samples above a given threshold for each of the largest four posteriors. By calculating the difference between these percentages at each threshold level, a maximum difference was found for each thresholding condition. It is at this point that the threshold would maximize the number of incorrectly classified samples relabeled as "no motion" while minimizing the number of correctly classified samples relabeled as "no motion".

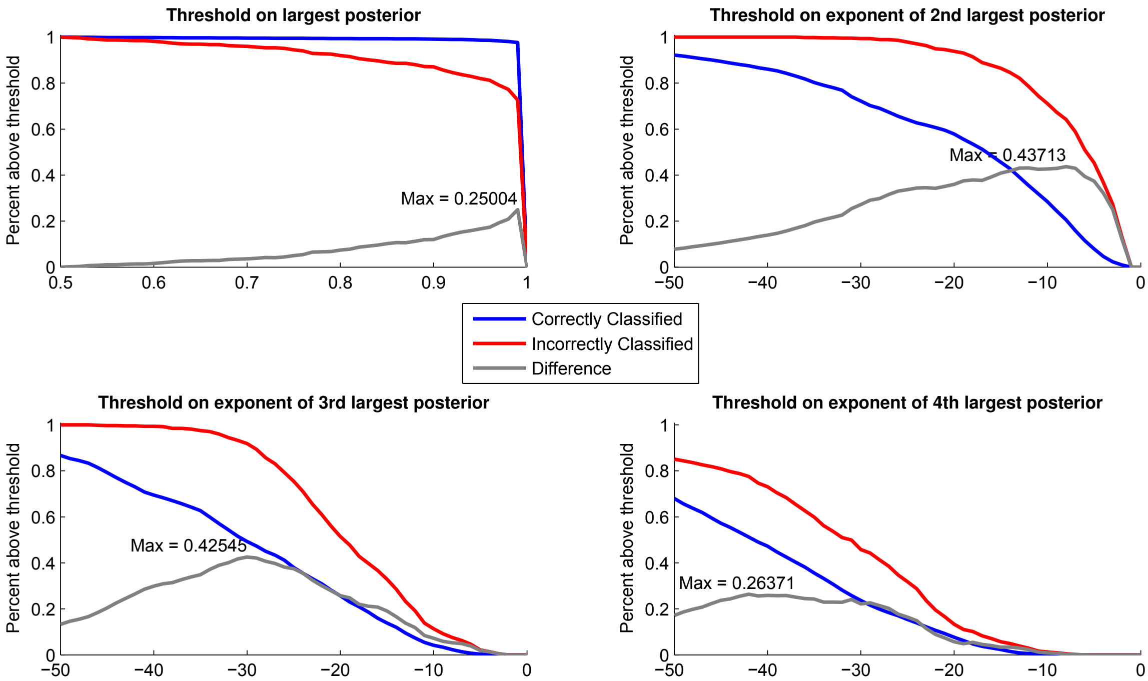

Figure 5.13: Plots showing the percent of correctly and incorrectly classified samples above a given threshold. The difference between these percentages is also shown.

The thresholds found to maximally distinguish between correctly and incorrectly classified classes were then applied to the data. Those samples which met the criteria of the threshold were relabeled as "no motion". Fig 5.14 shows the confusion matrices resulting from this action. It is apparent that, like reported by Scheme et al., for any threshold level, the percent of incorrectly classified active motions was lowered from when no threshold was applied [25]. Such an implementation however, would result in the prosthesis being less responsive. It is observed that with a confidence threshold, data from an active motion that may have otherwise been correctly classified are occasionally classified as “no motion”.

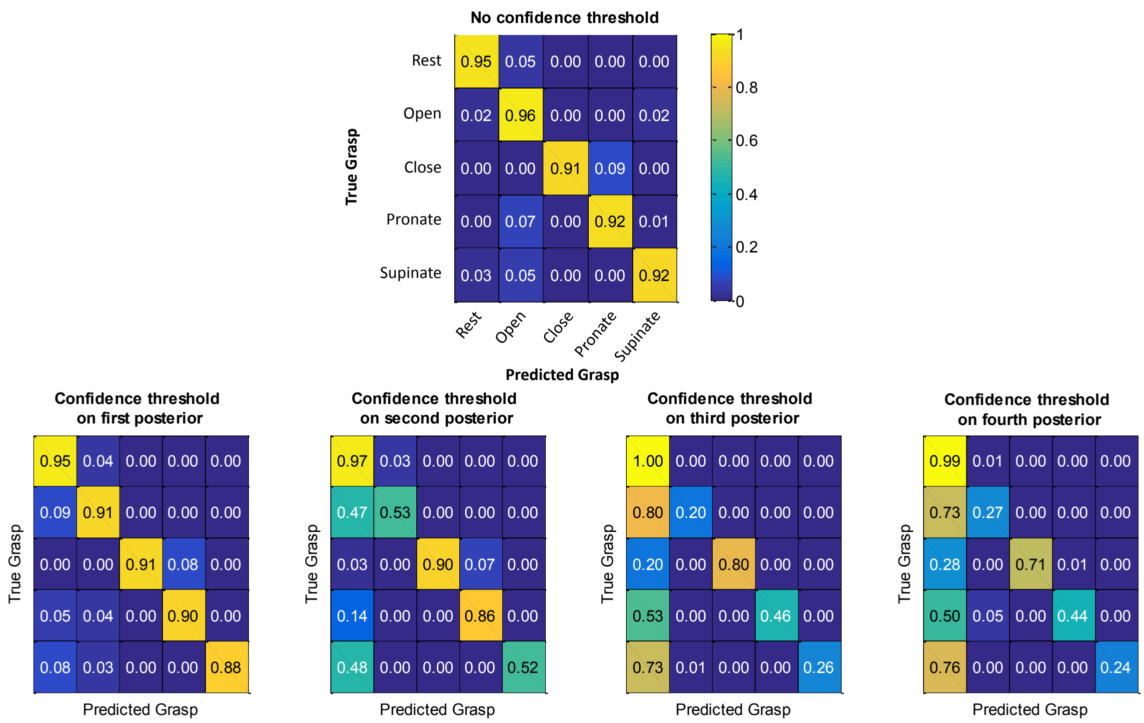

Figure 5.14: Confusion matrices showing the effect of applying a confidence threshold to the decision stream of an LDA classifier. In all cases in which a confidence threshold is applied, the percent of misclassified active grasps is decreased. Active grasps are hand open, hand close, wrist pronate, and wrist supinate.

As in methods previously examined to improve robustness, there is a tradeoff between robustness and responsiveness when applying a confidence threshold to the decision stream of the classifier. The robustness of the system is improved by minimizing the frequency of incorrectly classified active grasps, yet the system's responsiveness is hindered by more frequently classifying active grasps as rest or “no motion.” Future efforts may find an optimal balance between these parameters or provide the ability for the user to determine this level.

Appendix A

Real-Time Arm Tracking using Inertial Measurement Units

Adapted from the author's publication:

M. R. Masters, L.E. Osborn, A. B. Soares, and N. V. Thakor, "Real-Time Arm Tracking for HMI Applications," *Accepted by IEEE Body Sensor Networks Conference*, 2015.

A.1 Appendix Abstract

Limb tracking is an important aspect of human-machine interfaces (HMI). These systems, however, can often be limited by complex algorithms requiring significant processing power, obtrusive and immobile sensing techniques, and high costs. In

this work, we utilize a sensor fusion algorithm implemented in commercial inertial measurement units (IMU) to combine accelerometer and gyroscope measurements in an effort to minimize computational requirements of the limb tracking system. In addition, previously developed methods were implemented to eliminate sensor drift by including information from a magnetometer. We tested the accuracy of our system by computing the root mean squared error (RMSE) of the true angle between the headings of two sensors and the estimate of that angle through quaternion-vector manipulations. An average RMSE of approximately 2.9° was achieved. Our limb tracking system is wearable, minimally complex, low-cost, and simple to use which has proven useful in multiple HMI applications discussed herein.

A.2 Introduction

Many human machine interfaces (HMI) require limb tracking for effective user interaction. Currently the majority of such systems are expensive, difficult to set up, and/or difficult to use [72–74]. To address this issue, a network of inertial measurement units (IMUs) was engineered to provide robust, low-cost, and simple to use motion tracking for use in and outside the laboratory. By understanding the intended application of the sensor network, we were able to use a less robust algorithm to minimize the computational complexity and memory storage requirement of the system.

APPENDIX A. REAL-TIME ARM TRACKING FOR HMI APPLICATIONS

Body movement can be measured using a variety of techniques and sensors. One study analyzed how eye tracking, a motion tracking glove, and even electroencephalography (EEG) signals could all be used to predict the targets of human reaching movements [75]. Other techniques for tracking limb motion include computer vision techniques [76, 77], and other sensing technologies such as optical encoders and goniometers [78].

Inertial measurement units (IMUs) utilize microfabricated sensing elements to acquire information about the device's motion and/or orientation. Due to their decreasing cost in recent years and advancements in sensor fusion algorithms, IMUs are increasingly becoming more accepted as wearable technology for orientation and position tracking. Incorporating magnetic, angular rate, and acceleration measurements to form a single representation of an object's orientation in space and minimize error is known as sensor fusion. By incorporating the information from multiple sensors, it it possible to minimize error that would have otherwise accumulated over time [79]. For example, integrating angular velocity from gyroscopes to calculate the orientation of a sensor leads to accumulated error over time from an imperfect measure of velocity. This drift can be mitigated by incorporating information from an on-board accelerometer and/or magnetometer. Some groups have worked around issues such as this by limiting the amount of time data can be collected during a movement [80]. Although not a feasible solution to many other applications, the solution was adequate for the given task.

APPENDIX A. REAL-TIME ARM TRACKING FOR HMI APPLICATIONS

Many algorithms have been designed for the purpose of IMU sensor fusion. In the case of limb-tracking, combining kinematic models of an arm's motion with the unscented Kalman filter has proven highly accurate [81]. Bachmann et al. perform sensor fusion using a complementary filter in the quaternion space which is less computationally intensive than the Kalman filter [82]. Gallagher et al. similarly implemented a complementary filter yet applied it in the linear space which filters the inputs individually [83]. Madgwick et al. developed and tested a computationally efficient algorithm using a form of gradient descent to update the quaternion estimation of the IMUs orientation [84].

As in previous works in which constraints to the system provided useful information [80, 81], we utilize the knowledge of the location of each of sensor to minimize the computational complexity and storage requirements of our system. Our system is able to provide real-time tracking of limb movement in a low-profile package that is easily portable and customizable to the application while being drift resistant due to the fusion of multiple sensors.

Many applications exist for low-cost, low-profile, and easy to use human motion tracking systems. A few examples already researched incorporating IMU technology include: real-time tracking for rehabilitation of stroke patients [85], evaluating the impact of neuromuscular disorders [79], and predicting targets of human reaching for human-computer interactions [75]. The device described in this work has been applied to multiple other applications which are presented hereafter.

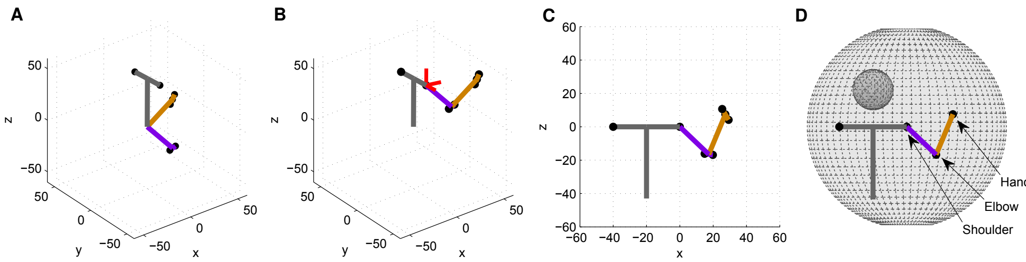

Figure A.1: Progression of transforming quaternion information to vector representations and finally a body-representation for prosthesis training in a virtual environment. (A) The quaternions are transformed to vector representations before (B) being added together in the appropriate location to make up the human body. (C) A transformation from a global to a local coordinate system allows centering on the user's shoulder and (D) the final virtual display to be used in a prosthesis training experiment.

A.3 Methods

We utilized the sensor fusion algorithm implemented on-board the InvenSense MPU9150 MotionTracking device to join the accelerometer and gyroscope measurements into a quaternion representation of the device's orientation in space. This method of sensor fusion was used to minimize the computational complexity of the algorithm and illustrate its effectiveness as a low footprint solution to sensor fusion. Subsequent inclusion of magnetometer data was then implemented to eliminate drift in yaw using an open source algorithm released by Pansetti, LLC (MPULIB9150) on a Teensy2.0 microcontroller (PJRC, Sherwood, OR). Implementation of this algorithm yielded a quaternion representation of each sensor's orientation in space relative to earth's magnetic field. By understanding that the system was to be worn with the reference sensor mounted to a person's upright chest, we mitigated gimbal lock-related errors introduced by the algorithm by fixing the reference sensor having its z-axis perpendicular to the ground. Interested readers are referenced to works providing rigorous analysis of the sensor fusion process and methods to avoid errors from gimbal locking [81–84, 86].

Fig. A.1 illustrates the progression of computation from the the quaternion representation of each IMU to a 3-dimensional human body representation. The transmit of the quaternion information of each IMU to the PC was conducted through a serial connection and managed by a custom MATLAB program (MathWorks, Inc., Natick, MA). Once received, the quaternions q are transformed to vector representations by first computing the conjugate of each quaternion according to equation A.1. Each quaternion is then normalized by dividing by its modulus according to equation A.2. The normalized quaternion conjugates are then used to generate corresponding direction cosine matrices as given by equation A.3. Finally, the rotation is applied to the vector v_o according to its respective DCM with equation A.4.

$$q' = (q_1 - q_2 - q_3 - q_4); \tag{A.1}$$

$$|q'| = q'/\sqrt{q_1^2 + q_2^2 + q_3^2 + q_4^2}; \tag{A.2}$$

$$DCM = \begin{pmatrix} q_1^2 + q_2^2 - q_3^2 - q_4^2 & 2q_2q_3 + q_1q_4 & 2q_2q_4 - q_1q_3 \\ 2q_2q_3 - q_1q_4 & q_1^2 - q_2^2 + q_3^2 - q_4^2 & 2q_3q_4 + q_1q_2 \\ 2q_2q_4 + q_1q_3 & 2q_3q_4 - q_1q_2 & q_1^2 - q_2^2 - q_3^2 + q_4^2 \end{pmatrix} \tag{A.3}$$

$$v_{rotated} = (DCM * v_{init}^{\intercal})^{\intercal}; \tag{A.4}$$

The result of this process is depicted in Fig. A.1.A where each uniquely colored "T-shaped" object represents the orientation of one IMU. The body representation is then constructed by translating the vectors to their proper locations as is shown in Fig. A.1.B. A coordinate transform was then performed to view the arm's motion from a "body-centered" perspective. Each point p was transformed into the local coordinate system by applying equation A.5 where A is the rotation matrix containing the normalized axes for the new coordinate system and d is the location at which the new coordinate system has its origin.

$$p^* = A(p - d) \tag{A.5}$$

The normalized axes for the local coordinate system are shown with red lines in Fig. A.1.B having its origin d at the subject's shoulder. Finally, a visual display is presented to the user in real-time (Fig. A.1.D).

Now in the local coordinate system, relevant joint angles were calculated including elbow angle, shoulder flexion/extension, shoulder ab/adduction, and medial/lateral humeral rotation.

A.4 Results and Applications

The physical system is shown on the left of Fig. A.2. To the right, it is being worn to track a subject's limb posture in real-time.

To validate the performance of the sensor network, two of the three sensors were mounted to a custom goniometer which consisted of two beams joined by a linear potentiometer mounted as the axis of the device. The apparatus was then repeatedly opened and closed as the angle between the two rods was recorded separately by the potentiometer and the IMU system. The tracking achieved by the sensor network is illustrated in Fig. A.3. The action was performed in the vertical plane, horizontal plane, and as the apparatus was randomly rolled in all directions. Total root mean squared error (RMSE) over the duration of each trial was computed by fitting cubic splines to the sampled data and calculating the RMSE. The resulting error was 2.32°, 3.53°, and 2.95° for each scenario respectively.

The developed system has been utilized in multiple experimental paradigms including: virtual prosthesis training, trajectory analysis of human reach, and neural correlation analysis. A short description of each of these applications is provided.

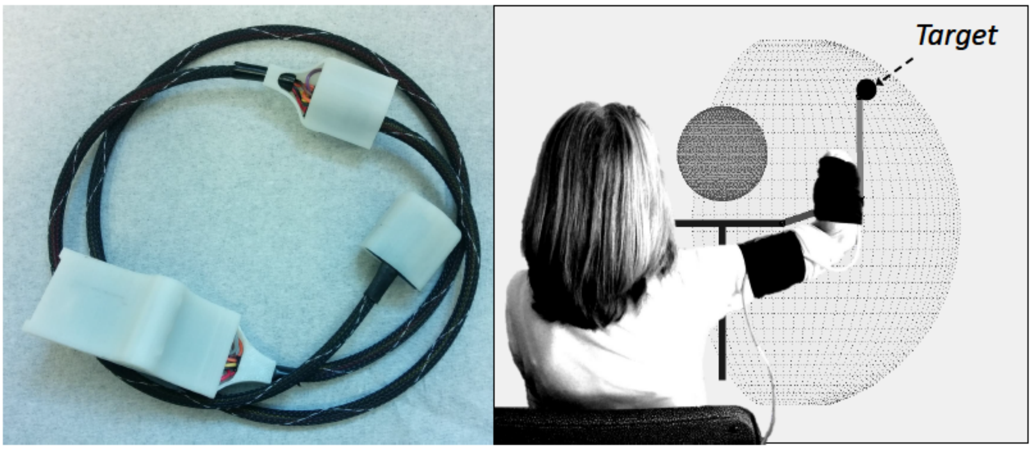

Figure A.2: The completed IMU system (left). Use of the IMU system being worn by an amputee subject (right). The amputee subject is viewing an image of her limb's orientation as estimated by the IMU system.

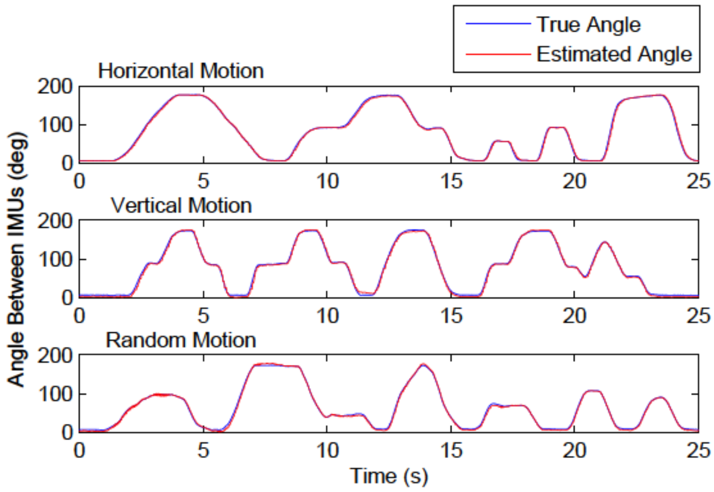

Figure A.3: An illustration of the tracking achieved by the network of the IMUs where horizontal, vertical and random movements were performed.

A.4.1 Prosthesis Evaluation and Training

The IMU system has been used to analyze how electromyogram (EMG) changes as myoelectric prosthesis users navigate through their working space. While wearing the IMU system, the amputees located target positions shown to them in a display similar to that seen in Fig. A.1.D and performed grasping actions with their phantom hand. This data has been used to suggest methods for improving the robustness of upper-limb prostheses [7]. Virtual prosthetic use may also prove beneficial for training amputees who have not yet received a prosthetic limb. Finally, manipulating a virtual arm may reduce phantom limb pain and discomfort [87].

A.4.2 Trajectory Analysis

A limb tracking system also has applications in rehabilitation through trajectory analysis. The trajectories of a subject's hand as they reach to, manipulate, and return from target positions using the IMU system is shown in Fig. A.4. Some systems require patients make contained movements in a laboratory setting [74]. With a portable and wearable system, a patient could perform unrestrained movements with ease while simultaneously having their limb movements recorded for analysis by a clinician. Among many other things, trajectory analysis has the potential to benefit stroke or post-surgery rehabilitation providing a metric of performance and progression. Additionally, limb trajectory analysis has applications in optimizing athletic performance such as in weight lifting, running, and cycling where body position plays an important role in performance.

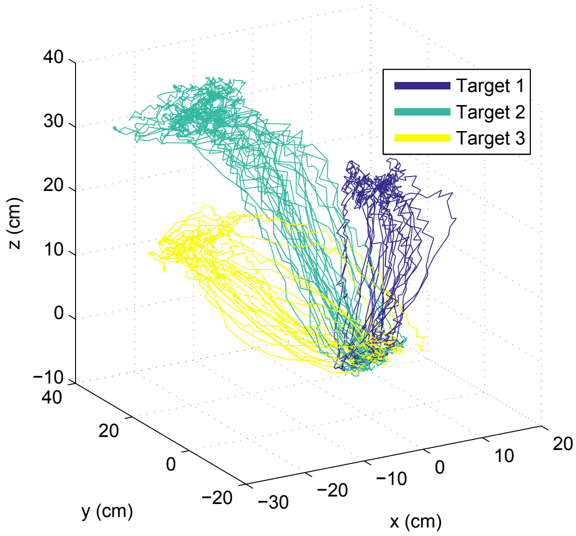

Figure A.4: Trajectories of a subject's hand traced through 3D space as they approach, manipulate, and return from targets located in three unique target locations. Each color represents the movements corresponding to a particular target.

A.4.3 Neural Correlation

A recent study has demonstrated the use of electrocorticographic (ECoG) signals for controlling a prosthetic limb [72]. In a related work, our wearable IMU system was used to record limb motion while ECoG was simultaneously recorded from a human subject. This data can be seen in Fig. A.5. One goal of this experiment was to learn neural correlations between physical activity and brain activity which might then allow for ECoG-based control of a prosthesis or other mechanical arm.

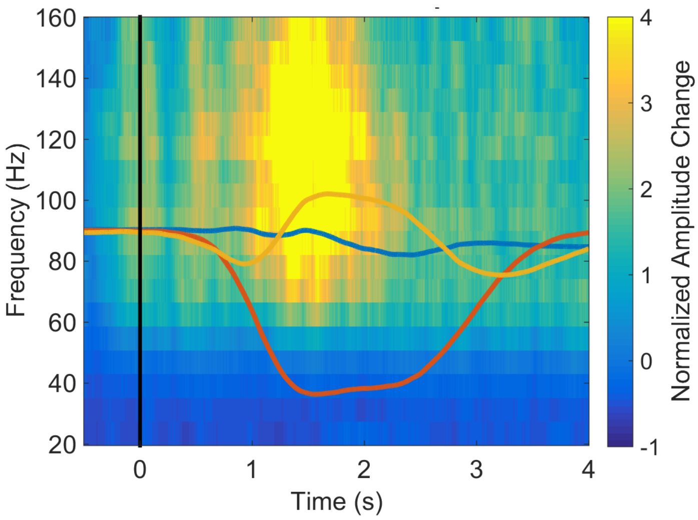

Figure A.5: Spectrogram of average ECoG from a human subject collected during multiple reach-grasp tasks with the subject's average hand position overlaid. The blue line is the trace of average lateral motion; red is central motion; and gold is motion in the vertical direction. The data illustrates that the ECoG electrodes were principally recording hand-related activity as opposed to shoulder or elbow activity.

A.5 Discussion

We have presented a limb motion tracking system that uses IMUs and combines accelerometer, gyroscope, and magnetometer sensor information to prevent sensor drift and create an accurate representation of a limb in 3-dimensional space. Understanding the use of our system and the scenario in which it is to be used, we are able to use a sensor fusion algorithm processed on the IMU itself in conjunction with an open-source algorithm to yield a system with minimal storage and computation requirements while maintaining its capabilities as a limb tracking system.

Using an RMSE evaluation of our system, we have demonstrated the ability to successfully track limb position with an accuracy of approximately 2.9°. Our entire system costs approximately $60 USD which enables measurement and tracking of limb position in both laboratory and at-home settings.

Our system has applications for at-home training and rehabilitation for patients of stroke, surgery or amputations attributable to its mobility and ease of use. Data from the IMU system can be analyzed in real-time or stored for offline offline analysis.

A.6 Conclusion

We have presented a wearable limb tracking system constructed using low-cost commercially available IMUs. We methodically convert from a quaternion representation of each sensor's orientation to a body-centered local coordinate system. In this form, the limb tracking system has been implemented in multiple applications including virtual prosthesis training, limb trajectory analysis, and an experiment correlating physical movement with human ECoG. It is evident that the system provides a means for limb tracking in many environments and for various applications.

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Vita

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