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Pattern Recognition-Based Myoelectric Control of Partial-Hand Prostheses

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Abstract

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Pattern recognition-based myoelectric control of upper limb prostheses has been made clinically available to individuals with more proximal upper limb amputations and can restore intuitive control of a prosthetic hand. This control method has yet to be implemented for individuals with amputations distal to the wrist (i.e. partial-hand amputations) and who constitute over 90% of all upper limb amputees. Unique to this population of amputees is the presence of a functional wrist. The purpose of this work was to evaluate strategies that would facilitate the novel use of pattern recognition-based myoelectric control of electrically powered, partial hand prostheses and allow partial-hand amputees to maintain wrist function while effectively controlling the prosthesis. My initial offline studies showed that a functional wrist significantly diminishes the performance pattern recognition algorithms ($p < 0.001$). To resolve this challenge, this dissertation evaluated (1) different paradigms to collect decoding algorithm training data, (2) contributions of discriminatory information from intrinsic and extrinsic EMG muscles sources, (3) classification algorithms, (4) time and frequency domain EMG features and (5) the use of wrist kinematics to improve the decoding of hand grasps in different wrist positions in non-amputee and amputee subjects. Finally, real time control tests with four partial-hand amputees using the Touch Bionics i-limb digits were performed and demonstrated that pattern

recognition myoelectric control allows for the control of electrically-powered partial hand prostheses while allowing the user to retain residual wrist function.

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List of Abbreviations

ANOVA: Analysis of variance

AR: Auto-regressive

DIP: Distal interphalangeal

EMG: Electromyography

FSR: Force sensitive resistor

LDA: Linear discriminant analysis

LNN: Linear Neural Network

LogDet: Log-detector

MAV: Mean absolute value

MCP: Metacarpophalangeal

MdF: Median frequency

MLPANN: Multilayer perceptron artificial neural network

MnF: Mean frequency

MP: Mean power

PF: Peak frequency

PIP: Proximal interphalangeal

PSD: Power spectrum descriptors

QDA: Quadratic discriminant analysis

RMS: Root mean square

SFS: Sequential Forward Searching

SI: Separability Index

SSC: Slope sign changes

TD: Time Domain

TDAR: Time Domain – Autoregressive

VAR: Variance

V-ord: V-order

WAMP: Willison amplitude

WL: Waveform length

ZC: Zero crossings

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Chapter 1 Introduction

1.1 Motivation

There are an estimated 541,000 individuals in the United States with an upper limb amputation [1], with over18,000 new cases each year [2]. Over 90% of these amputations occur below the wrist (i.e. partial-hand amputations). They include thumb amputations (18%), amputations through the hand at the transmetacarpal or transcarpal levels (1.5%), or amputations of one or more digits (80.5%) [2]. The most common prosthetic treatment of partial-hand amputations involve the use of passive cosmetic devices or body-powered devices that harness motion about proximal joints to actuate distal finger joints [3, 4].

Though partial-hand amputations are traditionally considered “minor” amputations, recent work exploring the impact of this level of amputation on function, employment, and self-image has brought more focus on partial hand amputation. More than half of partial-hand amputees are unable to do the same work as before the amputation and of those that return to work, less than one-third find their prosthesis useful [5], citing limited grip strength for grasping large and objects and tools as a main reason [5, 6]. Reemployment rates after partial-hand amputation is in the range as that of more proximal limb amputations, from 64% [7] to 72.2% [5]. Partial-hand amputees perceive themselves to be at a higher disability level than those with unilateral transradial or transhumeral upper-limb amputations [8, 9] and are more likely to reject their prostheses than any other category upper limb amputee [10].

The prosthetic management of partial-hand amputations poses challenges to prosthetists, researchers and clinical professionals [4] as clinical presentation of this amputation level is highly variable. The introduction of two new commercially-available, electrically-powered, myoelectric partial-hand prostheses offers exciting possibilities for restoring function to the partial-hand amputee. However, the control strategies currently available that utilize electromyographic signals (EMG) as control signals require the user to have reliable EMG signals from the often damaged intrinsic hand muscles or they prevent the independent control of the wrist and hand. Because the traumatic nature of partial-hand amputations may prevent the successful use of intrinsic muscle EMG as a control signal, and the preservation of wrist motion is necessary for optimal hand function [3, 11-13], better control methods that preserve wrist function are necessary.

The recent clinical application of pattern recognition control to upper limb prostheses has the potential to offer more functionality to electrically powered partial-hand prostheses [14]. By employing classification of multiple surface EMG signals to decode the user's intent, pattern recognition can allow the user more intuitively to select hand grasps [14, 15] . This control method has been made clinically available for individuals with more proximal amputations, but has yet to be implemented for use by partial-hand amputees. This work focused on investigating the application of pattern recognition-based myoelectric control to the control of partial-hand prostheses. The main components of a pattern recognition system were evaluated and optimized for its novel use by partial-hand amputees. This dissertation aimed to identify and target interventions that would allow partial-hand amputees to maintain wrist function while effectively controlling their prostheses thus increasing function and usability of electrically powered partial-hand prostheses.

1.2 Background

1.2.1 Clinically available partial-hand prostheses

Despite the high incidence of partial-hand amputations, powered prosthetic treatment is limited compared to the advances of full, articulated arm or leg prostheses. Because partial-hand amputations have a wide range of anatomical and functional clinical presentations, they are difficult to treat effectively with a prosthesis [3] and consequently partial-hand amputees have relatively fewer prosthetic options than individuals with higher-level amputations [16].

Partial hand prostheses can be either passive or active. Passive prostheses provide no active movement but can be used to stabilize or push against objects [17]. They are generally aesthetic, lightweight, and require little maintenance [3, 4]. Silicone hand restorations are commonly used and offer the psychological benefit of restored body image [18, 19]. When residual fingers are present, opposition posts which consist of a rigid post attached to the residual hand can oppose any remaining fingers and be used for grasping and manipulating objects. These opposition posts are generally simple and durable [4].

Active prostheses provide more function and are either body-powered or electrically-powered (i.e. battery-powered). Body-powered devices allow the individual to actively operate the prosthesis by harnessing residual limb movements. Mechanical forces generated by more proximal joints are transmitted to the terminal device and can thus provide kinesthetic and proprioceptive feedback regarding the force, position and speed of movement via a control cable or mechanical linkage. The X-fingers (Didrick Medical, Inc.) and Biomechanical prosthetic fingers

(Naked Prosthetics, Inc.) typically utilize the force and excursion of the metacarpophalangeal (MCP) joint to power the distal interphalangeal (DIP) and proximal interphalangeal (PIP) joints. This mechanism requires the user to have enough of a lever arm distal to the MCP joint to produce useable force [4]. The M-Fingers use a cable actuated, wrist driven mechanism where wrist flexion causes finger flexion at the MCP or PIP joints. However, because of its wrist driven design, wrist motion is coupled to finger motion and neither joint can be actuated independently. The M-fingers can also be finger-driven, where MCP flexion drives PIP flexion via a cable that runs over an intact and functional MCP joint. As with the X-fingers, this option requires that the user have a long enough residual finger distal to the MCP to allow sufficient force and excursion. Also, actuation wrist or finger driven deices may inadvertently position the fingers in a less functional position [3]. Historically, the Robin Aids hand and Handi-hook were body-powered options that used a figure 8 shoulder harness for control though they are no longer commercially available as they have been replaced by the less obtrusive wrist and finger devices [4]. Though body-powered devices provide more function than passive prostheses, the amount of grip force and the independent function of more proximal joints are limited [3, 4, 17].

Electrically-powered devices are motorized devices activated by user independent input signals that can be processed and used to command the intentional operation of the terminal device. Though they have been available to upper limb amputees with more proximal amputations for decades [20], they have only recently become accessible to partial-hand amputees in part because of the limited space available in the hand for replacing finger function with a motorized prosthetic finger [4]. The commercially available i-limb digits (Touch Bionics Inc.)

and Vincentpartial (Vincent Systems GmbH) have independently functioning digits built into a custom socket that accommodates the patient's remaining hand [4, 21]. Each finger contains a motor and drive train that articulates at the MCP joint. A tendon transmission couples MCP flexion/extension to PIP flexion/extension of digits 2-5. There is no articulation at the DIP and the thumb interphalangeal joint does not articulate [17]. They can be used for the treatment of amputations distal to the wrist and at or proximal to the level the MCP joint. They do not require a harness or control cable, can be operated independent of proximal joint movement and are entirely self-contained which is helpful for donning and doffing the device [22]. As they do not require any user produced force, they are better suited for individuals with sensitive residual limbs. These electrically powered devices can generate more force in many circumstances and offer a wide range of functional hand grasps not previously available to partial-hand amputees.

1.2.2 Conventional Control

There are two main inputs for controlling electrically powered partial-hand prostheses, namely pressure from force sensitive resistors (FSR) and EMG from myoelectrodes, though others have suggested the use of linear transducers and switches [23]. One or more FSRs can be placed between the socket and the styloid processes of the radius and ulna. Wrist movement applies pressure to the FSRs that can be used as a direct, proportional input for the prosthesis. Both methods can use single or dual-site control, though dual-site control is clinically preferred [4]. When clinically feasible, myoelectric control is more advantageous than FSR control as it does not couple wrist motion to finger motion.

Conventional control refers to amplitude-based methods where one or two inputs control the movement of one prosthetic degree of freedom. In this dissertation, we employ dual-site differential control where the sign of the difference between two inputs determines whether the prosthetic hand opens or closes and the absolute value of this signal relative to a threshold is proportional to the velocity of the prosthesis. To switch between different hand grasp modes the user must activate a trigger such as the co-contraction of the two muscle groups or the generation of rapid double or triple impulses [24]. This style of conventional control is well-established and a popular clinical option.

The controlling muscles for myoelectric control can be located in the hand itself (*intrinsic* hand muscles) or in the forearm (*extrinsic* hand muscles). Controlling the prosthesis using intrinsic hand muscles has the advantage of providing finger control independent of wrist motion [21]. The thenar, hypothenar and dorsal interossei muscles have been used for control. Though two-site control is preferred, often only one usable muscle site is possible when using the intrinsic muscles [4]. Furthermore, many of the muscles that control the fingers are extrinsic to the hand so restoring full biomimetic control is not possible.

Alternatively, extrinsic hand muscles, which remain mostly intact in partial-hand amputees, may be used for conventional myoelectric prosthesis control. Typically, an electrode is placed on the anterior side of the forearm and used to close the device and another is placed on the dorsal side and used to open the device. Users must be able to isolate and generate myoelectric activity without producing significant wrist movement. Moreover, the prosthetist is tasked to locate myosites that do not contain significant crosstalk from wrist muscle EMG. In cases where intrinsic muscle EMG is not available and the user is not able to control the device without producing significant wrist motion, the prosthetist may physically immobilize the wrist which is undesirable as this compromises normal wrist movement and thus limits hand function. Though widely clinically accepted, conventional myoelectric control, using either the intrinsic or extrinsic hand muscles, is limited to the control of one or two degrees of freedom [25, 26] and mode switching as previously described is required to control additional degrees of freedom.

1.2.3 Pattern recognition control

Pattern recognition–based myoelectric control of upper-limb prostheses offers a promising alternative for control of powered prostheses [27-33]. Unlike conventional control it does not require cumbersome switching mechanisms to control more degrees of freedom and combines information across multiple EMG signal sources [15, 34, 35]. Clinical evaluations have found that it is easier to learn and more intuitive than conventional control for many patients [14]. This control methods operates on the assumption that the features that describe the EMG are repeatable for a given muscle activation state and distinct from other muscle activation states

[36]. The main components of a typical pattern recognition myoelectric system are shown in Figure 1-1 and each component has been described in detail in prior work [26, 37].

Pattern recognition of EMG signals relies on the user's ability to generate repeatable and differentiable muscle contractions [26]. Effective EMG features are those that both provide unique information about limb movement intention and are minimally sensitive to factors that degrade performance by altering the EMG signals—such as electrode shift [38], muscle fatigue, muscle contraction effort [39], force variation [40], and limb position [41]. The robustness of numerous features to such factors have been evaluated; however, because these studies focus on applications to more proximal amputations they have not evaluated the sensitivity of features to wrist motion. Typically, the performance of features and feature combinations are evaluated across all channels. Few studies have investigated the importance of selecting individual features from different channels. This may be important for the partial-hand application where extrinsic muscles may be corrupted with cross-talk from wrist muscles, but intrinsic muscles may be relatively free of muscle crosstalk.

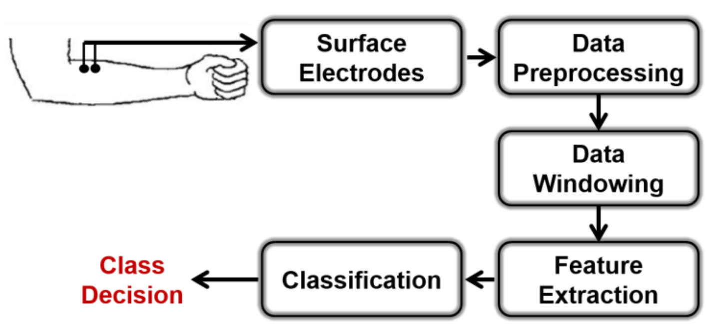


Figure 1-1: A general block diagram of myoelectric pattern recognition control.

The selection of the classification algorithm is also important in pattern classification. Previous studies that investigated classifiers such as Artificial Neural Networks [42], Hidden Markov Models [43], Linear Discriminant Analysis (LDA) [35], Support vector machines [44], Gaussian Mixture Models [45], and Quadratic Discriminant Analysis [37] found little difference in classification error between different classifiers within non-amputee and amputee groups [37]. Generally linear and non-linear classification methods perform equivalently. Consequently, an LDA classifier is used most commonly because it provides a good balance between classification performance and computational efficiency. However, as noted previously, most studies have focused on individuals with more proximal amputations, it remains unclear whether these findings hold for partial-hand amputees whose forearm muscle activity is significantly modulated by wrist movement during a task [46, 47].

If pattern recognition control is to be implemented for controlling partial-hand prostheses, we must determine how a functional wrist affects the controller's performance. Several studies have demonstrated modulation of the EMG amplitude as a function of wrist joint angle [46, 48]. Another study demonstrated modulation of the mean frequency of the EMG power spectrum as a function of both static and dynamic changes in joint angle [49]. Various internal physiological factors may be responsible for an influence of joint angle on the EMG features. Changing the joint angle about which a muscle is fixed can alter muscle geometry and affect not only changes in the relative positions of muscle fibers and motor units with respect to themselves but also with respect to the detecting surface of the electrodes [49]. Montagnani *et al.* showed that when non-amputees are limited to two degrees of freedom at the wrist (pronation/supination and flexion/extension) and one degree of freedom at the hand (open/close), they perform similarly in activities of daily living to when they are limited to a one degree-of-freedom wrist (rotation) coupled with their intact, twenty-two degree-of-freedom hand [12]. Thus, a clinically successful partial-hand pattern recognition control system must maintain high performance while allowing the individual to use their wrist.

1.3 Specific Aims

Research investigating control of hand movements using pattern recognition has successfully shown high decoding accuracies by utilizing surface EMG from the extrinsic muscles. Since the EMG recordings in these studies were acquired from the extrinsic muscles, they hold great potential for achieving similar results with individuals with partial-hand amputations because these muscles remain mostly intact. While these results are significant, they fail to address an essential challenge that is unique to this population of individuals: **the presence of wrist motion.** Not only can the wrist be in any position when the user initiates movement of their prosthesis, it can also be in active motion during the movements. The overall objective of this dissertation was to evaluate the effect of wrist motion on myoelectric pattern recognition of functional hand grasps and to develop strategies that accommodate these effects and improve hand control. The long-term goal is to improve pattern recognition control of partial-hand prostheses such that they are a clinically viable option for partial-hand amputees.

Aim 1: Quantify the additional EMG data contribution of the intrinsic hand muscles to pattern recognition-based classification.

In order to utilize potential information rich EMG data from intrinsic muscles of the residual limb of partial-hand amputees, we must first determine (1) how EMG muscle source affects control and (2) how a functional wrist affects control using different EMG muscles sources.

Aim 1.1 Determine the contribution of the intrinsic muscles to pattern recognition control of hand grasps and finger motions while the wrist is in a neutral wrist position for non-amputee and amputee subjects.

Aim 1.2 Quantify the effect of wrist motion on pattern recognition control of two hand grasps in offline and online studies for non-amputee and amputee subjects.

Aim 2: Evaluate strategies in non-amputees and partial-hand amputees for improving classification of hand grasps performed in varying wrist positions.

Aim 2.1 Evaluate the performance of optimal EMG feature subsets that are most robust against wrist position variation**.**

Aim 2.2 Compare the performance of linear and non-linear control strategies with

- EMG data alone
- EMG data and wrist position sensor data

Aim 2.3 Develop a control system that provides wrist position invariant control after being trained in one wrist position by using recorded wrist kinematic information to model the relationship between wrist position and EMG features.

Aim 3: Test the performance of a real-time control strategy that enables partial-hand amputees to control a prosthetic hand with unrestricted wrist motion.

1.4 Document Overview

Chapter 2 addresses Aim 1 and is an article published in Transaction on Neural Systems and Rehabilitation Engineering that investigates the use of extrinsic and intrinsic muscle EMG for pattern recognition control in offline and virtual settings. It also quantifies the impact of wrist motion on pattern recognition control for intact limb control subjects and partial hand amputees. Chapter 3 is an article published in Frontiers in Neurobionics and evaluates optimal EMG feature sets and classifiers for decoding hand grasp patterns across multiple wrist positions. Chapter 4 is an article submitted to the Journal of Neural Engineering and Rehabilitation that addresses Aims 2.2, and 2.3 by evaluating the benefit of incorporating wrist position sensor information into linear and non-linear controllers and proposing a control system that provides wrist position-independent control after being trained in one wrist position. Chapter 5 is an article submitted to PLOS ONE (Veteran Disability and Rehabilitation Research) and implements EMG control of the i-limb digits and compares pattern recognition performance to conventional myoelectric control performance in functional tasks. The equations for the features evaluated in Chapter 3 can be found in the Appendix.

Chapter 2 An Analysis of Intrinsic and Extrinsic Hand Muscle EMG for Improved Pattern Recognition Control

2.1 ABSTRACT

Pattern recognition control combined with surface electromyography (EMG) from the extrinsic hand muscles has shown great promise for control of multiple prosthetic functions for transradial amputees. There is, however, a need to adapt this control method when implemented for partial-hand amputees, who possess both a functional wrist and information-rich residual intrinsic hand muscles. We demonstrate that combining EMG data from both intrinsic and extrinsic hand muscles to classify hand grasps and finger motions allows up to 19 classes of hand grasps and individual finger motions to be decoded, with an accuracy of 96% for non-amputees and 85% for partial-hand amputees. We evaluated real-time pattern recognition control of three hand motions in seven different wrist positions. We found that a system trained with both intrinsic and extrinsic muscle EMG data, collected while statically and dynamically varying wrist position increased completion rates from 73% to 96% for partial-hand amputees and from 88% to 100% for non-amputees. Our study shows that incorporating intrinsic muscle EMG data and wrist motion can significantly improve the robustness of pattern recognition control for partial-hand applications.

2.2 INTRODUCTION

The human hand is an amazingly precise and agile apparatus, used to perform actions that range from delicate and intricate to forceful and strenuous. Full or partial loss of the hand thus profoundly affects many activities of daily living. Of the 18,500 individuals in the United States who undergo upper-limb amputations each year, 91% have amputations that are distal to the wrist [1, 2]. These partial-hand amputations include transmetacarpal amputations (1.5%), thumb amputations (18%) or amputations of one or more digits [2]. Because partial-hand amputation can involve various levels of longitudinal and transverse loss, it is difficult to treat successfully with a prosthesis [3], consequently partial-hand amputees have relatively fewer prosthetic options than individuals with higher-level amputations [16].

Passive prostheses can provide good cosmesis and act as an oppositional post for a remaining finger but do not offer active functionality [3]. Body-powered devices provide more function and grasps, but are uncomfortable to wear, have cumbersome control mechanisms, and often limit the range of motion of the wrist [21, 50]. Partial-hand amputees perceive themselves to be at a higher disability level than those with unilateral transradial or transhumeral upper-limb amputations [8] and are more likely to reject their prostheses, citing limited function as a key reason [51]. Moreover, more than half of partial-hand amputees are unable to return to previous employment and of those that do, most do not find their prosthesis useful [5]. Partial-hand amputees are therefore in need of better, more functional prostheses.

Though externally-powered prostheses have been available to upper-limb amputees for decades [20], they have only recently become accessible to partial-hand amputees. The commercially available i-limb digits (Touch Bionics Inc.) and Vincentpartial (Vincent Systems GmbH) systems are externally-powered prostheses with independently functioning digits built into a custom socket that accommodates the patient's remaining hand [21]. These devices offer a wide range of functional hand grasps not previously available to partial-hand amputees.

Though force sensitive resistors can be used, these devices are typically controlled using conventional myoelectric strategies, where an estimate of the surface electromyogram (EMG) amplitude controls the speed of an actuated joint [21, 25, 52]. The controlling muscles can be located in the hand itself (*intrinsic* hand muscles) or in the forearm (*extrinsic* hand muscles). Controlling the prosthesis using intrinsic hand muscles has the advantage of providing finger control independent of wrist motion [21] but it is challenging to obtain separate signals from these small, closely spaced muscles. Thus, the number of available independent control sites is limited.

Alternatively, extrinsic hand muscles, which remain mostly intact in partial-hand amputees, may be used for conventional myoelectric prosthesis control; however, doing so compromises normal wrist movement and thus limits hand function. Though widely clinically accepted, conventional myoelectric control, using either the intrinsic or extrinsic hand muscles, is limited to the control of one or two degrees of freedom [25, 26] and mode switching through co-contraction is required to control additional degrees of freedom.

Pattern recognition–based myoelectric control of upper-limb prostheses offers a promising alternative for control of powered partial-hand prostheses. It has the potential to restore control of more degrees of freedom than conventional myoelectric control because it can combine and utilize information across multiple EMG signal sources [15, 34, 35]. Previous research has shown that pattern recognition techniques, using EMG from the extrinsic hand muscles of transradial amputees, can control multiple hand grasps in real time with high accuracy [53, 54].

Unlike individuals with higher-level amputations, partial-hand amputees may possess residual intrinsic hand muscles that may provide additional information-rich EMG data for improved prosthetic control. Li *et al.* used EMG from intact and residual arms of unilateral transradial amputees and found that the intact arms were more successful at performing grasps [53]. Although this was presumably due to EMG data from intrinsic hand muscles, the contribution of intrinsic muscle EMG to the improvement of offline accuracies and online control was not explicitly evaluated. Since intrinsic and extrinsic muscles play different roles in control of the intact hand [32] incorporating EMG information from intrinsic muscles may improve prosthetic hand control.

Most partial-hand amputees have a functional and useful wrist. Preservation of wrist range of motion allows positioning of the hand in space, greatly adding to overall hand function [3, 11, 50]. Thus, a clinically successful pattern recognition control system for a partial-hand prosthesis must provide high performance while enabling use of the wrist. Studies have shown that variations in arm position substantially impact the ability to classify hand grasps in higher level amputees [55, 56] and have suggested training with multiple limb positions or multi-stage classification to improve performance. Recent studies with non-amputees show that static and dynamic wrist motion adversely affect pattern recognition performance in offline studies [57, 58], and training with multiple wrist positions improves performance. As the impact of wrist posture in amputee subjects cannot be inferred from non-amputee studies [59], it is not clear if and to what extent wrist position will affect performance in partial-hand amputees.

In this paper we quantify the contribution of EMG data from intrinsic hand muscles to pattern recognition–based control of hand grasps and finger movements in amputees and non-amputees. We build upon previous results [57] and quantify the effect of wrist motion on pattern recognition control in partial-hand amputees and the effect of training with multiple wrist positions in online studies.

2.3 METHODS

Nine non-amputees (5 males, 4 females, mean age = 23 ± 2 years) with no known neurological or physical deficits performed the experiments described in the first part of the offline studies. Seven non-amputees (4 males, 3 females, mean age = 23 ± 2 years) performed the experiments described in the second part of the offline studies. Four individuals with partial-hand amputations participated in both parts of the offline study [Table I]. None of the amputees routinely used a prosthesis, and all had good residual wrist mobility. All subjects gave written consent, and experiments were performed at the Rehabilitation Institution of Chicago under an approved Northwestern University Institutional Review Board (IRB) protocol. All subjects were naïve to pattern recognition control with the exception of two non-amputee subjects.

For all subjects, 9 self-adhesive bipolar surface Ag/AgCl EMG electrodes (Bio-Medical Instruments) were evenly spaced around the dominant forearm with an inter-electrode distance of 2.5cm: 5 electrodes on the proximal forearm, 2-3cm distal to the elbow and 4 electrodes on the distal forearm, 2-3 cm proximal to the wrist (Fig. 1. (a)-(d)). For non-amputees, 12 bipolar electrodes were placed on the dominant hand (7 electrodes on the palmar side and 5 electrodes on the dorsal side) to provide a dense spatial sampling of intrinsic muscle activity (Fig. 1(e)-(f)). For amputees, due to limited surface area on the residual hand, only 4 electrodes were placed on the hand: 2 electrodes on the palmar side and 2 electrodes on the dorsal side (Fig. 1(c)-(d)). For one amputee subject (PH4) only one electrode was placed on the dorsal side. For all subjects, ground electrodes were placed on the olecranon of the elbow. Subjects were seated facing a computer screen, with their elbow at a 90 degree angle.

2.3.1 Familiarization

All pattern recognition–naïve subjects received 2 hours of practice with pattern recognition control in a virtual environment on a separate day prior to performing the experiments. Custom computer software called Control Algorithms for Prosthetics Systems (CAPS) [15] prompted users to perform functional hand grasps, an open hand posture, and a rest posture. Data were collected and used to train a linear discriminant classifier for online classification. Subjects were then allowed to practice performing each grasp in a virtual environment, where a virtual hand provided visual feedback of the classifier output.

2.3.2 Procedure

I. Classification of Hand Grasps and Finger Motions

CAPS software was used to prompt subjects to perform 5 functional hand grasps (key grip, chuck grip, power grip, fine pinch grip, tool grip), an open hand posture, and a rest posture.

Subjects were also asked to perform 12 individual finger motions: thumb adduction, thumb abduction, thumb flexion, thumb extension, index finger flexion and extension, middle finger flexion and extension, ring finger flexion and extension, pinky finger flexion and extension. When flexing or extending each digit, subjects were asked to follow a visual prompt where metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints were both flexed or both extended. Each grasp and finger motion was held for 3 seconds (s) and repeated 10 times while subjects held their wrist in a neutral position, for a total of 30s of data collection per hand or finger motion. Subjects rested for 3s between each repetition. To avoid fatigue, subjects were allowed 2-5 minutes of rest between trials, where a trial consisted of 15 hand or finger motions. All data were aligned with the stimulus image.

II. Classification of Hand Grasps with Wrist Motion

Subjects were prompted to perform 2 functional hand-grasps (chuck and key grip), an open hand posture, and a rest posture. Each hand posture was held for 3s and repeated 10 times while subjects held their wrist in a neutral position. Subjects rested for 3s between each repetition. This protocol was repeated while the subjects held their wrist comfortably in the following 6 static positions: flexed, extended, pronated, supinated, abducted, and adducted. A total of 210 s of data were collected for each hand posture over all 7 static wrist positions.

To ensure that non-amputee subjects maintained the same pinch force throughout each grasp, subjects received visual feedback of pinch forces produced during chuck and key grip using an electronic pinch gauge (12-0023, Fabrication Enterprises). Subjects were required to maintain a grasp force that was 15-20% of their maximal voluntary grasp force made in a neutral wrist position; this force level was comfortable for all grasps in all wrist positions. To avoid fatigue, subjects were allowed 2-5 minute rests between trials, where a trial consisted of 5 repetitions of the four hand postures in one wrist position.

Subjects were also asked to make combined movements of the wrist and hand. They performed chuck grip and the open hand posture while simultaneously moving their wrist from a neutral position to one of the following positions: fully flexed, extended, pronated, supinated, abducted, and adducted. Subjects were also explicitly asked to move their wrist from neutral to each of these 6 positions with relaxed hand and fingers. Subjects were asked to move their wrist at a medium, comfortable, and constant velocity. Each combined movement was performed within 3s and repeated 10 times. A total of 180s of data were collected over all 7 dynamic wrist motions. Constraints were placed on pinch forces using feedback as previously described. Amputee subjects were not provided with any visual feedback on pinch forces.

2.3.3 EMG Signal Processing

EMG signals were acquired using a custom built EMG amplifier with a gain of 2000x for each channel. Data were digitally sampled at 1000 Hz using a custom-built A/D converter based on a TI AD1298 bioamplifier chip and band pass-filtered (30-350Hz) with a Type 1, 8^{th} order Chebyshev filter.

2.3.4 Data Analysis

Offline analyses were performed using MATLAB 2012a software (The Mathworks, Natick, MA, USA). Data were segmented into 200ms windows with a 20ms frame increment [60]. A combination of four EMG time-domain features (mean absolute value, number of zero-crossings, waveform length, and number of slope sign changes) and six coefficients of a 6th order autoregressive model were extracted from each EMG channel. Preliminary studies showed that the linear discriminant analysis (LDA) classifier performed comparably to a support vector machine and Gaussian mixture model classifier. Thus the LDA classifier was used for all analyses presented here. The combination of LDA classifier and time domain and autoregressive features has been used extensively and shown to result in high classification performance [34, 44]. The LDA classifier was trained using (1) only extrinsic muscle EMG data, (2) only intrinsic muscle EMG data, or (3) a combination of all extrinsic and intrinsic muscle EMG data**.** Data were divided into training data sets (odd-numbered trials) and testing data sets (even-numbered trials) and each classifier was evaluated using two-fold cross-validation with these sets.

I. Classification of Hand Grasps and Finger Motions

A classifier was trained and tested using data from (1) all hand grasps, the open hand posture, and the rest posture (2) all finger motions and the rest posture, or (3) all hand grasps, all finger motions, the open hand posture, and the rest posture. Classification error, defined as the number of incorrectly classified samples divided by the total number of test samples and averaged across hand grasps, finger motions, or a combination of hand and finger motions was used to assess classifier performance. To determine the effect of each EMG channel on classifier performance, we used an electrode selection algorithm based on the sequential forward searching (SFS) method described by [61].

II. Classification of Hand Grasps with Wrist Motion

A classifier was trained using data from the neutral wrist position and tested on data from (1) a neutral wrist position, (2) all static wrist positions, or (3) a neutral wrist position and all dynamic wrist motions. A classifier was also (4) trained and tested on data from all static wrist positions or (5) trained and tested on data from the neutral wrist position and all dynamic wrist motions.

2.3.5 Statistical Analysis

To analyze the effect of muscle set on the classification of hand grasps and finger motions, three, one–way repeated measures analysis of variance (ANOVA) tests were performed with subject as a random effect and muscle set as a fixed effect. Post-hoc comparisons were made using a Bonferroni correction factor to determine significance. To determine the effect of static wrist positions or dynamic wrist motions on classifier performance, a two–way repeated measures ANOVA was performed with subject as a random effect, and muscle set and the training/testing paradigm as fixed effects. Post-hoc comparisons were also made using a Bonferroni correction factor to determine significance. Analyses were performed separately for amputees and non-amputees using Minitab 16.2.4 (Minitab Inc. PA, USA), with a significance level set at 0.05.

2.3.6 Online Study

We completed an online study to quantify the benefits of combining extrinsic and intrinsic muscle EMG and training with multiple wrist positions on real-time pattern recognition control of hand grasps. Six non-amputees (4 males, 2 females, mean age = 25 ± 2 years, who did not take part in the offline studies) and three partial-hand amputees (PH2, PH3, PH4) participated in this study. Electrode placements for amputees, EMG signal processing and familiarization for naïve

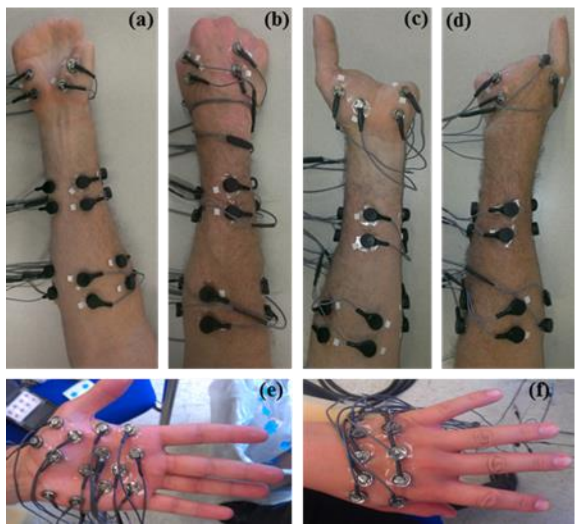


Figure 2-1: Experimental Setup.

(a) and (b) Anterior and posterior view, respectively, of the right forearm and hand of a partial-hand amputee (PH1). (c) and (d) Anterior and posterior view, respectively, of the left forearm and hand of PH1. (e) and (f) Anterior and posterior view, respectively, of the hand of a non-amputee subject.

subjects were as described for offline studies. For non-amputees, only 4 channels of EMG were recorded from intrinsic muscles at the locations depicted in Fig. 2-1(a)-(b).

Subjects performed 2 hand grasps (chuck grip, key grip), an open hand posture and a rest posture, all in a neutral wrist position. Each posture was held for 4s and repeated four times for a total of 16s of data for each hand posture. Because training with multiple static wrist positions and dynamic wrist motions is time-consuming, we used a hybrid static/dynamic training protocol. Subjects were asked to perform each hand posture while holding the wrist in a comfortable flexed position for 2s after which they were instructed to move the wrist to a comfortable extended position over a period of 2s while maintaining the grasp. They then held the posture in that extended position for 2s then moved the wrist back to a comfortable flexed position over a period of 2s. This hybrid protocol lasted a total of 8s. Subjects repeated this sequence of movements moving the wrist from (1) flexed to extended to flexed (2) extended to flexed to extended (3) supinated to pronated to supinated (4) pronated to supinated to pronated (5) abducted to adducted to abducted and (6) adducted to abducted to adducted. In total, 48s of the hybrid wrist training protocol data were collected for each grasp. No visual pinch force feedback was provided to subjects during data collection.

Four separate classifiers were trained with data collected from either (1) extrinsic EMG signals in a neutral wrist position, (2) extrinsic EMG signals with the hybrid wrist motion training protocol, (3) extrinsic and intrinsic EMG signals in a neutral wrist position, or (4) extrinsic and intrinsic EMG signals with the hybrid wrist motion training protocol. A 5-vote majority vote was implemented**.** The offline performance of these classifiers was also evaluated using two-fold cross validation and random sub-selection of 16s of training data.

Motion tests as described by Kuiken *et al.* using a virtual prosthesis were performed immediately after classifier training [15]. Subjects were instructed to follow visual prompts for each hand grasp. The virtual hand allowed subjects to observe the real-time outputs of the classifier. A hand grasp could only be selected when the hand was fully open. Thus, if the initial hand grasp selected was incorrect, the subject would have to fully open the virtual hand and try again.

One of the four classifiers was randomly assigned to a trial and used for online control. Within each trial, each of the three hand motions was randomly presented twice. This was repeated while the subject held their wrist in one of 7 randomly assigned static wrist positions. These four trials were repeated twice (i.e., 8 trials) for a total of 84 hand motions per classifier. Subjects were blinded to the control method. The subset of channels used during each condition was the same as that used to train the classifier.

Four metrics were used to quantify real time prosthesis control performance. The *motion selection time* was the time taken to correctly select a target movement. The *motion completion time* was the time taken to successfully complete a movement through the full range of motion, measured as the time from the onset of movement to the completion of the intended movement. Fifty accumulated correct classifications were required for a motion completion. The minimum possible time to complete any motion was normalized to 1s, corresponding to fifty consecutive correct classifications with a new classification occurring every 20ms. The *motion completion rate* was defined as the percentage of successfully completed motions within a time limit of 10s. *Dynamic efficiency* was defined as the percentage of correct classifications for each trial. Thus misclassifications would increase motion selection and completion times and decrease motion completion rates and dynamic efficiency. To determine the effect of muscle set and classifier training paradigm on online performance, a two–way repeated measures ANOVA was performed with subject as a random effect, and muscle set and wrist position training paradigm as fixed effects.

2.4 RESULTS

2.4.1 Classification of Hand Grasps and Finger Motions

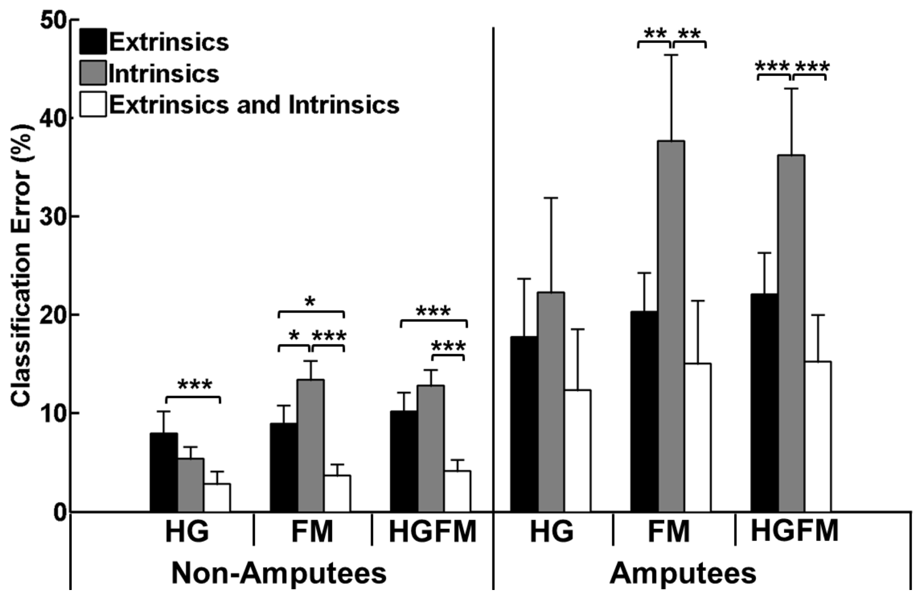


Figure 2-2: Average classification errors across all non-amputees and amputees.

HG: all hand grasps (7 classes), FM: all finger motions (13 classes), HGFM: all hand grasps and finger motions (19 classes). (*) represents p<0.05; (**) represents p<0.01; (***) represents p<0.001. Error bars represent standard error.

For all subjects, classifiers trained with a combination of extrinsic and intrinsic muscle EMG data performed better than classifiers trained with extrinsic muscle EMG data alone (Fig. 2-2). These results were significant for non-amputees for hand grasps (p<0.001), finger motions (p<0.05), and all hand grasps and finger motions (p<0.001). For amputees, these same trends were observed but were not statistically significant for hand grasps (p=0.60), finger motions (p=0.7), or all hand grasps and finger motions (p=0.15). A classifier trained with intrinsic muscle

EMG alone was worse at distinguishing between individual finger motions than one trained with extrinsic muscle EMG for both non-amputees ($p<0.05$) and amputees ($p<0.01$).

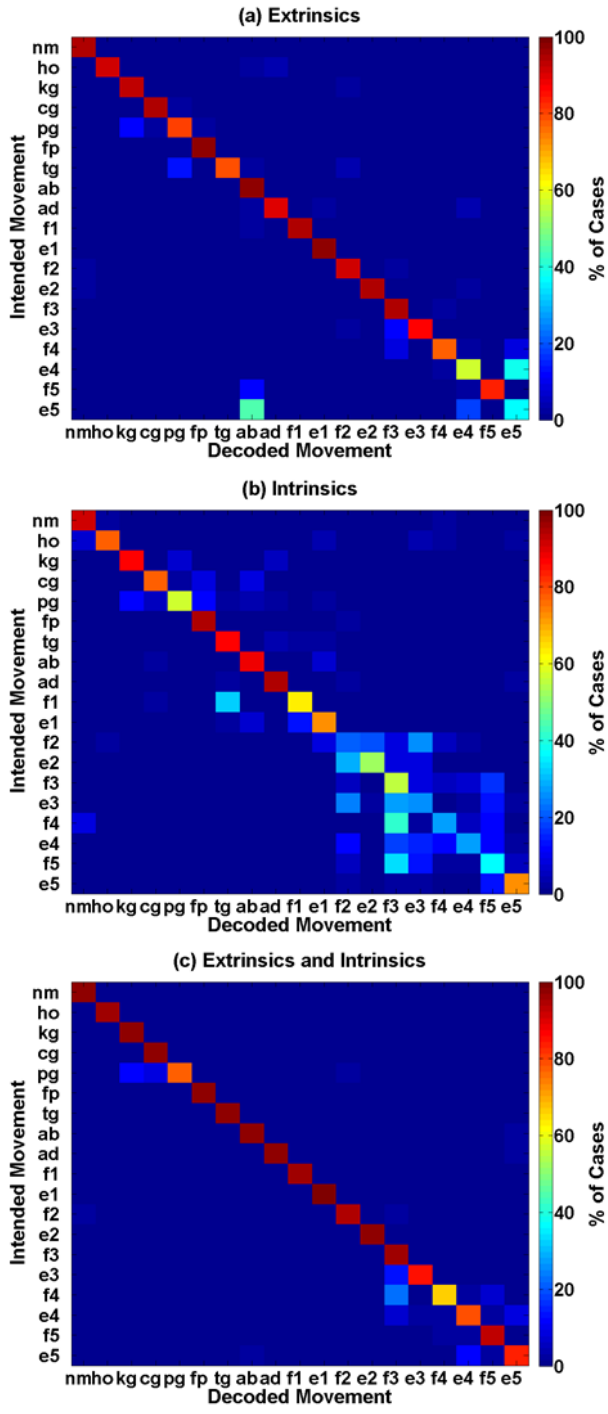


Figure 2-3: Confusion matrices showing the error distribution for a partial-hand amputee (PH1, right hand).

All classifiers were trained to distinguish between all 19 motion classes of hand and finger motions. (a) Classifier trained with only extrinsic muscle EMG. (b) Classifier trained with only intrinsic muscle EMG. (c) Classifier trained with both intrinsic and extrinsic muscle EMG. The symbols represent the following hand grasps–rest posture (nm), hand open (ho), chuck grip (cg), key grip (kg), power grip (pg), fine pinch grip (fp), tool grip (tg); and finger motions– thumb abduction (ab), adduction (ad), flexion (f1), and extension (e1); index finger flexion (f2) and extension (e2); middle finger flexion (f3) and extension (e3); ring finger flexion (f4) and extension (e4); pinky finger flexion (f5) and extension (e5).

Fig. 2-3 shows confusion matrices for a representative subject (PH1, right partial-hand amputation). A classifier trained with intrinsic muscle EMG alone was worse at distinguishing between flexion and extension of digits two through five than a classifier trained with extrinsic muscle EMG alone; however, it was able to decode individual thumb movements with high accuracy. This result was observed across all subjects.

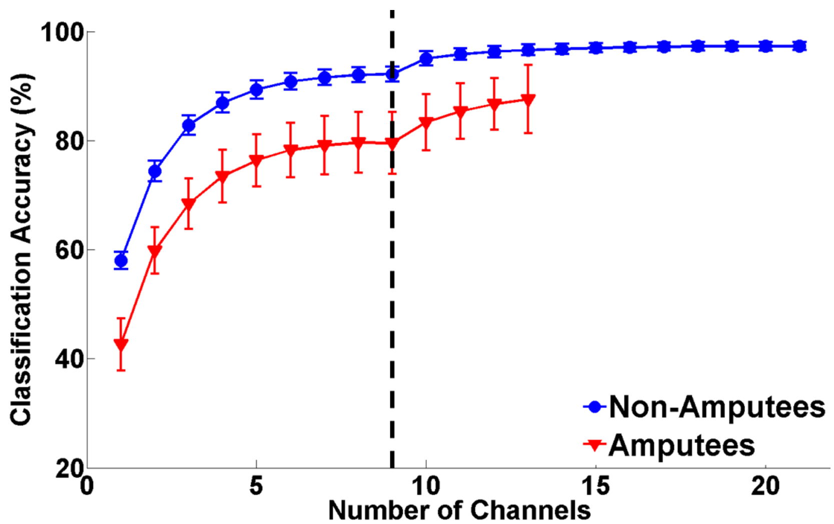


Figure 2-4: Classification accuracy for 19 hand and finger motion classes as a function of number of EMG channels.

For both subject groups all 9 extrinsic channels were analyzed (left of the dashed line). Each available intrinsic channel was then added in order of most to least important (right of the dashed line). Error bars represent standard error.

Fig. 2-4 shows the relationship between the number of electrodes and classification accuracy. The first 9 channels are all extrinsic muscle channels. Accuracy increases considerably at the beginning of the curve and eventually plateaus; however, the additional of intrinsic EMG data (to the right of the vertical line) allows higher accuracies to be achieved.

Fig. 2-5 illustrates the relative importance of each intrinsic EMG channel location. Each circle represents the approximate location of one bipolar electrode; the intensity of the circle

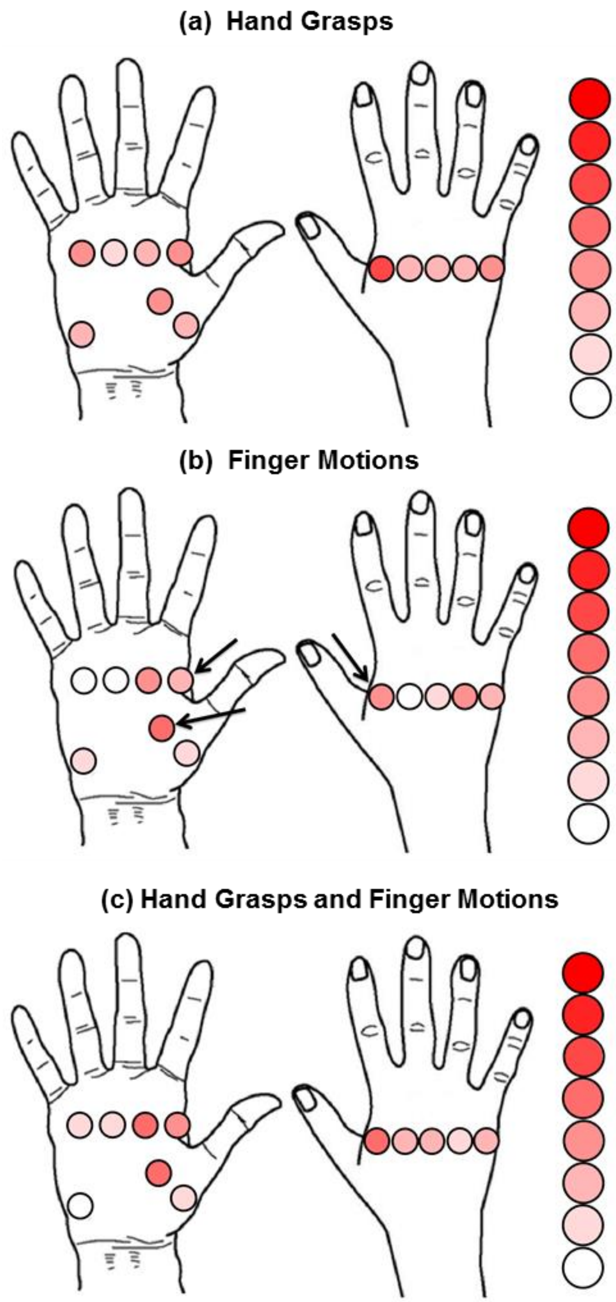


Figure 2-5: Relative importance of intrinsic muscle electrode locations.

The classifier was trained using a combination of all extrinsic and intrinsic EMG channels. The figure depicts how often an intrinsic EMG channel was one of the six channels that contributed the most to classification accuracy for all non-amputees. Each circle represents the approximate location of one bipolar electrode. White circles correspond to no occurrence and the deepest red circle corresponds to 7 occurrences. Arrows indicate channels that were consistently the most important intrinsic EMG channels.

proportional to the importance of that particular intrinsic EMG channel. This was determined by how often that channel was one of the six channels that contributed the most to classification accuracy as determined by applying the SFS algorithm to the full set of all 9 extrinsic and 12 intrinsic muscle EMG channels. For hand grasps, finger motions, or both hand grasps and finger motions, electrodes placed over the thenar eminence and the palmar and dorsal region between the first and second metacarpals (indicated by the arrows in Fig. 2-5) were consistently the most important intrinsic EMG channels.

2.4.2 Classification of Hand Grasps with Wrist Motion

I. Effect of Static Wrist Positions

Training and testing the classifier using data collected with a neutral wrist position resulted in low average error rates of less than 2% and 7% for non-amputees and amputees, respectively. Error was significantly higher for a classifier trained with data collected with a neutral wrist position and tested with data from all static wrist positions for both non-amputees ($p<0.001$) and amputees ($p<0.001$). This classifier performed worse when trained with extrinsic EMG data alone than when trained with intrinsic or combined intrinsic and extrinsic EMG data for both subject groups as implied by the significant interaction term between muscle set and training/testing paradigm for non-amputees ($p<0.001$) and amputees ($p<0.01$).

For non-amputees, there was no significant difference between the performance of a classifier trained and tested with data from all static wrist positions and a classifier trained and tested with data collected in a neutral wrist position ($p=0.46$, Fig. 2-6). However, for amputees, a classifier trained and tested using data from all wrist positions did not perform as well as one

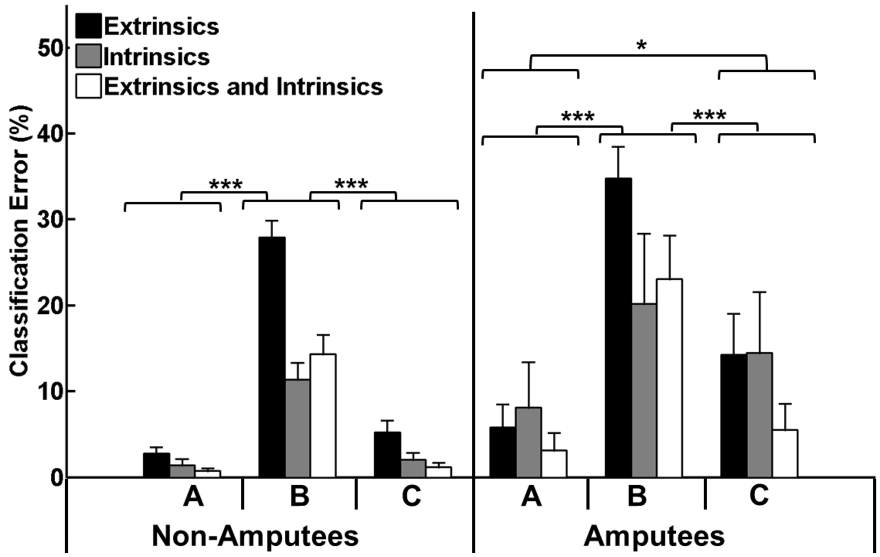


Figure 2-6: Effect of varying *static wrist positions* on classification error.

The three classifier training/testing paradigms were (A) train and test in a neutral wrist position (B) train in a neutral wrist position and test in all wrist positions (C) train and test in all wrist positions. (*) represents p<0.05; (***) represents p<0.001. Error bars represent standard error.

trained and tested with data acquired for a neutral wrist position (p<0.05) though it performed better than a classifier trained in a neutral wrist position and tested with data from all wrist positions (p<0.001).

II. Effect of Dynamic Wrist Motions

Error was significantly greater when the classifier was trained with EMG data collected in a neutral wrist position and tested with data from all dynamic wrist motions than when the classifier was trained and tested with data from a neutral wrist position for both subject groups (p<0.001, Fig. 2-7). This classifier performed worse when trained with extrinsic EMG data alone than when trained with intrinsic or combined intrinsic and extrinsic EMG data for both subject groups as implied by the significant interaction term between muscle set and training/testing paradigm for non-amputees (p<0.001) and amputees (p<0.05).

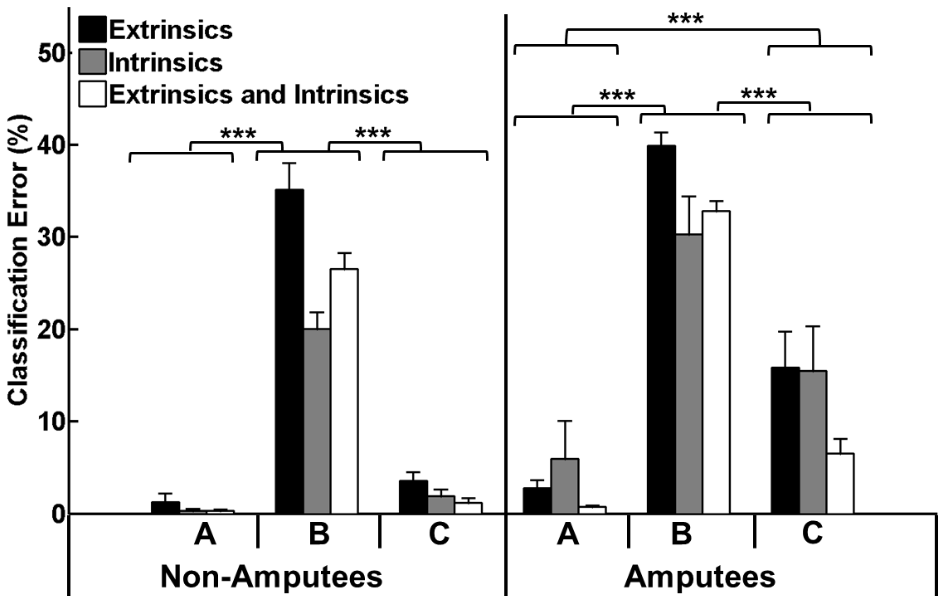


Figure 2-7: Effect of *dynamic wrist motions* on classification error.

The three classifier training/testing paradigms were (A) train and test in a neutral wrist position (B) train in a neutral wrist position and test with all dynamic wrist motions (C) train and test with all dynamic wrist motions. (***) represents $p<0.001$. Error bars represent standard error.

For non-amputees, there was no significant difference in performance between a classifier trained and tested with data from all dynamic wrist motions and a classifier trained and tested with data collected in a neutral wrist position ($p=0.36$, Fig. 2-7). However, for amputees, a classifier trained with data from all dynamic wrist motions did not perform as well as one trained and tested in a neutral wrist position ($p<0.05$) though it performed better than a classifier trained in a neutral wrist position and tested in all wrist positions ($p<0.001$).

2.4.3 Online Studies

For the online studies we used a modified training protocol that was less time-consuming, and more clinically feasible. Fig. 2-8 demonstrates the benefits of using additional intrinsic muscle channels and including wrist motion with this modified protocol. For non-amputees and

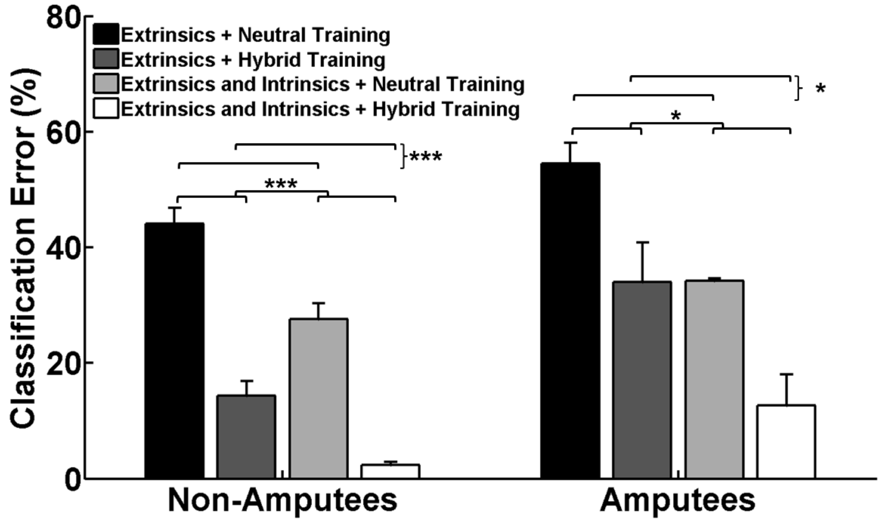


Figure 2-8: Effect of classifier training paradigm on offline classification error.

All classifiers were tested with data collected from different static wrist positions and wrist motions. Each classifier was trained with (1) data from the extrinsic muscles alone or with data from the extrinsic and intrinsic muscles and (2) data collected from a neutral wrist position or with data collected from hybrid static and dynamic wrist motions as indicated by the legend. (*) represents $p<0.05$; (***) represents $p<0.001$. Error bars represent standard error.

amputees, the hybrid training paradigm resulted in lower offline classification errors than the neutral wrist training paradigm ($p<0.001$ and $p<0.05$, respectively). The combination of extrinsic and intrinsic muscles resulted in lower classification errors than extrinsic muscles alone for both non-amputees and amputees ($p<0.001$ and $p<0.05$, respectively). There was no significant interaction term for non-amputees and amputees ($p=0.2$ and $p=0.09$, respectively).

I. Motion Completion Rate

For non-amputees and amputees, the combination of extrinsic and intrinsic muscles resulted in higher completion rates than extrinsic muscles alone ($p<0.001$, $p<0.05$, respectively). For non-amputees, the hybrid training paradigm resulted in higher completion rates than the

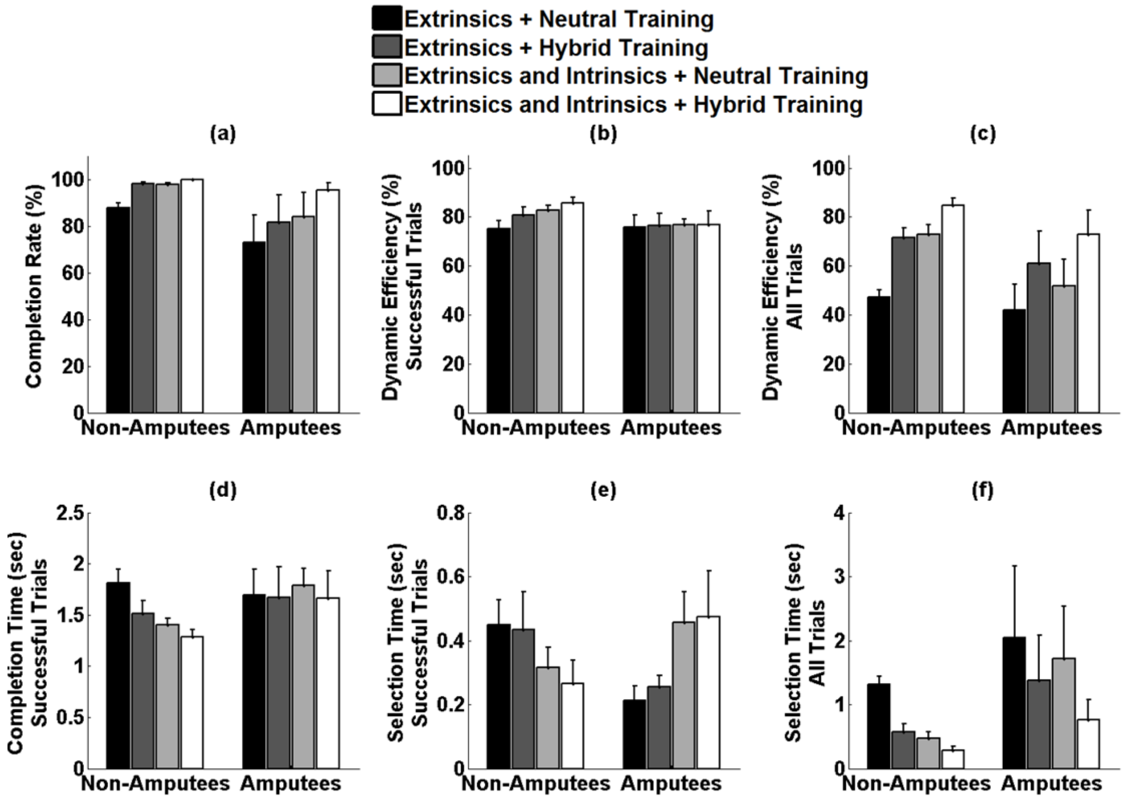


Figure 2-9: Effect of classifier training paradigm on online performance.

(a) completion rate (b) dynamic efficiency across successfully completed trials (c) dynamic efficiency across all attempted trials (d) completion time across all successfully completed trials, (e) selection time across all successfully completed trials (f) selection time across all attempted trials.

neutral wrist training paradigm (p<0.001, Fig. 2-9(a)). The same trends were observed for amputees and though not significant (p=0.06). There was no significant interaction term (p=0.74).

II. Dynamic Efficiency

For successful trials completed by non-amputees, the hybrid training paradigm resulted in higher dynamic efficiencies than the neutral wrist training paradigm (p<0.01). The combination of extrinsic and intrinsic muscles resulted in higher dynamic efficiencies than extrinsic muscles alone (p<0.001). There was no significant interaction term (p=0.31, Fig. 2-9(b)). This was also true for the dynamic efficiency across all trials attempted by non-amputee subjects. For successful trials completed by amputees, there was no significant main effect of wrist position training paradigm (p=0.98) or muscle set (p=0.80) on dynamic efficiency. However, across all trials attempted by amputees, the hybrid training paradigm performed better than the neutral wrist training paradigm, (p<0.01). The combination of extrinsic and intrinsic muscles resulted in higher completion rates than extrinsic muscles alone (p<0.05). There was no significant interaction term (p=0.78, Fig. 2-9(c)).

III. Motion Completion Time

The motion completion time for a given movement was counted if the movement was successfully completed within 10s. For non-amputees, the hybrid training paradigm resulted in lower completion times than the neutral wrist training paradigm (p<0.05). The combination of extrinsic and intrinsic muscles resulted in lower completion times than extrinsic muscles alone (p<0.01). There was no significant interaction term (p=0.30) between the two factors. For amputees, there was no significant main effect of wrist position training paradigm (p=0.74) or muscle set (p=0.85) on completion time (Fig. 2-9(d)).

IV. Motion Selection Time

For successful trials completed by non-amputees, there was no significant main effect of wrist position training paradigm on selection time (p=0.61). The combination of extrinsic and intrinsic muscles resulted in lower selection times than extrinsic muscles alone (p<0.05). There was no significant interaction term (p=0.78, Fig. 2-9(e)). However, across all trials attempted by non-amputees, the hybrid training paradigm performed better than the neutral wrist training paradigm (p<0.001) and the combination of extrinsic and intrinsic muscles resulted in lower selection times than extrinsic muscles alone (*p*<0.001, Fig. 2-9(f)). For successful trials completed by amputees, there was no significant main effect of wrist position training paradigm on selection time (*p*=0.74). The combination of extrinsic and intrinsic muscles resulted in higher selection times than extrinsic muscles alone (*p*<0.05). There was no significant interaction term (*p*=0.89). However, across all trials attempted by amputees, the hybrid training paradigm performed better than the neutral wrist training paradigm approaching significance (*p*=0.06). The combination of extrinsic and intrinsic muscles resulted in lower selection times than extrinsic muscles alone though this was not statistically significant (*p*=0.2, Fig. 2-9(f)).

2.5 DISCUSSION

Pattern recognition is a promising control method that circumvents many of the disadvantages of conventional myoelectric control. In this study we demonstrated that combining extrinsic and intrinsic hand muscle EMG data and incorporating multiple wrist positions during training improves pattern recognition control in offline and online studies. These results are promising for the clinical application of pattern recognition to partial-hand prosthesis control.

We found that even after classifier performance seemed to have plateaued when trained with EMG from 6-8 extrinsic muscle channels, the addition of intrinsic muscle EMG further increased classifier performance. Though both extrinsic and intrinsic hand muscles in the intact hand interact and contribute to modulate fingertip forces, they can be functionally differentiated by their roles in grasping and manipulation. It is thought that the intrinsic muscles, which are generally smaller in size than the extrinsic muscles, play a key role in hand grasps (particularly chuck grip, fine pinch grip and key grip) [62, 63], have a greater impact on fingertip direction than force magnitude, and are important for subtle manipulation of finger movements, whereas the extrinsic muscles provide stability of the joints [64, 65]. Our results indicate that intrinsic muscle EMG provides information that, though not sufficient for control, complements extrinsic muscle EMG data to improve classification performance, perhaps because intrinsic muscles provide more precise control of finger position and direction than extrinsic muscles.

A closer examination of the confusion matrices shows that the higher classification errors of a classifier trained with only intrinsic muscle EMG is mostly due to confusion between flexion and extension of the second through fifth digits. These observations are expected given that finger flexion and extension forces are particularly dependent on the extrinsic muscles [66]. The intrinsic thumb muscles are an exception and provide enough information to discriminate between individual thumb motions. Though there is no specific extensor of the thumb in the thenar compartment, it is possible that EMG from the both the *abductor pollicis brevis* and *adductor pollicis* contributed to the control of thumb extension due to their attachment to the thumb extensor mechanism.

Given that the passive biomechanics and interconnections of soft tissues within the hand significantly couple finger movements [67], and that common neural input across the finger muscles limits the extent to which fingers can move independently [68-70], a classifier trained with only extrinsic EMG is still able to equally discriminate between individual finger motions with accuracies of 91% for non-amputees. Other studies have also shown that extrinsic muscle EMG data is sufficient to discriminate between individual finger motions [44, 71, 72].

Though it may seem that the extrinsic muscles can provide relatively good control, their performance significantly deteriorates with changes in wrist position, with offline error rates up to 28% and 35% in non-amputees and amputees, respectively, for control of only 4 hand motion classes. Not surprisingly, extrinsic muscle EMG was more sensitive to static wrist position and dynamic wrist motion than intrinsic muscle EMG. Here, we focused on the effect of wrist motion on two grasps (chuck and key grip) because these grasps are the most common grasps used in activities of daily living [73]. Moreover, controlling 2-3 grasp patterns and preserving residual wrist motion without the cumbersome switching methods required for conventional myoelectric control would be a significant improvement over current partial-hand prosthesis control methods.

We tested two methods to mitigate the wrist position effect: (1) using both extrinsic and intrinsic muscle EMG data and (2) training with a hybrid static/dynamic wrist motion protocol. In online studies, using a classifier trained with extrinsic muscle EMG in a neutral wrist position resulted in completion rates of 73% for amputees and 87% for non-amputees. Adding information from the intrinsic muscles increase the completion rates to 84% and 98%, respectively. Thus an improvement in control was achieved without the need for the extensive multi-wrist position training. It is worthwhile to note that the intrinsic muscles may be damaged or absent in some partial-hand amputees thus rendering them unsuitable as an EMG data source. For such cases, we show that classifier training with extrinsic muscle EMG and a hybrid wrist motion training protocol instead of a neutral wrist position increased completion rates from 73% to 82% for amputees and from 87% to 98% for non-amputees. Combining both intrinsic muscle EMG data and a hybrid wrist motion training protocol ultimately achieved completion rates of up to 96% in amputees. For amputees, we found no significant effect of wrist position training paradigm or muscle set on dynamic efficiency or completion time, in fact combining extrinsic and intrinsic muscle EMG increased selection times for successful trials. These results are most likely confounded by the completion rates for each training condition since we do see the expected effects of wrist position training paradigm and muscle set when we consider all attempted trials instead of only successful trials.

A virtual arm was used in these experiments since a physical partial-hand prosthesis was not available. There are several important differences between virtual and physical prostheses including differences in visual feedback and the effect of prosthesis weight, particularly on the intrinsic muscles. It is possible that loading from the prosthesis may make intrinsic muscle EMG too unstable to allow for good control, in which case a control strategy that uses extrinsic muscle EMG and a hybrid wrist motion training paradigm may outperform all other control methods. Further studies to evaluate control of powered, multifunctional partial-hand prostheses are warranted.

2.6 CONCLUSION

This research study examined the (i) contribution of intrinsic hand EMG data to pattern recognition–based classification of hand grasps and finger motions and (ii) the effect of static wrist position and dynamic wrist motion on the classification accuracy of a pattern recognition control system. We found that intrinsic muscles provide valuable EMG data that enables a pattern recognition system to better discriminate between up to 19 different hand grasp patterns and individual finger motions. Real-time studies demonstrated that wrist motion significantly decreased control system robustness and that this decrease was mitigated by training the pattern recognition system with multiple static and dynamic wrist motions and with both extrinsic and intrinsic muscle EMG. Based on the results of this study, the clinical implementation of a pattern recognition system capable of controlling multiple hand grasps while allowing use of the wrist appears promising for partial-hand amputees.

Chapter 3 Evaluating EMG Feature and Classifier Selection for Application to Partial Hand Prosthesis Control

3.1 ABSTRACT

Pattern recognition-based myoelectric control of upper limb prostheses has the potential to restore control of multiple degrees of freedom. Though this control method has been extensively studied in individuals with higher-level amputations, few studies have investigated its effectiveness for individuals with partial-hand amputations. Most partial-hand amputees retain a functional wrist and the ability of pattern recognition-based methods to correctly classify hand motions from different wrist positions is not well studied. In this study, focusing on partial-hand amputees, we evaluate (1) the performance of non-linear and linear pattern recognition algorithms and (2) the performance of optimal EMG feature subsets for classification of four hand motion classes in different wrist positions for 16 non-amputees and 4 amputees. Our results show that linear discriminant analysis and linear and non-linear artificial neural networks perform significantly better than the quadratic discriminant analysis for both non-amputees and partial-hand amputees. For amputees, including information from multiple wrist positions significantly decreased error ($p<0.001$) but no further significant decrease in error occurred when more than 4, 2, or 3 positions were included for the extrinsic ($p=0.07$), intrinsic ($p=0.06$), or combined extrinsic and intrinsic muscle EMG ($p=0.08$), respectively. Finally, we found that a feature set determined by selecting optimal features from each channel outperformed the commonly used time domain ($p<0.001$) and time domain/autoregressive feature sets ($p<0.01$). This method can

be used as a screening filter to select the features from each channel that provide the best classification of hand postures across different wrist positions.

3.2 INTRODUCTION

Pattern recognition–based myoelectric control of externally powered prostheses has demonstrated remarkable potential to restore function to individuals with upper limb amputations. This control method has shown promise in laboratory settings [15, 37], and a pattern recognition myoelectric controller is now clinically available for individuals with high-level upper limb amputations [14]. However, this population comprises less than 10% of all upper-limb amputations in the United States [1, 2]. The majority of amputations are distal to the wrist (i.e., partial-hand amputations) [2]. Since this level of amputation can involve a variety of clinical presentations, it is difficult to treat successfully with a prosthesis [74]. Though, partial-hand amputations are often termed "minor" amputations [1], successful treatment is of significant importance because the effects of partial-hand amputation on employment and self-image are comparable to those of more proximal amputations [5, 6]. Partial-hand amputees perceive themselves to be at a higher disability level than do individuals with unilateral transradial or transhumeral amputations [8, 9], they are more likely to reject their prosthesis [51], and more than half are unable to return to their previous occupation [5].

Though externally-powered myoelectric prostheses for more proximal upper-limb amputees have been commercially available for decades [20], they have only recently become available to partial-hand amputees, in part because of the technological complexities of replacing the motor function of a finger within the size limits of a prosthetic digit [4]. Externally powered partial-hand prostheses such as the i-limb quantum (Touch Bionics Inc.) and Vincentpartial (Vincent Systems GmbH) have independently functioning digits and thus offer a wide range of articulated grasps not previously available to partial-hand amputees. Commercial prostheses use conventional control algorithms that use an estimate of the EMG amplitude for proportional control of the speed of an actuated joint [4, 52]. Though pattern recognition control has the potential to intuitively restore control of more degrees of freedom than conventional methods [15, 34, 35], it has not yet been shown to be sufficiently robust for partial-hand prosthesis control.

Partial-hand amputees often retain the ability to move their wrists, and preservation of residual wrist motion is critical for functional everyday activities. Montagnani *et al.* showed that when non-amputees are limited to two degrees of freedom at the wrist (pronation/supination and flexion/extension) and one degree of freedom at the hand (open/close), they perform similarly to when they are limited to a one degree-of-freedom wrist (rotation) coupled with their intact, twenty-two degree-of-freedom hand [12]. Thus, a clinically successful partial-hand pattern recognition control system must maintain high performance while allowing the individual to use their wrist. Our previous studies demonstrate that varying wrist position adversely affects pattern recognition performance in offline and real-time virtual studies, though the severity of this wrist position effect is diminished by training the classifier with data from multiple wrist positions and combining EMG data from the extrinsic and intrinsic muscles of the hand [75, 76].

The selection of effective features and robust classifiers are critical in the design of pattern recognition–based control systems. Previous studies that investigated classifiers such as Artificial Neural Networks [42], Hidden Markov Models [43], Linear Discriminant Analysis (LDA)

[35], Support vector machines [44], Gaussian Mixture Models [45], and Quadratic Discriminant Analysis [37] found little difference in classification error between different classifiers within non-amputee and amputee groups [37]. An LDA classifier is used most commonly because it provides a good balance between classification performance and computational efficiency. However, because most studies have focused on individuals with more proximal amputations, it remains unclear whether these findings are true for partial-hand amputees whose forearm muscle activity is significantly modulated by wrist movement during a task [46, 47].

Pattern recognition of EMG signals is dependent on the user's ability to generate repeatable and differentiable muscle contractions. Effective EMG features are those that both provide unique information about limb motion and are minimally sensitive to factors that degrade performance by altering the EMG signals—such as electrode shift [38], muscle fatigue, muscle contraction effort [39], force variation [40], and limb position [41]. The robustness of numerous features to such factors have been evaluated; however, typically, the performance of features and feature combinations are evaluated across all channels. Few studies have investigated the importance of selecting individual features from different channels, and no studies, to our knowledge, have specifically evaluated which feature subsets are most robust to changes in wrist position. To search for important subsets in the feature/channel space, Oskoei *et al.* [77] used separability indices and classification rate as objective functions and a genetic algorithm as a search strategy, whereas Khushaba *et al.* [78] used classification rate as an objective function and particle swarm optimization as an evolutionary computation search technique. Both of these studies aimed to increase the efficiency of pattern recognition by finding optimal feature subsets, but the selection of best features and channels was not done simultaneously. More recently, Al-Angari *et al.* [41] used feature/channel subset selection (using correlation-based and distance-based methods) to determine whether selecting optimal features from each channel would improve the limb position effect.

This work evaluates several strategies in non-amputees and partial-hand amputees for improving classification of hand grasps performed with varying wrist positions. In this study, we (1) compare the performance of linear and non-linear classification techniques and (2) evaluate the performance of optimal EMG feature subsets that are most robust to wrist position variation.

3.3 METHODS

3.3.1 Data Collection

Data from non-amputee subjects, previously collected by Adewuyi *et al.* (n = 7) [57, 75] and Earley *et al.* (n = 9) [79] using similar protocols, were combined and used for this study. According to Adewuyi et al., nine self-adhesive bipolar surface Ag/AgCl EMG electrodes (Bio-Medical Instruments) were evenly spaced around the dominant forearm with an inter-electrode distance of 2.5cm: 5 electrodes on the proximal forearm, 2-3cm distal to the elbow and 4 electrodes on the distal forearm, 7-8 cm proximal to the wrist. However, for the data from Earley et al., eight self-adhesive bipolar surface Ag/AgCl EMG electrodes (Bio-Medical Instruments) were evenly spaced around the forearm: 6 electrodes on the proximal forearm and 2 electrodes on the distal forearm (one on the anterior side and one on the posterior side). EMG data from intrinsic hand muscles were recorded with 4 electrode pairs on the hand. Two electrode pairs were placed on the palmar side (over the thenar and hypothenar eminence) and two electrode pairs were placed on and dorsal sides (over the first and third dorsal interossei). Data from partial-hand amputee subjects (n = 4), previously obtained by Adewuyi *et al.,* were also evaluated [57, 75]. All subjects gave written consent, and experiments were performed at the Rehabilitation Institute of Chicago under an approved Northwestern University Institutional Review Board (IRB) protocol.

3.3.2 EMG Signal Processing

EMG signals were acquired using a custom-built EMG amplifier with a software gain of 2000x for each channel. All EMG data were digitally sampled at 1000 Hz using a custom-built A/D converter based on a TI AD1298 24-bit bioamplifier chip and band pass filtered (30-350Hz) with a Type 1, 8th order Chebyshev filter.

3.3.3 Procedure

Custom-designed computer software was used to visually prompt subjects to perform two functional hand grasps (key grip and chuck grip), one open hand posture, or a rest posture. All four hand postures were performed with a neutral wrist position and repeated while the subjects held their wrist in the following comfortable positions: flexion, extension, pronation, supination, abduction, and adduction, for a total of 7 wrist positions. Each hand posture was held for 3 seconds. Subjects from Earley *et al.* performed 4 repetitions of each hand posture in each wrist position [79], and subjects from Adewuyi *et al.* performed 10 repetitions of each hand posture in each wrist position [57].

3.3.4 Data Analysis

Offline analyses were performed using MATLAB 2015a software (The Mathworks, Natick, MA, USA). For all conditions, data were segmented into 200ms windows with a 20ms frame increment [60].

3.3.4.1 Effect of classifier type on classification error

A combination of four EMG time domain (TD) features (mean absolute value, number of zero-crossings, waveform length, and number of slope sign changes) and six coefficients of a 6th order autoregressive model (AR) features (hereafter called TDAR features) was extracted from each EMG data window. Four classifiers were examined: (1) a linear discriminant analysis classifier (LDA), (2) a quadratic discriminant analysis classifier (QDA), (3) a multilayer perceptron neural network with linear activation functions in its one hidden layer (LNN), and (4) a multilayer perceptron artificial neural network with nonlinear hyperbolic tangent sigmoid activation functions in its one hidden layer (MLPANN). The LDA was selected because it is the most commonly used for the classification of limb movements using EMG. It was compared to a QDA because they make very similar assumptions about the data except that it allows non-linear boundaries between data. These were compared to a LNN and MLPANN because they are on the opposite side of the spectrum in that they make no assumptions about the underlying distribution of the data.

All classifiers were trained using data from (1) only extrinsic muscle EMG data, (2) only intrinsic muscle EMG data, or (3) a combination of all extrinsic and intrinsic muscle EMG data**.** Data were divided into training data sets (50% of all data), testing data sets (30% of all data) and validation data sets (20% of all data). Each classifier was evaluated using two-fold cross-validation with these sets. The validation data sets were used to minimize overfitting of the neural networks; training of the neural networks stopped once the classification error of the validation sets began to increase. Seven hidden layer neurons were empirically chosen for the MLPANN, and the LNN had four neurons in its hidden layer. Since the LNN has linear activation functions, it simply maps the weighted inputs to the output of each neuron and is thus mathematically equivalent to a reduced two-layer input-output model [80]. The neural networks were trained using scaled conjugate gradient descent [81].

An exhaustive search was performed to determine the optimal number of wrist positions needed for classifier training. An LDA classifier was trained using data from 1 to 7 wrist positions and tested on data from all 7 wrist positions. All possible combinations of data from *n* wrist positions were evaluated, and the combination with the lowest error was chosen for each subject and plotted as a function of number of wrist positions.

3.3.4.2 Effect of EMG feature subsets on classification error

Twenty five time and frequency domain features were extracted from each EMG channel. Nineteen of these features were: mean absolute value (MAV), zero crossings (ZC), slope-sign changes (SSC), waveform length (WL), Willison amplitude (WAMP), root-mean-square (RMS), variance (VAR), v-order (order of 3), log-detector (LogDet), auto-regressive (AR) coefficients (order of 6), mean frequency (MnF), median frequency (MdF), peak frequency (PF), and mean power (MP). The frequency domain features MnF, MdF, PF, and MP were derived from the short time Fourier transform using Hamming windows. Previous studies have shown that feature sets based upon the short time Fourier transform perform better than TD features and are comparable to feature sets based upon the wavelet transform and the wavelet packet transform [28]. The remaining six features were a set of power spectrum descriptors (PSD) proposed by Al-Timemy *et al.* [40]. These features were derived as the orientation between features extracted from a nonlinearly mapped EMG record and the original EMG record and as such the resultant features were shown to be less affected by different contraction efforts.

Two main approaches can be used to select an optimal feature subset: the filter or the wrapper. The filter approach typically evaluates features based on their discriminative power using their content (e.g. within- and between-cluster separability, distance measures). The wrapper approach applies a classifier to evaluate feature subsets by minimizing classification error. Here, we used the Bhattacharyya distance as a filter function and an LDA as a wrapper function.

The Bhattacharyya distance is used as an important measure of the separability between distributions [82, 83]. Because it evaluates features based on their discriminative power using their content, it is independent of the classifier type and can be generalized to other classifiers. We evaluated and defined the separability index for each feature/channel combination (SI) as:

$$SI \ = \min_{X=1:N_c-1, Y=X+1:N_c} D_B \{c_X, c_Y\}$$

where N_c is the total number of classes available, which for this study was 4. $D_B\{c_1,c_2\}$ is the Bhattacharyya distance between the distributions of classes c_X and c_Y. *SI* is therefore the minimum separability between all classes, for a given feature/channel combination. This was calculated using data from all the wrist positions. The larger the separability index, the greater the feature's ability to distinguish one class from another, thereby leading to an increased likelihood of correct class selection by a pattern recognition classifier. The separability indices were sorted in descending order. The final number of feature/channel combinations selected from this ordered list was equivalent to the number of features in the TDAR feature sets.

The wrapper method used an LDA classifier in combination with a feature selection algorithm based on the sequential forward searching (SFS) method [84]. In SFS method, there are two sets: set A which is initially empty and set B which includes all the features. This algorithm employs an iterative search method where it selects the feature from set B that produces the minimum classification error as the first selected feature in set A. It then pairs each of the remaining features in set B with all the features in set A. The feature in set B paired with all the features in set A that generates the minimum classification error is identified and moved to set A. In each iteration, one feature in set B is selected and added to set A as the most informative feature. This method thus does not just select individual features that have the lowest classification error but selects features that result in the lowest classification error when paired with other features. This was performed using EMG data from the (1) extrinsic, (2) intrinsic and, (3) combination of the extrinsic and intrinsic muscles. In total, five feature sets were compared. These were: TDAR features, TD features (MAV, ZC, SSC and WL), SI features, (features selected from each channel based on separability index), SFS features (features selected from each channel using the SFS method), and all features. The final number of features in the SI and SFS feature subsets was equivalent to the number of features in the TDAR feature sets. The 5 feature subsets were compared using an LDA classifier alone.

To test the reliability of these feature sets, sensitivity and specificity were calculated where sensitivity was defined as the number of recognized true hand motion classes divided by the total number of true hand motion classes. Specificity was defined as the number of rejected false hand motion classes divided by the total number of false hand motion classes.

To determine which features were most important, the features were added one-by-one as inputs into an LDA classifier in the order of their separability index or in the order of selection by the SFS method. Principal component analysis was used to transform the data into a new coordinate system such that the greatest variance in the data was explained by the first coordinate and the least variance in the data was explained by the last coordinate. The newly transformed coordinates were added one-by-one, as feature inputs into an LDA classifier in descending order of the amount of variance explained by each principal component. The minimum classification error was determined for all methods and the feature set was reduced to the set of X features that decreased error by 99%. This was done separately for extrinsic, intrinsic, and combination extrinsic and intrinsic muscle EMG data for non-amputees and amputees. The frequency of selection of each feature in this set of X features was determined and averaged across subjects.

3.3.5 Statistical Analysis

To determine the effect of classifier type on classification error, a two-way repeated measures analysis of variance (ANOVA) test was performed with subject as a random effect, and muscle set and classifier type as fixed effects. This analysis was performed separately for amputees and non-amputees. To determine the effect of feature set on classification error, a two-way repeated measures ANOVA test was performed with subject as a random effect, and muscle set and feature set as fixed effects. Post-hoc comparisons were made using a Bonferroni correction factor to determine significance. All analyses were performed separately for amputees and non-amputees using Minitab 17.3.1 (Minitab Inc. PA, USA), with a significance level set at $\alpha = 0.05$.

3.4 RESULTS

3.4.1 Effect of classifier type, muscle set, and wrist position on classification accuracy

For non-amputees, performance was comparable across classifiers, except that the QDA performed significantly worse than all other classifiers. The combination of extrinsic and intrinsic muscle EMG performed significantly better than either intrinsic or extrinsic muscle EMG alone ($p<0.001$). Using EMG from intrinsic muscles alone was significantly better than EMG from extrinsic muscles alone [Fig 3-1A] ($p<0.001$). There was no significant interaction between the two factors ($p=0.06$). For amputee subjects, the QDA also performed worse than all other classifiers, though this was not statistically significant ($p=0.2$). Performance using combined EMG data from extrinsic and intrinsic muscles was significantly better than using intrinsic or extrinsic muscle EMG alone. Unlike the non-amputee data, there was no difference in performance when using EMG from extrinsic or intrinsic muscles (p=0.86) [Fig 3-1B].

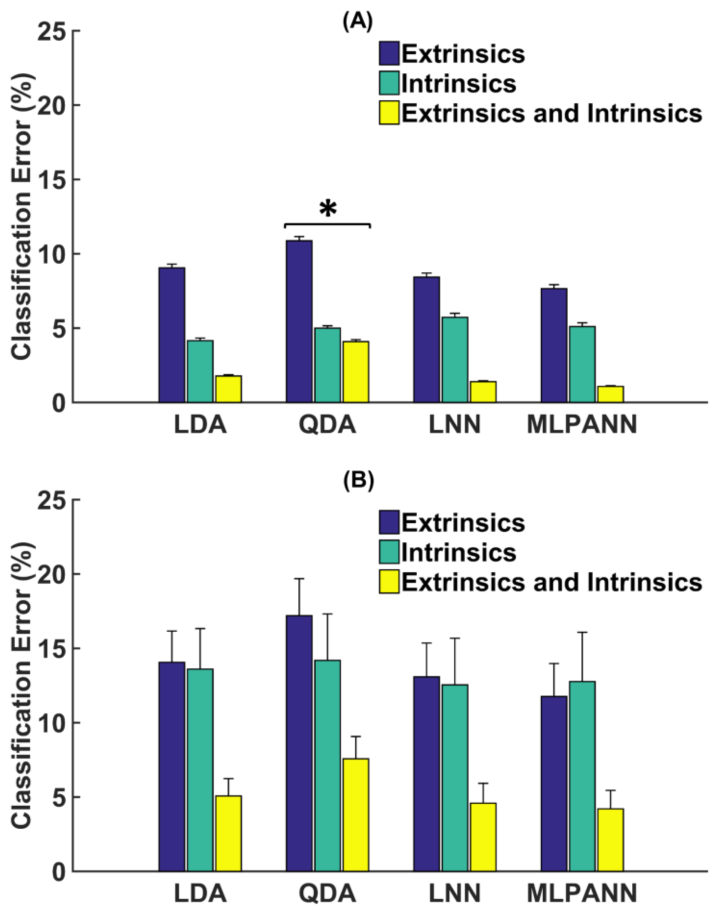
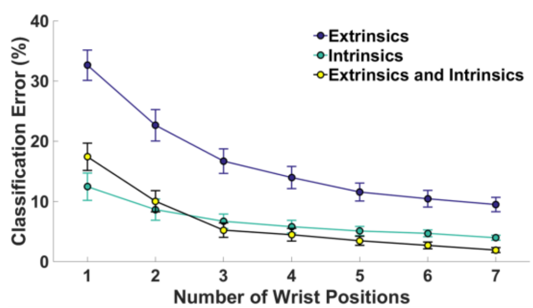


Figure 3-1: Linear and non-linear offline classification of 4 hand postures.

(A) and (B) show results from 16 non-amputees and 4 partial hand amputees (including 1 bilateral partial-hand amputee), respectively. Each classifier was trained and tested using data from 7 wrist positions. LDA: Linear discriminant analysis. QDA: Quadratic discriminant analysis. LNN: Neural Network with linear activation functions. MLPANN: Neural Network with non-linear activation functions. Error bars represent standard errors. (*: Significantly lower than LDA, LNN and MLPANN).

Figure 3-2 shows the relationship between the number of wrist positions and classification error. For amputees, classification error decreased as the number or wrist positions increased, but no significant decrease in error occurred when more than 4, 2, or 3 positions are included for extrinsic (p=0.07), intrinsic (p=0.06), and the combination of extrinsic and intrinsic muscle EMG (p=0.08), respectively. For non-amputees, error continued to significantly decrease with each additional wrist position for the extrinsic muscle and combined extrinsic and intrinsic muscle EMG. For the intrinsic muscles, no significant decrease in error occurred when more than 4 wrist positions were included (p=0.09). The analysis of the

(A)



(B)

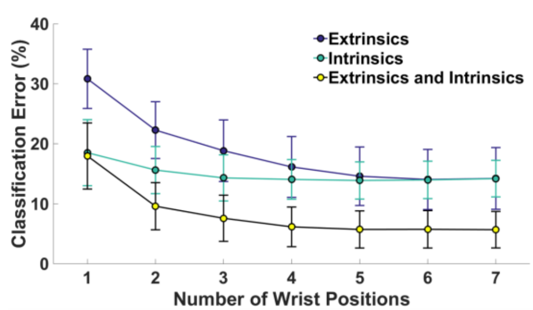


Figure 3-2: Classification error for 4 hand grasp classes as a function of number of wrist positions.

(A) 16 non-amputees and (B) 4 partial-hand subjects. Error bars represent standard error.

TABLE 3-1: AVERAGE SPECIFICITY AND SENSITIVITY OF THE 5 FEATURE SETS FOR ALL HAND MOTION CLASSES, AVERAGED ACROSS SUBJECTS

	Muscle Set	Feature Set	All features	TDAR	TD	SFS	SI
Non-amputees	Extrinsic Muscles	Sensitivity (%) ± SD	93.15±3.66	91.89±4.07	90.01±4.25	94.12±3.6	92±4.06
		Specificity (%) ± SD	97.72±1.22	97.3±1.36	96.67±1.42	98.04±1.2	97.33±1.35
	Intrinsic Muscles	Sensitivity (%) ± SD	96.49±2.58	95.32±2.94	94.67±3.02	96.98±2.16	95.78±2.87
		Specificity (%) ± SD	98.83±0.86	98.44±0.98	98.22±1.01	99±0.72	98.59±0.96
	Extrinsic and Intrinsic muscles	Sensitivity (%) ± SD	98.49±1.35	98.09±1.68	97.68±1.83	98.87±1.08	98.29±1.44
		Specificity (%) ± SD	99.5±0.45	99.36±0.56	99.23±0.61	99.62±0.36	99.43±0.48
Amputees	Muscle Set	Feature Set	All features	TDAR	TD	SFS	SI
	Extrinsic Muscles	Sensitivity (%) ± SD	86.73±10.78	85.30±10.54	82.9±11.26	89.66±9.66	84.48±11.37
		Specificity (%) ± SD	95.58±3.59	95.10±3.5	94.3±3.75	96.55±3.22	94.82±3.79
	Intrinsic Muscles	Sensitivity (%) ± SD	87.17±14.4	85.87±14.3	82.15±13.98	88.37±13.62	84.43±13
		Specificity (%) ± SD	95.73±4.8	95.29±4.76	94.05±4.65	96.12±4.53	94.81±4.32
	Extrinsic and Intrinsic muscles	Sensitivity (%) ± SD	95.15±6.56	94.31±6.82	93.13±6.91	96.13±4.54	94.82±6.53
		Specificity (%) ± SD	98.38±2.18	98.1±2.27	97.71±2.3	98.88±1.51	98.27±2.18

sensitivity and specificity of the feature sets revealed the same trends observed with classification accuracy and are presented in Supplementary Table 3-1.

3.4.2 Effect of feature selection on classification error.

Figure 3-3 shows the average classification errors across 5 EMG feature sets. For both amputees and non-amputees, there was a main effect of muscle set and feature set and no significant interaction between these factors ($p = 0.98$, $p = 0.1$, respectively). The SFS feature set performed better than all other features, including feature sets that used all features, and performed significantly better than the TDAR feature set, TD feature set, and SI feature set (Table 1). For amputees, the SFS feature set also performed the best but was only significantly better than the TD feature set ($p = 0.03$). Figure 3-4 shows the relationship between classification error and number of features using SFS, separability indices (SI), and principal component analysis (PCA) as feature selection methods. For both non-amputees and amputees, and across all muscle groups, feature selection using SFS reached a minimum error rate at a much faster rate and with fewer features than the PCA or SI methods. For example, with the SFS method, a

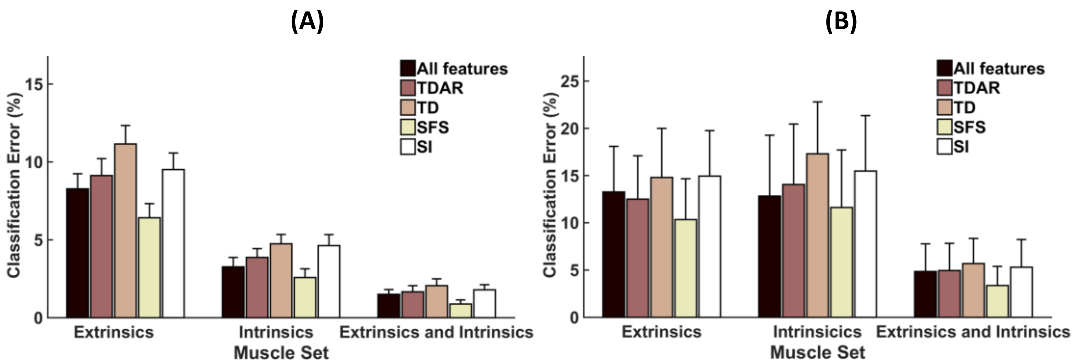


Figure 3-3: Average classification error for 5 feature sets.

(A) 16 non-amputees and (B) 4 partial-hand amputees. LDA classifiers were trained and tested with data from 7 wrist positions. TDAR: Time Domain and autoregressive features, TD: Time Domain features. SFS: Optimal feature/channel combinations as determined by Sequential Forward Search algorithm, SI: Optimal feature/channel combinations as determined by the separability index. Error bars represent standard error.

minimum error of 6.18% was achieved with 139 features, but with only 36 features, classification error had decreased by 99%, to 6.625%.

TABLE 3-2: P-VALUE TABLE FOR PAIR-WISE COMPARISONS BETWEEN DIFFERENT EMG FEATURE SETS FOR NON-AMPUTEES

	ALL Features	TDAR	TD	SFS	SI
All Features	------	0.99	**<0.001**	0.12	0.4
TDAR		------	0.09	**<0.0001**	0.94
TD			------	**<0.001**	0.65
SFS				------	**<0.001**
SI					------

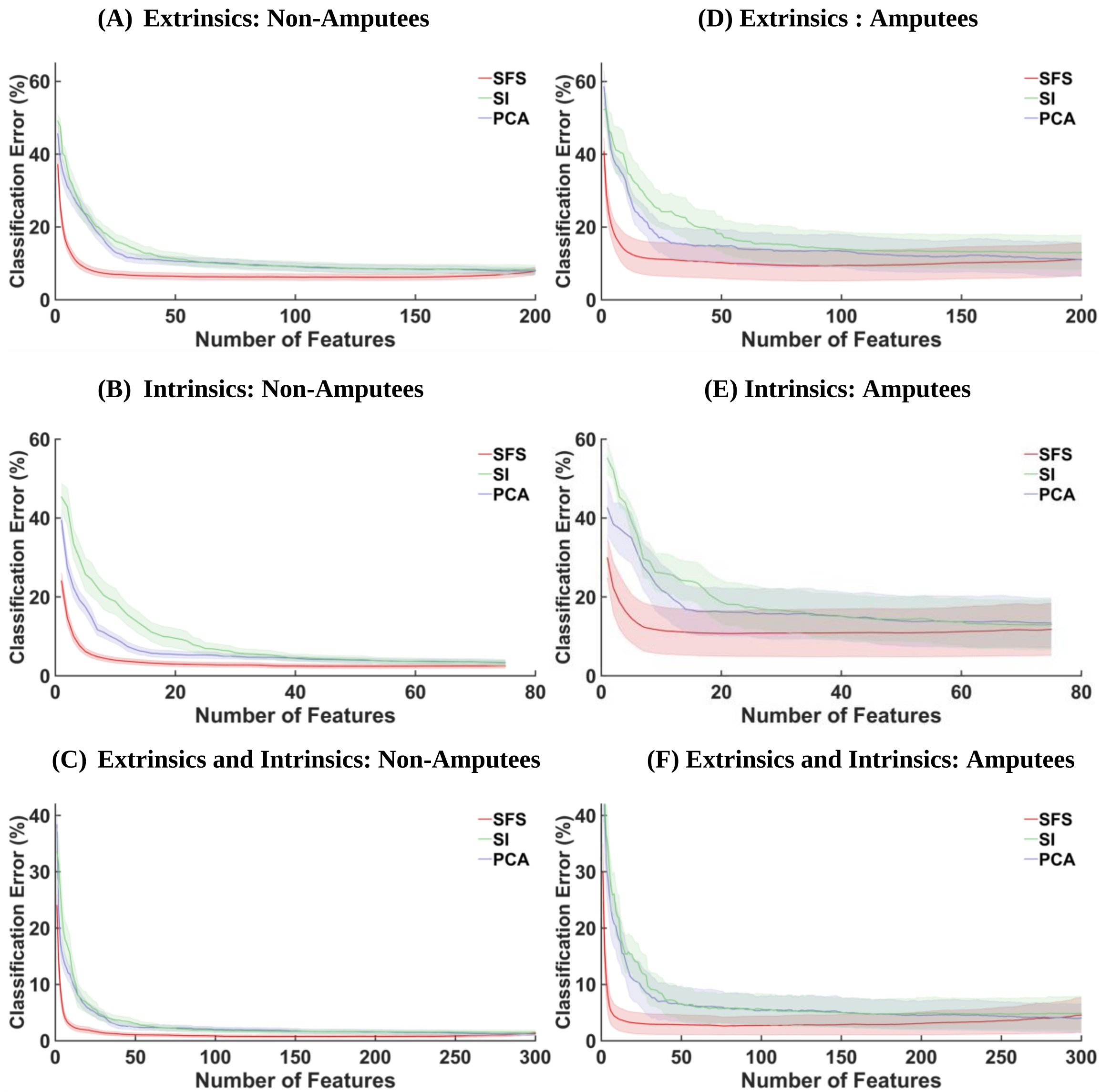
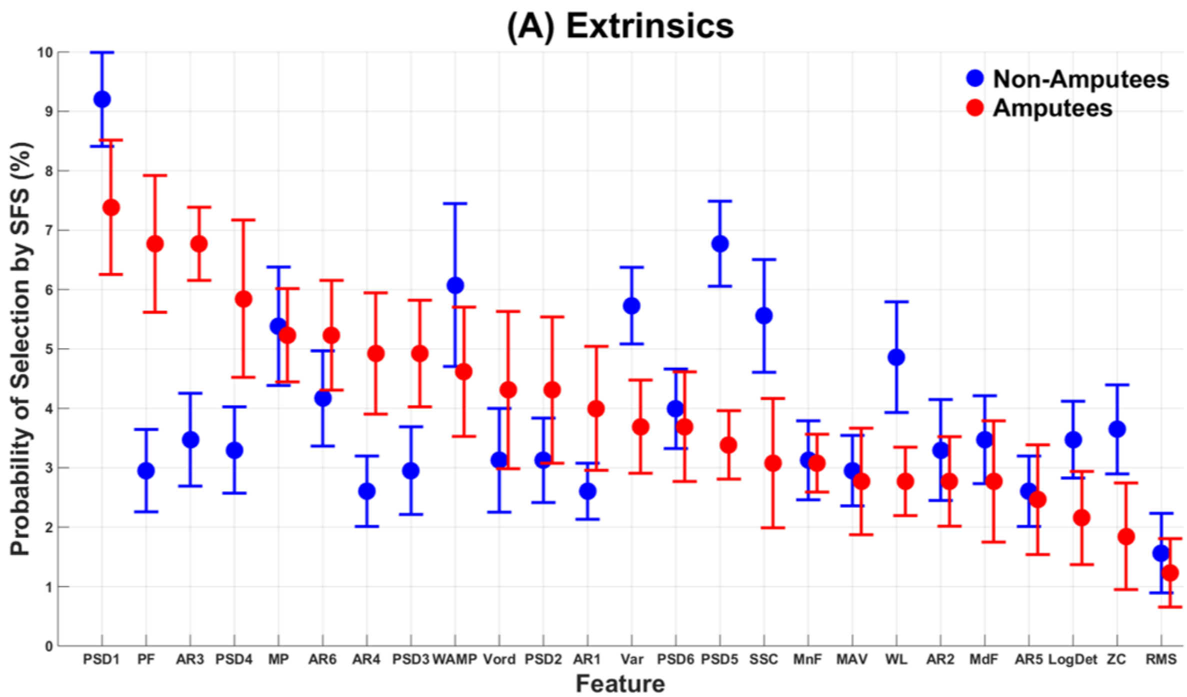
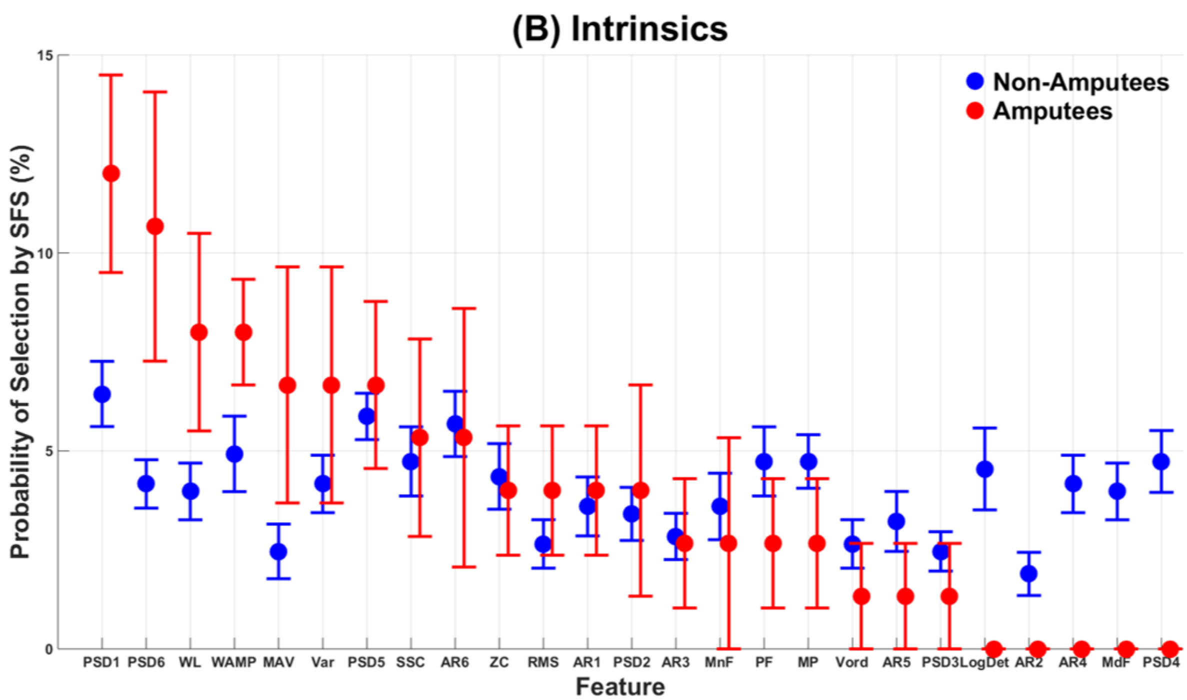


Figure 3-4: Average classification errors as a function of number of feature numbers for 3 feature selection methods.

SFS: Feature selection using Sequential Forward Selection. SI: Feature Selection using the Separability Indices of each feature. PCA: Principal component analysis. LDA classifiers were trained and tested with data from 7 wrist positions to recognize 4 motion classes. Shaded error bars represent standard error.


(A) Extrinsics
Non-Amputees
Amputees
Probability of Selection by SFS (%)
Feature
PSD1
PF
AR3
PSD4
MP
AR6
AR4
PSD3
WAMP
Vord
PSD2
AR1
Var
PSD6
PSD5
SSC
MnF
MAV
WL
AR2
MdF
AR5
LogDet
ZC
RMS


(B) Intrinsics
Non-Amputees
Amputees
Probability of Selection by SFS (%)
Feature
PSD1
PSD6
WL
WAMP
MAV
Var
PSD5
SSC
AR6
ZC
RMS
AR1
PSD2
AR3
MnF
PF
MP
Vord
AR5
PSD3
LogDet
AR2
AR4
MdF
PSD4

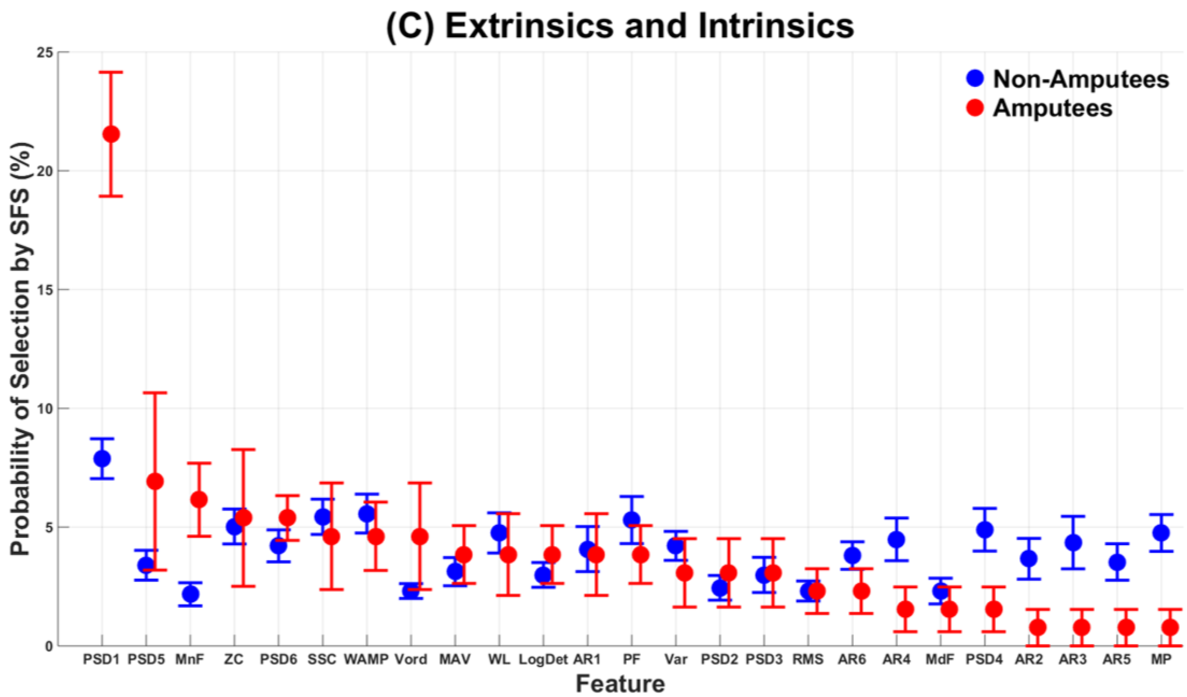
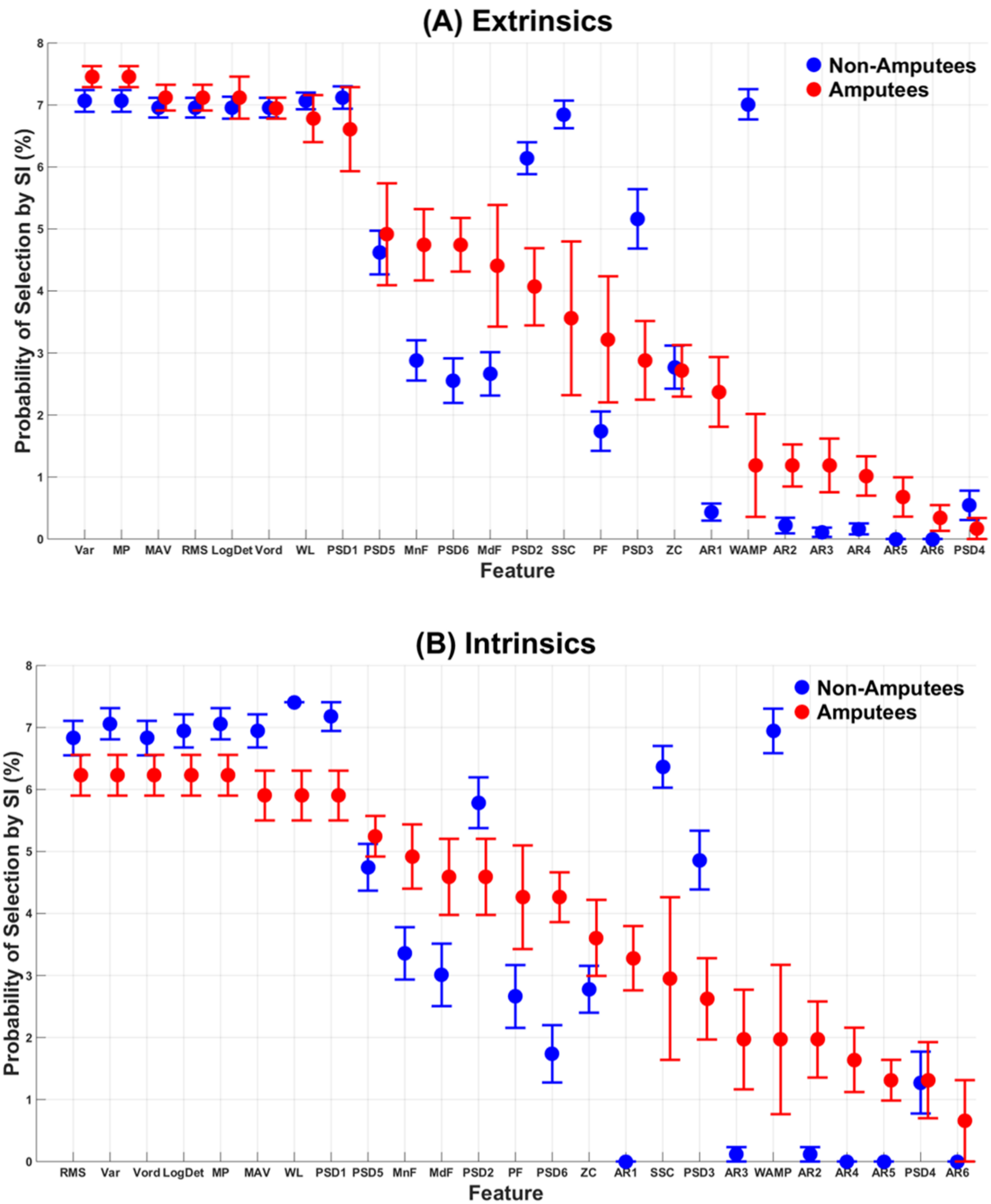


Figure 3-5: Probability of selection of the 25 features using the SFS method.

Features are ordered from most to least often selected for amputee and non-amputee subjects. Mean absolute value (MAV), zero crossings (ZC), slope-sign changes (SSC), waveform length (WL), Willison amplitude (WAMP), root-mean-square (RMS), variance (VAR), v-order (V-ord, order of 3), log-detector (LogDet), auto-regressive (AR1 – AR6) coefficients, mean frequency (MnF), median frequency (MdF), peak frequency (PF), mean power (MP), and power spectrum descriptors (PSD1 – PSD6). Error bars represent standard error.

The probability of selection of each of the 25 features in the subset of features that account for 99% of the maximum classification accuracy, averaged across subjects, is presented using the SFS method (Fig. 3-5) and SI method (Fig. 3-6). Using the SI method, the features that were most and least often selected were generally consistent between amputees and non-amputees. The autoregressive features were much less likely to be selected for both non-amputees and amputees using the SI method than using the SFS method. Moreover, though the importance of the features was relatively consistent across muscles using the SI method, the importance of features differed drastically across muscle sets for the SFS method for amputees.



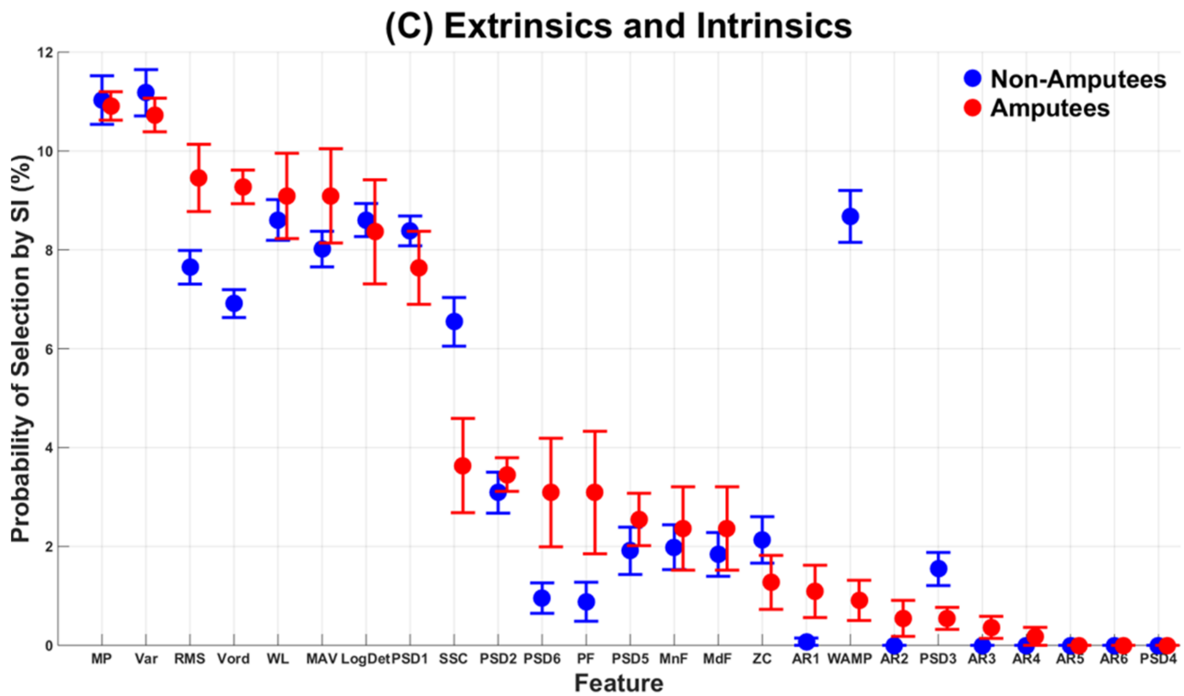


Figure 3-6: Probability of selection of the 25 features using the separability indices (SI).

Features are ordered from most to least often selected for amputee subjects. Mean absolute value (MAV), zero crossings (ZC), slope-sign changes (SSC), waveform length (WL), Willison amplitude (WAMP), root-mean-square (RMS), variance (VAR), v-order (V-ord, order of 3), log-detector (LogDet), auto-regressive (AR1 – AR6) coefficients, mean frequency (MnF), median frequency (MdF), peak frequency (PF), mean power (MP), and power spectrum descriptors (PSD1 – PSD6). Error bars represent standard error. (A) Extrinsic muscles, (B) Intrinsic muscles and (C) Extrinsic and intrinsic muscles.

For example, the MAV, WL, and SSC features were, respectively, the 18th,19th, and 16th most often chosen feature from extrinsic muscle EMG data for amputees, but were the 5th, 3rd, and 8th most often chosen features, respectively, from intrinsic muscle EMG data in amputees. Some features, however, were consistently selected across EMG datasets, such as the first power spectrum descriptor (PDS1), which was the most commonly selected feature across all muscle sets, non-amputees and amputees.

3.5 DISCUSSION

The application of pattern recognition techniques for control of externally powered myoelectric partial-hand prostheses promises to restore more function to partial-hand amputees than previously available. This work evaluated two approaches for improving the robustness of pattern recognition control against the effect of wrist position: (1) comparison of linear and non-linear control strategies and (2) the selection of the best features taken from each channel.

Overall, the performance of all classifier types was comparable for amputees and non-amputees though the QDA performed worse than all other classifiers. This may be because unlike the LDA, the QDA is a more complex model that allows for the heterogeneity of covariance matrices for each class of data. Consequently, it requires more data to estimate more parameters and achieve high accuracies. It is also possible that the QDA performed worse because of overfitting of the training data. Although the average performance of non-amputees and amputees was different, the relative performance of different classifiers was consistent within the two groups. These findings are consistent with those of Scheme *et al.* [37], who evaluated offline classifier performance for individuals with transradial amputations.

Among numerous possible combinations of features, TD and TDAR features (MAV, SSC, ZC, WL and autoregressive coefficients) are commonly used. Our results show that the optimal feature set determined by sequentially adding one feature from each channel using the SFS method outperformed all other feature sets. Few studies have investigated the importance of selecting the best features from different channels. Al-Angari *et al.* [41] used the Mahalanobis distance and a correlation-based method to determine the best features in each channel that were most resistant to changes in limb position. They also found a significant variation in the probability of selection of the AR features using the two feature selection methods. This is most likely because the Bhattacharyya distance, like the Mahalanobis distance, looks at the separability of different classes for each feature, whereas SFS indirectly considers the mutual information between each feature and class and selects the feature that best improves error in conjunction with other features already in the chosen set.

Not only are some features more important only in the context of other features, but the muscle group from which EMG is extracted greatly affects feature selection. The commonly used time-domain features MAV, WL, ZC and SSC, which have been found to be effective in classifying hand postures, were among the least important features selected from the extrinsic muscle EMG, and the most important features selected from the intrinsic muscle data. This is most likely because these features are significantly affected by changes in extrinsic muscle EMG in different wrist positions, but the intrinsic muscles, which do not cross the wrist joint, are less affected by changes in wrist position. Because the majority of partial-hand amputations are caused by trauma [1], the intrinsic muscles can be severely damaged, or absent and thus not viable for EMG-based control. In such cases, it becomes more important to optimize control using extrinsic muscle EMG by selecting the appropriate features.

An optimal feature is one that both allows for discrimination between hand postures across multiple wrist positions as well as providing information that is distinct from other features. Methods such as the SFS method that select the best performing features that provide distinct discriminatory information about hand grasps patterns could be useful for proper preselection of features for classification of different hand postures in different wrist positions. We found that the time-dependent power spectrum descriptors proposed by Al-Timemy *et al.* [40] were reasonably well selected for both SI and SFS methods across all muscle groups, suggesting that they are less affected by changes in wrist position and provide good classification of hand grasps. The set of power spectrum descriptors are extracted directly from the time domain using Fourier transform relations and Parseval's theorem and thus, keep computational costs low. Given their consistently good performance across muscle sets and subject groups, these features should be taken into consideration for future clinical implementation of pattern recognition-based systems for partial-hand prostheses.

We collected data from seven wrist positions, which can be burdensome for the user especially as the user trains the pattern recognition system with more hand grasps. We found that for amputee subjects, training in more than 2-4 positions provided no significant additional improvement. This study has a potential limitation in that the analyses for non-amputees were performed offline. Some previous research has demonstrated a minimal correlation between offline performance and usability with a virtual task [85, 86]; however other studies have shown significant correlation between offline classification error and real-time control [60, 87]. Though the improvement in performance using the SFS method particularly for the extrinsic muscles is promising, further analysis of data from amputees performing similar experiments in a virtual environment or with a physical prosthesis is warranted.

3.6 CONCLUSION

In order for pattern recognition techniques to be used for control of partial-hand prostheses, the control system must be robust enough to main good control when the user moves their wrist. This research study compared the performance of linear and non-linear control strategies and evaluated the performance of different EMG feature sets for improving pattern recognition control of hand grasps in multiple wrist positions. We found that the commonly used LDA classifier performed just as well as linear and non-linear artificial neural networks for amputees and non-amputees. We also found that selecting the best features from each channel using an SFS algorithm resulted in significant improvements over the commonly used time domain feature sets and optimal feature sets. Finally, our results suggest that some of the widely used time domain features are better suited for use with intrinsic muscle EMG data than extrinsic muscle data for good control across multiple wrist positions.

Chapter 4 Resolving the Effect of Wrist Position on Myoelectric Pattern Recognition Control

4.1 ABSTRACT

The use of pattern recognition-based methods to control myoelectric upper-limb prostheses has been well studied in individuals with high-level amputations and offers exciting opportunities for restoring hand function to partial-hand amputees. However, few studies have demonstrated that pattern-recognition control is suitable for partial-hand amputees, who often possess a functional wrist. Six non-amputees and 2 partial-hand amputees performed 4 hand motions in 13 different wrist positions. The performance of 4 control systems using EMG data alone from the extrinsic and intrinsic hand muscles or EMG data combined wrist positional information data was evaluated. Using recorded wrist positional data, we modeled the relationship between EMG features and wrist positions and used this model to develop a wrist position-independent control system. For non-amputees, a multi-layer perceptron artificial neural network (MLPANN) classifier was better able to discriminate four hand motion classes in 13 wrist positions than a linear discriminant analysis (LDA) classifier ($p=0.006$), quadratic discriminant analysis (QDA) classifier ($p<0.0001$) and a linear perceptron artificial neural network (LNN) classifier ($p=0.04$). For partial-hand subjects, similar trends were observed: the LDA, QDA and LNN resulted in small changes in classification error with the inclusion of wrist position information, and the MLPANN classifier performed the best. The addition of wrist position data to EMG data significantly improved control system performance ($p<0.001$). The combination of

extrinsic and intrinsic muscle data performed significantly better than using intrinsic ($p<0.0001$) or extrinsic muscle data alone ($p<0.0001$), and intrinsic muscle data performed significantly better than extrinsic muscle data ($p<0.001$). For amputees, the combination of extrinsic and intrinsic muscle data performed better than the two muscle group data sets alone but the intrinsic muscle data, on average, performed worse than the extrinsic muscle data. Finally, we propose a wrist position–independent controller that simulates data from multiple wrist positions and is able to significantly improve performance by 48-74% ($p<0.05$) for non-amputees and by 45-66% for partial-hand amputees, compared to a classifier trained only with data from a neutral wrist position and tested with data from multiple positions.

4.2 BACKGROUND

The application of advanced signal processing and innovative surgical procedures has expanded the use of pattern recognition of electromyographic (EMG) signals to control prosthetic devices [14, 15, 37]. The majority of this work has focused on restoring function to individuals with high-level amputations, who make up less than 10% of all upper-limb amputees in the United States [1, 2]. Few studies have sought to apply pattern recognition control to individuals with partial-hand amputations, who constitute the majority of upper-limb amputees. Although often termed a “minor” amputation [1], the impact of partial-hand amputation on employment and self-image is increasingly recognized as being comparable to that of more proximal level amputations [5, 6]. Partial-hand amputations are difficult to treat effectively with a prosthesis [3, 4, 16] and cause individuals to perceive themselves as having a greater disability than those with higher level unilateral amputations [8, 9]. The recent introduction of externally powered, independently functioning digits, such as the i-limb quantum (Touch Bionics Inc.) and Vincentpartial (Vincent Systems GmbH), offer exciting possibilities for improving hand function of partial-hand amputees.

Partial-hand amputees often retain the ability to move their wrists, and preservation of residual wrist motion is critical for functional performance of everyday activities. With conventional myoelectric control, where an estimate of EMG amplitude is used for proportional control of an actuated joint, the prosthetist must use the EMG from the extrinsic hand muscles when intrinsic hand muscles do not provide viable control signals [4]. Since the forearm contains muscles that move both the fingers and the wrist, the user must generate EMG activity to control the prosthetic fingers without significant wrist movement, which may generate myoelectric signals that disrupt control [4]. One recent study showed that when non-amputees are limited to two degrees of freedom at the wrist (pronation/supination and flexion/extension) and 1 degree of freedom at the hand (open/close), they perform similarly to when they are limited to a 1 degree-of-freedom rotating wrist coupled with their natural 22 degree-of-freedom hand [12]. Thus, a clinically successful partial-hand pattern recognition control system must both provide high performance accuracy and allow the individual to retain use of their wrist.

Muscle contractions responsible for different wrist movements influence properties of the surface EMG recorded from the forearm during hand movements. Joint angle may also influence EMG patterns as a result of various internal physiological factors: changing the angle of the joint about which a muscle is fixed can alter muscle geometry and affect the relative positions of muscle fibers and motor units, not only with respect to themselves but also with respect to the skin surface electrodes [49]. Pattern recognition control depends on the user's ability to generate repeatable and differentiable muscle contractions. Thus, changes in EMG patterns due to wrist position can degrade performance of the control system. Studies have shown that variations in arm position substantially impact the ability of pattern recognition control systems to classify hand grasps [55, 56, 88]. Our previous studies demonstrate that varying wrist position adversely affects pattern recognition performance in both offline and real-time virtual studies [75, 76]. We showed that the severity of this wrist position effect is diminished by training the classifier with data from multiple wrist positions and combining EMG data from the extrinsic and intrinsic muscles of the hand [75, 76], but these interventions do not reduce classification error to the level seen when the wrist is in one position.

To attenuate the limb position effect in individuals with higher level amputations, other studies have suggested that (i) adding information from a limb position sensor as an additional input into a pattern recognition system [55] and (ii) using a two-stage cascade classifier that uses a position sensor in the first stage for limb position identification and EMG for limb motion classification in the second stage may reduce the effect of limb position variation on classification performance [55, 56]. However, these approaches require the user to train the pattern recognition system by performing each hand motion in multiple limb positions. Since this laborious training process must be repeated whenever retraining is needed, it would be beneficial to be able to predict changes in EMG features as a function of wrist position, such that future retraining procedures would only require data collected in one wrist position. An ideal controller would thus be able to provide wrist position–independent control after being trained in one wrist position.

This work evaluates several strategies in non-amputees and partial-hand amputees for improving classification of hand grasps performed with varying wrist positions. In this study, we (1) evaluate the benefit of incorporating wrist position sensor information into linear and non-linear controllers and (2) propose a potential method for developing a control system that provides wrist position-independent control after being trained in one wrist position.

4.3 METHODS

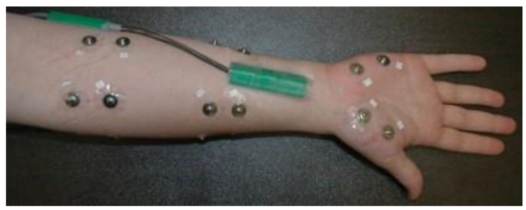
4.3.1 Data Collection

Six non-amputees with no known neurological or physical deficits performed the experiments described in this study. Two partial-hand amputees—one with an amputation of all 5 fingers at the metacarpophalangeal joints (Subject 1) and one with a thumb amputation (Subject 2) —also performed the experiments. All subjects gave written consent for the collection of data, images and video recordings, and experiments were performed at the Rehabilitation Institute of Chicago under a protocol approved by the Northwestern University Institutional Review Board.

Nine self-adhesive bipolar surface Ag/AgCl EMG electrodes (Bio-Medical Instruments) were evenly spaced around the dominant forearm for non-amputees or residual forearm for amputees with an inter-electrode distance of 2.5cm, with 5 electrodes on the proximal forearm, 2-3cm distal to the elbow, and 4 electrodes on the distal forearm, 7-8 cm proximal to the wrist

(A)

(B)



(C)

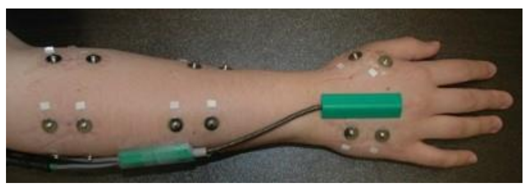


Figure 4-1: The experimental setup.

(A) Subjects were prompted by a computer to perform each hand grasp in 13 wrist positions and received wrist position visual feedback. (B) and (C) anterior and posterior view, respectively, of a non-amputee subject depicting electrode and goniometer locations on forearm and hand.

(Fig. 1). Four electrodes were placed on the hand: 2 electrodes on the palmar side and 2 electrodes on the dorsal side (Fig. 4-1). The ground electrode was placed on the olecranon of the elbow.

A single axis torsiometer (Q150, Biometrics Ltd) was used to record wrist pronation and supination (Fig. 4-1B). A biaxial flexible electrogoniometer (SG110, Biometrics Ltd) was used to record wrist flexion, extension, abduction and adduction (Fig. 4-1C). The distal end of the torsiometer was attached to the midline of the anterior forearm immediately proximal to the wrist joint and the proximal end of the torsiometer was attached to the forearm, immediately distal to the medial epicondyle of the humerus, in a position that did not interfere with the electrode placements on the forearm (Fig. 4-1B). The distal end of the biaxial goniometer was attached to the back of the hand, over the third metacarpal, such that it was parallel with the center axis of the hand and its proximal end was attached over the posterior midline of the forearm (Fig. 4-1C).

4.3.2 Procedure

Subjects were prompted to position their wrist in one of 13 wrist positions. These positions were located at the end-range and mid-range of motion for flexion, extension, supination, pronation, abduction and adduction, in addition to a “neutral” wrist position. For the neutral position, subjects held their wrist at 0 degrees in all 3 degrees of freedom. Subjects received visual feedback of their wrist position from a computer monitor. For each wrist position, subjects were required to maintain the other two wrist degrees of freedom at $0^{o}\pm 5^{o}$. Subjects were visually prompted to perform one of 4 hand motions (chuck grasp, key grasp, an open hand posture, and a rest posture). Chuck and key grasps were chosen because they are the most common grasps used in activities of daily living [89]. Each hand posture was held for 3 seconds and repeated 6 times in each wrist position for a total of 78 repetitions per hand grasp.

To ensure that non-amputee subjects maintained the same pinch force throughout each grasp, subjects received visual feedback of pinch forces produced during chuck and key grips using an electronic pinch gauge (12-0023, Fabrication Enterprises). Subjects were required to maintain a grasp force that was 15-20% of their maximal voluntary grasp force made in a neutral wrist position; this force level was comfortable for all grasps in all wrist positions. To avoid fatigue, subjects were allowed 2-5 minute rests between trials, where a trial consisted of 3 repetitions of the four hand postures in one wrist position.

4.3.3 Signal Processing

EMG signals were acquired using a custom built EMG amplifier with a total gain of 2000x (2x Hardware gain, 1000x Software gain) for each channel. All EMG data were digitally sampled at 1000 Hz using a custom-built A/D converter based on a TI AD1298 bioamplifier chip and band-pass filtered (30-350Hz) with a Type 1, 8^{th} order Chebyshev digital filter. Goniometer data were sampled at 1000Hz with a custom-built 16 bit A/D converter and low-pass filtered at 10Hz with a 3^{rd} order Butterworth filter.

4.3.4 Data Analysis

Offline analyses were performed using MATLAB 2015a software (The Mathworks, Natick, MA, USA). For all conditions, data were segmented into 200ms windows with a 20ms frame increment [60].

4.3.4.1 Effect of classifier type and wrist position on classification error

A combination of four EMG time-domain features (mean absolute value, number of zero-crossings, waveform length, and number of slope sign changes) and six coefficients of a 6^{th} order autoregressive model (hereafter called TDAR features) were extracted from each EMG data window. For each window, the average value of the goniometer and torsiometer data was also calculated (hereafter called POS, for position features). Four classifiers, two linear and two non-linear, were compared: (1) a linear discriminant analysis classifier (LDA), (2) a quadratic discriminant analysis classifier (QDA), (3) a multilayer perceptron neural network with linear activation functions in its one hidden layer (LNN), and (4) a multilayer perceptron artificial neural network with nonlinear hyperbolic tangent sigmoid activation functions in its one hidden layer (MLPANN).

All classifiers were trained using data from (1) only extrinsic muscle EMG data, (2) only intrinsic muscle EMG data, or (3) a combination of all extrinsic and intrinsic muscle EMG data. Data were divided into training data sets (50% of all data), testing data sets (30% of all data) and validation data sets (20% of all data). Each classifier was evaluated using two-fold cross-validation with these sets. The validation data set was used to minimize overfitting of the neural networks; training of the neural networks stopped once the error of the validation sets began to increase. Seven hidden layer neurons were empirically chosen for the MLPANN, and the LNN had four neurons in its hidden layer. Since the LNN has linear activation functions, it simply maps the weighted inputs to the output of each neuron and is thus mathematically equivalent to a reduced two-layer input-output model [80]. The neural networks were trained using scaled conjugate gradient descent [81]. This analysis was performed with two feature sets, (1) the TDAR feature set alone and (2) the TDAR combined with the POS feature set.

An exhaustive search was performed to determine the optimal number of wrist positions needed for classifier training. An LDA classifier was trained using data from 1 to 13 wrist positions and tested on data from all 13 wrist positions. All possible combinations of data from *n* wrist positions were evaluated, and the combination with the lowest error was chosen for each subject and plotted as a function of number of wrist positions.

To determine if position-specific classifiers performed better than one generalized classifier trained with data from all wrist positions, two training paradigms were evaluated. In training paradigm 1, one classifier was trained with data from all wrist positions and tested with data from each wrist position separately, with the results averaged across positions. In training paradigm 2, thirteen classifiers were trained and tested with data from each wrist position separately and results were averaged across classifiers.

4.3.4.2 Predicting changes in feature as a function of wrist position

To predict how each feature changes as a function of wrist position, a neural network was used for non-linear regression. The neural network had 3 inputs which were the wrist position in each of the three degrees of freedom. The network had 3 neurons in its one hidden layer with hyperbolic tangent sigmoid activation functions and 1 output neuron with a linear activation function. The neural network was trained using scaled conjugate gradient descent. A separate neural network was trained for each feature, from each channel, for each class. Fifty percent of the data from each wrist position was used to calculate the mean and variance of each feature in each position, which were then divided by the mean or variance, respectively, of each feature in a neutral wrist position. The neural network was then trained to predict the change in mean or variance of each feature (Fig. 4-2), where 20% of the data was used for cross-validation and

30% was used for testing. The coefficient of determination, r^2, was calculated to measure the performance of each neural network.

Three data sets were compared: (1) the real dataset, (2) a simulated dataset generated by randomly sampling from distributions described by the means and variances generated by the neural network and (3) a simulated dataset generated by randomly sampling from distributions described by the mean and variance generated by the neural network for *only* the neutral wrist position. The three datasets were used to train three LDA classifiers, which were tested using the real dataset. The number of data points used in all simulated datasets was equivalent to the number of data samples in the original real data set. For this analysis, only TDAR features were evaluated, and the LDA classifier was used to determine average classification error across subjects.

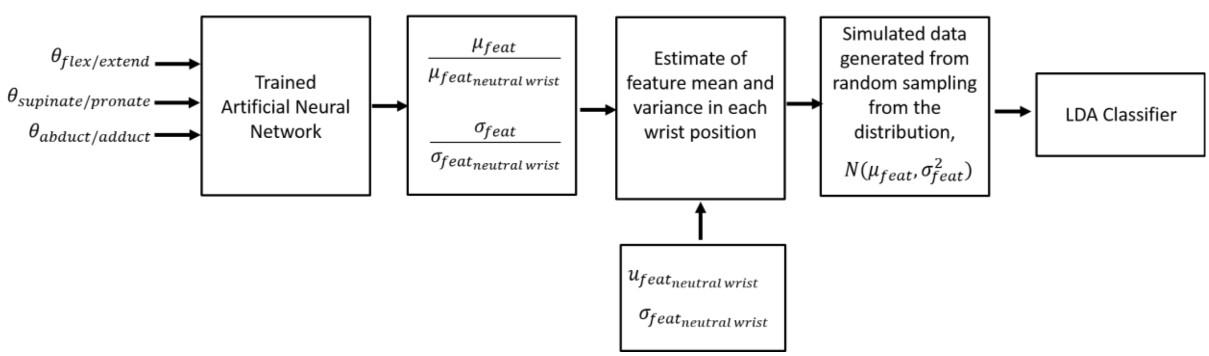


Figure 4-2: Predicting changes in feature as a function of wrist position

A neural network was trained to predict changes in the mean and variance of each EMG feature, from each channel, for each class as a function of the mean and variance of the feature in a neutral position. The output of each neural network was used to generate data to simulate real data collected from all wrist positions. This simulated data was then used to train an LDA and tested using real data.

4.3.5 Statistical Analysis

To determine the effect of classifier type and wrist position on classification error, a three-way repeated measures analysis of variance test (ANOVA) was performed with subject as a random effect, and muscle set, feature set, and classifier type as fixed effects. A two-way repeated measures ANOVA, with subject as a random effect and muscle set and training paradigm as fixed effects, was used to determine the effect of training paradigm on classification performance. To test the performance of the simulated datasets, a two-way ANOVA test was performed with subject as a random effect and muscle set and data set as fixed effects. All post-hoc comparisons were made using a Bonferroni correction factor to determine significance. All statistical analyses were performed using Minitab 16.2.4 (Minitab Inc. PA, USA), and the significance level was set at 0.05.

4.4 RESULTS

4.4.1 Effect of classifier type, muscle set and wrist position information on classification

Fig. 4-3 shows the effect of three factors (muscle set, feature set, and classifier type) on classification error. For non-amputees (Fig. 4-3A), there was a significant main effect of all three factors ($p<0.001$). No interaction terms were found to be significant. The use of wrist position information as an additional feature improved relative performance for the LDA, QDA, and LNN classifiers by 14%, 13% and 16% for the extrinsic muscle data, 19%, 14%, and 26% for the intrinsic muscle data and 8%, 6%, and 3% for the combination of extrinsic and intrinsic muscle data, respectively.

The addition of wrist position information had a much greater effect on the performance of the MLPANN, improving relative error by 43% for the extrinsic muscle, 48% for the intrinsic muscles and 30% for the combination of extrinsic and intrinsic muscle data (Fig. 4-3D) with absolute improvements in error of up to 5.4%. Pairwise comparisons showed that the MLPANN performed significantly better than the LDA ($p=0.006$), QDA ($p<0.0001$) or LNN ($p=0.04$) classifiers, and the LNN performed significantly better than the QDA ($p=0.02$). The combination of extrinsic and intrinsic muscle data performed significantly better than using intrinsic ($p<0.0001$) or extrinsic muscle data alone ($p<0.0001$), and intrinsic muscle data performed significantly better than extrinsic muscle data ($p<0.001$). For partial-hand subjects 1 and 2, similar trends were observed: the LDA, QDA and LNN resulted in small changes in classification error with the inclusion of wrist position information, and the MLPANN classifier performed the best. The QDA was the worst performing classifier for both amputees, and the combination of extrinsic and intrinsic muscle data performed better than the two muscle group data sets alone. In contrast to non-amputees, for both amputee subjects the intrinsic muscle data, on average, performed worse than the extrinsic muscle data.

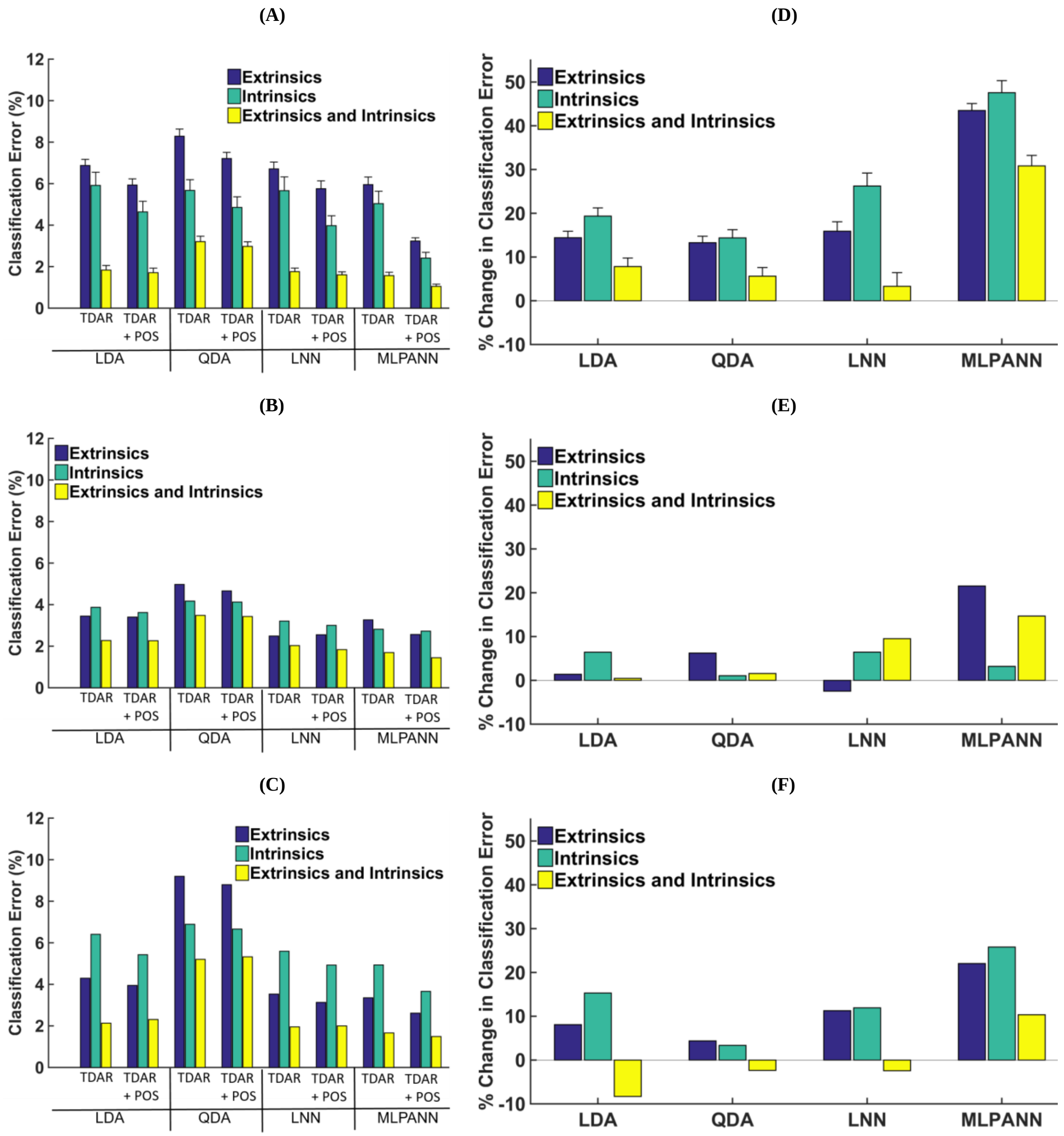


Figure 4-3: Effect of wrist position information on linear and non-linear classification of 4 hand motions in 6 non-amputees and 2 partial-hand amputees.

Each classifier was trained and tested using data from 13 wrist positions. Each classifier was trained with either EMG features alone (TDAR) or EMG features combined with wrist position features (TDAR + POS). Results are shown for (A) non-amputees, (B) Partial-hand subject 1 and (C) Partial-hand subject 2. The percent change in classification error when wrist position data was combined with EMG features is shown in figures D-F. A positive change represents an improvement in performance with the addition of wrist position features. Results are shown for (D) non-amputees, (E) Partial-hand subject 1 and (F) Partial-hand subject 2. Error bars represent standard errors; LDA: Linear discriminant analysis; QDA: Quadratic discriminant analysis; LNN: Neural Network with linear activation function; MLPANN: Neural Network with non-linear activation functions.

Figure 4-4 shows the relationship between the number of wrist positions included in the training data and classification error. Error decreases substantially at the beginning of the curve as more wrist positions are added, but there is no further significant decrease in error for the extrinsic when more than 9, 4, or 6 wrist positions are included, for the extrinsic (p=0.39), intrinsic (p=0.14), or combination of extrinsic and intrinsic muscle data (p=0.13), respectively.

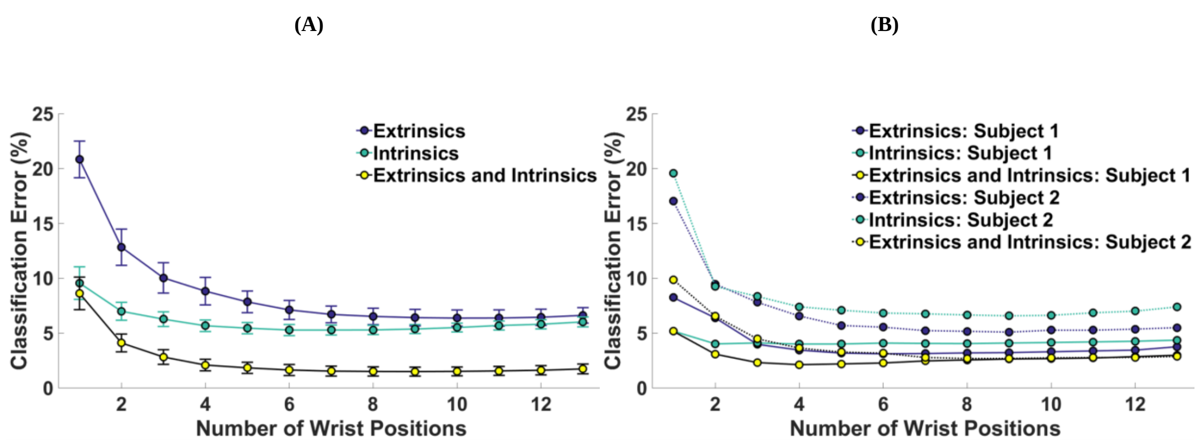


Figure 4-4: Classification error for 4 hand motion classes as a function of number of wrist positions used to train the classifier.

(A) 6 non-amputees and (B) 2 partial-hand amputees. Error bars represent standard error.

Similar trends were observed for amputee subjects. We found no statistically significant difference in average classification error between a classifier trained with data from all wrist positions and tested with data from each wrist position separately and 13 classifiers trained and tested with data from each wrist position separately (p=0.47) (Fig. 4-5).

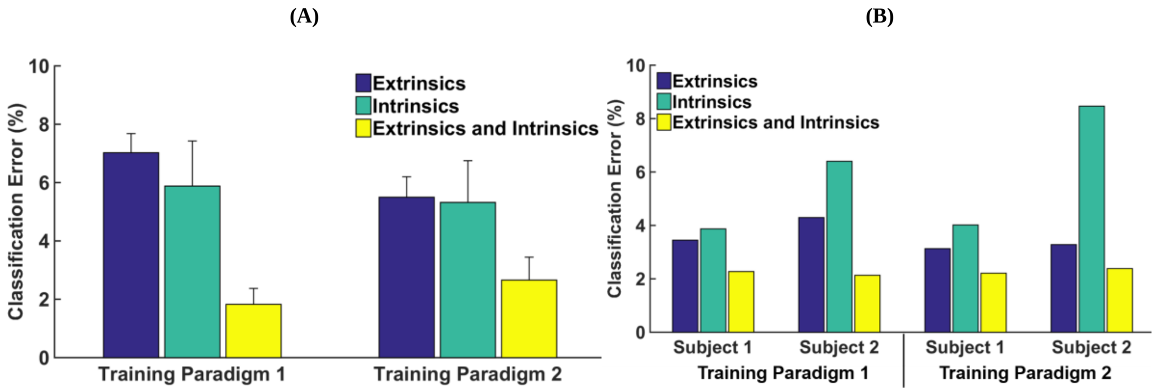


Figure 4-5: Classification error for 4 hand motion classes.

(A) 6 non-amputees and (B) two partial-hand amputees. In training paradigm 1, one classifier was trained with data from all wrist positions and tested with data from each wrist position separately. In training paradigm 2, thirteen classifiers were trained and tested with data from each wrist position separately and the results of all 13 classifiers were averaged.

4.4.2 Predicting changes in feature as a function of wrist position

The neural networks were able to accurately predict the change in mean of each feature in each wrist position relative to the mean of the respective feature in a neutral wrist position. On average, for non-amputees, the r^2 values were 0.84 for extrinsic muscle data, 0.82 for intrinsic

TABLE 4-1: SUMMARY OF THE R^2 VALUES FOR ESTIMATING THE MEAN OF EACH FEATURE AS A FUNCTION OF WRIST POSITION

		Non-Amputees	Amputees	
Muscle Set	**Grasp**	**Non-Amputees**	**Subject 1**	**Subject 2**
Extrinsics	No Movement	0.898 ± 0.04	0.836	0.836
	Hand Open	0.812 ± 0.04	0.719	0.806
	Key Grip	0.831 ± 0.03	0.755	0.862
	Chuck Grip	0.825 ± 0.05	0.777	0.73
Intrinsics	No Movement	0.913 ± 0.05	0.845	0.847
	Hand Open	0.837 ± 0.07	0.677	0.712
	Key Grip	0.771 ± 0.06	0.743	0.796
	Chuck Grip	0.74 ± 0.07	0.612	0.621
Extrinsics and Intrinsics	No Movement	0.902 ± 0.04	0.839	0.839
	Hand Open	0.819 ± 0.05	0.706	0.777
	Key Grip	0.813 ± 0.03	0.752	0.842
	Chuck Grip	0.799 ± 0.05	0.727	0.697

muscle data and 0.83 for the combination of extrinsic and intrinsic muscle data. For the amputee subjects, the r^2 values were on average 0.79, 0.73 and 0.77 for the extrinsic, intrinsic, and the combination of extrinsic and intrinsic muscle data, respectively (Table 4-1). The neural network was less able to predict the variance of the features. The r^2 values for non-amputees and amputees, respectively, were 0.55 and 0.6 for the extrinsic muscle data, 0.54 and 0.57 for the

TABLE 4-2: SUMMARY OF THE R^2 VALUES FOR ESTIMATING THE VARIANCE OF EACH FEATURE AS A FUNCTION OF WRIST POSITION

		Non-Amputees	Amputees	
Muscle Set	**Grasp**	**Non-Amputees**	**Subject 1**	**Subject 2**
Extrinsics	No Movement	0.576 ± 0.06	0.701	0.707
	Hand Open	0.486 ± 0.09	0.569	0.602
	Key Grip	0.572 ± 0.05	0.527	0.615
	Chuck Grip	0.56 ± 0.06	0.536	0.539
Intrinsics	No Movement	0.652 ± 0.05	0.73	0.646
	Hand Open	0.507 ± 0.09	0.527	0.57
	Key Grip	0.504 ± 0.1	0.423	0.69
	Chuck Grip	0.512 ± 0.1	0.456	0.523
Extrinsics and Intrinsics	No Movement	0.6 ± 0.05	0.71	0.688
	Hand Open	0.493 ± 0.06	0.557	0.592
	Key Grip	0.551 ± 0.06	0.495	0.638
	Chuck Grip	0.545 ± 0.07	0.511	0.534

intrinsic muscle data and 0.55 and 0.59 for the combination of extrinsic and intrinsic muscle data (Table 4-2).

Training the LDA classifier with real data from *only a neutral* wrist position and testing with real data from *all positions* resulted in high errors of 27%, 22% and 15%, for extrinsic muscles, intrinsic muscles and the combination of both sets of muscles, respectively. However, when the LDA was trained with simulated data from all wrist positions, the error significantly decreased for all three muscle groups (Fig. 5A); by 48% for extrinsic muscle data ($p<0.001$), by 54% for intrinsic muscle data ($p<0.001$), and by 74% ($p<0.001$) for combined data from both muscle groups. The

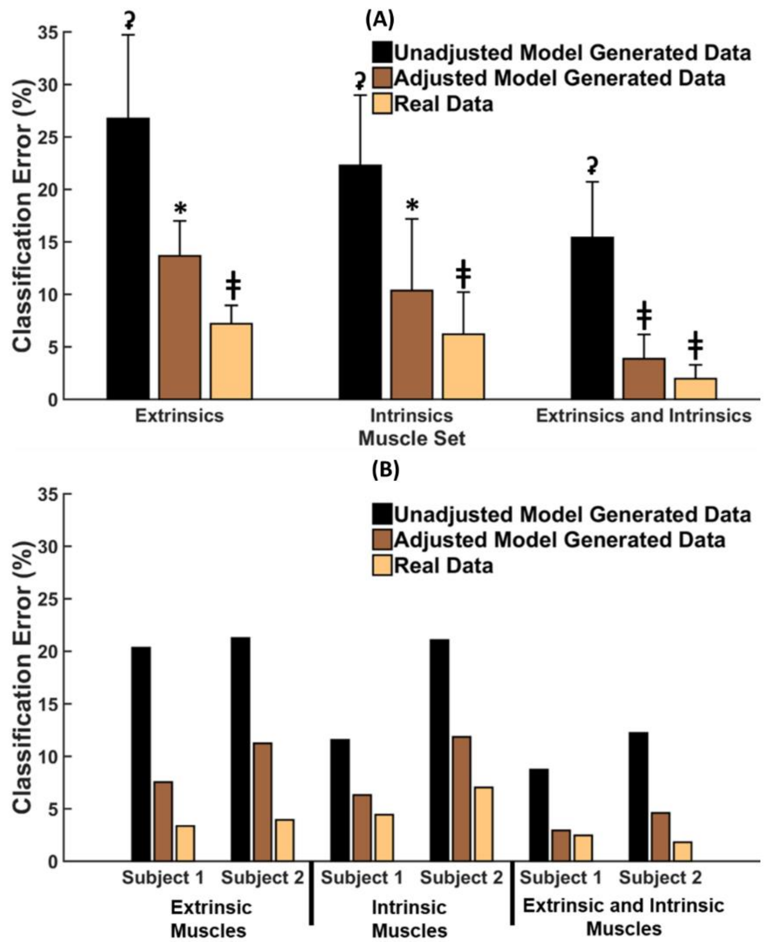


Figure 4-6: Classification using three datasets

These datasets were: (1) unadjusted model-generated data which was a simulated dataset generated by randomly sampling from distributions described by the mean and variance generated by the neural network for *only* the neutral position; (2) adjusted model-generated data which was a simulated dataset generated by randomly sampling from distributions described by the means and variances generated by the neural network from all positions; and (3) the real data set. (A) Results from non-amputee subjects; for each muscle set, datasets that are significantly different from each other do not share the same symbol. (B) Results from two partial-hand amputee subjects. Error bars represent standard deviation. (B) Results from two partial-hand amputee subjects.

same trends were observed in both partial-hand amputees, where error decreased by 63% and 47%, 45% (Subject 1) and 44%, 66% and 63% (Subject 2) for the extrinsic, intrinsic, and the combination of extrinsic and intrinsic muscle data, respectively (Fig. 4-6). Moreover, there was no significant difference between the performance of the adjusted simulated data set and the real data set (p=0.76) when data from the extrinsic and intrinsic muscles were combined.

4.5 DISCUSSION

This work sought to evaluate strategies that mitigate the effect of varying wrist position on pattern recognition classification of hand grasps, to facilitate the application of pattern recognition control to externally powered myoelectric partial-hand prostheses. We evaluated the benefit of incorporating wrist position sensor information into linear and non-linear controllers and established a control system that is capable of providing wrist position–independent control after being trained in one wrist position.

Overall, the performance of the LDA, LNN, and MLPANN classifiers were comparable for amputees and non-amputees, although the QDA performed worse than all other classifiers. This is likely because unlike the LDA, the QDA is a more complex model that allows for the heterogeneity of covariance matrices for each class of data. Consequently, it requires more data to estimate more parameters and its poorer performance may be attributed to overfitting of the training data. Though the use of wrist position information as an additional feature significantly improved performance across all classifiers, a multi-layer perception was better able to utilize the additional wrist position information, improving performance by 30-48%. The LDA is commonly used because it provides a good balance between classification performance and computational efficiency and performs as well as the MLPANN and LNN [37]. However, these studies do not consider classification performance for multiple wrist positions because they focus on applications to individuals with more proximal amputations. Our results suggest that for controlling partial-hand prostheses in multiple wrist positions, the benefit of wrist position information is best realized when it is incorporated into a multi-layer perception neural network.

In agreement with our previous studies [75], we found that combining extrinsic and intrinsic muscle data consistently resulted in significant improvement in performance over extrinsic or intrinsic muscle data alone for amputees and non-amputees. For non-amputees, training with intrinsic muscle EMG data alone performed significantly better than training with extrinsic muscle EMG data alone. However, for the amputee subjects, the extrinsic muscles generally performed better than the intrinsic muscles. It is worthwhile to note that it is clinically difficult to stably record from the intrinsic muscles. Moreover, 93% of partial-hand amputations are due to traumatic injury [1] and as such, the intrinsic hand muscles may be damaged or absent rendering them unsuitable as an EMG signal source. The differences between non-amputee and amputee performance may be due to damage to the intrinsic muscles of amputee subjects. Though there is high degree of variability in partial-hand amputations, the extrinsic muscles of partial-hand amputees are relatively intact and our results demonstrate that it is feasible to achieve control that is comparable to that of non-amputee subjects with extrinsic muscle EMG data.

In an attempt to resolve the limb position effect, Fougner *et al.* [55] proposed a two-stage position-aware classifier where the limb position was first detected and then a classifier specific for that position was used for motion classification. We performed a similar analysis and found that a position aware, two-stage classification system did not perform better than a classifier trained with EMG data from all wrist positions, as demonstrated by overall small, nonsignificant changes in offline classification error. Thus the use of a position sensor provided no benefit when used for two-stage classification.

Because training in multiple wrist positions can be burdensome for the user, it is important to minimize the number of wrist positions necessary to train the control system. Though classification performance generally improved with each additional wrist position, there was small improvement after more than 6 positions were included. In some instances, including data from too many wrist positions may increase error (e.g., an increase in the number of wrist positions from 6 to 13 increased classification error from 5.3% to 6%, 4% to 4.4% and from 6.8% to 7.4% for the intrinsic muscle data for non-amputees, Subject 1, and Subject 2 respectively). This is likely because data from one wrist position had class labels that directly contradicted class labels from another wrist position. We further analyzed the data to determine if the classification of hand grasps from all wrist positions was better when the classifier was trained with the wrist positions in the mid-range of motion or at the end-ranges of motion and found that there was no significant difference between the two training sets. These findings suggest that the number of training positions is more important than the training position.

The previously discussed strategies require the collection of data from different wrist positions, which can be quite time consuming and possibly fatiguing for the user, especially when retraining of the control system is necessary. Ideally, a controller would be able to provide wrist position–independent control after being trained in one wrist position. By using a neutral network for non-linear regression, we demonstrate that it is feasible to accurately predict how EMG data features change as a function of wrist position, and thus we can use data collected from a neutral wrist position to generate simulated data for all wrist positions. Here, we used an artificial neural network to implement a “black box” approach, which does not consider the individual factors that could be contributing to the wrist position effect such as the changes in muscle length, moment arms, electrode position relative to the innervation zone, or muscle fiber recruitment [90]. Alternatively, one could use other approaches such as a biomechanical model that can model the effects of changes in musculoskeletal geometry on muscle activation patterns and muscle force. However, by using a black-box approach, we forego the complexities and challenges associated with such models. For example, the moment arms for the extrinsic hand muscles used in musculoskeletal models are based on results from cadaver studies which assume the same proximal muscle origins and insertions across subjects [91], but for partial-hand amputees, the insertions of the extrinsic muscle tendons would be highly variable, depending on each individual’s surgical procedure.

These results are limited in that the training and testing data sets are from the same day and experimental session. Though pattern recognition control deteriorates when classifiers are trained and tested with data collected from different days or sessions, a recent study has shown that between-day performance improves and approaches within-day performance when subjects perform contractions over 11 consecutive days [92]. These results imply that subjects are better able to make more consistent contractions when training over multiple days. It is thus possible that the mapping between EMG features and wrist position will be stable if subjects are trained over multiple days. Further multi-day experiments are needed to determine if the neural network maintains its performance across sessions.

Another potential limitation is that the analyses were performed offline and with only 4 hand motion classes (2 grasps, hand open and no movement). We expect classification error to increase when more hand grasps are available to the classifier though future work is needed to evaluate the extent to which wrist position information improves error and to determine if the performance of the simulated dataset generalize to more grasps. The relationship between offline error and real-time performance is unclear. Some previous research has demonstrated a minimal correlation between offline performance and usability with a virtual task [85, 86]; however other studies have shown significant correlation between offline classification error and real-time control [60, 87]. Though the findings of this study are promising, further real-time experiments in a virtual environment or with a physical prosthesis are warranted.

4.6 CONCLUSION

The application of pattern recognition technology to control externally powered partial-hand prostheses offers exciting opportunities for restoring hand function. This study evaluated strategies that would promote this application while allowing a partial-hand amputee to retain residual wrist function. In this study, we compared the performance of linear and non-linear control strategies, and we also evaluated the benefit of adding information from a wrist position sensor to EMG data for improving pattern recognition control of hand grasps in multiple wrist positions. We found that adding wrist position information improved performance when incorporated into a neural network classifier for both amputees and non-amputees. We also successfully used non-linear regression to model the relationship between EMG features and wrist position and exploited this relationship to significantly improve performance of a control system trained with real data from one wrist position and tested with real data from multiple wrist positions.

Chapter 5 A Comparison of Conventional and Pattern Recognition Myoelectric Control of Powered Partial-Hand Prostheses

5.1 ABSTRACT

Pattern recognition-based myoelectric control of upper limb prostheses has recently been clinically implemented for individuals with higher-level amputations but few studies have demonstrated its effectiveness for individuals with partial-hand amputation. As most partial-hand amputees have functional wrists, control systems for partial-hand prostheses must be robust to the effects of wrist motion. The objective of this study was to determine whether pattern recognition algorithms can be used to control a partial-hand prosthesis during tasks that require wrist movement. Four partial-hand amputees were fit with the Touch Bionics i-limb digits and completed functional tasks that required coordinated movements of the wrist and arm. Our results demonstrate that pattern recognition algorithms trained using extrinsic hand muscle EMG data, intrinsic hand muscle EMG data, or a combination of both sets of data allows users to choose hand grasp patterns in different wrist positions and to maintain these grasps when the wrist is in motion. We show that for functional tasks, pattern recognition control performs just as well as conventional myoelectric control.

5.2 INTRODUCTION

The human hand is a complex instrument that allows us to manipulate objects, communicate manual gestures, and receive tactile information about our environment. Full or partial loss of the hand can thus result in significant functional and psychological loss and a decrease in life satisfaction [93, 94]. An estimated 541,000 individuals in the United States live with an upper limb amputation, and a majority of these amputations are distal to the wrist (i.e., partial-hand amputations) [1, 2]. Because partial-hand amputations are typically the result of trauma, and can involve any number of fingers at various levels, they are difficult to successfully treat with a prosthesis [3, 16].

Until recently, passive or body-powered prostheses were the main options available to partial-hand amputees. Passive prostheses are aesthetic, lightweight, require little maintenance, and provide an oppositional post for remaining fingers, but they do not offer active functionality [3]. Studies show that more than half of partial-hand amputees are unable to do the same work as before their amputation. Of those who return to work, less than one-third regularly wear their passive prostheses at work [5]; subjects stated that grip strength was not sufficient for grasping large and heavy objects and tools [5, 6]. Body-powered devices provide more function, but require uncomfortable harnesses, have cumbersome control mechanisms, and often limit the range of motion of the wrist [21, 50]. Devices such as the M-fingers (Liberating Technologies Inc.) or Biomechanical prosthetic fingers (Naked Prosthetics, Inc.) that actuate distal finger joints require good strength and range of motion in the residual limb. These devices are also limited by the level of amputation (i.e. the biomechanical prosthetic fingers are most successful for loss between the distal and proximal interphalangeal joints). The traumatic nature of partial-hand amputations (93% of all cases) [1], often leaves individuals with limited mobility of the residual fingers, which can compromise the ability to a body-powered device. Studies show that partial-hand amputees perceive themselves to be at a higher disability level than those with unilateral transradial or transhumeral upper-limb amputations [8, 9] and are more likely to reject their prostheses, citing limited function as a key reason [51]. Partial-hand amputees thus require better, more functional prostheses.

Externally powered myoelectric prostheses are a relatively recent treatment option for individuals with partial-hand amputations. These devices provide more grasps, have greater grip force, and do not require a harness system, thus providing better comfort and an improved range of motion [21, 52, 95]. With the commercially available i-limb digits (Touch Bionics Inc.) and Vincentpartial (Vincent Systems GmbH), one to five missing digits can be replaced with individually motorized digits to create multiple grip patterns. A flexible connection between the digits and the battery pack on the forearm allows for wrist movement.

These devices are typically controlled using conventional myoelectric strategies, where an estimate of the surface electromyogram (EMG) amplitude controls the speed of an actuated prosthetic joint [21, 25, 52]. The muscles used for conventional control can be the *intrinsic* muscles of the hand (located in the hand) or the *extrinsic* muscles of the hand (located in the forearm). If the intrinsic hand muscles are intact with little scar tissue or hypersensitivity present, then controlling the prosthesis using intrinsic muscle EMG has the advantage of providing finger control relatively independent of wrist motion [21], although it is challenging to obtain independent control signals from these small, closely spaced muscles.

Alternatively, EMG from the extrinsic hand muscles, which are typically mostly intact in partial-hand amputees, may be used for myoelectric prosthesis control; however, doing so compromises normal wrist movement and thus limits hand function. Since the forearm contains muscles that move both the wrist and hand, the prosthetist must locate myoelectric control sites that do not pick up wrist muscle EMG activity, which can disrupt control [3]. The user must also learn to isolate muscle contractions to control the prosthetic hand without producing significant wrist motion [21]. If this cannot be done, the prosthetist may physically immobilize the wrist. In either case, the ability to freely move the wrist is compromised. Studies show that limiting wrist motion increases the amount of time it takes to perform activities of daily living, increases compensatory movements in the extremity and trunk, and increases perceived disability [12, 13].

Though widely clinically accepted, conventional myoelectric control, using either the intrinsic or extrinsic hand muscles, is limited to the control of one degree of freedom [25, 26], and mode switching— via co-contractions or quick double- or triple-impulse contractions—is required to control additional hand grasps. Thus the user must often control a prosthesis movement with muscles that are not physiologically related to that movement.

Pattern recognition–based myoelectric control of upper-limb prostheses offers a promising alternative for control of powered partial-hand prostheses. Unlike conventional control, EMG information is combined from across multiple muscles, and controlling additional degrees of freedom does not require cumbersome switching mechanisms [15, 34, 35]. Pattern recognition control is thus easier to learn and more intuitive than conventional control [14]. Previous research has shown that pattern recognition techniques, using EMG from the extrinsic hand muscles of transradial amputees, can control multiple hand grasps in real time with high accuracy [53, 54]. Our previous work has demonstrated that pattern recognition control can be used to decode multiple hand grasp patterns in various wrist positions using EMG signals from both the extrinsic and intrinsic hand muscles in offline and virtual settings [58, 75].

The objectives of this study were to determine whether pattern recognition control algorithms can (i) be used to control a physical partial-hand prosthesis, (ii) allow users to choose hand grasp patterns in different wrist positions, and (iii) allow users to maintain grasps when the wrist is in motion. To our knowledge, this is the first study to demonstrate the use of pattern recognition-based myoelectric control of physical partial-hand prostheses. We compared the performance of four control methods: (1) conventional dual-site myoelectric control, pattern recognition control using (2) extrinsic muscle EMG, (3) intrinsic muscle EMG, or (4) a combination of extrinsic and intrinsic muscle EMG.

5.3 METHODS

5.3.1 Experimental Setup

Four partial-hand amputees performed the experiments described in this study (Table 5-1), except that subject 4 did not perform the functional Cubby Task (Task 3) using pattern recognition control or any of the tasks using conventional control methods. Subjects gave written consent, and experiments were performed at the Rehabilitation Institute of Chicago under a protocol approved by the Northwestern University Institutional Review Board. Each subject was

TABLE 5-1: DEMOGRAPHIC INFORMATION OF THE FOUR PARTIAL-HAND SUBJECTS

	Subject 1	Subject 2	Subject 3	Subject 4
Gender	M	M	M	M
Age	47	50	55	73
Time Since Amputation	10 year	1 year	5 years	11 years
Cause of Amputation	Infection	Trauma	Trauma	Trauma
Amputation Side	Right	Right	Left	Right
Myoelectric Prosthesis User?	No	No	Yes	No
Residual Hand				
Residual hand fitted with i-limb digits				

clinically fit with i-limb digits (Touch Bionics Inc.) by a prosthetist. The prosthetic sockets were custom silicone sockets in a thermoplastic frame. Adjustment and fitting were performed by a certified prosthetist trained to work with the Touch bionics i-limb digits. Six bipolar snap dome electrodes (3010426, Motion Control) were embedded in a 3mm thick silicone cuff and evenly spaced around the forearm, 2-3 cm below the antecubital fossa, with an inter-electrode distance of 3 cm (Fig. 5-1). Two bipolar dome electrodes (EL13, Liberating Technologies, Inc.) were embedded in each subject's prosthetic socket. Due to the nature of Subject 4's amputation, one set of self-adhesive bipolar electrodes was used to record EMG information from the thenar compartment to maintain the thumb's range of motion (see Table 5-1). These electrodes were secured to the hand using multiple layers of tegaderm film dressing. The locations of these electrodes was determined by clinical testing performed by a prosthetist. Before placing the electrodes, the skin was cleaned with an alcohol swab.

A biaxial flexible electrogoniometer (SG110, Biometrics Ltd) was used to record wrist flexion, extension, abduction and adduction. The distal end of the biaxial goniometer was attached to the back of the hand, over the third metacarpal, such that it was parallel with the center axis of the hand and its proximal end was attached over the posterior midline of the forearm (Fig. 5-1).

A single axis torsiometer (Q150, Biometrics Ltd) was used to record wrist pronation and supination. The distal end of the torsiometer was attached to the midline of the anterior forearm immediately proximal to the wrist joint and the proximal end of the torsiometer was attached to the forearm, immediately distal to the medial epicondyle of the humerus, in a position that did not interfere with the electrode placements on the forearm (Fig. 5-1).

5.3.2 Signal Conditioning and Acquisition

EMG signals were acquired using a custom built EMG amplifier with a total gain of 4000 (4x Hardware gain, 1000x Software gain) for each channel. All EMG data were digitally sampled

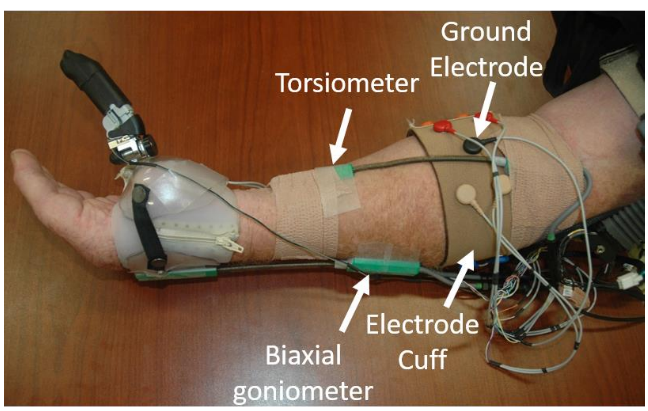


Figure 5-1 Experimental setup showing electrode and goniometer locations on a subject's forearm and hand. Two electrode pairs (not shown) were embedded in the socket to sample intrinsic hand muscle EMG activity and 6 electrode pairs wre inserted in a silicone electrode cuff to sample extrinsic muscle EMG activity.

at 1000 Hz using a custom-built A/D converter based on a TI AD1298 bioamplifier chip and band pass filtered (85-350Hz) with a Type 1, 8^{th} order Chebyshev digital filter. Goniometer data were sampled at 1000Hz with a custom-built 16 bit A/D converter and low pass filtered at 10Hz with a 3^{rd} order Butterworth filter. Feature extraction and classification of EMG signals were performed in real-time using a custom-built Control Algorithms for Prosthetics System (CAPS) embedded system. A 21-vote majority vote was implemented for grasp selection. Once a grasp was selected, all hand grasps were mapped to a hand close position and the grasp mode could not change until the prosthetic hand was fully opened.

5.3.2.1 Prosthesis Control Methods

Four control methods were tested: (1) conventional dual-site myoelectric control and pattern recognition control using (2) extrinsic muscle EMG, (3) intrinsic muscle EMG or a (4) combination of extrinsic and intrinsic muscle EMG.

Conventional Myoelectric Control: EMG data recorded from the intrinsic hand muscles using the socket-mounted electrodes were used for dual-site differential control, in which the difference between the amplitudes of the two channels is used to determine whether the hand opens or closes. The mean absolute values of the two intrinsic muscle EMG signals were calculated from 250ms sliding windows, with a frame increment of 25ms [60]. Appropriate gains and thresholds were applied by a prosthetist to each channel to optimize dual-site control and minimize the effect of wrist motion. A co-contraction trigger was applied, and thresholds were set such that subjects could switch between hand grasp modes, while minimizing accidental mode switching due to wrist motion. Although subjects practiced mode switching and received visual feedback during this time via a computer screen, they were not required to mode switch while performing conventional control during tasks. This was done to allow comparison of task performance across all subjects, because two of the subjects (2 and 3) had thumb-only amputations and could not receive visual feedback information about their prosthetic hand grasp mode because there was no difference in the function of the prosthetic thumb in the two modes. The co-contraction trigger was applied solely to determine if any accidental mode switches would occur as a result of wrist movement.

Pattern Recognition Control: Subjects controlled the prosthesis using EMG from three different sets of muscles: (a) extrinsic muscles, (b) intrinsic muscles, and (c) a combination of extrinsic and intrinsic muscles. Subjects trained the pattern recognition system to recognize four hand motion classes (chuck grasp, power grasp, hand open and no movement). The pattern recognition system was trained in three separate ways to perform three real-time tasks.

Training for Task 1: Subjects were visually prompted to perform power and chuck grasp, hand open and no movement in a neutral wrist position with the elbow at about 90^{o}, while seated. Each hand posture was held for 3 seconds and repeated 4 times.

Training for Task 2: Subjects performed power and chuck grasp, hand open and no movement while seated. For each hand posture, subjects were instructed to begin by performing the hand posture in a neutral wrist position, then to maintain the grasp while moving the wrist at a medium, comfortable velocity. Subjects were not given specific instructions as to how to move the wrist but were asked to fully explore all degrees of freedom of the wrist. Each hand posture was held for 3 seconds and repeated 4 times. For the no movement class, subjects were instructed to move their wrist freely at a medium, comfortable velocity while relaxing their hand.

Figure 5-2: Cubby Task.

Subjects practiced picking up the items from the cubby locations shown in the left image. During testing, subjects picked up items from the cubby lcoations shown at right, placing the items in a bin on their prosthesis side. For training pattern recognition control systems, data were collected while the subject held their arm at the level of the bottom, middle, and top cubbies.

Training for Task 3: Subjects performed power and chuck grasp, hand open and no movement while standing. For each hand posture, subjects were instructed to freely move their wrist at a medium, comfortable velocity while maintaining the hand posture in three arm positions. These positions were at the levels of the 1st, 3rd and 5th rows of the cubby system used in Task 3 (Fig. 5-2). Each hand posture was held for 3 seconds and performed 2 times in each arm position. For the no movement class, subjects were instructed to freely move their arm and wrist around their workspace while relaxing the hand. This was repeated two times and each repetition lasted 3 seconds.

The pattern recognition system segmented data into 250ms analysis windows with a 25ms increment. A combination of four EMG time-domain features (mean absolute value, number of zero-crossings, waveform length, and number of slope sign changes) and six coefficients of a 6^{th} order autoregressive model were extracted from each analysis window. A linear discriminant analysis classifier (LDA) was used to train the pattern recognition system. The system was trained using data from the six forearm electrodes (extrinsic muscle EMG), two hand electrodes (intrinsic muscle EMG), or a combination of all hand and forearm electrodes (extrinsic and intrinsic muscle EMG). After the classifier was trained, it was used to control a physical prosthesis in real-time.

5.3.3 Procedure

Subjects were asked to complete three tasks. For Task 1, subjects performed hand open, chuck grasp and power grasp with their prosthesis, with the wrist in a neutral position. For Task 2, subjects performed chuck and power grasps while moving their wrists. For Task 3, subjects performed a custom-designed “Cubby Task” where they used power and chuck grasps to grasp two objects (a tennis ball and a small square block).

5.3.3.1 Task 1: Controlling the prosthesis in a neutral wrist position

The object of this task was to quantify how well subjects could operate the prosthesis when the wrist was in a neutral position. Beginning with the prosthesis fully open, subjects performed chuck or power grasp and fully closed the prosthesis with the wrist in a neutral position. With the prosthesis fully closed, subjects were also asked to fully open their prosthesis. For subjects 2, 3, and 4 who had residual fingers, the closed position was when the prosthesis was in contact with their residual fingers while the fingers were relaxed. Each hand posture was performed 3 times for each control method and the order of hand postures was randomized.

5.3.3.2 Task 2: Controlling the prosthesis in different wrist positions

The objective of this task was to quantify how often the prosthesis opened unintentionally when the wrist was in a different position or while the wrist was moving, as this would prevent an individual from being able to successfully grasp an object in different wrist positions or cause them to drop an object while moving their wrist. Beginning with the prosthesis fully open, subjects were asked to select either chuck or power grasp and fully close the prosthesis with the wrist in one of four positions: flexed, extended, supinated, and pronated. Once the prosthesis was closed, subjects were instructed to relax their hand and move their wrist in the following ways:

1. For flexed wrist: move wrist to a maximum comfortable extended position and return to a flexed position.
2. For extended wrist: move wrist to a maximum comfortable flexed position and return to an extended position.

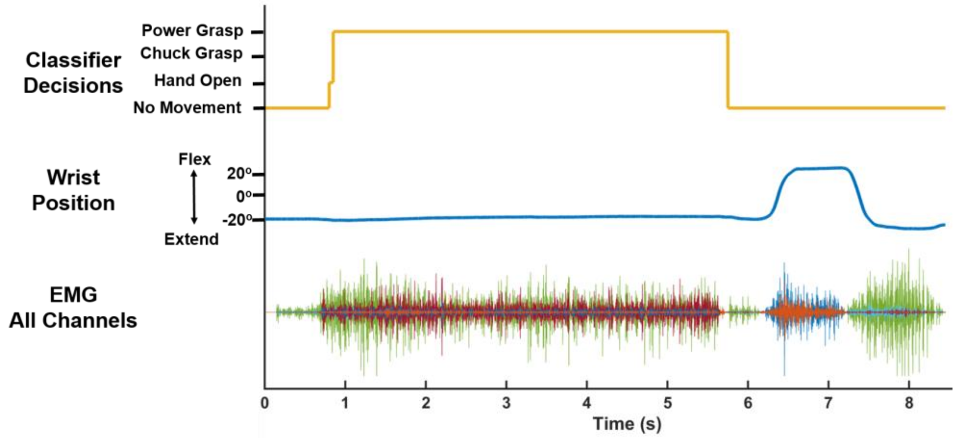


Figure 5-3: Example of a real-time Task 2.

Subject 1 was asked to perform power grasp in an extended wrist position. Once the prosthesis was fully closed, he was instructed to relax his hand, then flex and extend his wrist without opening the prosthesis. The classifier was trained with EMG data from extrinsic and intrinsic muscles.

3. For supinated wrist: rotate forearm to a fully pronated position and return to a supinated position.

4. For pronated wrist: rotate forearm to a fully supinated position and return to a pronated position.

An example of the data recorded during this task is shown in Fig. 5-3. If the hand fully opened while performing the task, subjects were asked to return to their original wrist position and reattempt the task. Subjects were given 3 attempts to complete each movement. The order of wrist movements and hand grasps were randomized.

5.3.3.3 Task 3: Controlling the Prosthesis during a Functional Test with full wrist movement

A number of tests are used to assess hand function, such as the Jebson-Taylor Test of Hand Function, the Box and Block Test, and the Southampton Hand Assessment Procedure test [96]. However, these tests do not require an individual to move their wrist to complete each task

[13]. We designed a Cubby Task, which required subjects to pick up items located in set horizontal and vertical positions within a cubby system, in order to compel subjects to move their wrist while performing the task.

The cubby system was set up on an adjustable table, 7 inches from the edge of the table. The items (either blocks or tennis balls) were placed in the appropriate cubbies (Fig. 2), approximately 2 inches from the front edge. The table height was adjusted so that the top item was at eye level. A container was placed on the prosthesis side to the left or right of the cubby system, aligned with the edge of the table. A timer was placed in front of the center cubbies.

Prosthesis Control Training: Subjects practiced picking up the blocks and tennis balls from the four cubbies in Fig. 5-2 (left). They were given up to 10 minutes of practice for each control method and were instructed to use a chuck grasp to pick up the blocks and a power grasp for the tennis balls.

Testing: Subjects started the timer, picked up an item from a cubby (Fig. 5-2, right), dropped the item into the bin, and stopped the timer. Subjects stood aligned with the center cubbies and had to reach each item with only their arm (i.e. they could not step to the left or right), to promote coordinated movements of the arm joints. Items had to be picked up and not swiped out of the cubby. Subjects had three chances to complete each cubby task. Each subject had 10 seconds to successfully select a grasp and grasp the object. If unsuccessful within this time period, the subject had to return their arm to their starting position and re-attempt the task without stopping the timer. An object dropped on the floor or accidentally dropped before the subject reached the bin constituted a failed attempt; the item was immediately replaced by the experimenter, and the subject then had to reattempt the task without stopping the timer.

Real-time performance using the three pattern recognition control methods were evaluated on the same day, and conventional myoelectric control testing occurred on a separate day. Subjects were blind to which pattern recognition control method was being used (which was randomized) and were instructed to perform the tasks in the same manner. Subjects 1, 2, and 4 were naïve to conventional myoelectric control, whereas subjects 2, 3, and 4 were naïve to pattern recognition control. All subjects were trained and then practiced using conventional control or pattern recognition control on separate days. The practice time varied for each subject, depending on their previous experience with each control method *Data Analysis*

5.3.4 Data Analysis

Offline analyses were performed using MATLAB 2015a software (The Mathworks, Natick, MA, USA). Data were segmented into 250ms windows with a 25ms frame increment [60]. Classification error was used to assess offline performance of the pattern recognition system for all three tasks and each muscle set using four-fold cross-validation. Given that subjects 2 and 3 had no visual feedback from the prosthesis, the chuck and power grasp classes were combined to form one 'hand close' class to allow for comparison across all subjects. Functional error was used to assess real-time performance for Tasks 1 and 2, and was defined either as the percentage of hand-open decisions made by the classifier when the subject was instructed to perform a chuck or power grasp, or the percentage of hand-close decisions made when the subject was instructed to open the prosthetic hand. Completion time and completion rate were used to

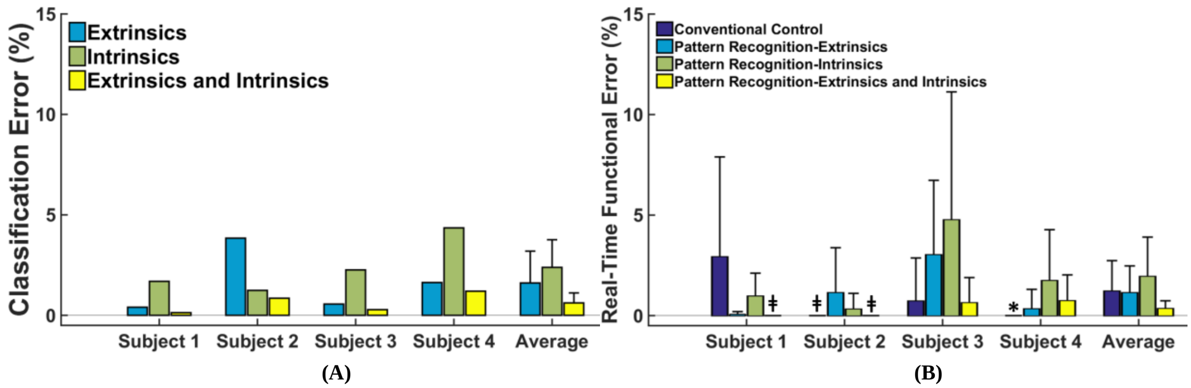


Figure 5-4: Offline and real-time functional error of hand grasps with wrist in a neutral position (Task 1).

(A) Offline classification error for three hand motion classes performed in a neutral wrist position. (B) Real-time functional error. The pattern recognition system was trained with 4 hand motion classes (hand open, chuck and power grasps, and no motion), and a functional error occurs when a hand open decision is made during hand closed tasks (chuck or power grasp) or when a hand close decision is made during hand open tasks. Error bars for individual subjects represent standard deviation across all trials. Error bars for the average represent standard deviation across subjects. ǂ: Error is 0%. *: No data available for conventional control for Subject 4.

assess real-time performance for Task 3. Finally, subjects were given a questionnaire for a subjective assessment of conventional and pattern recognition control.

5.4 RESULTS

5.4.1 Controlling the prosthesis in a neutral wrist position

Consistent with our previous findings [75], a pattern recognition system trained with EMG data from extrinsic and intrinsic muscles had better offline performance than one trained with either extrinsic or intrinsic muscle EMG data alone (Fig. 5-4). On average, a system trained with extrinsic muscle EMG alone performed better than one trained with intrinsic muscle EMG data alone and this observation was consistent for subjects 1, 3 and 4. These trends in offline performance were directly reflected in the real-time functional errors for all subjects. On average, real-time error with conventional control was equivalent to real-time error with pattern recognition control using extrinsic muscle EMG.

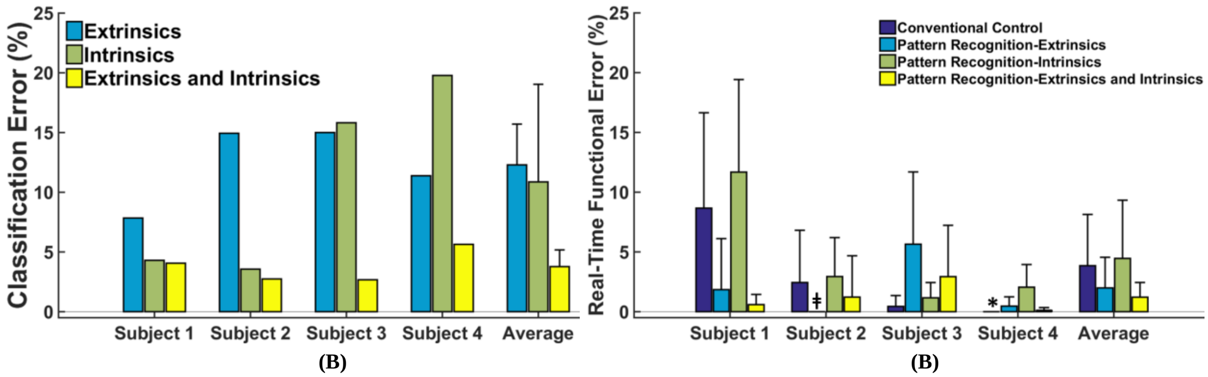


Figure 5-5: Offline and real-time functional error of hand grasps performed with different static and dynamic wrist positions (Task 2).

(A) Offline classification error for three hand motion classes performed while the wrist was dynamically moving. (B) Real-time functional error. The pattern recognition system was trained with 4 hand motion classes (hand open, chuck and power grasps, and no motion), and a functional error occurred when a hand open decision was made by the classifier. Error bars for individual subjects represent standard deviation across all trials. Error bars for the average represent standard deviation across subjects. **ǂ**: Error is 0%. *****: No data available for conventional control for Subject 4.

5.4.2 Controlling the prosthesis in different wrist positions

As with prosthesis control in a neutral wrist position, a system trained with EMG data from the extrinsic and intrinsic muscles performed better in offline studies than one trained with either extrinsic or intrinsic muscle EMG data alone (Fig. 5-5). This observation also held for real-time functional error. However, there was more variability in the offline performance of a system trained with either intrinsic or extrinsic muscle EMG data alone. For subjects 1 and 2, the classification error of a system trained with extrinsic muscle EMG data alone was higher than one trained with intrinsic muscle EMG data, though the opposite was true for subject 4. For subject 3, classification error of systems trained with only extrinsic or intrinsic muscle EMG data were comparable. In contrast to results from the neutral wrist position, the real-time performance of a system trained with extrinsic or intrinsic muscle EMG data was not consistent with the offline performance. On average, the offline performance of both systems was equivalent, but real-time error was lower for a system trained with intrinsic muscle EMG than for one trained with extrinsic muscle EMG

5.4.3 Controlling the prosthesis during a functional test with unrestricted wrist movement

Subjects 1,2 and 3 completed all tasks using pattern recognition control and at least 9/10 tasks using conventional control (Fig. 5-6A). As expected, subjects adequately used three degrees of wrist movement to complete the Cubby Task (Fig. 5-6B). As for Task 2, a classifier trained with EMG data from both extrinsic and intrinsic muscles performed the best, while across-subject performance variability was observed in systems trained with either extrinsic or intrinsic muscle EMG data alone. On average, the performance of pattern recognition systems trained with extrinsic or intrinsic muscle EMG data alone were comparable. Unexpectedly, average

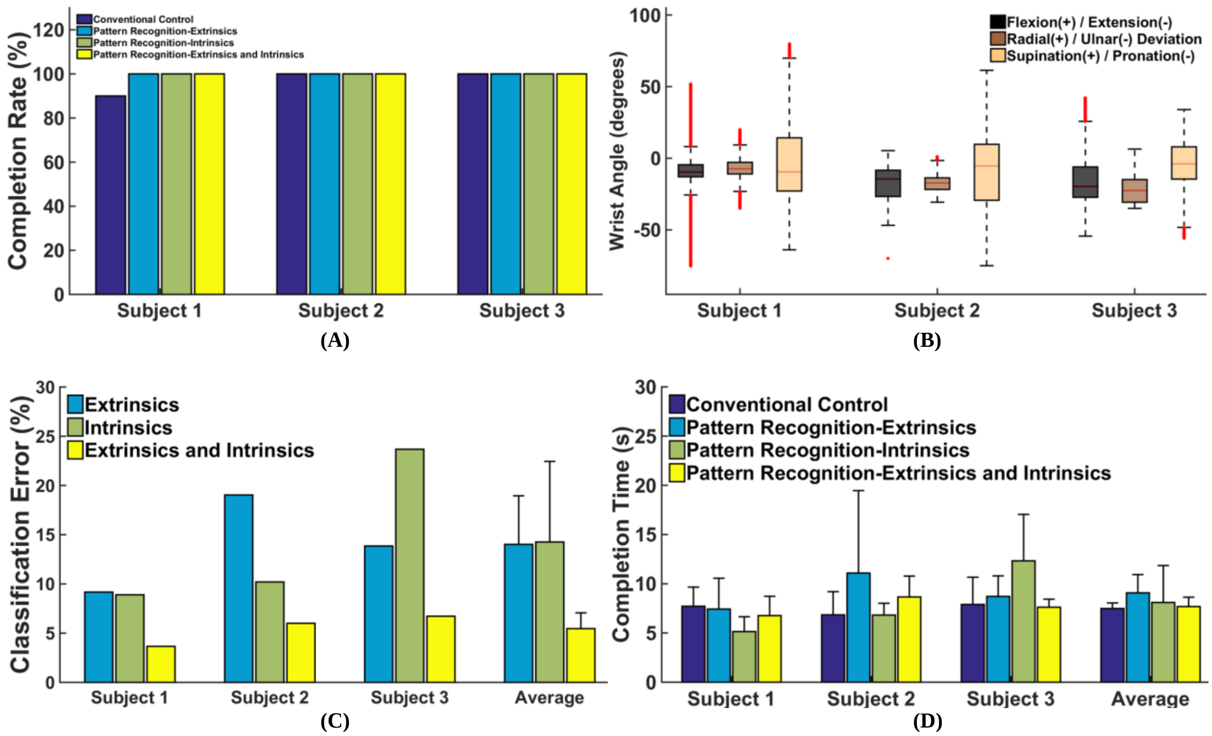


Figure 5-6: Outcome measures of Functional Cubby Task (Task 3).

(A) Completion Rate. (B) Measured wrist angles recorded across all cubby tasks using pattern recognition control. Boxes represent median and inter-quartile ranges. Red points represent outliers. (C) Offline classification error for three hand motion classes performed with the wrist dynamically moving and at 3 arm positions. (D) Completion time averaged across all cubby tasks. The classifier was trained with 4 hand motion classes (hand open, chuck and power grasps, and no motion), and a functional error occurred when a hand open decision was made by the classifier. Error bars for individual subjects represents standard deviation across all trials. Error bars for 'Average' represent standard deviation across subjects.

completion time was not much improved for a system trained with combined extrinsic and intrinsic muscle EMG data over systems trained with extrinsic or intrinsic muscle EMG data alone. Overall, task completion times were comparable across all pattern recognition control methods and conventional control.

When asked if they would like to continue using conventional or pattern recognition control at home, all subjects responded favorably with the highest rating (Table 5-2) but when asked to choose between the control methods, subjects 2 and 3 chose conventional control and subject 1 chose pattern recognition control. Subject 1 stated that he preferred pattern recognition control because "it was easier to understand and get used to the manner in which to change grips".

5.5 DISCUSSION

In this study we demonstrated that pattern recognition-based algorithms can be used for the real-time control of externally powered partial-hand prostheses. We showed that for functional tasks, pattern recognition control using extrinsic or intrinsic muscle EMG data alone, or a combination of extrinsic and intrinsic muscle EMG data performed just as well as conventional myoelectric control.

Clinically, use of intrinsic muscle EMG for conventional myoelectric control is preferred over using extrinsic muscle EMG, as the former does not couple wrist motion to finger motion and is less susceptible to unintended movements of the prosthesis due to wrist motion. In cases

TABLE 5-2: SUBJECT RESPONSES TO SURVEY QUESTIONS

	Subject 1		Subject 2		Subject 3		Subject 4	
	CC	PR	CC	PR	CC	PR	CC	PR
The prosthetic hand responded as I expected	3	4	5	5	5	4	N.A.	5
It was easy to make the prosthetic hand move when I wanted	4	3	5	5	5	3	N.A.	5
It was easy to correctly select the hand grasps I wanted to make	2	4	5	5	4	4	N.A.	4
I felt fatigued after using the prosthetic hand	2	2	1	1	1	3	N.A.	2
There were a lot of unintended movements of the prosthetic hand	4	3	1	1	1	4	N.A.	3
I was frustrated using the prosthetic hand	2	3	1	1	1	2	N.A.	2
I would like to continue to use this control at home	5	5	5	5	5	5	N.A.	5
Which system do you prefer?		PR	CC		CC		N.A.	N.A.

*CC: Conventional Control, PR: Pattern Recognition, NA: Not Applicable
Survey responses on the scale of 1-5, 1: Strong disagree, 5: Strongly agree.

where the intrinsic muscles are severely damaged or scarred and thus rendered unusable for EMG control, options for conventional control include either extrinsic muscle EMG, with associated limits on wrist function, or force sensitive resistors that couple wrist motion to finger motion. Here, we demonstrate that for tasks that require coordinated hand, wrist and arm movements, partial-hand subjects can successfully complete functional tasks with pattern-recognition control using extrinsic hand muscle EMG data, without any restriction on residual wrist motion. Thus, the absence of a suitable intrinsic muscle EMG site should not preclude a partial-hand amputee from using a myoelectric prosthesis. Certainly, if intrinsic muscle EMG is available, we would recommend using both extrinsic and intrinsic muscle EMG for pattern recognition control. For our Cubby Task, we found that a system trained with extrinsic and intrinsic muscle EMG data did not result in much improvement in average completion time over one trained with extrinsic or intrinsic muscle EMG data alone. However, this finding may be due to the nature of the task, and further studies using more complicated activities of daily living may be needed to further differentiate performance of the three pattern recognition control methods.

Even though we found that, on average, the performance of conventional control and all pattern recognition control methods were comparable, it is important to note that the pattern recognition systems were trained with four hand motion classes (compared to hand open/close only for conventional control) and we did not require mode switching for conventional control. This is significant in that it demonstrates that pattern recognition performance is comparable to conventional control at its best (i.e., a simple open/close signal). In the first independent, clinical case series implementing pattern recognition in 14 upper–limb amputees with more proximal amputations, Uellendahl *et al.* found that pattern recognition is equal or superior to conventional myoelectric control [14]. If mode switching were required in our study, it is likely that pattern recognition control performance would have surpassed that of conventional control.

In our previous studies [75], pattern recognition systems were trained in a laboratory setting with a hybrid wrist motion training paradigm, where subjects performed a grasp in one of 6 static wrist positions and then moved the wrist along one degree of freedom (e.g., perform grasp in wrist extension, then flex and extend the wrist). Subjects were given visual prompts as to what wrist movements to make. However, such a training paradigm may be challenging for a prosthesis user to initiate in a home setting. Preferably, users would be able to perform prosthesis-guided training, which allows individuals to self-initiate calibration by following along with their prosthesis as it moves though a sequence of hand movements [97]. In this study, subjects trained the system by simply performing hand grasps while freely moving the wrist. This training paradigm can potentially be self-initiated in a home setting using prosthesis-guided training for performing the hand grasps.

<u>Limitations and Future Studies</u>

One major limitation of this study is the small sample size and the limited number of grasps tested. With a larger sample size of individuals with varying levels of amputations involving multiple fingers, we would be able to test the control of more hand grasps. Future studies would also incorporate required mode switching with conventional control, which would allow for a more comprehensive and realistic comparison between conventional and pattern recognition control schemes. We expect that subjects with fewer remaining fingers would be more likely to choose pattern recognition control over conventional control, though further studies are needed to determine the point at which pattern recognition is preferred. Further studies with more complex activities of daily of living that require wrist movement are needed, as such tasks may demonstrate greater differences in the performance of the different control systems.

5.6 CONCLUSION

In order to use pattern recognition techniques to control partial-hand prostheses, the control system must be robust enough to main good control when the user moves their wrist. In this research study, we demonstrated for the first time that pattern recognition methods can be used to control an externally powered myoelectric prosthesis during tasks that require coordinated movements of the hand, wrist and arm. We demonstrate that EMG from both extrinsic and intrinsic hand muscles can be successfully used as control signals, resulting in comparable performance to conventional myoelectric control.

Chapter 6 Discussion

6.1 Summary of Main Findings

6.1.1 Demonstrating the feasibility of surface EMG from the extrinsic and intrinsic hand muscles for the control of a prosthetic hand in variable wrist positions.

Chapter 2 found that intrinsic muscle EMG data provides information that complements that of the extrinsic muscles for distinguishing between hand grasps and individual finger motions. It follows from the anatomy of the forearm that the extrinsic muscles provided more information about individual finger motions and the intrinsic muscles provided information that allowed better discrimination between hand grasps than the extrinsic muscles for non-amputees [62-65]. Non-amputees generally performed better than amputees when either extrinsic, intrinsic or a combination of extrinsic and intrinsic muscle EMG data was used to control the prosthesis which is not unexpected given that non-amputee subjects have additional sensory feedback which would promote the generation of more consistent forces for each hand grasp.

For non-amputees, control using intrinsic muscle EMG data was better than with extrinsic muscle EMG data. Conversely for amputees, control using intrinsic muscle EMG data was *worse* than with extrinsic muscle EMG data. Though in Chapter 2, twelve intrinsic muscle EMG channels were collected for non-amputees and only 4 intrinsic muscle EMG channels were collected for amputees, these findings remained consistent in chapters 3 and 4 where the same number of intrinsic muscle EMG channels were used for non-amputee and amputee subjects. Prosthesis control between amputee and non-amputee subjects were much more comparable for extrinsic muscle EMG data then they were for intrinsic muscle EMG data. Also, control using intrinsic muscle EMG data was also more variable across amputee subjects than the extrinsic muscle EMG data. These findings were generally consistent across the results presented in Chapters 3-5. These findings can be attributed to the nature of partial-hand amputations. The degree to which the intrinsic muscles remain intact varies significantly from subject to subject and may explain the higher variability in performance across amputee subjects when controlling the prosthesis with intrinsic muscle EMG data. The extrinsic muscles which remain largely intact (albeit with different distal attachment sites in amputees) provide EMG data that is not only more consistent across amputee subjects, but also between amputee and non-amputee subjects. Ultimately, combining data from both groups of muscles results in the best performance but when control using intrinsic muscle EMG data is not feasible, extrinsic muscle EMG data provides good hand prosthesis control when the wrist is in one position.

6.1.2 Evaluating the effect of wrist motion on pattern recognition control

To maximize hand function, a control scheme for partial-hand prostheses must maintain good control when the wrist is in different static positions or when the wrist is moving. The findings in Chapter 2 show that prosthesis control using data collected form one wrist position does not generalize well to other wrist positions. It also found that the detrimental effects of wrist motion was worse for extrinsic muscle EMG data than for intrinsic muscle EMG data. Chapter 2 proposed training a pattern recognition system with EMG data collected from multiple wrist positions in order to improve control. This method of multi-position training has been used in other studies to improve classification of hand and wrist motion classes across different arm positions [55, 56]. Though this significantly improved performance, the proposed solution can be burdensome for the user as it requires additional training that increases proportionally with the number of wrist positions and hand grasp patterns and can thus be time-consuming and fatiguing. The results of Chapters 3 and 4 show that with the addition of information from multiple wrist positions, improvement in performance plateaus, thus suggesting that only a few of the wrist positions are necessary. Moreover, the findings in Chapter 4 suggest that as long as data from enough wrist positions are included, the identity of the wrist positions is not vital.

In another approach to further reduce the number of wrist positions needed for training, Chapter 4 demonstrated that one can feasibly use non-linear regression to estimate the change in EMG features as a function of wrist position to generate a simulated data set that significantly improves performance compared EMG data collected from one wrist position. This approach is similar to those currently being pursued for the simultaneous control of the hand and wrist for transradial amputees. These methods aim to predict EMG features of 2 degree of freedom motions (i.e. of the wrist and hand or multiple fingers) from the EMG features of 1 degree of freedom motions using a linear [98] or non-linear [99]combination of the related single degree of freedom movements. The implementation of using regression methods for estimating EMG features requires that the user make consistent contractions with each combined hand and wrist movements. Studies show a significant difference between novice and experienced pattern recognition control users [100] and that with training, users are able to generate contractions that are more consistent and less variable [92, 101]. Thus is feasible that the mapping between EMG features and wrist position will be stable if subjects are trained over multiple days.

Finally, the findings of Chapter 5 suggest that instead of training in various static wrist positions, a user can perform hand grasps while freely moving the wrist as this would be easier for a user to implement in a home setting. Certainly, pattern recognition performance is optimal when it is tested or used in the same manner in which it is trained (i.e. training and testing with data from static wrist positions performs better than training with data from dynamic wrist motions and testing with data from static wrist positions [58]). Perhaps a better solution would be to combine these results by collecting data while the wrist is dynamically moving and using the model developed in Chapter 5 to simulate data from different static positions.

6.1.3 Challenging established norms in myoelectric control of upper limb prostheses

The combination of LDA classifier and TDAR features commonly used in literature has become the standard for myoelectric control of upper-limb prostheses. Though Chapter 3 found that the LDA performed just as well as other classifiers when using EMG data as inputs, the results of Chapter 4 demonstrate that the LDA classifier is not the most suitable option for combining EMG and mechanical data. Studies that combine mechanical sensor and EMG data for mitigating the arm position effect have relied on the LDA classifier to combine information from multiple sources but results suggest that there is value in utilizing other non-linear classifiers.

Chapter 3 found that TDAR features may not be the ideal feature set for pattern recognition control of partial-hand prostheses. Typically, TDAR features are extracted from all EMG channels. For partial-hand prosthesis control, an ideal feature should be able to discriminate between different hand grasp patterns regardless of the wrist position. A feature such as the MAV may have good discriminatory properties in the neutral wrist position but may not be preferable to another feature that may not perform as well in one wrist position, but performs well but across all wrist positions. Secondly, a feature that results in excellent classification performance across different wrist positions in one channel may be the worst performing feature in another channel as EMG from one channel may less affected by crosstalk from activation of the wrist muscles than other channels. Chapter 3 suggests that pre-selecting the optimal features from each channel may be a better approach to this challenge. Also, this process may be automated so that prosthetists do not have to physically locate myosites that provide EMG signals without cross talk from the wrist muscles as is done when using the extrinsic muscles for conventional myoelectric control. Third, by evaluating the extrinsic and intrinsic muscles separately, Chapter 3 found that the ideal features in each of the muscles sets are quite different. For example, though the commonly used TD features are the least important for the extrinsic muscles, they are among the most often selected for the intrinsic muscles. Finally, though studies that evaluate the robustness of features to disturbances in limb position, electrode shift, often evaluate each feature individually, the results of Chapter 3 indicate the features need to be evaluated in the context of other features. Just as the intrinsic muscles provide information that complements the extrinsic muscle EMG data, combining two features that are not as robust to the effect of wrist motion may be more important than combining two features that are most robust to the effect of wrist motion but do not provide mutually exclusive information about the user’s intent. Thus, an optimal feature is one that both allows for discrimination between hand postures across multiple wrist positions as well as providing information that is distinct from other features.

6.2 Limitations and Future Directions

Though the findings in Chapters 3 and 4 are quite promising, the analyses were completed offline. The relationship between offline and real-time control has not yet been established. Some previous research has demonstrated a minimal correlation between offline performance and usability with a virtual task [85, 86]; however other studies have shown significant correlation between offline classification error and real-time control [60, 87]. The implementation of a control system that uses both EMG data and wrist kinematic information using a neural network is a foreseeable future study whose results may have significant impact on partial-hand prosthesis control training paradigms.

The findings of Chapter 4 are also limited in that the training and testing data sets are from the same day and experimental session. Though pattern recognition control deteriorates when classifiers are trained and tested with data collected from different sessions, studies show that with training and experience, users make more consistent and repeatable contractions [100, 101] and between-day performance improves and approaches within-day performance with practice [92]. It is thus possible that the mapping between EMG features and wrist position found in Chapter 4 will be stable if subjects are trained over multiple days. Further multi-day experiments are needed to determine if the neural network maintains its performance across sessions.

There are certain challenges present when using physical partial-hand prostheses that are absent when performing virtual tasks. It is possible that a heavy load applied to the prosthesis may destabilize intrinsic muscle EMG electrodes and render them too unstable to allow for good control, in which case a control strategy that uses extrinsic muscle EMG and employs a method that mitigates the effect of wrist motion (such as a hybrid wrist motion training paradigm or regression based modeling of EMG features from other positions) may outperform all other control methods. Another factor that would affect the reliability of intrinsic or extrinsic muscle EMG data that was not explored in this dissertation is the effect that loading the prosthesis with a heaving object would have on muscle activity itself (as opposed to electrode stability). In Chapter 4, the relationship between wrist position and EMG features was determined while there was no load applied to the wrist and it is not clear whether the same relationships would hold true when a load *is* applied to the wrist. For real time control, one could bypass potential misclassifications due to this issue by “locking” the prosthesis in a grasp once an item is grasped.

The purpose of the study presented in Chapter 5 was to determine the feasibility of using pattern recognition methods to control a partial-hand prosthesis in tasks that require wrist motion. Though promising, further studies with (1) more subjects, (2) more complicated activities of daily living that require manipulating objects of varying weights, and (3) activities that require the use of more grasps are necessary for a more comprehensive evaluation of conventional and pattern recognition-based of partial-hand prostheses. Such studies that require more complex functions may demonstrate greater differences in the performance of the control methods.

Chapter 7 Conclusion

The overall objective of this dissertation was to evaluate the effect of wrist motion on myoelectric pattern recognition of functional hand grasps and to develop strategies that accommodate these effects and improve hand control. The studies described in this dissertation:

- demonstrated for the first time, the feasibility of using pattern recognition-based methods to control a partial-hand prosthesis for functional tasks using EMG from the extrinsic or intrinsic hand muscles
- challenged established norms in myoelectric control of upper limb prostheses by providing evidence that the commonly used features and classification schemes may be situation dependent and are not optimal for the control of a partial-hand prostheses
- elucidated the effect of wrist motion on prosthesis control and proposed several effective methods for mitigating this effect.

The benefits of pattern-recognition based control of upper limb prosthesis, described in this work, have recently been made clinically available to individuals with proximal amputations. This study is an important first step for the eventual application of this control method for clinical use by partial hand amputees, whose prosthetic options have historically lagged behind their counterparts with more proximal amputations.

Chapter 8 References

[1] K. Ziegler-Graham, E. J. MacKenzie, P. L. Ephraim, T. G. Travison, and R. Brookmeyer, "Estimating the prevalence of limb loss in the United States: 2005 to 2050," *Archives of Physical Medicine and Rehabilitation,* vol. 89, pp. 422-429, Mar 2008.

[2] T. R. Dillingham, L. E. Pezzin, and E. J. MacKenzie, "Limb amputation and limb deficiency: epidemiology and recent trends in the United States," *South Med J,* vol. 95, pp. 875-83, Aug 2002.

[3] C. Lake, "Partial Hand Amputation: Prosthetic Management," in *Atlas of Amputations and Limb Deficiencies: Surgical, Prosthetic, and Rehabilitation Principles*, D. G. Smith, J. W. Michael, and J. H. Bowker, Eds., 3 ed Rosemont, IL: American Academy of Orthopaedic Surgeons, 2004, pp. 209-217.

[4] J. E. Uellendahl and E. N. Uellendahl, "Experience Fitting Partial Hand Prostheses with Externally Powered Fingers," in *Grasping the Future: Advances in Powered Upper Limb Prosthetics*, V. P. Castelli and M. Troncossi, Eds., ed: Bentham Science Publishers, 2012, pp. 15-27.

[5] H. Burger, T. Maver, and C. Marincek, "Partial hand amputation and work," *Disabil Rehabil,* vol. 29, pp. 1317-21, Sep 15 2007.

[6] J. S. Hebert and H. Burger, "Return to Work Following Major Limb Loss," in *Handbook of Return to Work: From Research to Practice*, I. Z. Schultz and R. J. Gatchel, Eds., ed New York: Springer 2016, pp. 505-518.

[7] P. Sagiv, S. Shabat, M. Mann, H. Ashur, and M. Nyska, "Rehabilitation process and functional results of patients with amputated fingers," *Plastic and reconstructive surgery,* vol. 110, pp. 497-503; discussion 504-5, 2002.

[8] J. Davidson, "A comparison of upper limb amputees and patients with upper limb injuries using the Disability of the Arm, Shoulder and Hand (DASH)," *Disabil Rehabil,* vol. 26, pp. 917-23, Jul 22-Aug 5 2004.

[9] L. V. McFarland, S. L. Hubbard Winkler, A. W. Heinemann, M. Jones, and A. Esquenazi, "Unilateral upper-limb loss: satisfaction and prosthetic-device use in veterans and servicemembers from Vietnam and OIF/OEF conflicts," *Journal of Rehabilitation Research and Development,* vol. 47, pp. 299-316, 2010.

[10] Z. Wedderburn, R. R. Caldwell, E. R. Sanderson, and M. Olive, "A wrist-powered prosthesis for the partial hand," *Journal of the Association of Children's Prosthetic-Orthotic Clinics,* vol. 21, pp. 42-5, 1986.

[11] M. Lang, "Challenges and Solutions in Control Systems for Electrically Powered Articulating Digits," in *MyoElectric Controls/Powered Prosthetics Symposium*, Frederickton, New Brunswick, Canada, 2011.

[12] F. Montagnani, M. Controzzi, and C. Cipriani, "Is it Finger or Wrist Dexterity That is Missing in Current Hand Prostheses?," *IEEE Trans Neural Syst Rehabil Eng,* vol. 23, pp. 600-9, Jul 2015.

[13] B. D. Adams, N. M. Grosland, D. M. Murphy, and M. McCullough, "Impact of impaired wrist motion on hand and upper-extremity performance(1)," *J Hand Surg Am,* vol. 28, pp. 898-903, Nov 2003.

[14] J. Uellendahl, J. Tyler, and K. Hung, "A Case Series Study of Pattern Recognition for Upper-Limb Prosthesis Control," in *American Academy of Orthotists and Prosthetists 42nd Academy Annual Meeting and Scientific Symposium*, Orlando, Florida, 2016.

[15] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield*, et al.*, "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," *JAMA,* vol. 301, pp. 619-28, Feb 11 2009.

[16] C. Lake, "Experience With Electric Prostheses for the Partial Hand Presentation: An Eight-Year Retrospective," *Journal of Prosthetics and Orthotics,* vol. 21, pp. 125-130, 2009.

[17] I. Imbinto, C. Peccia, M. Controzzi, A. Cutti, and C. Cipriani, "Treatment of the Partial Hand Amputation: An Engineering Perspective," *IEEE Reviews in Biomedical Engineering,* 2016.

[18] J. Pillet, "Partial-hand amputation-aesthetic restoration," *Atlas of limb prosthetics: surgical, prosthetic and rehabilitation principles. CV Mosby, St. Louis,* pp. 227-235, 1992.

[19] J. Michael, "Partial-hand amputation: prosthetic and orthotic management," *Atlas of limb prosthetics: Surgical, prosthetic and rehabilitation principles. St. Louis: CV Mosby,* pp. 217-26, 1992.

[20] P. A. Parker and R. N. Scott, "Myoelectric control of prostheses," *Critical Reviews in Biomedical Engineering,* vol. 13, pp. 283-310, 1986.

[21] J. E. Uellendahl and E. N. Uellendahl, "Experience Fitting Partial Hand Prostheses with Externally Powered Fingers," ed: Bentham Science, 2012, pp. 15-27.

[22] R. F. Weir and E. C. Grahn, "Development of externally-powered prostheses for persons with partial hand amputations," *Proceedings of the 22nd Annual International Conference of the Ieee Engineering in Medicine and Biology Society, Vols 1-4,* vol. 22, pp. 427-430, 2000.

[23] S. Schulz, "Introducing a new multiarticulating myoelectric hand system," in *Proceedings of the 13th World Congress of the International Society of Prosthetics and Orthotics*, 2010, pp. 10-15.

[24] T. Williams, "Control of powered upper extremity prostheses," *Functional restoration of adults and children with upper extremity amputation,* pp. 207-224, 2004.

[25] R. Merletti and P. Parker, *Electromyography: Physiology, Engineering and Noninvasive Applications.* . Hoboken, USA: IEEE Press and John Wiley & Sons, 2004.

[26] M. A. Oskoei and H. S. Hu, "Myoelectric control systems-A survey," *Biomedical Signal Processing and Control,* vol. 2, pp. 275-294, Oct 2007.

[27] B. A. Lock, A. M. Simon, K. Stubblefield, and L. Hargrove, "Prosthesis-Guided Training for Practical Use of Pattern Recognition Control of Prostheses," in *Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton*, New Brunswick, Canada, 2011, p. 4.

[28] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med Eng Phys,* vol. 21, pp. 431-8, Jul-Sep 1999.

[29] K. Englehart, B. Hudgins, and P. A. Parker, "A wavelet-based continuous classification scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 48, pp. 302-11, Mar 2001.

[30] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 50, pp. 848-54, Jul 2003.

[31] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered limb prostheses," *J Electromyogr Kinesiol,* vol. 16, pp. 541-8, Dec 2006.

[32] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Trans Biomed Eng,* vol. 54, pp. 847-53, May 2007.

[33] L. Hargrove, Y. Losier, B. Lock, K. Englehart, and B. Hudgins, "A real-time pattern recognition based myoelectric control usability study implemented in a virtual environment," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2007, pp. 4842-5, 2007.

[34] L. J. Hargrove, K. Englehart, and B. Hudgins, "A comparison of surface and intramuscular myoelectric signal classification," *IEEE Transactions on Biomedical Engineering,* vol. 54, pp. 847-53, May 2007.

[35] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering,* vol. 50, pp. 848-54, Jul 2003.

[36] L. J. Hargrove, G. Li, K. B. Englehart, and B. S. Hudgins, "Principal components analysis preprocessing for improved classification accuracies in pattern-recognition-based myoelectric control," *IEEE Trans Biomed Eng,* vol. 56, pp. 1407-14, May 2009.

[37] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," *J Rehabil Res Dev,* vol. 48, pp. 643-59, 2011.

[38] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "Improving myoelectric pattern recognition robustness to electrode shift by changing interelectrode distance and electrode configuration," *IEEE Transactions on Biomedical Engineering,* vol. 59, pp. 645-52, Mar 2012.

[39] D. Tkach, H. Huang, and T. A. Kuiken, "Study of stability of time-domain features for electromyographic pattern recognition," *J Neuroeng Rehabil,* vol. 7, p. 21, 2010.

[40] A. Al-Timemy, R. Khushaba, G. Bugmann, and J. Escudero, "Improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper-Limb Prostheses for Transradial Amputees," *IEEE Trans Neural Syst Rehabil Eng,* Jun 23 2015.

[41] H. M. Al-Angari, G. Kanitz, S. Tarantino, and C. Cipriani, "Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements," *Biomedical Signal Processing and Control,* vol. 27, pp. 24-31, 2016.

[42] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Trans Biomed Eng,* vol. 40, pp. 82-94, Jan 1993.

[43] A. D. Chan and K. B. Englehart, "Continuous myoelectric control for powered prostheses using hidden Markov models," *IEEE Trans Biomed Eng,* vol. 52, pp. 121-4, Jan 2005.

[44] A. H. Al-Timemy, G. Bugmann, J. Escudero, and N. Outram, "Classification of Finger Movements for the Dexterous Hand Prosthesis Control With Surface Electromyography," *IEEE Journal of Biomedical and Health Informatics,* vol. 17, pp. 608-618, May 2013.

[45] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Trans Biomed Eng,* vol. 52, pp. 1801-11, Nov 2005.

[46] J. A. Johnston, L. R. Bobich, and M. Santello, "Coordination of intrinsic and extrinsic hand muscle activity as a function of wrist joint angle during two-digit grasping," *Neurosci Lett,* vol. 474, pp. 104-8, Apr 26 2010.

[47] J. P. Mogk and P. J. Keir, "The effects of posture on forearm muscle loading during gripping," *Ergonomics,* vol. 46, pp. 956-75, Jul 15 2003.

[48] H. Onishi, R. Yagi, M. Oyama, K. Akasaka, K. Ihashi, and Y. Handa, "EMG-angle relationship of the hamstring muscles during maximum knee flexion," *Journal of Electromyography and Kinesiology,* vol. 12, pp. 399-406, Oct 2002.

[49] D. T. MacIsaac, P. A. Parker, R. N. Scott, K. B. Englehart, and C. Duffley, "Influences of dynamic factors on myoelectric parameters," *IEEE Eng Med Biol Mag,* vol. 20, pp. 82-9, Nov-Dec 2001.

[50] R. F. Weir and E. C. Grahn, "A New Externally Powered, Myoelectrically Controlled Prosthesis for Persons with Partial-Hand Amputations at the Metacarpals," *Journal of Prosthetics and Orthotics,* vol. 13, pp. 26-31, 2001.

[51] E. Biddiss and T. Chau, "Upper Limb Prosthetics: Critical Factors in Device Abandoment," *American Journal of Physical Medicine and Rehabilitation,* vol. 86, pp. 977-987, 2007.

[52] S. L. Phillips, M. S. Harris, L. Koss, and G. Latlief, "Experiences and Outcomes With Powered Partial Hand Prostheses: A Case Series of Subjects With Multiple Limb Amputations," *Journal of Prosthetics and Orthotics,* vol. 24, pp. 93-97, 2012.

[53] G. Li, A. E. Schultz, and T. A. Kuiken, "Quantifying pattern recognition-based myoelectric control of multifunctional transradial prostheses," *IEEE Trans Neural Syst Rehabil Eng,* vol. 18, pp. 185-92, Apr 2010.

[54] C. Cipriani, C. Antfolk, M. Controzzi, G. Lundborg, B. Rosen, M. C. Carrozza*, et al.*, "Online myoelectric control of a dexterous hand prosthesis by transradial amputees," *IEEE Trans Neural Syst Rehabil Eng,* vol. 19, pp. 260-70, Jun 2011.

[55] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and O. Stavdahl, "Resolving the limb position effect in myoelectric pattern recognition," *IEEE Trans Neural Syst Rehabil Eng,* vol. 19, pp. 644-51, Dec 2011.

[56] Y. Geng, P. Zhou, and G. Li, "Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees," *J Neuroeng Rehabil,* vol. 9, p. 74, Oct 5 2012.

[57] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "Towards Improved Partial-Hand Prostheses: The Effect of Wrist Kinematics on Pattern-Recognition-Based Control," *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER),* pp. 1489-1492, 2013.

[58] E. Earley, A. Adewuyi, and L. Hargrove, "Optimizing pattern recognition-based control for partial-hand prosthesis application," in *Engineering in Medicine and Biology Society (EMBC), 36th Annual International Conference of the IEEE*, Chicago, IL, 2014.

[59] N. Jiang, S. Muceli, B. Graimann, and D. Farina, "Effect of arm position on the prediction of kinematics from EMG in amputees," *Medical & Biological Engineering & Computing,* vol. 51, pp. 143-51, Feb 2013.

[60] L. H. Smith, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 19, pp. 186-192, Apr 2011.

[61] H. Huang, P. Zhou, G. Li, and T. A. Kuiken, "An analysis of EMG electrode configuration for targeted muscle reinnervation based neural machine interface," *IEEE Trans Neural Syst Rehabil Eng,* vol. 16, pp. 37-45, Feb 2008.

[62] F. E. Liss, "The interosseous muscles: the foundation of hand function," *Hand Clinics,* vol. 28, pp. 9-12, Feb 2012.

[63] S. K. Lee and J. R. Wisser, "Restoration of pinch in intrinsic muscles of the hand," *Hand Clinics,* vol. 28, pp. 45-51, Feb 2012.

[64] T. E. Milner and S. S. Dhaliwal, "Activation of intrinsic and extrinsic finger muscles in relation to the fingertip force vector," *Experimental Brain Research,* vol. 146, pp. 197-204, Sep 2002.

[65] R. Balasubramanian and V. J. Santos, *The Human Hand as an Inspiration for Robot Hand Development* vol. 95. New York: Springer, 2014.

[66] M. H. Schieber, "Muscular production of individuated finger movements: the roles of extrinsic finger muscles," *Journal of Neuroscience,* vol. 15, pp. 284-97, Jan 1995.

[67] C. E. Lang and M. H. Schieber, "Human finger independence: limitations due to passive mechanical coupling versus active neuromuscular control," *Journal of Neurophysiology,* vol. 92, pp. 2802-10, Nov 2004.

[68] K. T. Reilly and M. H. Schieber, "Incomplete functional subdivision of the human multitendoned finger muscle flexor digitorum profundus: an electromyographic study," *Journal of Neurophysiology,* vol. 90, pp. 2560-70, Oct 2003.

[69] K. T. Reilly, M. A. Nordstrom, and M. H. Schieber, "Short-term synchronization between motor units in different functional subdivisions of the human flexor digitorum profundus muscle," *Journal of Neurophysiology,* vol. 92, pp. 734-42, Aug 2004.

[70] D. A. Keen and A. J. Fuglevand, "Common input to motor neurons innervating the same and different compartments of the human extensor digitorum muscle," *Journal of Neurophysiology,* vol. 91, pp. 57-62, Jan 2004.

[71] F. V. G. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. V. Thakor, "Decoding of Individuated Finger Movements Using Surface Electromyography," *IEEE Transactions on Biomedical Engineering,* vol. 56, pp. 1427-1434, May 2009.

[72] R. N. Khushaba, S. Kodagoda, M. Takruri, and G. Dissanayake, "Toward improved control of prosthetic fingers using surface electromyogram (EMG) signals," *Expert Systems with Applications,* vol. 39, pp. 10731-10738, Sep 15 2012.

[73] C. L. Taylor and R. J. Schwarz, "The anatomy and mechanics of the human hand," *Artificial Limbs,* vol. 2, pp. 22-35, 1955.

[74] C. Lake, "Partial hand amputation: Prosthetic management," in *Atlas of Amputations and Limb Deficiencies: Surgical, Prosthetic and Rehabilitation Principles*, D. G. Smith, J. W. Michael, and J. H. Bowker, Eds., 3 ed Rosemont, IL, USA: American Academy of Orthopaedic Surgeons, 2004, pp. 209-217.

[75] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "An Analysis of Intrinsic and Extrinsic Hand Muscle EMG for Improved Pattern Recognition Control," *IEEE Trans Neural Syst Rehabil Eng,* vol. 24, pp. 485-94, Apr 2016.

[76] E. J. Earley, L. J. Hargrove, and T. A. Kuiken, "Dual Window Pattern Recognition Classifier for Improved Partial-Hand Prosthesis Control," *Front Neurosci,* vol. 10, p. 58, 2016.

[77] M. A. Oskoei, H. Hu, and J. Q. Gan, "Feature-channel subset selection for optimising myoelectric human-machine interface design," *International Journal of Biomechatronics and Biomedical Robotics,* vol. 2, pp. 195-208, 2013.

[78] R. N. Khushaba and A. Al-Jumaily, "Channel and feature selection in multifunction myoelectric control," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, 2007, pp. 5182-5185.

[79] E. J. Earley, A. A. Adewuyi, and L. J. Hargrove, "Optimizing pattern recognition-based control for partial-hand prosthesis application," in *Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE*, 2014, pp. 3574-3577.

[80] S. Haykin, *Neural Networks: A Comprehensive Foundation*, 2 ed. Singapore: Pearson Education Inc. , 1999.

[81] M. F. Møller, "A scaled conjugate gradient algorithm for fast supervised learning," *Neural networks,* vol. 6, pp. 525-533, 1993.

[82] A. Bhattacharyya, "On a Measure of Divergence between Two Multinomial Populations," *The Indian Journal of Statistics,* vol. 7, pp. 401-406, 1946.

[83] S. H. Park and S. P. Lee, "EMG pattern recognition based on artificial intelligence techniques," *IEEE Transactions on Rehabilitation Engineering,* vol. 6, pp. 400-5, Dec 1998.

[84] G. John, R. Kohavi, and K. Pfleger, "Irrelevant Features and the Subset Selection Problem," in *Machine Learning: Proceedings of the Eleventh International Conference*, San Franscisco, CA, 1994, pp. 121-129.

[85] B. A. Lock, K. Englehart, and B. Hudgins, "Real-time myoelectric control in a virtual environment to relate usability vs. accuracy," presented at the MyoElectric Controls Symposium, Fredericcton, New Brunswick, 2005.

[86] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina, "Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control?," *IEEE Trans Neural Syst Rehabil Eng,* vol. 22, pp. 549-58, May 2014.

[87] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift," *IEEE Trans Biomed Eng,* vol. 58, pp. 2537-44, Sep 2011.

[88] E. Scheme, A. Fougner, O. Stavdahl, A. C. Chan, and K. Englehart, "Examining the adverse effects of limb position on pattern recognition based myoelectric control," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2010, pp. 6337-40, 2010.

[89] C. L. Taylor and R. J. Schwarz, "The anatomy and mechanics of the human hand," *Artif Limbs,* vol. 2, pp. 22-35, May 1955.

[90] C. J. De Luca, "The use of surface electromyography in biomechanics," *Journal of applied biomechanics,* vol. 13, pp. 135-163, 1997.

[91] J. W. Ramsay, B. V. Hunter, and R. V. Gonzalez, "Muscle moment arm and normalized moment contributions as reference data for musculoskeletal elbow and wrist joint models," *Journal of biomechanics,* vol. 42, pp. 463-473, 2009.

[92] J. He, D. Zhang, N. Jiang, X. Sheng, D. Farina, and X. Zhu, "User adaptation in long-term, open-loop myoelectric training: implications for EMG pattern recognition in prosthesis control," *J Neural Eng,* vol. 12, p. 046005, Aug 2015.

[93] S. D. Lifchez, J. Marchant-Hanson, H. S. Matloub, J. R. Sanger, W. W. Dzwierzynski, and H. H. Nguyen, "Functional improvement with digital prosthesis use after multiple digit amputations," *J Hand Surg Am,* vol. 30, pp. 790-4, Jul 2005.

[94] M. J. Pilley and D. N. Quinton, "Digital prostheses for single finger amputations," *J Hand Surg Br,* vol. 24, pp. 539-41, Oct 1999.

[95] M. S. Harris, S. L. Phillips, G. Latlief, and L. Koss, "Case Study: Multiple-Limb Amputees Fit with Powered Partial Hand Prostheses," presented at the The 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton, New Brunswick, Canada, 2011.

[96] S. Ashford, M. Slade, F. Malaprade, and L. Turner-Stokes, "Evaluation of functional outcome measures for the hemiparetic upper limb: a systematic review," *J Rehabil Med,* vol. 40, pp. 787-95, Nov 2008.

[97] A. M. Simon, B. A. Lock, and K. A. Stubblefield, "Patient training for functional use of pattern recognition-controlled prostheses," *Journal of Prosthetics and Orthotics,* vol. 24, pp. 56-64, April 24, 2012.

[98] C. Castellini and M. Nowak, "EMG-based prediction of multi-DOF activations using single-DOF training: a preliminary result," in *Proc. of Myoelectric Control Symposium (MEC)*, 2014, pp. 45-49.

[99] K. A. Ingraham, L. H. Smith, A. M. Simon, and L. J. Hargrove, "Nonlinear mappings between discrete and simultaneous motions to decrease training burden of simultaneous pattern recognition myoelectric control," in *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2015, pp. 1675-1678.

[100] N. E. Bunderson and T. A. Kuiken, "Quantification of feature space changes with experience during electromyogram pattern recognition control," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 20, pp. 239-246, 2012.

[101] M. A. Powell, R. R. Kaliki, and N. V. Thakor, "User training for pattern recognition-based myoelectric prostheses: improving phantom limb movement consistency and distinguishability," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 22, pp. 522-532, 2014.
[102] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications,* vol. 39, pp. 7420-7431, 2012.
[103] M. Zecca, S. Micera, M. Carrozza, and P. Dario, "Control of multifunctional prosthetic hands by processing the electromyographic signal," *Critical Reviews™ in Biomedical Engineering,* vol. 30, 2002.

Chapter 9 Appendix

8.1 Time Domain Features

Hudgins *et al.* [42] proposed the extraction of 4 time-domain features mean absolute value, zero crossings, slope sign changes, and waveform length from each EMG channel.

1. **Mean absolute value (MAV):** This is an estimate of the mean absolute value of the EMG signal and is calculated from each analysis window, where N is the window size and j each sample in a window.

$$MAV = \frac{1}{N}\sum_{j=1}^{N}|x(j)| \tag{2}$$

2. **Zero crossings (ZC):** This time domain estimate of a frequency measure obtained by counting the number of times the waveform crosses zero. Given two consecutive samples $x_j and\ x_{j+1}$, ZC is incremented if

$$sgn\left(-x_j *\ x_{j+1}\right) \text{ and } \left(\left|x_j - x_{j+1}\right|\ \geq threshold\right) \tag{3}$$

3. **Slope-sign changes (SSC)** is also a time domain estimate of a frequency measure and is incremented if, given three consecutive samples, $x_{j-1}, x_j\ , and\ x_{j+1}$

$$\left(x_j -\ x_{j-1}\right) *\ \left(x_j - x_{j+1}\right) \geq threshold \tag{4}$$

The threshold reduces noise and thus is determined by considering the level of noise in the data.

4. **Waveform length (WL)** is the cumulative length of the EMG waveform over an analysis window and is defined as

$$WL\ = \sum_{j=1}^{N} |x(j) -\ x(j-1)| \tag{5}$$

Other time and frequency domain features have been extracted from the EMG signal for use within a pattern-recognition based myoelectric paradigm. These features are summarized by Zecca *et al.* and Phinyomark *et al.* [102, 103].

5. **Willison amplitude (WAMP)** is the number of counts for each change of the EMG signal amplitude that surpasses a predefined threshold and is given by

$$WAMP = \sum_{j=1}^{N} f(|x(j) -\ x(j+1)| \tag{6}$$

With f(x) = 1 if x > threshold, 0 otherwise.

6. **Root-mean-square (RMS)** is an estimate of EMG amplitude defined as

$$RMS = \sqrt{\frac{1}{N}\sum_{j=1}^{N} x(j)^2} \tag{7}$$

7. **Variance (VAR)** is a measure of the power of EMG given by

$$VAR = \frac{1}{N-1}\sum_{j=1}^{N} x(j)^2 \tag{8}$$

8. **V-order (V-ord)** is a non-linear detector that implicitly estimates muscle contraction force [102] and is defined as

$$v_{ord} = \frac{1}{N}\left(\sum_{j=1}^{N} x(j)^v\right)^{\frac{1}{v}} \tag{9}$$

9. **Log-detector (LogDet)** also provides an estimate of muscle contraction force but the non-linear detector is based on the logarithm

$$LogDet = e^{\frac{1}{N}\sum_{j=1}^{N}\log(|x(j)|} \tag{10}$$

10. **Auto-regressive (AR) coefficients:** The autoregressive model describes each EMG signal sample as a linear combination of previous samples. Thus it regards the EMG signal within a short time interval as a stationary Gaussian process and models the EMG as

$$x(j) = \sum_{i=1}^{p} a_i x(n-i) + w_n \tag{11}$$

Where $x(j)$ is the sample of the model signal, a_i are the AR coefficients, w_n is the white noise and p is the order of the model. The sixth order model has widely used in literature.

8.2 Frequency Domain Features

11. Mean frequency (MnF) is the average frequency which is calculated as a sum of the product of the EMG power spectrum and the frequency divided by the total sum of the spectrum intensity

$$MnF = \frac{\sum_{k=1}^{M} f_j P_j}{\sum_{k=1}^{M} P_j}$$

Where f_j is the frequency of the spectrum at frequency bin j is, P_j is the EMG power spectrum at frequency bin j, and M is the length of the frequency bin.

12. Median frequency (MdF) is the frequency at which the spectrum is divided into two regions with equal amplitude.

$$\sum_{k=1}^{MDF} P_j = \sum_{k=MDF}^{M} P_j = \frac{1}{2}\sum_{k=1}^{M} P_j$$

13. Peak frequency (PF) is the frequency at which the maximum power occurs.

$$PF = \max(P_j), j = 1, \dots, M$$

14. Mean power (MP) is the average power of the EMG power spectrum

$$MP = \sum_{k=1}^{M} \frac{P_j}{M}$$

8.3 Power Spectrum Descriptors (PSD)

Al-Timemy *et al.* [40] proposed a set of features that were invariant to force level variability. These features termed, power spectrum descriptors (PSD features) are based on the orientation of the EMG power spectrum features and are derived directly from the time domain.

15. PSD 1: Root squared zero order moment

$$m_0 = \frac{\left(\sqrt{\sum_{j=0}^{N-1} x[j]^2}\right)^{\lambda}}{\lambda}$$

$$PSD1 = \log(m_0)$$

16. PSD 2: Root squared second order moment

$$m_2 = \frac{\left(\sqrt{\sum_{j=0}^{N-1} (\Delta x[j])^2}\right)^{\lambda}}{\lambda}$$

$$PSD2 = \log(m_0 - m_2)$$

17. PSD 3: Root squared fourth order moment

$$m_4 = \frac{\left(\sqrt{\sum_{j=0}^{N-1} (\Delta^2 x[j])^2}\right)^{\lambda}}{\lambda}$$

$$PSD3 = \log(m_0 - m_4)$$

18. PSD 4: Sparseness

$$PSD4 = \log\left(\frac{m_0}{\sqrt{m_0 - m_2}\sqrt{m_0 - m_4}}\right)$$

19. PSD 5: Irregularity Factor represents the ratio of the number of upward zero crossings divided by the number of peaks

$$PSD5 = log\left(\frac{m_2}{\sqrt{m_0 m_4}}\right)$$

20. PSD 6: Waveform Length Ratio is the ratio of the waveform length of the first derivative to that of the waveform length of the second derivative.

$$PSD6 = log\left(\frac{\sqrt{\sum_{j=0}^{N-1}|\Delta x|}}{\sqrt{\sum_{j=0}^{N-1}|\Delta^2 x|}}\right)$$

PSD 1-6 are extracted from the original EMG record to form the feature vector **a**. An additional set of features is extracted by calculating the PSD 1-6 features from a logarithmically scaled version of the EMG log (x^2) to form a second feature vector **b**. The final feature set is calculated as the orientation of the two vectors given by a cosine similarity.

$$PSD_i = \frac{-2a_i b_i}{a_i^2 + b^2}, i = 1,2,3, \ldots 6$$