FINGER MOVEMENT CLASSIFICATION USING FOREARM EMG SIGNALS

by

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Abstract

To a person with an upper limb amputation or congenital defect, a well-functioning prosthesis can open the door to many work and life opportunities. A fundamental component of many modern prostheses is the myoelectric control system, which uses the myoelectric signals from an individual's muscles to control prosthetic movements. Though much research has been done involving the myoelectric control of arm and gross hand movements, more dexterous finger control has not received the same attention. Consequently, the goal of this study was to determine an optimal approach to the myoelectric signal classification of a set of typing motions. Two different movement sets involving the fingers of the right hand were tested: one involving digits two through five (4F - "four finger"), and the other involving digits one and two (FT - "finger/thumb").

Myoelectric data were collected from the forearm muscles of twelve normally-limbed subjects as they performed a set of typing tasks. These data were then used to test a series of classification systems, each comprising a different combination of system element choices. The best classification system over all subjects and the best classification system for each subject were determined for both movement sets.

The optimal subject-specific classification systems yielded classification accuracies of 92.8 ± 2.7% for the 4F movement set and 93.6 ± 6.1% for the FT movement set, whereas the optimal overall classification systems yielded significantly lower performance ($p<0.05$): 89.6 ± 3.4% for the 4F movement set and 89.8 ± 8.5% for the FT movement set. No significant difference in classification accuracy was found between movement sets ($p=0.802$). A two-way repeated measures ANOVA ($\alpha=0.05$) was used to determine both significance results.

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Table of contents

List of abbreviations

Movement sets

4F	four finger (digits two through five)
FT	finger / thumb (digits one and two)

Feature sets

ACCC	autocorrelation and cross-correlation coefficients
CV	correlation variation
HOS	higher order statistics
RMS	root-mean-square
SPMs	spectral power magnitudes
STFT	short time Fourier transform
TD	Hudgins' time-domain features
WT	wavelet transform

Dimensionality reduction (DR) methods

PCA	principal components analysis
PCA-48	reduction to 48 dimensions using PCA
PCA-64	reduction to 64 dimensions using PCA

Classifiers

LDA	linear discriminant analysis
MLP	multilayer perceptron

Optimization methods

GO	general optimization
SO	scenario optimization

List of tables

List of figures

Chapter 1
Introduction

1.1 Introduction and motivation

Loss of hand and finger function presents a major obstacle to the rehabilitation of a person with an upper limb amputation or congenital defect. This loss may give rise to serious negative consequences on the individual's quality of life and specifically on his or her ability to fully participate in many work environments, such as those that involve typing. The development of an intuitive and accurate myoelectric control system for multiple finger movement in an upper limb prosthesis would open the door to work and life opportunities previously unavailable to the upper limb amputee. In addition to application in prostheses, a myoelectric control system for multiple finger movements has potential commercial applications, such as in advanced human-computer interfaces. Though there has been much research done involving the myoelectric control of gross arm movements at the elbow and wrist (1,4,6,7,9-12,18,19,21,25,26,28,34), relatively few investigations using multiple finger movements have been found in the literature (17,31,32). Therefore, the purpose of this work was to develop an optimal approach to finger movement classification for a set of typing tasks, which in future could be incorporated in an intuitive myoelectric control system.

Of fundamental importance to myoelectric control is the myoelectric signal, or electromyogram (EMG), which is a measure of neuromuscular activity detected directly from within the muscle or from the skin surface. A myoelectric control system maps a set of features drawn from the myoelectric signal to a particular function, such as flexion of a prosthetic wrist. This type of control system has been frequently used in the field of powered prostheses, as it provides a user with the potential for naturally-evoked movement control. A well-performing myoelectric control system maps muscle activity to a specific prosthesis function with high accuracy and an acceptable response time.

A successful myoelectric control system is one in which three key issues are sufficiently addressed: accuracy, intuitive control, and acceptable response time; the probability of rejection of a prosthesis by the user is strongly influenced by these factors. The control system must obviously aim to function such that the prosthesis performs the task desired by the user with nearly 100% accuracy. A measure of intuitive control has not yet been successfully quantified, though more natural control has been achieved with user-specific training of control systems (1-7,9-13,17-21,23,25,26,28,30-32,34). The response time of a myoelectric control system should not be perceptible by the user and it is generally accepted that it must be 300 ms or less (12).

Initial research into myoelectric control was performed in the 1940s (29), but due to limited technology at the time, it was not until several decades later that further progress was made. During the late 1960s to mid-1970s (14,22,24) the first pattern recognition systems were developed using myoelectric inputs, however once again technology proved to be a significant limiting factor. The next major step forward occurred when Hudgins *et al.* (19) introduced a multifunctional myoelectric control system in 1993, which achieved good performance in classifying multiple movements using multiple signal features and an artificial neural network classifier. Subsequent myoelectric classification research followed this lead by using a similar system structure for multifunctional classification. With the intent of maximizing classification accuracy for a given set of movements, the research often involves testing a variety of methods for the different control system elements (e.g. feature set, classifier).

Research into multifunctional, pattern recognition based myoelectric control systems often involves a common set of key steps (1-7,9-13,17-21,23,25,26,28,30-32,34). Though exceptions do occur, the general research structure is as follows. First, a set of limb movements is defined to be the system's possible set of functions. Subjects, often normally-limbed, are then asked to perform these movements as multiple channels of myoelectric data are collected from muscle sites assumed to be relevant to the movement. When a movement is detected, a corresponding window of data referenced to the initiation of movement is selected from each channel. A set of features is drawn from the windowed data, sometimes reduced in dimensionality (2-4,7,9-11,20,26,28), and then sent to a classifier for decision-making.

The structure outlined above necessitates selection of the following six elements, which form the basis of myoelectric control research:

- limb movement set (e.g. flexion/extension at elbow)
- movement detection
- classification window characteristics (e.g. length, number of divisions)
- feature set
- dimensionality reduction (DR) procedure
- classifier

where the latter five elements largely define the pattern recognition component of a myoelectric control system and the first element represents the system's function set.

The work presented here involves the investigation of an optimal approach to multiple finger movement classification for application in typing tasks, based on the six-element structure described above. Surface myoelectric data and corresponding keystroke data were collected from twelve healthy-limbed subjects and these data were used to test a set of myoelectric classification approaches. Different optimization methods, classifiers, DR methods, feature sets, classification window characteristics, and movement sets were tested in order to seek out the most effective approach to classification. One optimization method involved determining a single optimal classification system for each movement set, and the other involved also tailoring the system to each subject. Additionally, the classification accuracy characteristics of each system element, typing exercise, and keystroke were investigated.

Chapter 2
Literature review

2.1 Background

The myoelectric signal

A skeletal muscle is comprised of individual cells, or fibres, that are grouped into functional units called motor units. The muscle fibres of a motor unit are innervated by a single motor nerve and contract together upon receiving an electrical stimulus, called an action potential, which is sent from the motor cortex of the brain to the muscle fibres via the motor nerve. Upon excitation by the motor nerve, the motor unit fibres themselves generate action potentials, which are transient electrical signals that are conducted along the muscle fibre membranes. The summation of the action potentials in the single fibres of the motor unit is called the motor unit action potential. A single action potential sent to a motor unit will elicit a single motor unit action potential and cause a transient contraction, or twitch, of the associated muscle fibres. A sustained contraction requires a continuous stream of action potentials. As higher levels of muscular force are required, the average action potential firing rate increases and more motor units are recruited throughout the contracting muscle. The myoelectric signal, or electromyogram (EMG), represents the temporal and spatial summation of motor unit action potentials within the pickup region of the recording electrode.

Signal detection

The myoelectric signal is commonly detected in one of two ways: at the skin surface using a non-invasive surface electrode, or more invasively from within the muscle belly using a needle, fine wire, or implanted electrode. Invasive detection yields a signal heavily weighted towards motor units in close proximity to the electrode, whereas surface detection provides a more general picture of activity in the underlying motor units. Due to its non-invasive nature, information content, and equivalent effectiveness as a classification system input (16), the surface myoelectric signal is commonly used in myoelectric control system applications (1-7,9-13,17-21,25,26,28, 31,32,34).

History of myoelectric control

The first reported use of the myoelectric signal as input to a control system was in the 1940s (29), though technological barriers discouraged further progress until the late 1960s to mid-1970s (14,22,24) when pattern recognition systems were first integrated with myoelectric inputs. Multifunctional myoelectric control was the next major stage in prosthetic control research and achieved high performance in 1993 with the work of Hudgins *et al.* (19).

Current state of research

Research into myoelectric control using pattern recognition has involved many different methods for the feature extraction and classification of myoelectric data. Feature sets have included spectral power magnitude values (13,17,25,32), Hudgins' feature set (2,6,9-13,18,19) and other time-domain statistics (3-5,18,30,31,33,34), autoregressive coefficients (1,3,4,18,21,33,34), autocorrelation and cross-correlation values (10,23), features drawn from the short time Fourier transform (2,9-12,20,31) or wavelet transform (1-3,7,9-12,20), and higher order cumulants (28). Classifiers have included various artificial neural networks (4,6,7,9,11,13,17-21,25,26,30-32), linear discriminant analysis (3,9-12,18), fuzzy systems (6,21,23), hidden Markov models (3-5) and Gaussian mixture models (18). In addition to the feature sets and classifiers, complementary methods such as DR of the feature set (2-4,7,9-11,20,26,28) and majority vote post-processing for steady-state contractions (10,11) have been tested. Classification accuracies above 90% have become commonplace in recent literature for upper arm, wrist and gross hand movements (1,4,7,9-13,18,21,28).

Finger movement classification

Classification of finger movements using a myoelectric pattern recognition system has not received the same level of attention given to less dexterous arm movements, such as gross hand movements, grasping, and movement at the elbow, nor have corresponding classification accuracy results reached the same level of performance (17,31,32), as described below. To this author's knowledge, a thorough set of classification systems has not been previously tested for finger movement classification using a common set of data.

Uchida *et al.* (32) reported classification accuracy of 86% for a finger movement set consisting of flexion of digits one through three, flexion of all fingers, and relaxation of the hand for a single subject when using two channels of myoelectric data and training and test data set sizes of 30 movements each. Surface electrode units were placed over the subject's *flexor digitorum superficialis* muscle. For a similar movement set of flexion of digits one through three and hand closure, Tsenov *et al*. (31) achieved classification accuracy of 93% using two data channels and 98% using four data channels. The training and test set sizes were 100 movements each (25 movements per class) and again were collected from a single subject. For the two channel case, electrode units were placed over the subject's *palmaris longus* and *extensor digitorum* muscles; electrode positioning for the four channel case was not described.

Neither Uchida *et al.* (32) nor Tsenov *et al.* (31) stated whether or not the movements involved in their studies were of short duration. Given the dependency of optimal classification method on movement duration (11), the suitability of these systems for transient typing movements is unknown. Also, the conclusions reached by these two studies are limited by two characteristics of the training and testing data sets. Firstly, the data sets for each subject were small compared to many used in the classification of transient upper arm, wrist, and grip movements (1-4,7,10-12,18,20,23,28,30,34). Secondly, the data were collected from only one subject for each of the experiments. Both of these factors affect the generalization of the performance results, and therefore further testing on larger and more diverse data sets is justified.

Speech recognition

As the duration of arm and hand movements reported in the literature is often much longer than the duration of a typical typing movement (i.e. a keystroke), which is approximately 141 ms (see Section 3.7), classification methods designed for the shorter myoelectric bursts in speech recognition research (2,3,5,20) were also considered in this work. This allowed for the consideration of a larger variety of methods that have been used to classify transient tasks with good performance; accuracies as high as 92% for a six word set (20) and above 93% for a ten word set (2,3) were reported. These methods are discussed together with those used for arm and hand movements in the subsequent sections.

Elements of myoelectric data classification research

As described in Section 1.1, myoelectric data classification research involves six fundamental elements which together form the function set and classification system. The function set consists of the potential system outputs, i.e. limb movements that can be classified, and the classification system is largely defined by the movement detection method, set of classification window characteristics, feature set extracted from the myoelectric data, feature set DR method, and specific classifier used. The six different elements are shown in Figure 2-1 and discussed in Sections 2.2 to 2.7 below.

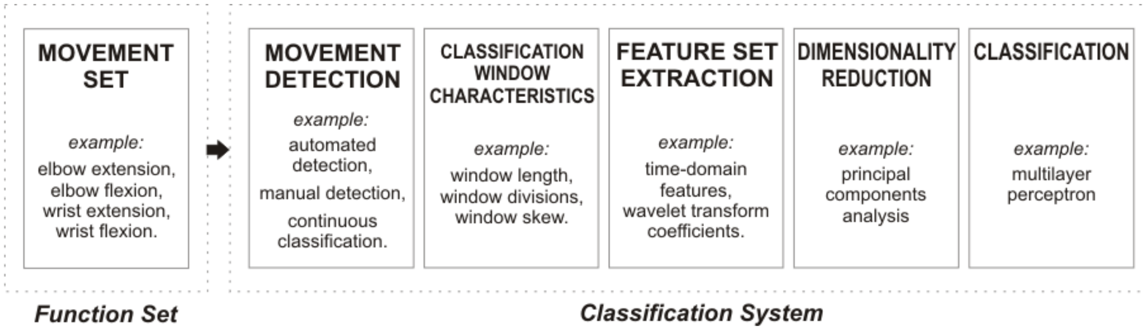


Figure 2-1 – Elements of myoelectric data classification research

2.2 Movement set

The majority of myoelectric classification literature investigated for this thesis involves data collected during hand or arm movements. In general, myoelectric data from these movements have been gathered from healthy-limbed individuals (1,4,6,7,9-13,17-19,21,25,26,28,31,32) with only a few exceptions where data were collected from amputees (19,30,33,34).

The movements that comprise function sets in the literature often fall into one of the following categories:

- movement at the elbow (1,6,7,9,11,21,25,26): *flexion/extension at the elbow, forearm pronation/supination*
- movement at the wrist (4,7,10-12,18,19,25,26): *flexion/extension at the wrist, ulnar/radial deviation*
- gross hand movement (4,7,10,11,13,17,18,21,31,32): *hand open/close, chuck grasp and key grasp*
- individual finger movement (13,17,31,32): *index finger flexion, middle finger flexion, thumb flexion, thumb abduction, thumb extension*

- other: *simulated upper-arm myoelectric data (23), finger joint angle analysis (32), amputee residual muscle contraction (19,30,33,34), isometric biceps contraction (28)*

Speech-recognition using myoelectric data generally involves the classification of a particular set of words, such as the ten words ‘zero’ to ‘nine’ (2,3,5) or the six words ‘stop’, ‘go’, ‘left’, ‘right’, ‘alpha’, and ‘omega’ (20).

Movements are often defined as steady-state (4,7,10-12,18,28,34) or transient (1-3,5,6,9-11,19,20,28). A steady-state movement can be defined as one that is held in a constant position for some duration of time, such as a sustained grasp. Conversely, a transient movement involves a brief deviation from rest, such as a keystroke or the speaking of a short word. However, it is not always clearly stated in the literature whether the movements tested were steady-state or transient (13,17,21,23,25,26,30-33).

2.3 Movement detection

After the data have been collected, the first step in off-line classification is to determine which points in the myoelectric signal correspond to physical movements, and therefore what windows of data to use for movement classification. Though movement detection methods are not always reported in the literature (17,23,25,26,31-33), documented methods fall into three categories: automated detection (1-3,6,9,13,19, 30,31), continuous classification (4,7,10-12,18,28,32,34) and manual detection (20).

Automated detection requires a trigger to be activated in order for a window of data to be used for movement classification. The trigger often takes the form of a mathematical test on the myoelectric data. Examples of this from the literature involve the energy difference between adjacent windows (13), amplitude characteristics of a sliding window relative to baseline values (6,9,19,30,31), or Al-Assaf's dynamic cumulative sum method (1).

A continuous classification process is one in which a series of adjacent or overlapping windows is used to classify movements at regular intervals, and therefore no trigger is required.

Manual detection depends on visual recognition of the myoelectric signal bursts that correspond to the physical movements performed by the research subjects (20). Consequently, this method is not usable for on-line classification and is therefore restricted to research applications.

Movement detection is not always required, however, as movements are sometimes collected one at a time - though often in the literature the distinction between this scenario and manual detection is not made clear (5,10,11,21).

2.4 Classification window characteristics

After a movement is detected, a corresponding window of myoelectric data must be selected. A feature set is then extracted from the windowed data, sometimes reduced in dimensionality (2-4,7,9-11,20,26,28), and then used as input to a classifier. The effects of window length, window skew relative to the point of movement detection, and number of window divisions on classification accuracy have received attention in the literature (2,3,10,19).

Given the likely rejection of a prosthesis by the user if there is perceivable delay between movement intent and actuation, the combined window length and subsequent computational time is generally limited to 300 ms (12). Consequently, window lengths reported in the literature are most commonly between 200 and 256 ms (1,4,7,10-12,18,19,28).

The classification window can be divided into multiple segments (6,13,19,21) in order to capture time varying characteristics of the data. Features are then calculated for each segment and combined into a single feature set. Segment numbers up to twelve have been tested (21) with particular success reported using five segments (19). However, due to the classification window segmentation inherent in certain feature sets, such as the wavelet transform (WT), this window characteristic is not always relevant.

The classification window placement relative to the point of movement detection is not always described in the literature (1,4-7,9-12,17,18,20,21,23,25,26,28,31-34), though some authors have reported intentional skewing of the classification window relative to the detection point (2,3,13,19,30). Though the choice is not always justified, the skewing of the classification window has been chosen to compensate for the delay associated with an automated movement detection method (30) or in order to include low amplitude anticipatory information in the classification window (13).

For speech detection, a comparison of skew values showed optimal results when using a 1024 ms window beginning 500 ms before the detection point (2,3). Due to the corresponding classification delay in excess of 300 ms, these results are not directly applicable to this thesis work; nonetheless, they show that shifting the classification window with respect to the point of movement detection can assist in myoelectric classification.

2.5 Feature sets

Out of the different classification system elements (see Figure 2-1), the feature set has been the most thoroughly researched. It has been shown to have a greater effect on classification accuracy than the type of classifier selected (9), and it can be determined using a wider variety of methods than the other major system elements, such as the classification window characteristics. The feature sets included in this thesis work are listed below and discussed in the following sections.

- Hudgins' time-domain features (TD)
- Spectral power magnitudes (SPMs)
- Autocorrelation and cross-correlation coefficients (ACCC)
- Short-time Fourier transform (STFT)
- Wavelet transform (WT)
- Higher order statistics (HOS)

2.5.1 Hudgins' time-domain features (TD)

A group of time-domain features referred to collectively as Hudgins' time-domain feature set (TD) was introduced in 1993 (19) and subsequently has been used in several published studies (2,6,9-13,18). The TD feature set originally comprised five different features that were calculated for a given classification window and for each of five equally-divided segments within this classification window, forming a total of 30 features per channel. These features are described below under their original labels, using the variable i to represent classification window index, x_k to represent the myoelectric data point at time k, and L to represent classification window length.

- *Mean absolute value (MAV).* The estimate of mean absolute value is given by:

$$\overline{X}_i = \frac{1}{L}\sum_{k=1}^{L}|x_k| \qquad (2\text{-}1)$$

- *Difference MAV, or Mean absolute value slope (MAVS)*. This quantity represents the difference in mean absolute value between the subsequent segment and the segment of interest, as shown below:

$$\Delta\overline{X}_i = \overline{X}_{i+1} - \overline{X}_i \qquad (2\text{-}2)$$

- *Zero crossings (ZC).* This feature is a simple frequency measure representing the number of times a waveform changes polarity. However, due to the possibility for noise induced zero crossings, a threshold must be defined. Therefore, a pair of consecutive samples constitutes a zero crossing only if their absolute difference exceeds both a noise threshold and their absolute sum (i.e. they have different polarity). Given two consecutive samples x_k and x_{k+1}, this condition is described by:

$$\left|x_{k+1} - x_k\right| > \max(\left|x_{k+1} + x_k\right|, T) \,, \qquad (2\text{-}3)$$

where T represents the noise threshold. Hudgins assumed a system noise value of 4 μV peak-to-peak and used this value, together with a system gain of 5000, to calculate T as 10 mV (19) when measured at the input to the A/D converter.

The ZC feature is therefore calculated as the number of times that the above condition is met in a given window.

- *Slope sign changes (SSC).* The number of times that a waveform changes slope polarity may provide additional frequency information about the signal. Using the same noise threshold T as above and three consecutive samples x_{k-1}, x_k and x_{k+1}, the conditions for a slope sign change at sample k can be expressed as:

$$x_k > \max(x_{k-1}, x_{k+1}) \;\; \textit{or} \;\; x_k < \min(x_{k-1}, x_{k+1})$$

$$\textit{and} \qquad (2\text{-}4)$$

$$\max(\left|x_{k+1} - x_k\right|, \left|x_k - x_{k-1}\right|) > T$$

The SSC feature is therefore calculated as the number of times that the above conditions are met in a given window.

- *Waveform length (WL).* The total length of the signal over the data window represents a combined measure of amplitude, frequency, and duration. This feature is calculated as the sum of absolute voltage differences between each pair of adjacent samples within the classification window, or:

$$WL = \sum_{k=2}^{L} \left| x_k - x_{k-1} \right| \qquad (2\text{-}5)$$

where x_k and x_{k-1} are consecutive signal samples.

Some of the features above have been omitted from the TD feature set when it has been used in other studies. Chan *et al.* (6) found that the inclusion of SSCs in the feature set contributed either a negative effect or no significant effect on classification performance. This feature is also not included in Farry *et al.*'s (13) implementation of the TD feature set (13), though no reason is given. The MAVS is another feature that is not always included in the set (11,12,18), presumably with reasoning similar to that of Chan *et al.* (6), though no clear justification for this omission is stated.

Though outperformed by several other feature sets in the classification of transient movements (2,9-11), the TD feature set has been shown to be very effective for the classification of steady-state arm movements, achieving classification accuracies of up to approximately 99.5% for a four movement, four channel problem (10). In addition to its good performance, a significant advantage of the TD feature set remains its simplicity. The implementation of these features into a classification structure was a defining moment in the field of myoelectric data classification, as it allowed for multiple movements to be classified with high accuracy (19). Its common use, good performance, and simplicity justified the inclusion of the TD feature set in this thesis work.

2.5.2 Autocorrelation and cross-correlation coefficients (ACCC)

The use of autocorrelation and cross-correlation coefficients (ACCC) as a feature set for multifunctional myoelectric classification was proposed by Leowinata *et al.* in 1998 (23), who suggested that useful information may reside in the crosstalk between electrodes in an array. Consequently, Leowinata *et al.* tested a feature set consisting of autocorrelation coefficients for each channel of myoelectric data and all unique cross-correlation coefficients between channels. High classification rates were achieved using this feature set, however testing was done on simulated data and therefore the results may not be meaningful to this thesis work. Englehart *et al.* (10) tested the ACCC feature set on real myoelectric data and found classification accuracies as high as 97% for a four class, four channel, transient arm movement problem; nonetheless, it was still outperformed by the TD, STFT, WT, and wavelet packet transform (WPT) feature sets.

In this thesis work, myoelectric data were collected from eight sites around the forearm, resulting in a high possibility of cross-talk between electrodes. Therefore, a variation of the ACCC feature set was tested in order to investigate its potential suitability to this application.

2.5.3 Spectral power magnitudes (SPMs)

The average spectral power magnitudes (SPMs) across disjoint bandwidths are a simple measure of frequency content within a signal and have been tested as a feature set in several studies (13,17,32). The power spectrum from which the SPMs are derived is calculated using an FFT of the classification window data and therefore the set includes no time-dependent information - unlike the more complex STFT and WT time-frequency feature sets tested in this study.

Hiraiwa *et al.* (17) and Uchida *et al.* (32) both tested feature sets comprised of average SPMs calculated across ten disjoint bandwidths between 63 and 500 Hz for the classification of finger movements. Though the specific bandwidths used were not documented in the former study, the latter specified central frequencies of 63, 80, 100, 125, 160, 200, 250, 315, 400, and 500 Hz (32). Maximum classification performance was found to be 67% using a single channel of myoelectric data (17) and 86% when using two channels of data (32). Farry *et al.* (13) used a Hamming window to calculate average SPMs for four bandwidths between 75 and 250 Hz and achieved classification accuracy of 93% for the classification of two grasp movements, though only 75% for the classification of three thumb movements. Two channels of data were used in each case. Given the simplicity of the SPM feature set, it was included in the thesis work in order to compare against more complex frequency-based methods.

2.5.4 Short-time Fourier transform (STFT)

The short-time Fourier transform (STFT) feature set is different from the SPM feature set in two ways. Firstly, whereas the SPM set involves a single calculation of the frequency spectrum over the entire data window, the STFT calculates the spectrum for a series of adjacent or overlapping segments within the classification window. Therefore, the STFT feature set contains time-dependent information while the SPM feature set does not. Secondly, the SPM feature set is comprised of average power magnitudes each calculated over a particular bandwidth; the STFT feature set involves no such averaging and retains all power magnitude values. Consequently, this feature set is very large and therefore depends heavily on feature set DR.

The segment length used in the division of the classification window determines the balance between time and frequency resolution. A shorter window will allow for greater time resolution at the expense of frequency resolution, whereas a longer window will provide greater frequency resolution at the expense of time resolution.

The STFT feature set has been implemented in several myoelectric signal classification studies (2,9-12,20,31), including many cases of transient data classification (2,9-11,20). Its performance has been good when used in combination with principal components analysis (PCA) DR, achieving classification accuracies of 98% for a four class (10) and 94% for a six class (10,11) arm movement prediction task using four channels of data. However, for each case of transient data classification using the STFT feature set, a wavelet-based feature set was reported to have achieved higher performance (2,9-11,20). The STFT feature set has nonetheless been included in this study because of its record of good performance and to examine the effects of feature set complexity on classification accuracy.

2.5.5 Wavelet transform (WT)

Feature extraction using the wavelet transform (WT) has been reported often in the literature (1-3,9-12,20). Though not optimal for steady state data (11), its performance has been good for speech and transient arm movement data (1-3,9-11,20).

The WT builds upon the STFT by partitioning the time-frequency plane in a variable manner. Whereas in the STFT frequency and time resolution are fixed, the WT offers increased time resolution at high frequencies and increased frequency resolution at low frequencies. The WT used in this study is the discrete wavelet transform (16), in which a series of high-pass and low-pass filter pairs are implemented, as shown in the Figure 2-2 example.

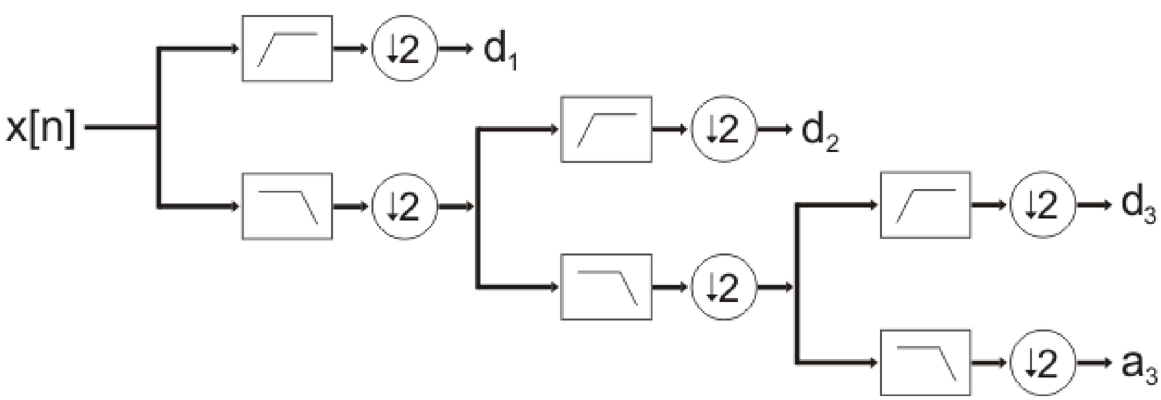


Figure 2-2 – A 3-layer discrete wavelet transform filter bank. The variables $\mathbf{d_1}$ through $\mathbf{d_3}$ represent the high-passed, down-sampled signals, or *detail* coefficients; the variable $\mathbf{a_3}$ represents the final low-passed, down-sampled signal (a scalar), or *approximation* coefficient.

At each stage in the filtering, the high-pass filtered signal is down-sampled and retained as a set of features, whereas the low-pass filtered signal is down-sampled and passed to the next filter bank. The process continues until the down-sampled, low-pass filtered signal is a scalar, at which point it too is retained as a feature.

The dimensionality of the WT feature set is approximately equal to the number of samples in the classification window; therefore, like the STFT, it is dependent on DR in order to meet classification delay time limits.

In the literature, classification accuracy above 97% has been achieved with the WT feature set for a four class, four channel, transient arm movement data set, using PCA DR and the linear discriminant analysis (LDA) classifier (10). Despite its good performance on transient arm and gross hand tasks, the WT feature set has nonetheless been outperformed by the WPT (10,11) and stationary wavelet transform (11) feature sets.

In comparison to the TD, STFT, and WPT feature sets for a speech recognition task, the WT feature set performed best (2). Furthermore, Jorgenson *et al.* (20) reported classification accuracy of 92% using the WT with matrix tessellation DR for sub auditory speech recognition – a level of performance exceeding that of the STFT, Hartley transform, and moving average feature sets.

The WT feature set is one of the top performing sets for transient movement classification and was therefore included in this thesis study.

2.5.6 Higher order statistics (HOS)

Higher order statistics (HOS) have been tested by Nazarpour *et al.* (28) as features for myoelectric signal classification. Their use has been justified by the non-Gaussian nature of myoelectric signals recorded during low level contractions (28). Whereas higher order statistics, such as cumulants, will be equal to zero for a signal with Gaussian distribution, they reveal information regarding kurtosis and skewness in non-Gaussian data.

Specifically, Nazarpour *et al.* (28) tested a feature set comprised of 19 features per channel, containing second, third, and fourth order cumulants. The second order cumulant is more familiarly known as variance, and the third and fourth order cumulants represent measures of skewness and kurtosis, respectively. Input data were first normalized (see Equation 2-6) and then unique cumulants were calculated with time lags of 0, 1 and 2 samples, as shown in Equation 2-7.

$$x'(t) = \frac{x(t) - \overline{X}}{\sigma} \tag{2-6}$$

where $x'(t)$ is the normalized value of sample $x(t)$, and $\overline{X}$ and σ are the mean and standard deviation of the data, respectively.

$$\begin{aligned} C_2(\tau_1) &= E[x'(t)x'(t+\tau_1)] \\ C_3(\tau_1,\tau_2) &= E[x'(t)x'(t+\tau_1)x'(t+\tau_2)] \\ C_4(\tau_1,\tau_2,\tau_3) &= E[x'(t)x'(t+\tau_1)x'(t+\tau_2)x'(t+\tau_3)] \\ &\quad - C_2(\tau_1)C_2(\tau_2-\tau_3) \\ &\quad - C_2(\tau_2)C_2(\tau_3-\tau_1) \\ &\quad - C_2(\tau_3)C_2(\tau_1-\tau_2) \end{aligned} \tag{2-7}$$

where C_n is the n[th] order cumulant and τ_1, τ_2, and τ_3 are time lags. The feature set consisted of three second order cumulants, six third order cumulants, and ten fourth order cumulants, as shown in Table 2-1.

Table 2-1 – Original HOS feature set (28)

Second order	Third Order	Fourth Order
$C_2(0)$, $C_2(1)$, $C_2(2)$	$C_3(0,0)$, $C_3(0,1)$, $C_3(0,2)$, $C_3(1,1)$, $C_3(1,2)$, $C_3(2,2)$	$C_4(0,0,0)$, $C_4(0,0,1)$, $C_4(0,0,2)$, $C_4(0,1,1)$, $C_4(0,1,2)$, $C_4(0,2,2)$, $C_4(1,1,1)$, $C_4(1,1,2)$, $C_4(1,2,2)$, $C_4(2,2,2)$

Using sequential forward selection for DR, Nazarpour *et al.* (28) found that a well performing feature set could be constructed from only 2 or 3 of the 19 features. Specifically, the feature sets [$C_2(0)$, $C_4(0,0,0)$] and [$C_2(0)$, $C_2(1)$, $C_4(0,0,0)$] yielded the best performance across subjects in comparison to other two- and three-feature sets, respectively, for a two channel, four class, transient arm movement application. Using the three-feature set and a K-nearest neighbour classifier, classification accuracy of 93.2% was achieved over a 16 subject database, in comparison to 94.1% using the entire 19 element set. Using the same data set, Englehart *et al*. (9) achieved a maximum classification accuracy of 93.8% using a WPT feature set, PCA DR, and an LDA classifier. All other classification systems tested by Englehart *et al.* produced accuracies lower than 93.2%. It should be noted, however, that these differences may not be statistically significant.

Though this feature set has received less attention in the literature than many of the other sets, its performance and low dimensionality warranted its inclusion in this thesis work.

2.6 Dimensionality reduction (DR)

Dimensionality reduction (DR) of the feature set has been frequently implemented in the literature in order to lessen the burden placed on the classifier and potentially increase classification accuracy (2-4,7,9-11,20,26,28). Principal components analysis (PCA) is particularly common in the literature as a method for DR (2-4,7,9-11,26). This method involves the eigenvalue decomposition of a data set's covariance matrix, followed by the concatenation of a subset of eigenvectors into a matrix that can then be used for DR.

Though other alternate (9,20,28) and supplementary (7) methods have been investigated, none have achieved the consistently good performance of PCA. Englehart *et al.* (9) found a significant improvement in classification accuracy when using PCA with a TD feature set and an LDA classifier for a four class, two channel, transient arm movement problem. Its record of good performance warranted the testing of PCA in the thesis work for the purpose of feature set DR.

2.7 Classification

Common classifiers implemented in the literature included artificial neural networks (4,6,7,9,11-13,17-21,25,26,30-32), LDA classifiers (2,3,10-12,18), fuzzy systems (6,21,23), and Hidden Markov Models (4,5). The most common artificial neural network successfully employed in the literature is the multilayer perceptron (MLP) (4,7,9,11,18,21,31). The two classifiers drawn from the literature that were implemented in this study were the MLP and the LDA classifiers, which are discussed in more detail below.

2.7.1 Multilayer perceptron (MLP)

The multilayer perceptron (MLP) artificial neural network is frequently implemented in myoelectric signal classification systems (4,7,9,11,18,21,31), and has achieved competitive performance for steady-state movement classification (4,11,21,31). An artificial neural network is a system comprised of many basic units operating in parallel - mimicking biological nervous systems. The system is trained to a specific task, such as classification in this case, primarily by adjusting the connections between these units such that the error between the system outputs and the desired outputs is minimized for a given set of training data.

The MLP has been shown to achieve a classification accuracy of 92.9% for a four class, transient arm movement problem (9) using two channels of data. It has also been the optimal classifier in comparison to the LDA classifier when using steady-state data (9), and has produced higher classification accuracy than the LDA classifier when the combination of transient data, PCA DR, and a TD (9) or STFT (9,11) feature set is used. However, in the latter case the LDA was able to achieve slightly better performance using other, wavelet-based, feature sets than any instance of the MLP.

Though the classification accuracy of the MLP has often been matched or outperformed (4,9,11,18,21) and the training is computationally complex (4), the MLP classifier has still been commonly implemented with consistently good performance, warranting its inclusion in this study. A clear, detailed description of MLP structure and function is given by Karlik (21).

2.7.2 Linear discriminant analysis (LDA)

Linear discriminant analysis (LDA) has been widely used to classify movements using myoelectric data (2,3,9-12,18). The LDA classifier is "trained" by using feature sets drawn from the training data to calculate mean feature sets for each movement and a pooled covariance matrix. Classification of a given feature set then occurs by determining which movement's mean feature set yields the maximum value for a discriminant function involving the pooled covariance matrix.

When compared to another frequently implemented classifier, the MLP, the LDA classifier was able to achieve higher levels of classification accuracy for both transient (9,11) and steady-state (11) data when the classifier inputs were first subject to PCA DR. LDA has been shown to achieve a classification accuracy of 93.8% for a four class, transient arm movement problem using two data channels (9) and 98% using four data channels (10). The performance of LDA for transient data classification was higher when used with wavelet-based feature sets, such as the WT (2,9-11), WPT (2,9-11), or stationary wavelet transform (11) sets, than when used with the TD or STFT feature sets.

LDA classifier performance is generally considered to be high, as it is often used either as the sole classifier (2,10,12) or as a standard against which a novel method is compared (3,18). Consequently, it was tested as a classifier in this thesis work. A thorough description of the LDA classifier can be found in Fukunaga (15).

* * *

For many elements of the typical myoelectric signal classification system (e.g. feature set, window length), there are a number of methods and values that have performed well in the literature. In order to find the optimal set of element choices, multiple combinations of these methods and values were tested on the myoelectric data collected from twelve subjects performing a set of typing tasks.

The purpose of this thesis work was to find an optimal classification approach for a set of typing motions. Two methods of optimization were tested and compared - one involved finding the best overall system (i.e. set of element choices) for each movement set, and the other involved determining the best system for each subject and movement set combination. Additionally, classification accuracy values were investigated and compared for different exercise characteristics, system element choices, and finger movements.

Chapter 3
Methods

3.1 Subjects

Twelve healthy subjects (six males and six females) volunteered for this study. Each subject was provided with a Letter of Information and Consent form approved by the Queen's University Research Ethics board (see Appendix A) outlining the experimental procedure and details regarding his or her participation. All subjects provided informed consent prior to their participation in the study. The subject's full name, gender, birth date, handedness, height, weight, right forearm length (between the head of the radius and the ulnar styloid process), and circumference (at approximately one third of the forearm length from the head of the radius) were recorded[1]. This information is summarized in Table 3-1. No subject presented health issues that would likely affect or be affected by this study. Subject information was stored in a secure location, where access was limited to the primary investigator and thesis supervisors.

Table 3-1 – Subject information summary

Characteristic	Mean ± SD
Age (years)	24.7 ± 2.5
Height (cm)	175 ± 9
Weight (kg)	73 ± 11
Forearm length (cm)	24.8 ± 1.7
Forearm circumference (cm)	25.4 ± 2.7
2 subjects were left-handed	
10 subjects were right handed	

3.2 Electrodes

At the point of forearm circumference measurement a 4-5 cm band was shaved around the subject's right forearm, unless there was very little hair present. The skin

[1] Weight for subjects 1 to 3, height for subject 2, and forearm circumference for subject 6 were not initially recorded. However, height and weight values were later collected and are included in the Table 3-1 statistics.

was cleaned using isopropyl rubbing alcohol to decrease skin impedance so that the myoelectric signal could be better detected by the recording electrodes. Eight differential electrode units (Delsys, DE-2.1) were attached to the skin, such that the detection surfaces of each were perpendicular to the line of action of most forearm muscles. The electrode units were spaced approximately equidistantly around the forearm, with the first electrode placed just superior to the ulna, as shown in Figure 3-1.

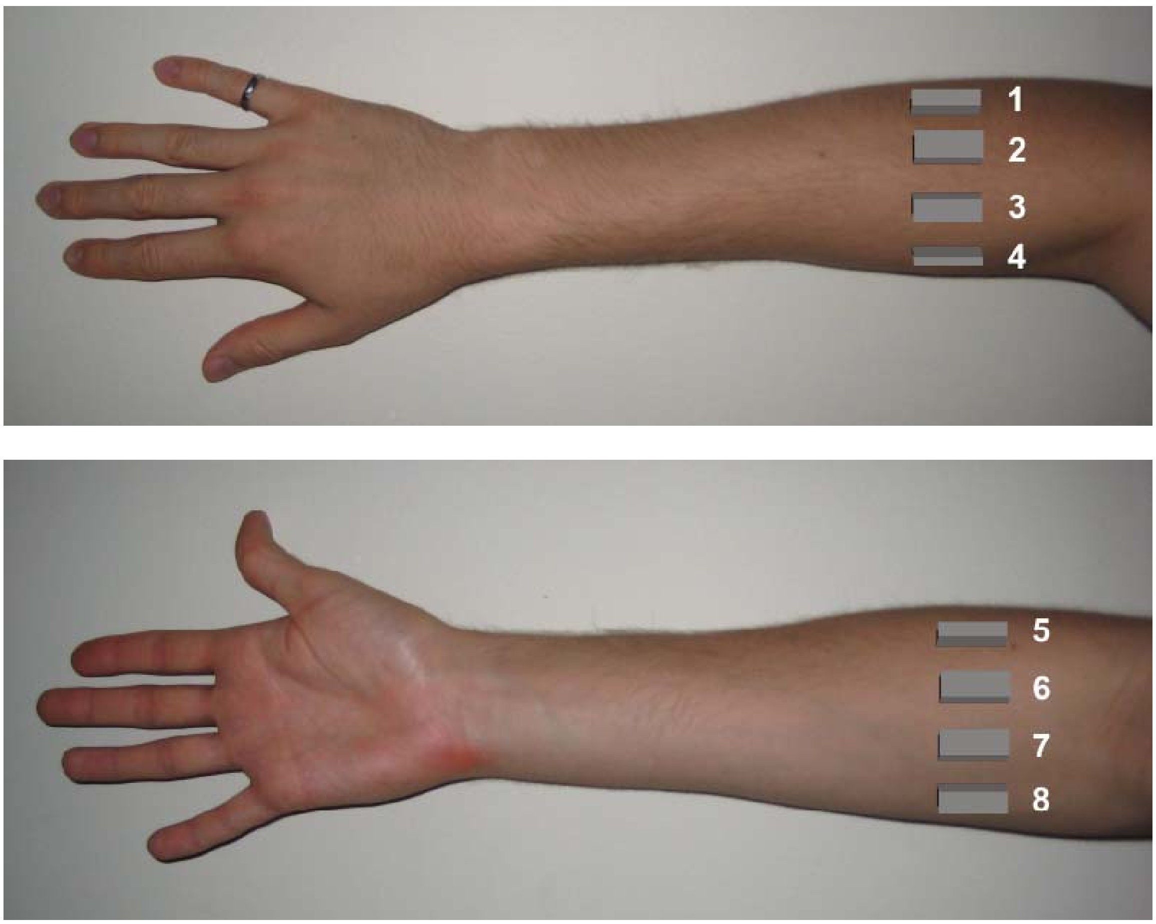


Figure 3-1 – Illustration of electrode placement

After cleaning the skin with isopropyl alcohol, a reference electrode (Harris Healthcare, HH5000) was placed on the manubrium (upper sternum) for subjects 1 to 3 and over the midpoint of the right clavicle for subjects 4 to 12 in order to provide a common reference for all channels. The location of the reference electrode was changed after a comparison between manubrium, right clavicle and right elbow reference locations, which revealed that the noise level was lowest with right clavicle placement.

3.3 Signal acquisition

Each of the eight myoelectric signals was collected using a Delsys DE-2.1 active differential electrode unit. Each unit has two 10 x 1 mm contact surfaces (99.9% Ag) spaced 10 mm apart and is coupled to a preamplifier in the electrode body with gain of 10 V/V, CMRR (60/10 Hz) of -92 dB, and input impedance of approximately 10^{15} Ω in parallel with 0.2 pF. The detected signals were then amplified to a total gain of 1000 using a Delsys Bagnoli-8 amplifier with bandwidth of 20 to 450 Hz and 80 dB/decade roll-off. After passing through a relay box (National Instruments, BNC-2090), the signal was sampled at 4000 Hz with a 12-bit analog-to-digital converter (National Instruments, PCI-MIO-16E-4, 500kS/s). Finally, the digitized signal was acquired using Delsys EMGWorks Acquisition software (version 3.1.0.5). A diagram of the signal-acquisition chain is given in Figure 3-2.

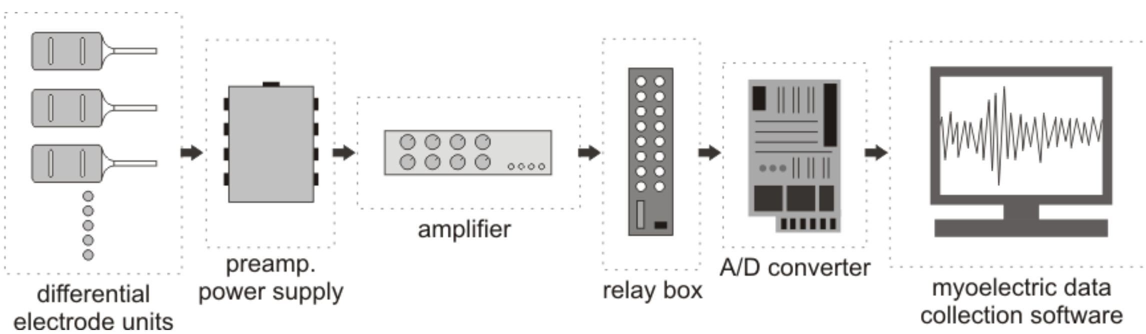


Figure 3-2 – Signal-acquisition chain

3.4 Data collection

Typing tasks on a computer keyboard were chosen as the finger movements to investigate in this study because of the prevalence and importance of typing tasks in our day-to-day activities. By testing both a four finger movement set (digits two through five) and a finger/thumb movement set (digits one and two), myoelectric signal classification across two levels of task complexity was investigated. The subjects performed two trials of each of eight different exercises. The first four exercises involved keystrokes using the four fingers of the right hand and last four exercises involved keystrokes using the index finger and thumb of the right hand. Data collected from the first trial of every exercise were later used to train the classification systems and the data from the second trial were used for system testing.

Before the typing exercises began, resting myoelectric data were collected for ten seconds while the subject was instructed to maintain a relaxed posture with his or her hand resting comfortably on the adjacent desk or in his or her lap.

The exercises were then carried out using a computer program, written in MATLAB 7, which presented each exercise to the subject while recording the characters typed and the corresponding keystroke times, as shown in Figure 3-3. The program also passed a pulse to the myoelectric data collection system at every keystroke instance that, together with the recorded keystroke time indices, was used for movement detection in off-line processing (i.e. determining when, in the myoelectric signal record, typing movements occurred).

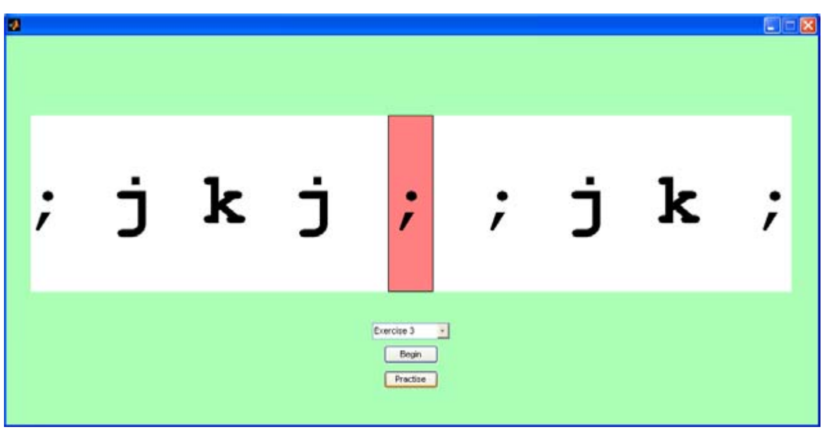


Figure 3-3 – Exercise program display, as presented to the subjects

Each experiment was defined by three parameters: the set of finger movements (i.e. keys typed), the typing pace and the keystroke order. These parameters are described below.

Experimental parameter 1 – Finger movements

For a given exercise, the finger movement set involved either a) typing 'j', 'k', 'l', and ';' with the 2nd, 3rd, 4th, and 5th digit, respectively, or b) typing '0' and '6' on the number pad with the thumb and index finger (i.e. digits 1 and 2), respectively. These sets are referred to as the four-finger (4F) and finger/thumb (FT) movement sets throughout the remainder of the thesis. Figure 3-4 shows the hand positions for the two movements.

a) 

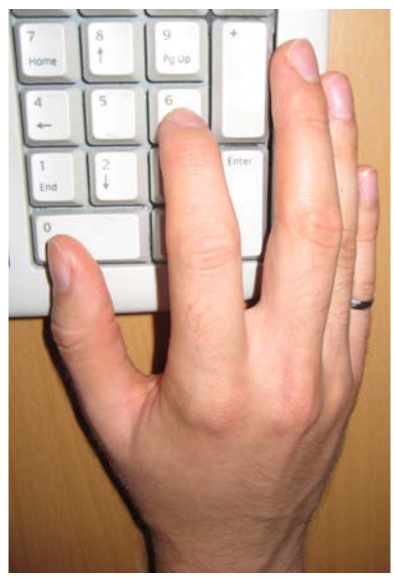
b) 

Figure 3-4 – Hand position for: a) 4F movement set, b) FT movement set

Experimental parameter 2 – Pacing option

The pacing option required the subject to either a) press a given series of keystrokes at an approximate rate of once per second, as moderated by the data collection program, or b) press a given series of keystrokes with minimal restrictions on pacing. For the latter case, the subject was simply instructed to relax his or her hand and arm briefly between keystrokes so that consecutive muscle bursts would not overlap.

Experimental parameter 3 – Keystroke order

The keystrokes could also be typed in either an a) ordered, or b) non-ordered fashion. For ordered keystroke exercises, the computer program presented each possible character to the subject in groups of twenty repetitions, for example:

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6

The non-ordered option required the subject to type each keystroke 20 times in a given non-ordered sequence as presented by the computer program. For example:

6 0 0 6 0 0 6 0 6 0 6 6 0 6 0 6 6 0 0 6 0 0 0 6 0 0 6 0 0 6 0 0 6 6 0 6 6 6 6 6

Eight exercises were formed using each combination of the aforementioned three exercise parameters, as detailed in Table 3-2. Each finger movement was repeated 20 times per exercise, resulting in a total of 80 keystrokes per 4F exercise and 40 keystrokes per FT exercise.

Table 3-2 – Exercise parameters

Exercise	Movement Set	Order	Pacing
1	4F	ordered	paced
2	4F	ordered	un-paced
3	4F	non-ordered	paced
4	4F	non-ordered	un-paced
5	FT	ordered	paced
6	FT	ordered	un-paced
7	FT	non-ordered	paced
8	FT	non-ordered	un-paced

The term *scenario* will be used throughout the remainder of the thesis to refer to a particular combination of subject and movement set; for example, the scenario [S03, 4F] comprises eight data files: both trials of exercises 1 to 4 recorded from subject 3.

There were a total of 24 scenarios of data collected (2 scenarios per subject x 12 subjects), where each scenario comprised eight data sets: two trials for each of four exercises. Consequently, the number of keystrokes per scenario was 640 for the 4F exercises and 320 for the FT exercises. The division of each scenario's data into training and testing sets is explained in the following section.

3.5 Classification system training and testing

Once data collection for all subjects was complete, the optimal movement classification systems were determined through off-line testing of the data. In order to approach each classification system’s ideal performance, an optimal classifier training process was determined through empirical analysis.

The second trial of each exercise was used in classification system testing. In order to determine the best data sets to use for classifier training, a variety of exercise and trial subsets were used as training data for a randomly selected subject. From this investigation, it was concluded that classifiers would be trained with the first trials of all exercises in the same scenario as the testing data. For example, in order to test the second trial of exercise 6 for a particular subject, the classifier was first trained using the first trials of exercises 5 through 8 from that subject. Thus, for each 4F exercise there were 320 keystrokes used for training and 80 keystrokes used for testing, and for each FT exercise there were 160 keystrokes used for training and 40 keystrokes used for testing.

3.6 Classification system optimization

In pursuit of an optimal classification system, several choices were tested for four of the control system's key elements. These elements are listed below with the number of choices tested for each given in parentheses.

- Classification window characteristics:
    - window length (3)
    - number of window subdivisions (3)
    - window skew relative to the keystroke trigger (3)
- Feature set (7)
- DR method (3)
- Classifier (3)

For the classification window characteristics, a particular parameter value was tested, such as a window length of 256 ms. For the latter three elements a particular method was tested, e.g. using an MLP as the classifier.

A total of 666 systems were tested using the LDA and statistical classifiers, and two systems were tested using the MLP classifier (see Section 3.10). For the former case, one might expect 3x3x3x7x3x2=1134 systems instead of 666 systems, however not all element choice combinations were tested:

- multiple window divisions were not tested for the wavelet transform (see Section 3.8);
- DR was always used with the STFT and WT feature sets (see Section 3.8), i.e. the "no DR" element choice was excluded;
- PCA-48 and PCA-64 DR were not used in systems where the feature set dimension was already less than or equal to the intended reduced dimension.

A breakdown of the LDA and statistical classifier systems is given by feature set in Table 3-3. For cases where only a subset of possible element choices was used, this subset is given in parentheses.

Table 3-3 – Breakdown of tested classification systems (LDA, Stat.)

Feature set	*Feature set dimension (prior to DR)*	*# of window division values*	*# of DR methods*	*# of classifiers*	*# of window length values*	*# of window skew values*	*# of classification systems*
RMS	8, 16	2 (1, 2)	1 (no DR)	2	3	3	36
RMS	56	1 (7)	2 (no DR, PCA-48)	2	3	3	36
TD	40	1 (1)	1 (no DR)	2	3	3	18
TD	80, 280	2 (2, 7)	3	2	3	3	108
CV	36	1 (1)	1 (no DR)	2	3	3	18
CV	72, 252	2 (2, 7)	3	2	3	3	108
SPM	32	1 (1)	1 (no DR)	2	3	3	18
SPM	64	1 (2)	2 (no DR, PCA-48)	2	3	3	36
SPM	224	1 (7)	3	2	3	3	54
STFT	648-1064*	3	2 (PCA-48, PCA-64)	2	3	3	108
WT	1952-2704**	1 (1)	2 (PCA-48, PCA-64)	2	3	3	36
HOS	24, 48	2 (1,2)	1 (no DR)	2	3	3	36
HOS	168	1 (7)	3	2	3	3	54
						Total:	666

**depending on window divisions, window length.*
*** depending on window length.*

The measure used to judge classification system performance was classification accuracy, which was defined as the percentage of correctly classified keystrokes. Software was designed using MATLAB 7 to train and test all classification systems in Table 3-3. Specifically, for each scenario the first trials of the corresponding four exercises were used to train a given classification system (see Section 3.5), and then the system was tested using the second trial of each exercise. Accuracy values for the test data were reported by the software. For each exercise, two additional pieces of information were determined: i) the list of classifier decisions (e.g. "006000006000..."), so that keystroke accuracies could later be determined, and ii) the average computational time for each keystroke classification, so that classification delays could later be calculated. The MATLAB Neural Network Toolbox 5.1 was used to implement the MLP classifier, as detailed in Section 3.10.

Optimization of the classification system was approached in two ways: general optimization and scenario optimization. In general optimization (GO), the single classification system that performed best over all 12 subjects and four exercises was determined for each movement set (i.e. 4F, FT). In scenario optimization (SO), the best-performing system was determined for each scenario (e.g. exercises 1-4 for S12). This latter method is specifically suited for prosthetic applications, where it could be a feasible and sensible approach to optimize performance for each subject and finger movement set.

The values/methods tested for each system element are described and justified in the following sections.

3.7 Classification window characteristics

Overview

For each keystroke, a corresponding window of data was selected and sent to the classification system. The electrical pulses generated by the typing program at each keystroke acted as offline triggers and were used to select the data window location corresponding to each keystroke. The classification window length, position relative to the trigger (skew), and number of window divisions were all considered as potential factors influencing classification performance. These characteristics are illustrated in Figure 3-5, below.

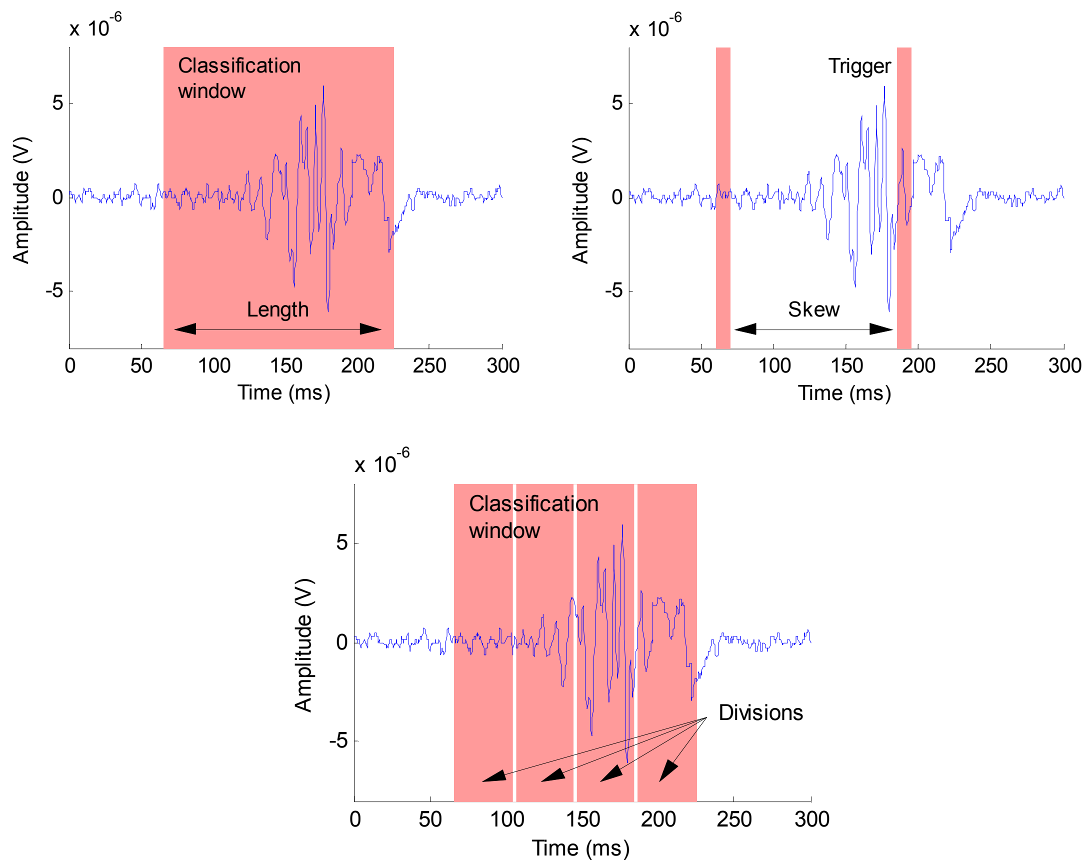


Figure 3-5 – Classification window characteristics: length, skew, divisions

Window length

A maximum window length of 256 ms was used in classification system testing for two reasons. Firstly, this window length was below the accepted classification delay limit of 300 ms for a prosthetic application (12) while still allowing time for computation. Secondly, it has been linked to repeated good performance on transient data in the literature (1,9-11,19).

Visual inspection of a set of 33 myoelectric bursts, randomly selected to include bursts from each subject and keystroke, indicated an average burst width of 141 ± 61 ms, with bursts as short as 61 ms and long as 274 ms. Therefore, smaller window lengths may still capture much relevant information from the bursts while allowing more time for computation. Consequently, the testing of window lengths shorter than 256 ms was warranted. Preliminary testing on data selected from a random subject using window lengths of 128 ms to 256 ms, in steps of 32 ms, showed the three most optimal lengths to be: 160 ms, 224 ms and 256 ms. These window lengths were selected for testing in this study in order to optimize the classification system, reveal classification accuracy trends based on classification window length, and perhaps allow for improved classification speed.

Window skew

The position of the classification window with respect to the trigger, or the classification window *skew*, was then considered. Given that the average time difference between visually detected myoelectric signal onsets and corresponding trigger pulses was 106 ± 37 ms for a subset of two subjects (S01,S03), skew values of -105 ms, -125 ms, -145 ms, and -165 ms were tested on a randomly selected subject; negative skew values correspond to windows shifted to precede the trigger. Due to their performance, the values of -105 ms, -125 ms and -145 ms were retained for testing.

Window divisions

The classification window was subdivided into a number of segments in order to integrate time-varying information into the feature set. Despite the particular success of dividing the window into 5 segments in the literature (34), it was found in preliminary analysis for this study that using 1, 2, and 7 segments produced optimal results. These values were subsequently used for testing in this thesis work.

3.8 Feature sets

A feature set was formed by extracting and combining features from each of the window divisions for all eight channels. For example, a data window segmented in two would result in a total of 16 windows used for feature set extraction: two window segments for each of 8 channels.

Seven feature sets were included in this thesis work based on their reported performance in relevant literature as discussed in Chapter 2, or on their particular suitability for this application. The feature sets tested are listed in approximate order of complexity below. As the effect of feature set choice on classification accuracy is considerable (9), the number of feature sets tested was consequently greater than the number of values or methods tested for other classification system elements.

Hudgins' (TD) and root-mean-square (RMS) feature sets

The TD feature set consists of *mean absolute value* (MAV), *mean absolute value slope* (MAVS), *slope sign changes* (SSC), *zero crossings* (ZC), and *waveform length* (WL), as described in Section 2.5.1. The threshold T used in calculations for zero crossings (ZC) and slope sign changes (SSC) was set to 230 nV, which was the average root-mean-square resting noise level across all subjects. In addition to the TD feature set, a very simple feature set containing only a root-mean-square (RMS) value was tested; the RMS set was included in this thesis work primarily to provide further information on the relationship between classification accuracy and feature set simplicity.

Correlation variation (CV)

Despite lower performance of the ACCC feature set in a comparison to other methods tested by Englehart *et al.* (10), the classification accuracy was still very high – approximately 97% for a four class, four channel, transient arm movement problem. Given the high number of data channels in this thesis work and consequently the large amount of cross-talk information available, the ACCC feature set was considered to have potential for good performance.

The high computational time associated with correlation calculations motivated a simplification of these features. In place of the autocorrelation values determined for a given classification window, the dot product of each channel's data vector with itself - equivalent to the squared norm - was determined, as shown in Equation 3-1. In place of cross-correlation values, the dot product was calculated for every different pair of channels' data vectors, weighted by their norms, as shown in Equation 3-2.

$$A(i) = \sum_{k=1}^{L} X(i)_k \bullet X(i)_k, \quad i = 1...8 \tag{3-1}$$

$$B(i, j) = \frac{\sum_{k=1}^{L} X(i)_k \bullet X(j)_k}{\sqrt{A(i) \times A(j)}}, \quad i, j = 1...8, i \neq j \tag{3-2}$$

In Equations 3-1 and 3-2 above, A and B represent variations of the autocorrelation and cross-correlation values, respectively, L represents the window length, and $X(i)_k$ is sample k from the ith channel of data set X. Comparison of the correlation variation (CV) feature set to the original ACCC set for a randomly selected subject yielded not only significantly lower computational time, but also approximately 10% higher classification accuracy.

Spectral power magnitudes (SPMs)

Given that the movement sets studied in this work more closely resemble that of Hiraiwa *et al.* and Uchida *et al.* (17,32) than that of Farry *et al.* (13), the former method for deriving SPMs was used (see Section 2.5.3). The feature set specifically consisted of the average SPMs from disjoint bandwidths of equal width for each window and channel. Prior to its implementation in this thesis work, the optimal bandwidth number and frequency range were first empirically determined to be four and 75 - 400 Hz, respectively, for a randomly selected subject.

Short-time Fourier transform (STFT)

The very large feature set created by the STFT required several modifications to the testing structure. Firstly, DR by PCA was required for all testing. Secondly, signals were down-sampled to 1000 Hz prior to the STFT calculations in order to prevent subsequent computer memory overloads during PCA calculations.

The STFT feature set required selection of three parameter values before it could be implemented. These are listed below, together with values used for each in empirical optimization.

- Window type: *Rectangular, Hamming, Hann*
- Window length: 32 ms, 64 ms, 128 ms
- Window overlap: 75%, 50%, 25%, 0%

The classification system used in testing involved a window length of 256 ms, PCA DR to 40 features, window skew of -125 ms, and an LDA classifier – a combination that had been found to give good performance. Optimal results were found for a randomly selected subject using a rectangular window of half the total classification window length and 0% overlap. Consequently, the rectangular window with 0% overlap was used throughout the testing. Due to the optimal overlap value of 0%, the STFT window length parameter can be expressed as a function of the window divisions element (see Section 3.7) and therefore did not need to be fixed.

Wavelet transform (WT)

The WT involves two parameters: the number of decomposition levels and the mother wavelet type; the latter is used to determine the high pass and low pass filters discussed in Section 2.5.5. Full decomposition has shown optimal performance in the literature (16) and was carried out in this thesis study. A variety of mother wavelets have been chosen for transient data applications in the literature, such as the Coiflet-2 (20), Coiflet-4 (9,10,16), Coiflet-5 (11), and Daubechies-5 (20). Empirical optimization showed the Coiflet-2 mother wavelet to have superior performance when Coiflet (orders 1 to 5), Daubechies (orders 1 to 10), and Symmlet (orders 1 to 8) mother wavelets were tested on a randomly selected subject in combination with PCA DR and the LDA classifier. Consequently, the Coiflet-2 mother wavelet was used throughout the testing. As explained above for the STFT feature set, the high dimensional feature set yielded by the WT necessitated both down-sampling of myoelectric data to 1000 Hz prior to wavelet calculations and PCA DR in every case. Additionally, window divisions greater than 1 were not tested due to the inherent windowing of the WT.

Higher order statistics (HOS)

The HOS feature set was initially tested on a random subject's normalized data in the three sizes tested by Nazarpour *et al.* (28):

- 19 features per channel, see Table 2-1.
- Three features per channel ([$C_2(0)$, $C_2(1)$, $C_4(0,0,0)$]), as determined by Nazarpour *et al* to be the best performing three-feature set (28).
- Two features per channel ([$C_2(0)$, $C_4(0,0,0)$]), as determined by Nazarpour *et al* to be the best performing two-feature set (28).

The features and normalization process are described in detail in Section 2.5.6. In initial testing of these three feature set sizes on a randomly selected subject's data, the best results were obtained for the three-feature set, and thus this set was used in this research work.

3.9 Dimensionality reduction

In order to test the merits of DR for this application, classification systems using three different DR options were tested:

- none: *no DR*
- PCA-48: *DR to 48 dimensions using PCA*
- PCA-64: *DR to 64 dimensions using PCA*

Initial testing of 48, 64 and 80 dimensions for a randomly selected subject's data showed that the two smaller values performed best; thus, they were used for subsequent testing.

Dimensionality was reduced equally across all channels for each feature set (e.g. to reduce dimensionality to 48, each channel's feature set was independently reduced in size to 6) except for the CV set, where the features were not grouped by channel. The same data used to train the classifier were used to create the PCA DR matrix.

3.10 Classification

After DR, the feature set was sent to a classifier either for training during the training phase or for classification during the testing phase. Three classifiers were tested, each of which represented a different classification approach: artificial neural networks, linear discrimination, and statistical classification. These three classifiers are explained below.

Multilayer perceptron (MLP)

The MLP was chosen to be the neural network classifier tested due to its prevalence in the literature and consistent good performance (4,7,9,11,18,21,31). The network was developed with the MATLAB Neural Network Toolbox 5.1 using a single hidden layer of eight nodes and tan-sigmoid and linear transfer functions for the hidden and output nodes, respectively, as commonly found in the literature (4,6,9,11,19). The network underwent training with the Levenberg-Marquardt backpropagation algorithm (20) until one of three conditions occured: 200 training iterations were completed, 0 misclassification results for the training data were found, or a performance gradient of $1x10^{-10}$ or below was found for the classifier's mean-square-error performance function.

Due to the lengthy training time for this classifier, it received limited testing. Whereas the LDA and statistical classifiers were tested with many combinations of other element choices, the MLP was tested in only one system for each movement set. This system contained the best performing combination of element choices determined using the LDA and statistical classifiers.

Linear discriminant analysis (LDA)

The literature has shown the LDA classifier to be a trusted (2,10,12) and relatively well performing (3,9,11,18) classifier; consequently, this classifier was included in this work. The method, as described in Section 2.7.2, was programmed in MATLAB 7.

Statistical classifier

A simple statistical classifier was tested which judged a feature set's compatibility with a particular classifier decision, or class (e.g. '0' or '6' for the FT set), using the z-value of each feature relative to the corresponding training data set distribution.

During the training phase, the mean and standard deviation of each feature were calculated across the training data for each class. The testing phase began by using these values to calculate the z-value of each feature from the test data, as shown in Equation 3-3.

$$Z(r)_C = \frac{X(r) - \overline{X}(r)_C}{\sigma(r)_C} \qquad (3\text{-}3)$$

where $Z(r)_C$ represents the z-value corresponding to class C for feature r of the testing data, $X(r)$ represents the feature r value from the testing data, and $\overline{X}(r)_C$ and $\sigma(r)_C$ represent the mean and standard deviation of feature r values, respectively, for the class C training set data.

The class to which the test data was mapped was that which yielded the lowest sum of squared z-values across all features, as shown in Equations 3-4 and 3-5 below.

$$Z_C^2 = \sum_{r=1}^{N_R} \left(Z(r)_C\right)^2 \qquad (3\text{-}4)$$

$$Class = \arg\min(Z_C^2) \qquad (3\text{-}5)$$

where Z^2_C is the sum of squared z-values for class C, N_R represents the total number of features, and $Class$ represents the classifier choice.

3.11 Statistical methods

The effect of optimization method and movement set on classification accuracy was tested using a two-way repeated measures analysis of variance, or ANOVA, with significance level of $\alpha=0.05$. The effect of pace and order options on classification accuracy was tested in the same manner.

The performances of different element choices were compared using paired t-tests ($\alpha=0.05$), as described in Section 4.5. First, the system that performed best, on average, over all subjects was determined for each value of a given system element (e.g. 160, 224, 256 ms in the case of window length). The accuracy values of the best performing system (the GO system) were then compared to those of each of the other systems using paired t-tests. The paired t-test ($\alpha=0.05$) was also used to compare the performances of MLP and GO systems.

The average classification accuracy for each different movement was determined for all GO and SO systems. A one-way repeated measures ANOVA ($\alpha=0.05$) was used to compare movement performances; post-hoc testing was performed using Tukey's method for multiple comparisons.

Statistical analyses were carried out using Minitab 15 and MATLAB 7.

Chapter 4
Results

4.1 Introduction

Classification system performance results are presented in the following sections. An overview of the collected myoelectric data is first provided; then, classification performances are given for the two different optimization approaches: GO and SO, as described in Section 3.6. For each optimization approach, classification accuracies corresponding to different exercise characteristics, element choices, and finger movements are given and compared.

4.2 Myoelectric data

Twelve subjects performed two trials each of eight typing tasks as eight channels of myoelectric data were recorded – resulting in 12x2x8x8=1536 myoelectric data sets. The data were all visually inspected and no unusable data sets were apparent. However, in six different data sets (i.e. trials), one keystroke was mistyped by the subject and therefore 19 (not 20) occurrences of that keystroke were collected. Furthermore, in the first trial of exercise 3, subject 6 performed a fifth finger keystroke in place of a fourth finger keystroke three times, resulting in 17 'l' keystrokes and 23 ';' keystrokes. The minor changes to data set sizes resulting from these typing errors were assumed not to significantly affect results and thus all data sets were included in the study.

Examples of myoelectric data collected during a 4F and an FT exercise are given in Figure 4-1. Both plots show an ordered, paced exercise so that the myoelectric characteristics of certain keystrokes can be more easily distinguished by the reader. For example, in the 4F exercise, the muscle bursts corresponding to fifth finger keystrokes are clearly visible between approximately 63 and 82 seconds; in the FT example, the second finger keystrokes between approximately 24 and 43 seconds appear to have slightly larger amplitudes, on average, than the first finger keystrokes preceding them.

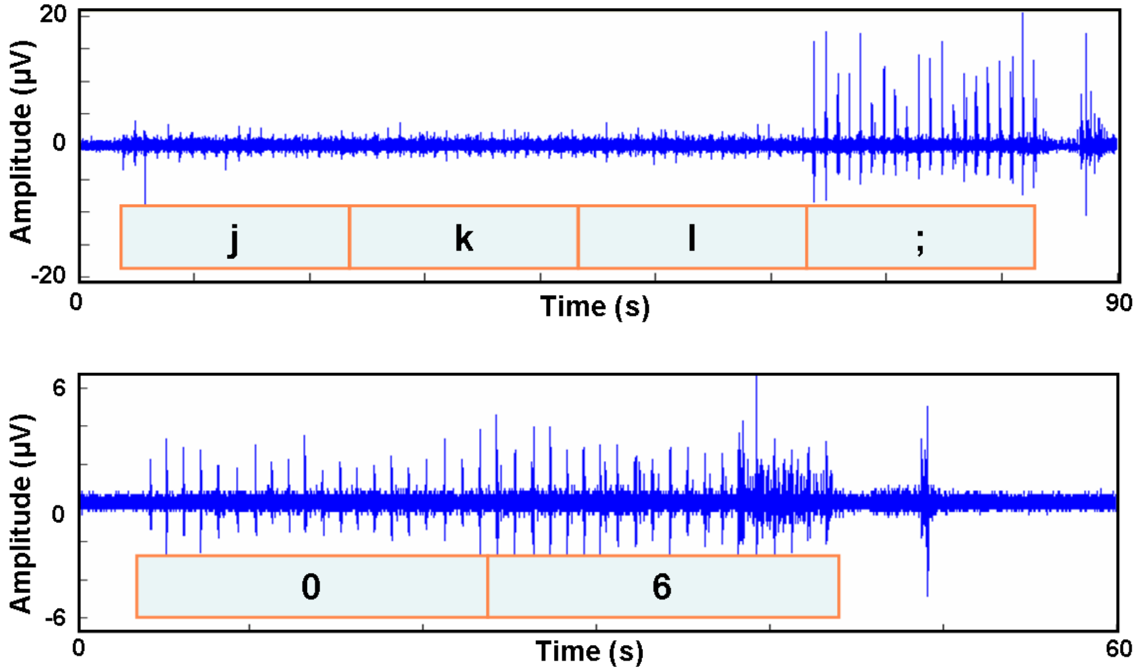


Figure 4-1 – Plots of 4F (top) and FT (bottom) myoelectric data

The data shown in Figure 4-1 have a relatively high signal-to-noise ratio (SNR) in comparison to data collected from other channels for the same trial. For a given data set, the SNR generally ranged from levels slightly below those shown above for some data channels to much lower levels for others.

4.3 Optimal performance

4.3.1 General optimization (GO)

The optimal classification system for each movement set was determined, as described in Section 3.6. As described in Section 3.10, the MLP classifier was omitted from this optimization procedure. The resulting GO systems and corresponding classification accuracy values are given in Tables 4-1a and 4-1b, respectively.

Table 4-1 – GO classification systems: a) element choices, b) performance

a)

Movement set	Classifier	DR method (reduced dimensions)	Feature set	Window divisions (ms)	Window length (ms)	Window skew (ms)
4F	LDA	none	TD	1	160	-125
FT	LDA	PCA (48)	RMS	7	256	-125

b)

Subject	*4F*	*FT*
1	88.4	97.5
2	83.4	94.9
3	95.0	88.1
4	91.3	95.6
5	92.8	93.1
6	89.1	76.3
7	84.7	85.6
8	89.4	85
9	89.7	73.1
10	91.8	91.9
11	92.5	96.3
12	86.6	100
Mean	*89.6*	*89.8*
S.D.	*3.4*	*8.5*

For the 4F scenarios, the optimal system yielded an average classification accuracy of 89.6 ± 3.4%. For the FT scenarios, the optimal system yielded an average accuracy of 89.8 ± 8.5%. The average computational time for each keystroke classification was 4.2 ± 0.2 ms for the 4F scenarios and 8.6 ± 0.6 ms for the FT scenarios, resulting in classification delay times well below the accepted limit of 300 ms for prosthetic application (12). Classification accuracy and computational time results for the GO systems can be found in Appendices B and C, respectively, for each subject and exercise.

4.3.2 Scenario optimization (SO)

The classification systems were then optimized for each scenario (i.e. combination of subject and movement set), as described in Section 3.6. As described in Section 3.10, the MLP classifier was omitted from this optimization procedure. The resulting SO systems and corresponding classification accuracy values are given in Tables 4-2a and 4-2b, respectively.

Table 4-2 – SO classification systems: a) element choices, b) performance

a)

Subject	Movement set	Classifier	DR method (reduced dimensions)	Feature set	Window divisions (ms)	Window length (ms)	Window skew (ms)
1	4F	LDA	none	CV	1	160	-125
1	FT	LDA	PCA (48)	RMS	7	224	-125
2	4F	LDA	PCA (48)	TD	2	160	-145
2	FT	LDA	PCA (48)	TD	2	224	-145
3	4F	LDA	PCA (48)	TD	2	160	-105
3	FT	LDA	PCA (64)	TD	2	224	-125
4	4F	LDA	none	CV	2	224	-125
4	FT	LDA	none	RMS	2	160	-105
5	4F	LDA	none	RMS	7	224	-105
5	FT	LDA	none	TD	1	256	-145
6	4F	Stat.	none	TD	2	224	-145
6	FT	Stat.	none	RMS	1	160	-125
7	4F	LDA	PCA (48)	RMS	7	224	-105
7	FT	LDA	PCA (64)	TD	2	160	-125
8	4F	LDA	none	TD	1	160	-125
8	FT	LDA	PCA (64)	TD	2	256	-105
9	4F	LDA	PCA (64)	CV	2	256	-105
9	FT	Stat.	PCA (48)	HOS	7	224	-105
10	4F	LDA	PCA (64)	TD	2	256	-125
10	FT	Stat.	none	TD	2	256	-125
11	4F	LDA	PCA (64)	TD	2	160	-105
11	FT	LDA	PCA (64)	TD	2	256	-105
12	4F	LDA	none	RMS	7	224	-145
12	FT	LDA	PCA (48)	TD	2	224	-105

b)

Subject	4F	FT
1	94.4	99.4
2	91.9	95.6
3	96.3	91.3
4	95.3	95.6
5	94.7	98.8
6	91.9	81.9
7	86.6	87.5
8	89.4	89.4
9	93.1	86.9
10	92.5	98.8
11	94.7	98.8
12	92.8	100
Mean	*92.8*	*93.6*
S.D.	*2.7*	*6.1*

The average classification accuracy across SO systems was 92.8 ± 2.7% for the 4F set and 93.6 ± 6.1% for the FT set. The average computational time for each keystroke classification was 6.1 ± 1.7 ms for the 4F set and 9.0 ± 10.8 ms for the FT set, resulting in classification delay times well below the accepted limit of 300 ms for prosthetic application (12). Classification accuracy and computational time results for the SO systems can be found in Appendices B and C, respectively, for each subject and exercise.

4.3.3 Optimization method and movement set results

Classification accuracy results for the GO and SO systems are given for each subject and movement set in Table 4-3.

Table 4-3 – Classification accuracy (%) for GO and SO systems

	4F		FT	
Subject	*GO*	*SO*	*GO*	*SO*
1	88.4	94.4	97.5	99.4
2	83.4	91.9	94.9	95.6
3	95.0	96.3	88.1	91.3
4	91.3	95.3	95.6	95.6
5	92.8	94.7	93.1	98.8
6	89.1	91.9	76.3	81.9
7	84.7	86.6	85.6	87.5
8	89.4	89.4	85	89.4
9	89.7	93.1	73.1	86.9
10	91.8	92.5	91.9	98.8
11	92.5	94.7	96.3	98.8
12	86.6	92.8	100	100
Mean	*89.6*	*92.8*	*89.8*	*93.6*
S.D.	*3.4*	*2.7*	*8.5*	*6.1*

A two-way repeated measures analysis of variance, or ANOVA, ($\alpha=0.05$) considering optimization method and movement set showed significant difference between GO and SO results ($p<0.05$), no significant difference between 4F and FT results ($p=0.802$), and no significant interaction effect ($p=0.694$). Consequently, it can be concluded that the SO systems yielded significantly higher classification accuracy values than the GO systems. Classification accuracy values for each subject and exercise are given in Appendix B.

4.4 Exercise results

Each exercise was characterized by movement set (4F, FT), keystroke pace option (paced, un-paced), and movement order (ordered, non-ordered). The average classification accuracy values for each exercise are given in Table 4-4.

Table 4-4 – Classification accuracy by exercise

Exercise	Movement set	Pace	Order	GO classification accuracy (%)	SO classification accuracy (%)
1	4F	paced	ordered	91.2 ± 7.1	94.1 ± 3.1
2	4F	un-paced	ordered	91.8 ± 4.8	92.9 ± 4.4
3	4F	paced	non-ordered	87.6 ± 10.3	92.8 ± 4.1
4	4F	un-paced	non-ordered	87.7 ± 8.7	91.4 ± 5.7
5	FT	paced	ordered	91.7 ± 8.7	94.6 ± 7.2
6	FT	un-paced	ordered	89.8 ± 10.9	94.8 ± 6.2
7	FT	paced	non-ordered	87.9 ± 11.4	93.1 ± 10.3
8	FT	un-paced	non-ordered	89.8 ± 8.4	92.1 ± 9.1

A two-way repeated measures ANOVA ($\alpha=0.05$) considering pace and order showed significant difference between ordered/non-ordered exercises ($p<0.05$), no significant difference between paced/un-paced exercises ($p=0.806$), and no significant interaction effect ($p=0.853$). Consequently, from the results in Table 4-4 it can be concluded that the ordered exercises yielded significantly higher classification accuracy values than the non-ordered exercises.

4.5 Element investigation

The results for each classification system element are presented in the following sections. The effect of classifier, DR, feature set, window divisions, window length, and window skew choice on classification accuracy is investigated in two ways: first, by determining the optimal performance of each element choice over all subjects; second, by calculating the number of SO systems that implement each element choice.

Determining the optimal performance of a given element choice involved first calculating the mean classification accuracy for each system that implemented that choice and then defining as optimal the accuracy distribution with the highest mean value. This procedure was carried out for every element choice for both movement sets. For example, when comparing window length values, the best overall classification system that used a 160 ms window was determined for each movement set; then, the best overall classification system that used a 224 ms window was determined for each movement set; finally, the best overall classification system that used a 256 ms window was determined for each movement set. To investigate whether there was more than one optimal choice for a given element, the accuracy values obtained by the best-performing choice were compared to those obtained by each of the other choices; paired t-tests (α=0.05) were used to determine significance. Results are given throughout the following sections.

On the following plots, each marker and vertical line represents the mean ± one standard deviation of the corresponding accuracy value distribution. A '●' marker indicates the optimal element choice, an 'o' marker indicates no significant difference from the optimal choice, and an 'x' marker indicates significant difference from the optimal choice, where paired t-tests (α=0.05) were used to calculate significance.

Each element choice was then investigated by determining the number of SO systems in which it was implemented; in other words, determining the number of scenarios for which it was optimal. For example, the TD feature set was optimal in six of twelve 4F scenarios. Results are expressed in pie-chart form throughout the following sections.

4.5.1 Classifier

The best performing systems for the LDA and statistical classifiers were determined and the corresponding classification accuracy values are represented in Figure 4-2. For both movement sets, there was a significant difference between the performance of the two classifiers at the α=0.05 level.

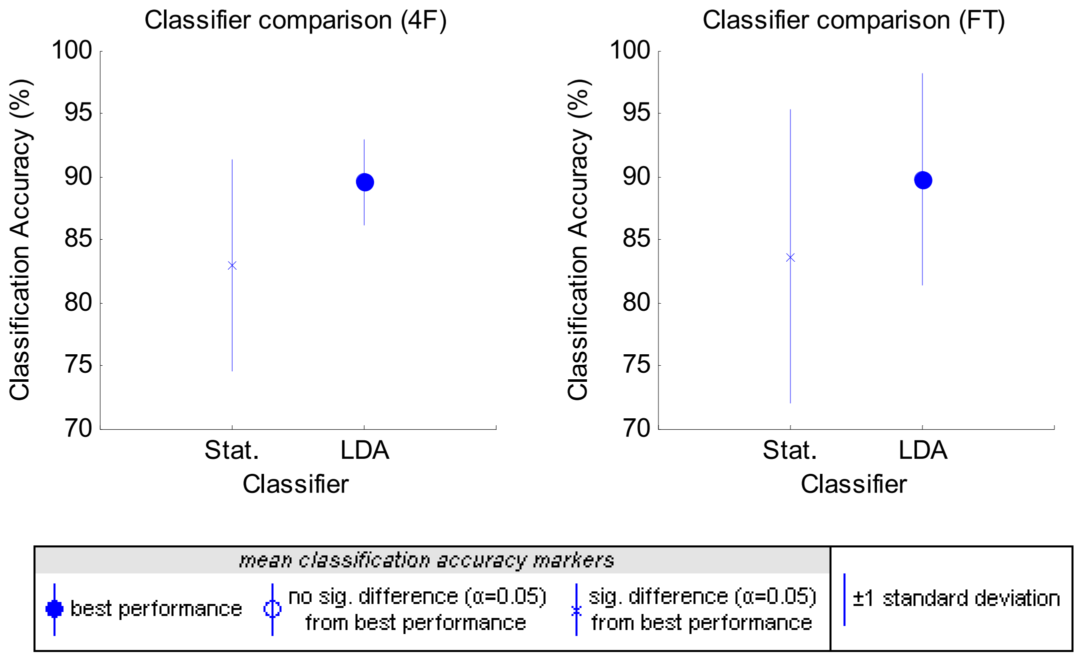


Figure 4-2 – Optimal performance for each classifier

Using the results from Table 4-2, the charts in Figure 4-3 show the proportion of different classifier choices across the SO systems. It is evident from the charts below that for both movement sets the LDA classifier is most often the optimal choice; nevertheless, the performance achieved by the statistical classifier is still superior in some scenarios.

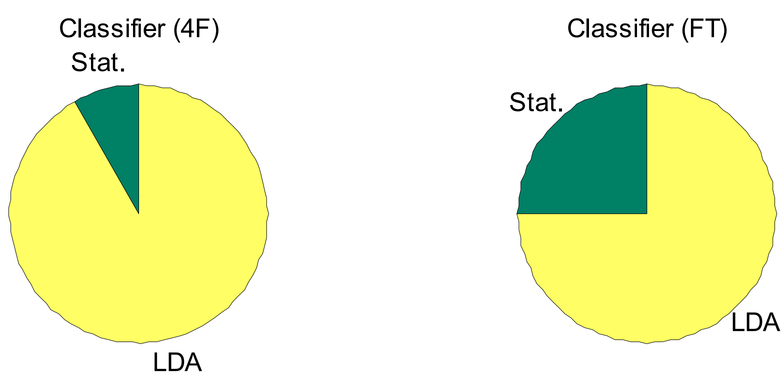


Figure 4-3 – Classifier distribution across SO systems

4.5.1.1 Multilayer perceptron

Due to much longer training times, the MLP classifier could not feasibly be tested as thoroughly as the LDA and the statistical classifiers. Consequently, the MLP classifier was tested in one classification system per movement set, using element choices determined for the GO systems (see Section 4.3.1) as shown in Table 4-5.

Table 4-5 – MLP classification systems

Movement set	Classifier	DR method (reduced dimensions)	Feature set	Window divisions (ms)	Window length (ms)	Window skew (ms)
4F	MLP	none	TD	1	160	-125
FT	MLP	PCA (48)	RMS	7	256	-125

The average classification accuracy was 86.3 ± 7.9 % for the 4F set and 84.1 ± 12.0 % for the FT set. The average computational time for each keystroke classification was 18.1 ± 0.3 ms for the 4F set and 22.1 ± 0.0 ms for the FT set, resulting in classification delay times below the accepted limit of 300 ms for prosthetic application (12). A paired t-test ($\alpha=0.05$) showed that the MLP systems yielded significantly lower classification accuracy than the original GO systems for both the 4F ($p<0.05$) and the FT ($p<0.05$) movement sets. Classification accuracy and computational time results for the MLP systems can be found in Appendices B and C, respectively, for each subject and exercise.

4.5.2 Dimensionality reduction

The best performing system for each of the three DR methods was determined and the corresponding classification accuracy values are represented in Figure 4-4. For the 4F set, the PCA-48 system yielded classification accuracy values significantly different ($p<0.05$) from those of the optimal system; however, this was the only case for both movement sets where the optimal system's performance was significantly different from another system.

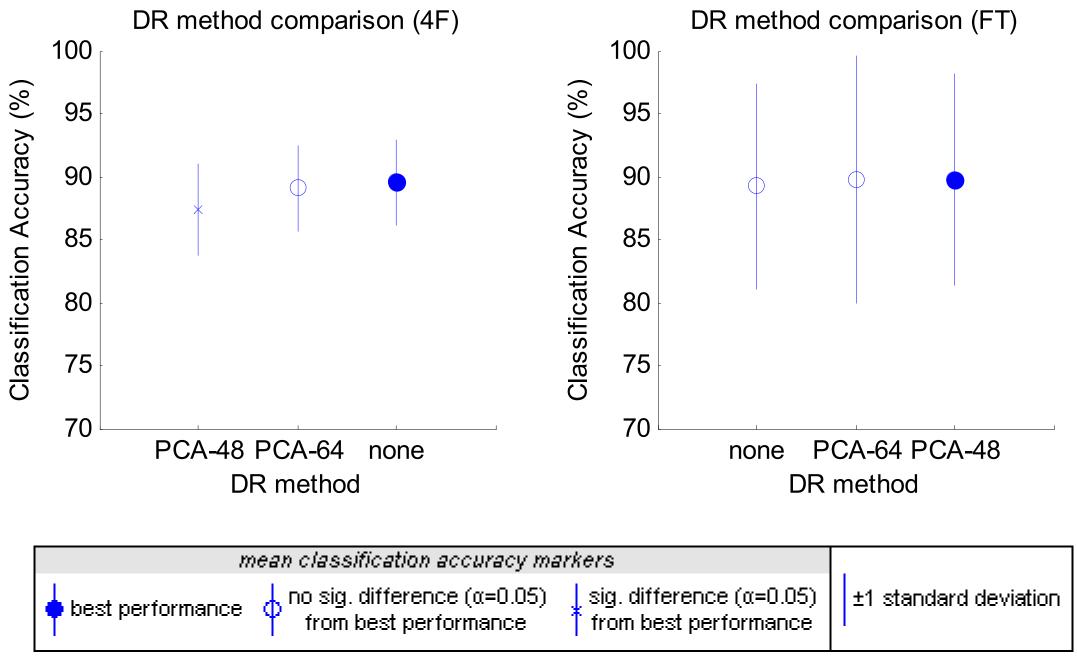


Figure 4-4 – Optimal performance for each DR method

Using the results from Table 4-2, the charts in Figure 4-5 show the proportion of different DR methods across the SO systems. From the charts below, it can be seen that each method is optimal for a similar number of scenarios, though the use of no DR is most common in the 4F systems.

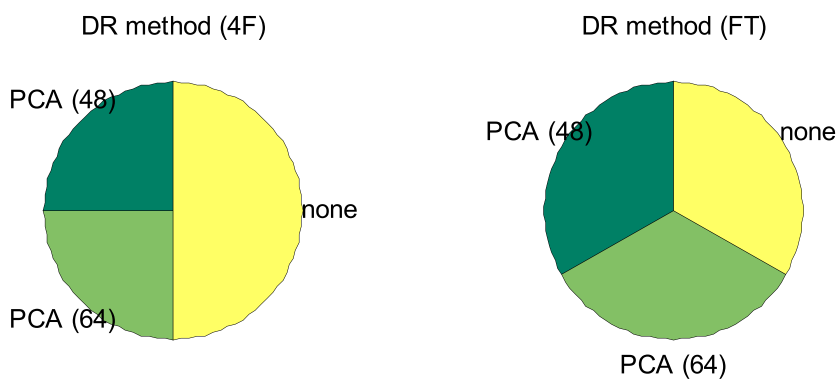


Figure 4-5 – DR method distribution across SO systems

4.5.3 Feature set

The best performing system for each of the seven feature sets was determined and the corresponding classification accuracy values are represented in Figure 4-6. For the 4F set, the classification accuracy values obtained using the optimal TD system were significantly different ($p<0.05$) from all other systems. For the FT set, the classification accuracy values obtained using the optimal RMS system were not significantly different from either the TD, HOS, or CV systems.

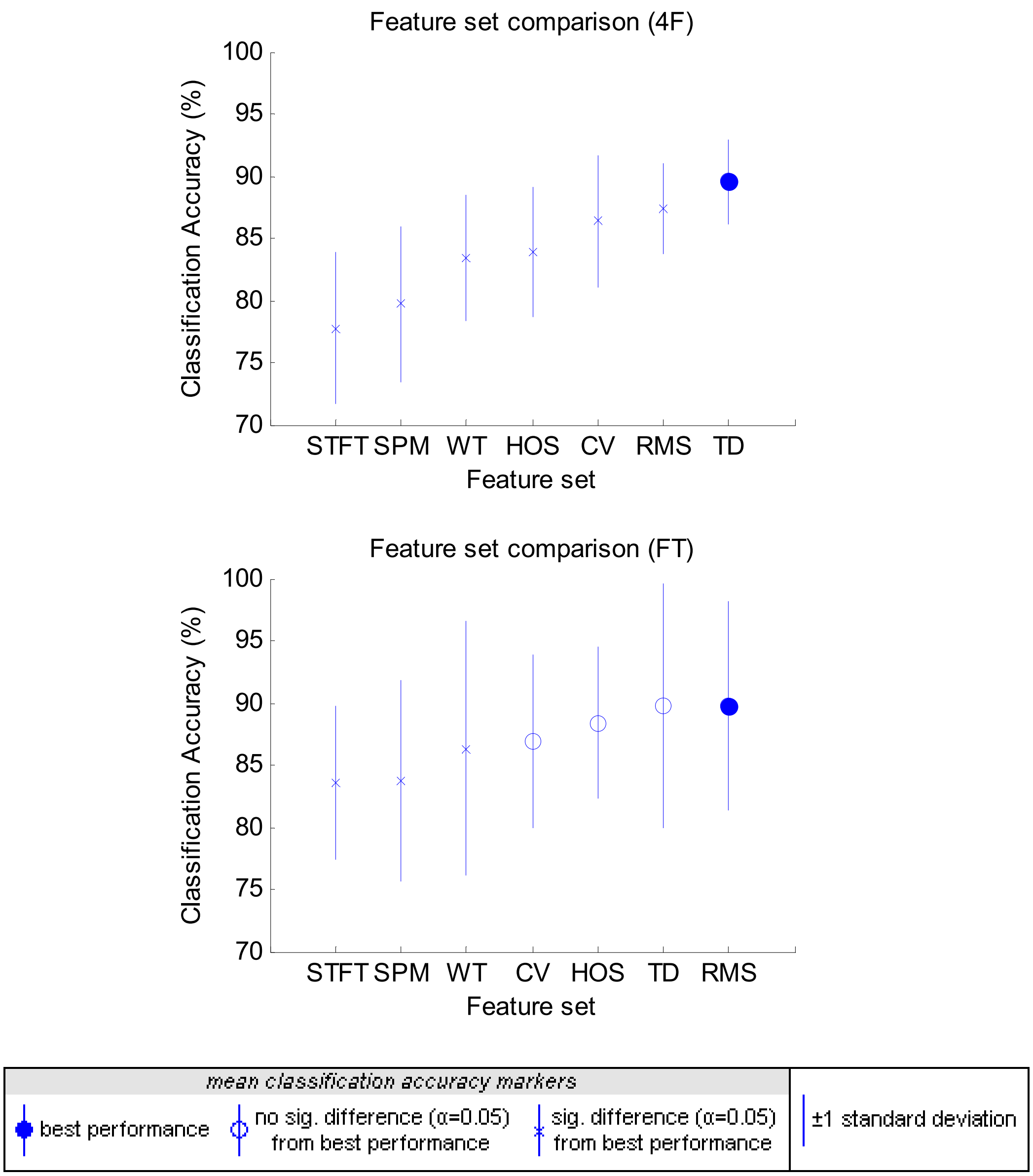


Figure 4-6 – Optimal performance for each feature set

Using the results from Table 4-2, the charts in Figure 4-7 show the proportion of different feature set choices across the SO systems; the TD feature set is most common, followed by the RMS set, whereas the STFT, SPM, and WT sets are not optimal for any scenario.

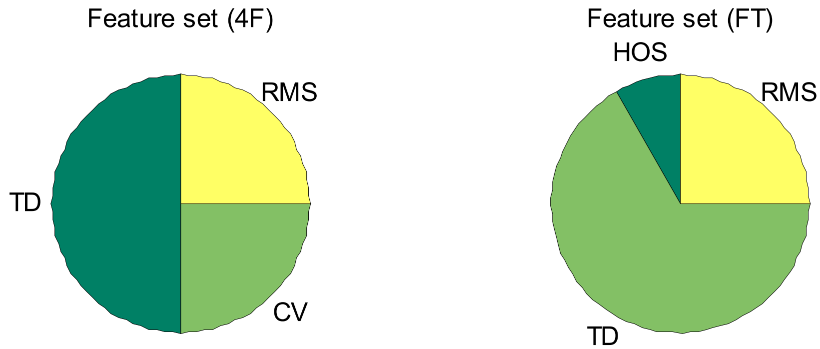


Figure 4-7 – Feature set distribution across SO systems

4.5.4 Window divisions

The best performing system for each of the three window division values was determined and the corresponding classification accuracy values are represented in Figure 4-8. For the 4F set, the seven-division system yielded classification accuracy values significantly different ($p<0.05$) from those of the optimal system; however, this was the only case for both movement sets where the optimal system's performance was significantly different from another system.

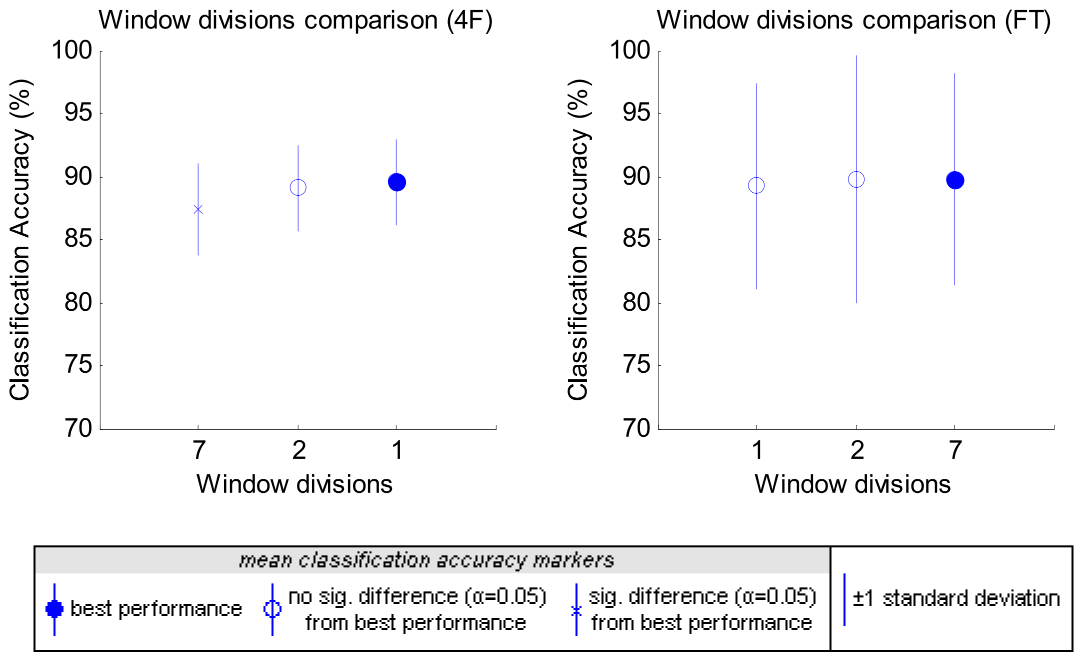


Figure 4-8 – Optimal performance for each window division value

Using the results from Table 4-2, the charts in Figure 4-9 show the proportion of different window division values across the SO systems. It is evident from the charts below that the choice of two window divisions is optimal for the majority of scenarios; however, for both movement sets each tested window division value is optimal in some cases.

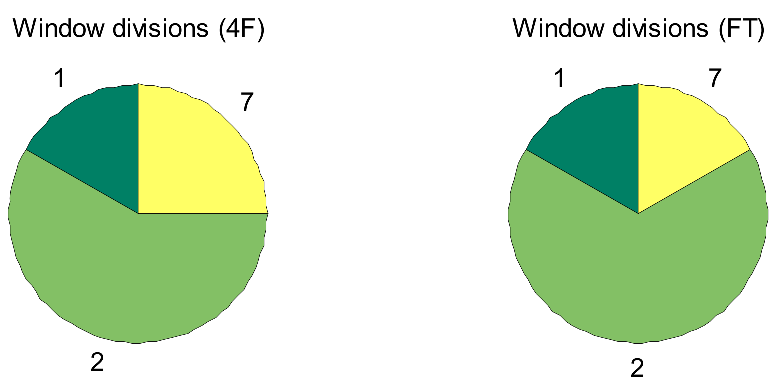


Figure 4-9 – Window division value distribution across SO systems

4.5.5 Window length

The best performing system for each of the three window length values was determined and the corresponding classification accuracy values are represented in Figure 4-10. For both movement sets, the most optimal window length value did not yield performance that was significantly different (α=0.05) from any other window length value.

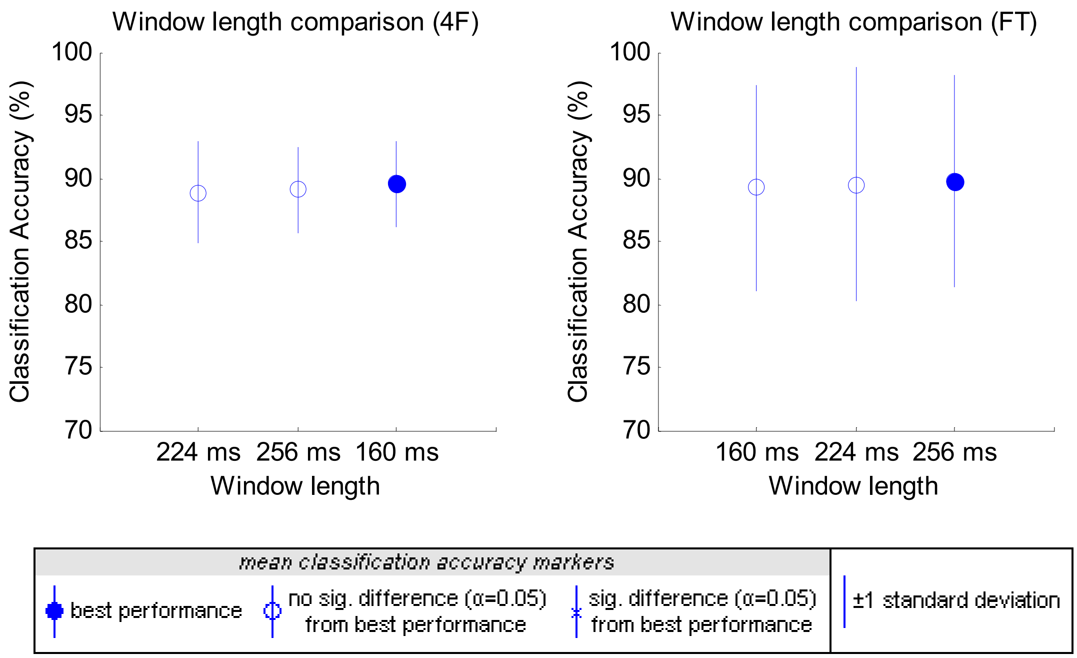


Figure 4-10 – Optimal performance for each window length value

Using the results from Table 4-2, the charts in Figure 4-11 show the proportion of different window length values across the SO systems. From the charts below, it can be seen that each window length value is optimal for a similar number of scenarios, though a value of 224 ms is most common.

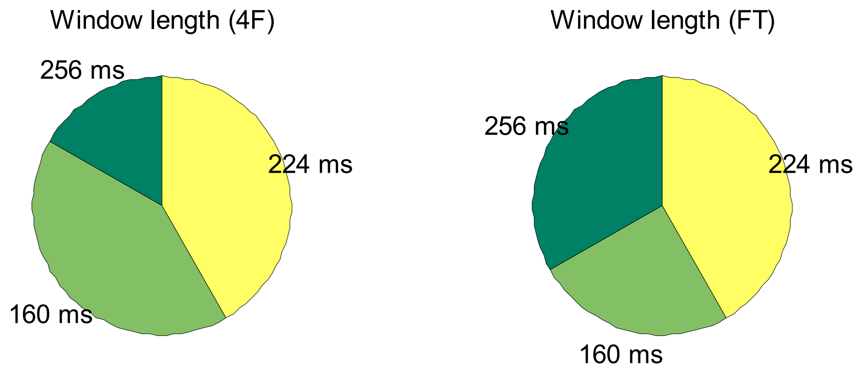


Figure 4-11 – Window length value distribution across SO systems

4.5.6 Window skew

The best performing system for each of the three window skew values was determined and the corresponding classification accuracy values are represented in Figure 4-12. For both movement sets, the most optimal window skew value did not yield performance that was significantly different (α=0.05) from any other window skew value.

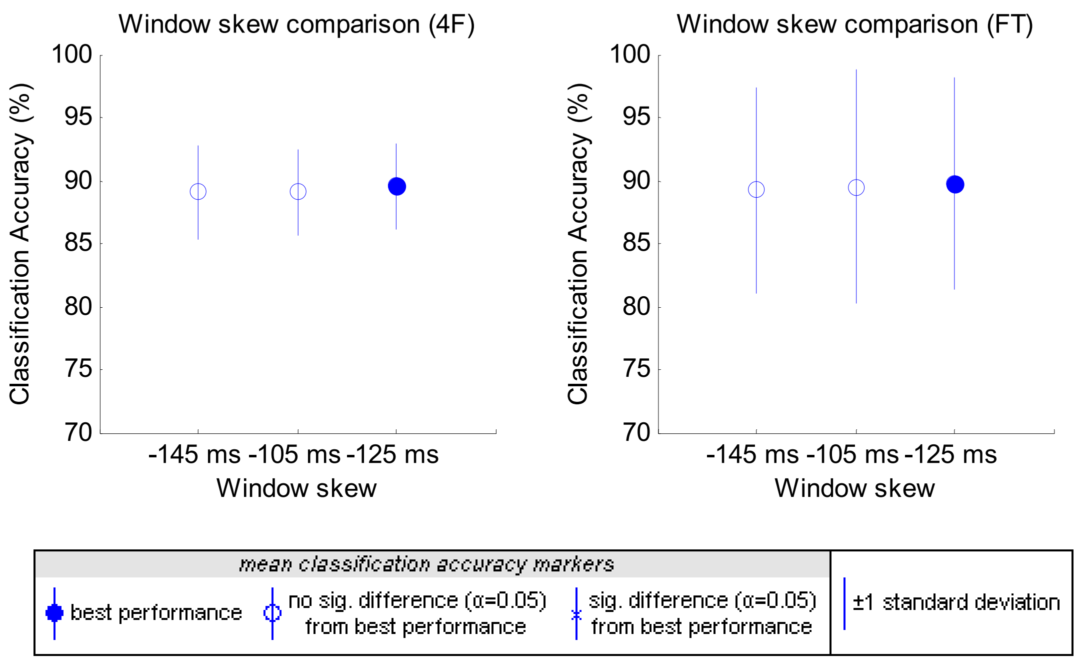


Figure 4-12 – Optimal performance for each window skew value

Using the results from Table 4-2, the charts in Figure 4-13 show the proportion of different window skew values across the SO systems. From the charts below, it can be seen that each window skew value is optimal for a similar number of scenarios, though a value of -145 ms is least common.

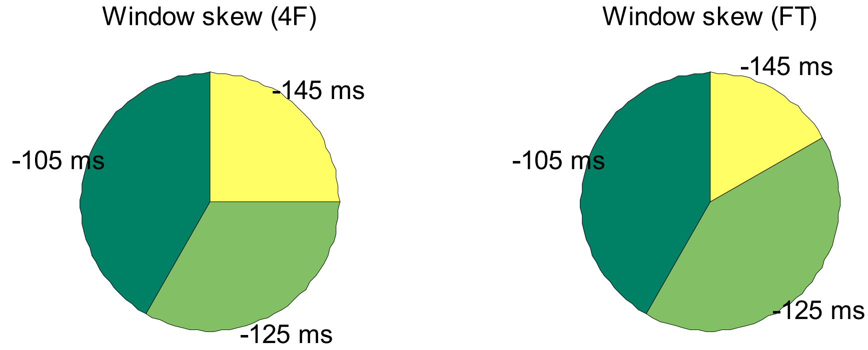


Figure 4-13 - Window skew value distribution across SO systems

4.6 Keystroke performance

Classification accuracy results for each keystroke are given in Tables 4-6 and 4-7 for the GO and SO systems, respectively. In the following tables, the row headings represent the keys pressed and the column headings represent the system decisions (i.e. the keystroke classifications); consequently, each given value in the table refers to instances where keystroke [row heading] was classified as keystroke [column heading]. Each table value uses *mean ± standard deviation* notation to reflect the distribution of classification accuracy values across all subjects and relevant exercises; all given values are percentages.

Table 4-6 – Keystroke classification accuracy (M±SD %) for GO systems

4F set		System decision: j	k	l	;
Key-press	j	88.5 ± 16.8	10.6 ± 16.7	0.6 ± 3.0	0.2 ± 1.0
	k	14.8 ± 19.5	82.9 ± 21.3	1.8 ± 7.0	0.5 ± 3.0
	l	2.5 ± 10.3	3.5 ± 6.8	92.8 ± 14.5	1.1 ± 4.2
	;	2.6 ± 4.7	2.9 ± 5.6	0.5 ± 2.1	93.9 ± 8.4

FT set		System decision: 0	6
Key-pres	0	89.9 ± 15.0	10.1 ± 15.0
	6	10.3 ± 12.5	89.7 ± 12.5

Table 4-7 – Keystroke classification accuracy (M±SD %) for SO systems

4F set		System decision: j	k	l	;
Key-press	j	91.4 ± 9.9	7.5 ± 9.7	1.0 ± 3.3	0.1 ± 0.7
	k	10.2 ± 11.7	87.7 ± 13.8	2.0 ± 7.1	0.1 ± 0.7
	l	0.7 ± 2.3	2.2 ± 4.8	96.9 ± 5.0	0.2 ± 1.0
	;	1.9 ± 3.9	2.3 ± 4.1	0.6 ± 1.7	95.2 ± 6.6

FT set		System decision: 0	6
Key-pres	0	95.5 ± 6.0	4.5 ± 6.0
	6	8.2 ± 12.9	91.8 ± 12.9

For both GO and SO, the highest mean classification accuracies were found for keystrokes 'l' and ';', and the lowest mean accuracies were found for keystroke 'k.' For SO, keystroke '0' yielded the highest mean classification accuracy. A one-way repeated measures ANOVA (α=0.05) showed a significant difference in keystroke classification accuracy for the 4F movement set for both GO ($p<0.05$) and SO ($p<0.05$), but no significant difference for the FT movement set for either GO ($p=0.943$) or SO ($p=0.092$).

Post-hoc testing on the 4F results using Tukey's method for multiple comparisons showed a significant difference between keystrokes [k ;] for GO and between keystrokes [k l] and [k ;] for SO.

Chapter 5
Discussion

5.1 Discussion

Optimization approach

In this work, average classification accuracies of 92.8 ± 2.7% for a typing task involving four fingers, and 93.6 ± 6.1% for a typing task involving the thumb and index finger, were obtained using a classification system that was optimized for each subject/task combination. These accuracies are significantly higher ($p<0.05$) than those achieved by using a generally optimized classification system, i.e. a system that was optimized for each task only. Consequently, future prosthetic control applications, particularly those involving movement of individual digits, could benefit by tailoring the classification system to each specific user and movement set in the manner demonstrated in this work.

The subject-specific optimization of classification systems presented in this work is the first of its kind; the myoelectric classification literature has given focus to determining GO systems that were tested in the same form across multiple subjects (1-7,9-12,18-20,26,28). Though these systems did incorporate classifier training for each subject, element choices were not subject-dependent.

The SO approach used in this study resulted in increased classification accuracy without significantly affecting the response time or the intuitive nature of the task. Thus, incorporating individualized classification systems would potentially result in a better myoelectric control system. However, there are several potential costs to consider, including increased training time and the need to produce personalized prosthesis control systems. If a large number of prostheses are to be produced, it may be more cost-effective to program all control systems with the same classification system than it would be to use a different system for each device. This problem could be alleviated with the implementation of a microcontroller-based prosthesis control system that allows for easy programming of the control algorithm.

To train a classification system, examples of myoelectric data corresponding to each movement (or class) must first be collected from a subject or potential user. Then, the system's classifier attempts to learn the relationships between the myoelectric data and the corresponding movements. The SO approach adds one level of complexity to this general training process: instead of training a single system, this approach involves training a large number of systems and selecting the system that performs best on a set of test data. Although overall training time will increase with the number of systems tested, this increase may not be problematic for several reasons: SO need not occur more than once per subject; mean classifier training times for all GO and SO systems presented in this work were in the order of seconds; and the training and testing of multiple systems can be fully automated, as they were in the current study (see Section 3.6).

Performance relative to the literature

In the finger movement classification studies of Hiraiwa *et al.* (17), Uchida *et al.* (32), and Tsenov *et al.* (31), classification accuracies of 66.7%, 86%, and 98%, respectively, were achieved using five movements and one data channel for the former two studies, and four movements and four data channels for the latter study. For several reasons, these results are not directly comparable to those obtained in this thesis work: the systems used by Hiraiwa *et al.* (17), Uchida *et al.* (32), and Tsenov *et al.* (31) were tested on a single subject only, relatively small data sets were used, and the movements reported were neither typing nor transient movements. Additionally, each movement set included at least one gross hand movement (e.g., flexion of all fingers, hand closure, relaxation of hand) and several finger flexion movements (17,31,32); these movements were less subtle than the typing movements used in this thesis work, and therefore possibly easier to classify.

Classification accuracies obtained in this thesis work for transient typing movements were similar to those obtained in the literature for transient arm and gross hand movements (6,9,10,13,19,28). The similarity of these results indicates an impressive performance by the proposed SO approach and the element choices involved, particularly considering the low SNR observed in the collected myoelectric data. Whereas the average accuracy obtained for the four-movement 4F set in this study was 92.8 ± 2.7%, optimal values reported in the literature for the classification of four transient arm movements are 91.2% (19), 93.8% (9), 89.7% (6), 98.0% (10), and 93.2% (28). In each case, multiple subjects and between one and four data channels were used. For classification of two grip movements, Farry *et al.* (13) achieved an accuracy value of 93% using two data channels, however only a single subject was tested. This is similar to the value of 93.6 ± 6.1% achieved in this thesis work for the two-movement FT set. Given that fewer than eight data channels were used in the previous studies (6,9,10,13,19,28), it is possible that the classification accuracy values achieved in this thesis work may not be compromised by using fewer data channels. In doing so, classification delay and training times would be reduced.

Element performance

For many classification system elements, several values or methods proved to be optimal for at least one subject; therefore, for these elements there is no overall clear best method or value that could be used for every potential user of such a classification system. Specifically, for DR and for each window characteristic there was no dominant choice implemented in the SO systems. As well, the DR method, the window length, and the number of window divisions were different between the two GO systems.

The similar performance across most DR methods and window characteristic values may imply that these particular system elements have the potential to yield high performance over a wide range of choices. This would suggest that the apparent differences between these element choices are due to statistical fluctuations, e.g. substituting PCA-48 for PCA-64 in a SO system does not result in a significant difference in accuracy. If this can be proven, then the optimization of a classification system for a specific subject and task could involve fewer element choices and therefore less training time. The results for the remaining system elements – classifier and feature set – yielded more significant differences among the different methods tested.

The LDA classifier emerged as the preferred choice in comparison to the statistical classifier, and in a more limited context, to the MLP classifier. The LDA classifier was used in both GO systems and 20 of 24 SO systems, however the statistical classifier did outperform it in 4 of 24 scenarios (see Figures 4-2, 4-3). It remains to be seen whether the accuracies obtained by these four SO systems are significantly greater than those obtained using the best possible LDA classification systems for each of the four scenarios. If no significant differences are present, then there is no clear advantage to the statistical classifier's use.

The MLP performance in this thesis work was reflective of its performance in the literature – it performs generally well, but is secondary to the LDA classifier for transient data classification (9,11). Further testing may be warranted as the MLP did not receive the same extensive optimization as the other classifiers, due to its very long training time. Whereas the LDA and statistical classifiers were each tested in 333 different classification systems, the MLP was tested in only a single system for each movement set. However, given the lack of promise shown for the MLP classifier in this work, its secondary performance for transient data classification tasks in the literature (9,11), and the greater effect of feature set choice on classification accuracy (9), further MLP testing is likely not an optimal route to improving system performance.

The TD, RMS, CV, and HOS feature sets were each selected for at least one SO system, whereas the SPM, STFT, and WT feature sets were not selected for any SO systems. The TD set was implemented in the 4F GO system; all other feature sets produced significantly different results from this optimal system at the $\alpha=0.05$ level. Though the RMS set was implemented in the FT GO system, results obtained using the TD, HOS, and CV feature sets were not significantly different at the $\alpha=0.05$ level. Therefore, both GO and SO results indicate that the TD, RMS, CV, and HOS feature sets perform better than the time-frequency sets (STFT, SPM and WT), and that the TD feature set performed best overall: it was selected for the 4F GO classification system and for 14 of 24 SO systems. No advantage to using the frequency and time-frequency feature sets for this application is evident.

Exclusion of certain features from the TD set has been found in the literature to have a beneficial effect on classification accuracy (6,11-13,18). Especially given the good performance of the simple RMS feature set in this study, it is possible that classification accuracy may improve in some cases when a set comprising fewer time-domain features is used. To determine if this is the case, future testing of various subsets of the TD feature set may be useful.

The performance of feature sets found in this thesis work contrasts the trend in the literature that transient movements are best classified using time-frequency methods, such as the STFT and various wavelet transforms (2,9,10,20). This discrepancy may be due to the eight data channels used in the current study as opposed to the one to four channels commonly used in the literature (1,4,6,7,9-13,17-21,23,25,26,28,30-34). It may be that more useful information can be drawn from a single data channel using the generally larger time-frequency feature sets (see Table 3-3), but that more useful information regarding between-channel relationships can be derived using the smaller TD, RMS, CV, and HOS feature sets. This could explain the performance achieved in this thesis work since many data channels were used relative to the literature, and therefore the amount of between-channel information was higher. It would be advantageous, however, if similar performance could be achieved using fewer data channels, as lower production costs of prostheses and their control systems may result. Further testing using subsets of data channels from this thesis work could address this issue.

Movement set performance

The FT set was not classified significantly better ($p<0.05$) than the 4F set, as one might have expected. Two factors that may have contributed to this outcome involve the particular movements in each set and the manner in which they were executed. Firstly, the fourth and fifth finger movements unique to the 4F set yielded particularly high classification accuracy values, consequently raising the average 4F set performance. Secondly, the FT movements may have yielded lower amplitude muscle bursts because the subjects adopted a more relaxed hand position, such that they were less inclined to lift their fingers between keystrokes than for the 4F exercises; this lower movement intensity may have caused an overall reduction in classification accuracy. Furthermore, it should be noted that the single movement common to both sets – the second finger movement – yielded slightly higher classification accuracy for the FT set, as one might expect for the smaller set; the small size of that difference may be attributed to the lower intensity of FT movements, as discussed above.

Pace, order, and keystroke performance

The classification accuracy values of paced and un-paced exercises were not significantly different ($p=0.806$). This result may appear counter-intuitive: it would seem that the generally faster typing in un-paced exercises would result in more misclassified movements due to i) the presence of muscle bursts from multiple movements in a single classification window, and ii) overlapping muscle bursts complicating movement detection and corresponding classification window placement. However, the results may be explained by the nature of the exercises and the movement detection method. In un-paced trials, subjects were instructed to type comfortably but avoid excessive speeds; consequently, muscle activity bursts likely remained disjoint regardless of pace option and therefore classification was not compromised. Additionally, the movement detection method did not determine muscle burst onsets using the myoelectric data, but referenced classification windows directly to an electrical pulse sent to the data collection system at each keystroke instance (see Sections 3.4, 3.7); therefore, classification was also not compromised by movement detection complications.

The significantly different results between ordered and non-ordered exercises ($p<0.05$) are likely due to i) differing myoelectric activity levels between exercise types (i.e. ordered/non-ordered), and ii) more consistent myoelectric burst shapes in ordered exercises. As subjects used the same finger for 20 repetitions at a time in ordered trials, they were inclined to keep their other fingers - and consequently their forearm muscles - more relaxed, resulting in less myoelectric data that was irrelevant to the present keystroke. Moreover, subjects may have gotten into a rhythm when typing the same key repetitively, which likely resulted in fewer burst irregularities and thus fewer misclassifications.

From Tables 4-6 and 4-7 it can be seen that for the 4F set the fourth and fifth finger movements yielded the highest mean classification accuracy for both optimization schemes, while the third finger yielded the lowest. For the FT set, the mean classification accuracy of the thumb movement was 3.7% higher than the second finger movement for SO. Furthermore, there were significant differences in classification accuracy at the α=0.05 level between keystrokes [k l] and [k ;] under SO and between keystrokes [k ;] under GO.

Forearm anatomy may help to explain the high classification accuracy values of the first, fourth, and fifth finger movements relative to the second and third finger movements. The *extensor digiti minimi* is a muscle responsible solely for fifth finger movement that is located superficially in the forearm (27); the consequent proximity of this muscle to the electrode array may have contributed to the high classification accuracy values of the ';' keystroke. The *abductor pollicis longus* and *flexor pollicis longus* are muscles responsible for thumb movement and originate at the approximate position of the electrode array (27); the location of these muscles relative to the electrode array may have contributed to the high classification accuracy values of the '0' keystroke. Finally, the *flexor digitorum superficialis*, which contributes to the movement of fingers two through five (27), may not always fully lie under the electrode array; the portions of this muscle responsible for second and third finger movement lie more distally in the forearm than the portions responsible for fourth and fifth finger movement (27), possibly contributing to the higher classification accuracy of the 'l' and ';' keystrokes relative to the 'j' and 'k' keystrokes.

Classification delay

The classification delay for a single movement consisted of the time required for both data collection (i.e. the window length) and data classification. For all GO and SO systems, the mean classification delay for each exercise did not exceed the generally accepted limit of 300 ms (12). Specifically, the maximum window length used was 256 ms (see Section 3.7) and the mean computational times for each exercise were all under 11 ms for both GO systems and 23 of 24 SO systems (see Appendix C); the [S09, FT] SO system involved mean computational times of 44 ms for each exercise, likely due to the use of the HOS feature set that is implemented in this system only. Regardless, given the associated window length of 224 ms for this system, the resulting classification delay was still below the 300 ms limit.

5.2 Limitations

Subject considerations

The myoelectric data used to test the classification systems were collected from normally-limbed subjects. Though this is far more common in the literature (1,4,6,7,9-13,17-19,21,25,26,28,31,32) than collection from amputee subjects (19,30,33,34), it is nevertheless a limitation. The target population for the proposed classification approach is the below-elbow amputee population; therefore, further testing of classification systems within this population would be an integral step towards useful application in a prosthesis control system. It is evident that the results achieved in this work are applicable only to below-elbow prostheses due to the electrode positioning used.

Movement detection

The trigger pulse and window skew used in this work represent the movement detection element of the classification system; together, these are a form of manual detection (see Section 2.3). This detection approach was used in order to allow for a more clear investigation of the effects of window characteristics, feature set, DR method, and classifier on classification accuracy - without added interference from detection-based classification error. However, due to the off-line nature of the detection method used, the classification approach proposed in this study is not immediately applicable to a typical on-line application. Consequently, the determination of an effective on-line movement detection method, such as automated detection or continuous classification (see Section 2.3), and its substitution into the proposed approach would allow for testing in the intended on-line application.

Statistical methods

The statistical methods in this thesis work were used to determine whether classification accuracy values were significantly different between two or more cases, though admittedly a more thorough statistical analysis is possible. Further analyses could be done to determine the main effects and interactions of the different optimization methods, element choices, movement sets, movements, and exercise characteristics. The investigation of interaction effects may highlight relationships useful to system development; for example, determining which feature set works best with the shortest data window would be beneficial in minimizing classification delay while optimizing system performance.

Computational time

All computational time values reported in this work could possibly be reduced by using a computer system dedicated and optimized to the classification task. However, this potential reduction may hold little value for the proposed approach as all classification delay values reported were significantly lower than the 300 ms limit (see Section 5.1).

5.3 Recommendations

An alternate approach

The study presented in this thesis involved the thorough optimization of a typing movement classification system using a variety of classifiers, DR methods, feature sets, window lengths, window divisions, and window skew values. The aim of this approach was to cast a wide net; many methods - often drawn from the literature - were tested in order to optimize a classification system for simple typing tasks. Following this study, a more tightly-focused approach could further assist in the development of classification techniques: in particular, investigating the characteristics of myoelectric signals associated with each keystroke and misclassification. Specifically, where the keystrokes 'j' and 'k' were not classified correctly, they were most often misclassified as one another; therefore, research into further differentiation of these two movements could greatly increase overall classification performance.

Further study of element choices

The results of this study showed that there is no clear optimal choice for many system elements; some elements may be dependent on subject or movement set, others may perform well over a variety of values. For elements where the latter case is true, there may be no significant loss to classification accuracy in discarding certain values from the testing set; in fact, this would drastically reduce the number of systems tested and consequently the training time. For example, if it can be shown that the optimal results obtained for each scenario using only a 256 ms classification window are not significantly worse than those obtained using all three window lengths, the other window lengths could be discarded; the total number of tested classification systems would then be cut down by two thirds. Though it would not directly increase classification accuracy, investigation into elements that yield good performance over a variety of values would both assist in the understanding of optimal element choices and possibly reduce system training time.

Though many different element choices were implemented in this work, the investigation of more element choices, such as the hidden Markov model (HMM) (3,4), Gaussian mixture model (GMM) (18), and fuzzy logic-based (6,21,23) classifiers, may lead to increased system performance.

Data channels

As discussed in Section 5.1, if fewer data channels can be used without compromising classification accuracy, then the resulting prosthesis production cost may be decreased. Furthermore, reducing the number of data channels may actually improve system performance if data from some channels are unrelated to the physical movement classified; however, the improvement may not be significant as the classifier and DR method likely emphasize these channels least already. Discerning the best electrode positions from the eight-channel array used in this thesis work could also indicate which muscles yield the most useful myoelectric data for the classification of typing movements; though this will not directly lead to higher performance, it may assist in the future design of prostheses and their control systems – and the understanding of control system function.

Electrode unit placement

Classification accuracy may be increased through the investigation of optimal electrode unit positions. Several muscles responsible for finger movement lie more distally in the forearm than the electrode array position used in this thesis work, such as: the *extensor pollicis brevis* and *extensor pollicis longus*, which contribute to thumb movement (27), the portions of the *flexor digitorum superficialis* that contribute to second and third finger movement (27), and the *extensor indicis* which contributes to second finger movement (27). Therefore, a change in electrode unit placement may yield more information from these muscles that in turn could increase overall classification performance. However, the electrode array position implemented in this work was chosen with the prosthesis user in mind: the muscles listed above may not be present or functional in these users as a result of amputation or congenital defect, and thus more distal electrode unit placement may in fact reduce classification accuracy.

Classification delay

The often-referenced 300 ms classification delay limit (12) should not be considered as a threshold below which all delays are equally acceptable. Lower values can help compensate for delays contributed by the mechanical action of a prosthesis and also allow for more rapid movements, such as those involved in typing. Future investigation into the effects of smaller window lengths on classification accuracy may help to minimize classification delay without compromising system performance.

5.4 Contributions

This thesis work offers several unique contributions to the field of myoelectric classification. Perhaps most significant is the large-scale approach to classification system testing: not only were multiple choices tested for four main system elements, but the testing involved all possible combinations of these choices. This was done in order to determine the optimal element choice combinations for the classification of subtle typing movements.

Large-scale testing allowed for the second main contribution of this work: the thorough optimization of system element choices for each scenario, allowing systems to be tailored to individual subjects. The resulting SO systems achieved significantly higher classification accuracies for both movement sets than the corresponding GO systems, which were optimized for movement set only. Consequently, the implementation of an SO approach should be considered in future myoelectric classification research and development.

Chapter 6
Conclusion

6.1 Summary and conclusions

Motivation and goal

The number of work and life opportunities for a person with an upper limb amputation or congenital defect is greatly reduced due to the loss of hand and finger function; therefore, research into myoelectric control for a dexterous prosthesis is of great value. Consequently, the goal of this thesis work was to determine an effective approach to finger movement classification in typing tasks using myoelectric data collected from the forearm.

Results summary

Classification accuracies of 92.8 ± 2.7% for the 4F movement set and 93.6 ± 6.1% for the FT movement set were obtained with acceptable delay using SO, which were significantly higher values than those obtained using GO ($p<0.05$). The SO accuracy values for the 4F and FT sets were comparable to those found in the literature for transient arm movement classification using four and two movements, respectively. No significant difference in performance was found between movement sets or paced and un-paced exercises; however, a significant difference in performance was found between ordered and non-ordered exercises ($p<0.05$). Under SO, the classification accuracies of both fourth and fifth finger keystrokes were significantly higher at the $\alpha=0.05$ level than those of third finger keystrokes.

The accuracy values obtained using SO are comparable to those found in the literature for arm and gross hand movements, where muscle activity is of higher intensity. Therefore, given the comparatively subtle nature of the finger movements in this thesis work and the resulting low SNR, the level of classification performance attained is impressive.

Optimal approach

The best-performing classification approach involved element choices optimized for each subject and movement set. It was clear for both movement sets that a single overall classification system could not achieve the same level of performance.

Every tested window characteristic value and DR method was optimal for at least one subject for each movement set. The SPM, STFT and WT feature sets were not present in any scenario's optimal system, whereas the TD, RMS, CV and HOS feature sets were each present in at least one. The TD feature set performed best: it was optimal for the largest number of scenarios and it was implemented in the 4F GO system. The RMS feature set was optimal for the second largest number of scenarios and it was implemented in the FT GO system. The MLP classifier showed no advantage in its limited testing.

Future steps

Several future paths of research have been suggested in this work, most importantly: integrating an on-line movement detection method into the proposed classification systems; determining characteristics of the myoelectric signal associated with different finger movements and misclassifications; and further developing the proposed classification systems using data collected from the amputee population, for which the systems are primarily designed.

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Appendix A

Letter of information and consent

FINGER MOVEMENT PREDICTION USING FOREARM EMG SIGNALS

Dear _________________

You are being invited to participate in a research study being done at Queen's University. Please read through this information and consent form to learn more about the study and details of your participation. Feel free to ask questions at any time and note that we will review experimental procedure together as necessary throughout the study.

Purpose and Aims of the Study:

The purpose of this study is to develop a system that can predict different finger movements given forearm muscle signals. A well performing system could have direct application in the field of prosthetics, allowing people with amputations or congenital hand control problems to attain dexterous finger control with the use of a prosthesis.

You will be performing several different typing tasks with your right hand. The computer on which you will be typing will record your keystrokes; the muscle activity in your forearm muscles will be recorded on a second computer. This muscle activity, commonly referred to as an electromyogram (EMG) signal, will be detected by small sensors placed around the circumference of your forearm. The recorded EMG and keystroke data will be used to develop a finger movement prediction system, which could be a significant step towards dexterous finger control in prosthetics.

Study Preparation:

First, your height, weight, forearm length and circumference will be measured and recorded. You may then be asked to shave a small 1-2" section around your forearm several inches from your elbow so that your muscle signals can be read without interference. Your skin will then be cleaned with rubbing alcohol to improve contact of the sensors. Finally, small sensors will be attached to the skin on your forearm and taped in place.

Procedure:

Sitting at a computer station, you will first be asked to remain relaxed while rest data is collected. Next, you will begin a series of typing exercises. There are two sets of eight exercises in total, and each exercise involves a specific character set, character order and typing pace. During each exercise you will type a series of characters as they appear on the screen. After completing the exercises, you will be asked to perform a set of high force contractions with your hand and individual fingers. Finally, more rest data will be collected and then the electrodes will be removed.

Risks of Participation:

The risks of participating in this study include skin irritation due to sensitivity under the EMG sensors and muscle discomfort following the high force contractions. If you experience any unpleasant effects, please report this to the principal investigator immediately.

Benefits of Participation:

The results obtained from your data will be used in the development of a dexterous prosthetic control system, which has the potential to benefit those people suffering from upper limb amputation or congenital hand control defects. If you are interested in hearing about the project's final results, enter your e-mail address below and you will be sent a summary.

e-mail: ________________________________

Exclusion Criteria:

You will not be considered for this study if you:

- have restricted finger mobility or a history of severe finger or hand control problems;
- have a history of dizziness, fainting, irregular heartbeat, or severe headaches;
- have been diagnosed with carotid or coronary artery disease;
- have been diagnosed with high blood pressure;
- have breathing problems;
- are overweight, such that the forearm muscle signals are of poor quality.

Confidentiality:

Your identity is strictly confidential and will be protected at all times. You will be identified by a subject number, not your name. Recorded information (gender, height, weight, and forearm measurements) will be kept on file under your subject number only. This signed consent form will be available only to the principle researcher.

Voluntary Nature of the Study:

Your participation in this study is completely voluntary. You may withdraw from this study at any time without penalty, by indicating to the investigator that you do not wish to continue.

Withdrawal of subject by principal investigator:

You may be withdrawn from this study if the investigator feels that you are becoming overly fatigued or uncomfortable because of the tasks required or if you experience arm pain or discomfort during the procedure.

Liability:

By signing the consent form, you do NOT waive your legal rights nor release the investigator and sponsors from their legal and professional responsibilities.

Subject Statement and Signature:

I have read and understand the consent form for this study. The purposes, procedures and technical language have been explained to me. I have been given sufficient time to consider the above information and to seek advice if I choose to do so. I have had the opportunity to ask questions which have been answered to my satisfaction. I am voluntarily signing this form. If desired, I can receive a copy of this consent form for future reference.

If at any time I have further questions, problems or adverse effects, I can contact the principal investigator, Alex Andrews at 613-453-7747 (0aja1@qlink.queensu.ca). If I have any questions regarding my rights as a research subject I can contact Dr. Albert Clark, Chair, Research Ethics Board at 533-6081. (clarkaf@post.queensu.ca).

By signing this consent form, I am indicating that I agree to participate in this study.

____________________________ ______________________

Signature of Subject Date

I understand that I may be photographed during the study. By signing below, I give my consent for use of my photograph in publication and presentation of this work, and I understand my identity will be masked in any such publications and presentations. I understand that if I do not sign below, I will not be photographed during the study.

____________________________ ______________________

Signature of Subject Date

By signing this consent form, I confirm that I have carefully explained to the subject the nature of the above research study. I certify that, to the best of my knowledge, the subject understands clearly the nature of the study and the demands, benefits, and risks involved to participants in this study.

____________________________ ______________________

Signature of Witness Date

Appendix B

Classification accuracy results

GO optimization

	Exercise:	1	2	3	4	5	6	7	8
	Movement set	4F	4F	4F	4F	FT	FT	FT	FT
	Ordered (O) / Non-ordered (N)	O	O	N	N	O	O	N	N
	Paced (P) / Un-paced (U)	P	U	P	U	P	U	P	U
Subject	1	85.0	91.3	86.3	91.3	100.0	100.0	95.0	95.0
	2	93.8	92.5	57.5	90.0	92.3	90.0	97.4	100.0
	3	91.3	97.5	95.0	96.3	87.5	95.0	90.0	80.0
	4	93.8	87.5	92.5	91.3	95.0	95.0	97.5	95.0
	5	96.2	86.3	96.3	92.5	100.0	87.5	90.0	95.0
	6	72.5	96.3	93.8	93.8	75.0	85.0	65.0	80.0
	7	86.3	90.0	87.5	75.0	90.0	82.5	87.5	82.5
	8	93.8	92.5	90.0	81.3	80.0	97.5	77.5	85.0
	9	96.3	82.5	92.4	87.5	82.5	62.5	70.0	77.5
	10	91.3	95.0	88.6	92.5	100.0	82.5	87.5	97.5
	11	96.3	91.3	88.8	93.8	97.5	100.0	97.5	90.0
	12	97.5	98.8	82.5	67.5	100.0	100.0	100.0	100.0

All values are percentages

SO optimization

	Exercise:	1	2	3	4	5	6	7	8
	Movement set	4F	4F	4F	4F	FT	FT	FT	FT
	Ordered (O) / Non-ordered (N)	O	O	N	N	O	O	N	N
	Paced (P) / Un-paced (U)	P	U	P	U	P	U	P	U
Subject	1	88.8	95.0	95.0	98.8	100.0	100.0	100.0	97.5
	2	91.3	92.5	93.8	90.0	97.4	90.0	97.4	97.5
	3	96.3	98.8	93.8	96.3	92.5	97.5	97.5	77.5
	4	96.3	95.0	95.0	95.0	95.0	95.0	97.5	95.0
	5	98.7	93.8	95.0	91.3	100.0	100.0	100.0	95.0
	6	88.8	85.0	98.8	95.0	85.0	87.5	67.5	87.5
	7	93.8	88.8	82.5	81.3	90.0	95.0	90.0	75.0
	8	93.8	92.5	90.0	81.3	77.5	100.0	80.0	100.0
	9	96.3	90.0	96.2	90.0	97.5	80.0	87.5	82.5
	10	96.3	87.5	91.1	95.0	100.0	95.0	100.0	100.0
	11	95.0	98.8	90.0	95.0	100.0	97.5	100.0	97.5
	12	93.8	97.5	92.5	87.5	100.0	100.0	100.0	100.0

All values are percentages

MLP classification

Exercise:		1	2	3	4	5	6	7	8
Movement set		4F	4F	4F	4F	FT	FT	FT	FT
Ordered (O) / Non-ordered (N)		O	O	N	N	O	O	N	N
Paced (P) / Un-paced (U)		P	U	P	U	P	U	P	U
Subject	1	80.0	91.3	78.8	86.3	100.0	95.0	92.5	92.5
	2	91.3	92.5	63.8	93.8	84.6	92.5	84.6	100.0
	3	98.8	97.5	88.8	97.5	70.0	82.5	77.5	75.0
	4	87.5	86.3	91.3	86.3	95.0	95.0	92.5	90.0
	5	87.3	87.5	88.8	96.3	90.0	95.0	82.5	85.0
	6	82.5	88.8	95.0	88.8	67.5	62.5	55.0	85.0
	7	76.3	86.3	80.0	60.0	80.0	85.0	65.0	77.5
	8	88.8	87.5	88.8	75.0	75.0	95.0	65.0	70.0
	9	88.8	88.8	78.5	78.8	72.5	57.5	67.5	80.0
	10	86.3	83.8	84.8	83.8	97.5	82.5	90.0	92.5
	11	98.8	97.5	86.3	90.0	97.5	92.5	87.5	80.0
	12	76.3	82.5	87.5	81.3	92.5	97.5	100.0	95.0

All values are percentages

Appendix C

Computational time results

GO optimization

Exercise:		1	2	3	4	5	6	7	8
Movement set		4F	4F	4F	4F	FT	FT	FT	FT
Ordered (O) / Non-ordered (N)		O	O	N	N	O	O	N	N
Paced (P) / Un-paced (U)		P	U	P	U	P	U	P	U
Subject	1	4.1	4.1	4.1	4.1	8.5	8.5	8.5	8.5
	2	4.2	4.5	4.5	4.6	10.6	10.3	10.5	10.4
	3	4.1	4.2	4.1	4.1	8.6	8.5	8.4	8.5
	4	4.4	4.4	4.4	4.4	8.5	8.5	8.5	8.5
	5	4.2	4.1	4.1	4.2	8.6	8.6	8.7	8.7
	6	4.0	4.0	4.0	4.0	8.3	8.4	8.4	8.4
	7	4.3	4.2	4.2	4.3	8.4	8.4	8.4	8.4
	8	4.0	4.0	4.0	4.0	8.4	8.4	8.3	8.4
	9	4.2	4.2	4.1	4.1	8.4	8.4	8.4	8.5
	10	4.5	4.5	4.5	4.4	8.4	8.4	8.4	8.4
	11	4.1	4.1	4.1	4.1	8.4	8.4	8.4	8.4
	12	4.0	4.0	4.0	4.0	8.4	8.4	8.4	8.4

All values in ms

SO optimization

Exercise:		1	2	3	4	5	6	7	8
Movement set		4F	4F	4F	4F	FT	FT	FT	FT
Ordered (O) / Non-ordered (N)		O	O	N	N	O	O	N	N
Paced (P) / Un-paced (U)		P	U	P	U	P	U	P	U
Subject	1	3.9	4.0	4.0	4.0	8.4	8.4	8.4	8.4
	2	6.9	6.8	6.8	7.1	6.6	6.6	6.9	6.5
	3	5.9	5.9	6.0	5.8	6.5	6.6	6.5	6.6
	4	4.1	4.1	4.1	4.1	2.7	2.7	2.7	2.7
	5	8.5	8.5	8.4	8.7	5.1	5.0	5.0	5.0
	6	6.4	6.4	6.4	6.4	1.7	1.6	1.7	1.7
	7	8.5	8.5	8.4	8.5	5.8	5.9	5.8	5.7
	8	4.0	4.0	4.0	4.0	6.9	6.8	6.8	6.8
	9	4.5	4.5	4.4	4.5	43.8	43.8	43.8	43.8
	10	6.9	6.9	6.9	6.9	6.7	6.7	6.7	6.7
	11	5.8	5.8	5.8	5.8	6.9	6.9	6.9	6.9
	12	8.2	8.3	8.3	8.4	6.4	6.4	6.4	6.4

All values in ms

MLP classification

	Exercise:	1	2	3	4	5	6	7	8
	Movement set	4F	4F	4F	4F	FT	FT	FT	FT
	Ordered (O) / Non-ordered (N)	O	O	N	N	O	O	N	N
	Paced (P) / Un-paced (U)	P	U	P	U	P	U	P	U
Subject	**1**	19.7	17.9	17.9	18.6	22.1	22.0	22.1	22.1
	2	17.8	17.8	17.9	17.8	22.1	22.0	22.1	22.1
	3	17.8	17.8	18.0	17.8	22.1	22.1	22.0	22.1
	4	17.8	17.8	17.8	17.9	22.1	22.0	22.1	22.0
	5	18.0	18.1	17.9	18.4	22.1	22.1	22.1	22.1
	6	17.8	17.8	18.0	17.8	22.1	22.1	22.1	22.1
	7	17.8	17.9	18.0	17.9	22.1	22.1	22.1	22.1
	8	18.3	18.3	18.3	18.2	22.1	22.1	22.1	22.1
	9	18.1	18.1	18.7	18.0	22.1	22.1	22.1	22.0
	10	18.0	18.2	18.2	18.2	22.1	22.1	22.1	22.0
	11	18.2	18.2	18.4	18.3	22.1	22.1	22.1	22.1
	12	17.7	17.8	18.6	18.5	22.2	22.1	22.1	22.0

All values in ms

Appendix D
Terminology

Classification system: The classification system, as it is referred to in this work, comprises a set of methods and values that together function to detect and classify physical movements using a myoelectric signal. Though the classification system normally comprises five different elements (see Figure 2-1), this study focuses on the following four:

- classifier
- dimensionality reduction (DR) method
- feature set
- window characteristics (number of divisions, window length, window skew)

Below is an example of a classification system tested in this thesis work.

{ LDA,	PCA-48,	RMS,	7,	256 ms,	-125 ms}
classifier	*DR method*	*feature set*	*# of divisions*	*window length*	*window skew*
			---------- window characteristics ---------		

Element: An element refers to one of the defining components of the classification system, such as the classifier type or window length (see Figure 2-1).

Scenario: A specific combination of subject and movement set, such as [S02, 4F] or [S11, FT], is referred to as a scenario. As twelve subjects and two movement sets were involved in this study, there were a total of 24 scenarios.