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DESIGN AND INTERACTIVE ASSESSMENT OF CONTINUOUS MULTIFUNCTION MYOELECTRIC CONTROL SYSTEMS

By

Blair A. Lock

B.Sc.E (EE) – University of New Brunswick, 2003

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

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In the Graduate Academic Unit of Electrical and Computer Engineering

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Abstract

Advancements in myoelectric signal (MES) control for upper-extremity prostheses have led to highly accurate, multifunction control schemes. However, availability of multiple degree of freedom prostheses is limited and hindered by slower development and high cost. The objective of this work is to develop a virtual environment wherein interactive assessments of these multifunction MES control schemes can occur without the present need for a physical multifunction device. A secondary objective is to employ the developed virtual system in a clinical assessment to relate a measure of virtual limb usability to MES classification accuracy. This investigation is motivated by the fact that real-time use of multifunction MES pattern recognition controllers has had limited quantitative assessment. Furthermore, the classification accuracy versus functionality relationship is not fully understood due, in part, to the absence of multifunction devices.

A fully integrated graphical user interface (GUI) system is developed providing means for tailored data acquisition and processing of multifunction control schemes. The GUI hosts a real-time, multifunction, virtual, upper-extremity limb and a clothes pin task for clinical assessment. Normally limbed subjects are recruited to participate in sessions where surface MES data are recorded for six classes of motion. From these data, thirty-six continuous multifunction MES control schemes are processed. Results are presented as percent classification accuracy. To complete each session, subjects perform a functional test with the virtual limb (which requires moving virtual "clothes pins" from a horizontal bar to a vertical bar in a set time) using the 'best', 'worst' and 'moderate' control schemes. Quantitative outcomes from the clothes pin tests expose the 'usability' (functionality) versus 'accuracy' (classification) relationship. Subjects repeat the process for five discrete sessions to provide insight into improved performance and repeatability of 'best' control algorithms.

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Table of Contents

List of Tables

List of Figures

List of Abbreviations

A/D	Analog to Digital
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Autoregressive
CEVEN	Classifier Evaluation in a Virtual Environment
DAQ	Data Acquisition
DC	Direct Current
DOF	Degrees of Freedom
EMG	Electromyography
GMM	Gaussian Mixture Model
GUI	Graphical User Interface
IBME	Institute of Biomedical Engineering
LDA	Linear Discriminant Analysis
MAV	Mean Absolute Value
MES	Myoelectric Signal
MLP	Multilayer Perceptron
MUAP	Motor Unit Action Potential
PCA	Principal Components Analysis
RMS	Root Mean Square
TD	Hudgins' Time Domain feature set
TDAR	Hudgins' Time Domain and Autoregressive feature set

Chapter 1: Introduction

1.1 Motivation

The control of upper extremity powered prosthetic limbs is, and has been for many years, the focus of extensive research and development. The common ambition is to provide increasingly advanced devices to limb deficient individuals who can thereby gain increased function with their residual limb. Efforts have led to successful prostheses employing various techniques of control; some of which use myoelectric signals (MES) as input. The MES are electrical signals, recorded on the skin surface by electrodes, which originate due to contractions of remaining musculature in residual limbs.

Much of the research at the University of New Brunswick's Institute of Biomedical Engineering (IBME) involves development of continuous multifunction MES control systems for upper extremity prosthetic limbs. Current state-of-the-art IBME multifunction controllers are capable of accurately and consistently discerning a large number of classes of motion [1]. These classes of motion can correspond to different degrees of freedom (DOF) from more than one upper extremity joint (e.g. shoulder, elbow, wrist, hand). Most commercially available prosthetic devices are not, however, economically available with means of on-board actuation for more than one or two joints' DOF. The prohibitive costs and lag in physical development expose the need for alternative assessment of current state-of the-art multifunction MES control. As mentioned before by Secord [2], there exists a great need for an interactive tool which can be used specifically for assessment and evaluation of multifunction MES control schemes. A PC-based virtual prosthetic environment developed under the scope of this project can help to bypass extensive prototyping costs and aid in faster delivery of multifunction MES control to market.

1.2 Research Objectives

The primary goal of this project can be considered to be completion of two sequential components: 1) the complete development of a virtual prosthetic environment tool for both clinical use and accommodation of various IBME research projects; and 2) the use of this tool in an interactive manner to relate MES control scheme classification accuracy to a measure of functional usability. Neither objective is considered secondary in research value to the other but software development is naturally accomplished prior to the clinical assessment of functionality.

The intent of this research project is to complement the MES control work of the IBME with an attempt to quantify functional usability of developed prosthetic controllers, previously evaluated in terms of classification accuracy. Uncovering how a measure of usability relates to system accuracy aids in the IBME’s end goal in this field: full implementation of a state-of-the-art MES control system.

1.3 Research Scope

Work on this project exists as staged software development followed by the MES control function assessment study. The MES control research tool is comprised of three major interfaces: 1) acquisition; 2) configurable MES controls processing; and, 3) the virtual arm environment, which are separately designed and constructed prior to their complete integration. The developed system achieves its purpose, encompassing both current and future clinical and research tool needs at the IBME. Also embodied by this project, the outcomes of the assessment study highlight the previously un-quantified relationship between multifunction MES control classification accuracy and its actual usability.

1.4 Thesis Outline

Continuing in Chapter 2, a brief review of the myoelectric signal is provided and state-of-the-art multifunction MES control schemes are discussed complete with a descriptive breakdown of the control components and algorithms. It is described how these control components lend to real-time implementations related to this project. Chapter 2 also includes a look at existing virtual environments, their uses for similar research projects, and how they support the efforts in this work. Chapter 3 documents the design and realization of the software tool itself while Chapter 4 describes the functional assessment research and associated results. Chapter 5 concludes the document and discusses the contributions, issues, and future directions of the research.

Chapter 2: Background

This section is included as a review of the associated MES processing as related to this work. Relevant histories of myoelectric control strategies and processing algorithms are provided, with citations, to establish a vocabulary and framework for later discussion.

2.1 The Myoelectric Signal

The MES is a biological signal generated by muscular contraction which propagates spatially through the body. During contractions, depolarization and repolarization of the muscle fiber cell membrane cause ionic currents which create measurable action potentials in the body [3]. A group of individual muscle fibers are innervated by a single nerve axon. These muscle fibers, nerve axon, and cell body of the nerve in the spinal cord comprise the 'motor unit', shown in Figure 2.1.

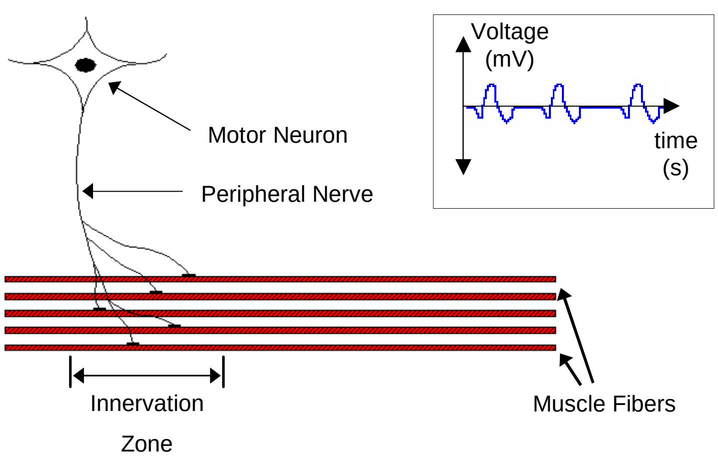


Figure 2.1 – Motor unit

Motor unit action potentials (MUAPs) from a group of motor units superimpose to form the MES which can be measured at the skin surface using surface electrodes, or underneath the skin using invasive techniques.

2.2 Multifunction Myoelectric Control

The concept of myoelectric control was first introduced in the late 1940s [3]; however, this work was not followed up. It was not until 1960 that another clinically useful myoelectric controlled prosthesis was fashioned and attracted considerable attention [4]. This development, along with advances in semiconductor technology, led to a dramatic increase in myoelectric controls research. Ever since, numerous myoelectric control strategies have been proposed and are in various stages of development.

It is generally accepted now that the instantaneous time value of the MES is not useful for control purposes [3]. Instead, parameters or features which are representative of MES activity over a window of time are used. Current conventions in MES control are systems using amplitude [5] or rate of change [6] of the MES, from one or two measurement sites, as the controlling feature. The simplest form of amplitude controllers, known as a two state-control, compares the root mean square (RMS) or mean absolute value (MAV) of the MES signal to a threshold value [4]. Under this application, an assigned actuating device is enabled when the RMS (or MAV) value exceeds the threshold. If two control (measurement) sites are used, the channel containing the highest level of energy dictates the device operation.

In a one-site, three state control system, one measurement site is used to control two active states and one rest state in a prosthetic device [5]. In this type of controller, the RMS value of the MES is considered against two different preset thresholds. The device remains idle in a 'do nothing' state until the first energy threshold is exceeded; this condition activates a DOF in one direction. An RMS signal exceeding the second threshold actuates the opposite motion of the device. A modified three state controller incorporates proportional control as the device activation speed is proportional to the RMS level of the MES signal [6]. Figure 2.2 shows the conventional controller process for making a decision to be sent to an actuator.

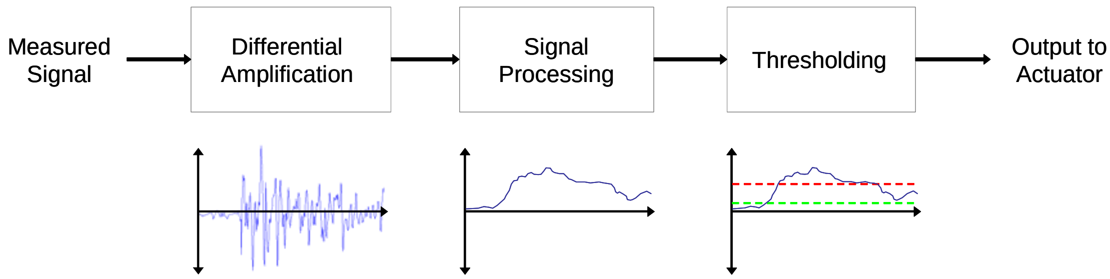


Figure 2.2 – Block diagram of a typical conventional controller

Three-state controllers work well and are in use; however, they are limited in that they control only one or two DOF. In attempts to achieve a truly multifunction device, the Boston Elbow [7] and Utah Arm [8] have been used in combination with an electric hand device. Unfortunately, these have required the use of mechanical switching or a switch based on muscle co-contractions to select which actuating device is to be operated [9].

Most recently, pattern recognition based myoelectric control systems have been developed from the assumption that, at a given electrode location, the set of features describing the MES will be repeatable for a given state of muscle activation [10]. Furthermore, it is assumed that the features will be different from one state of muscle activation to another. The stages of basic multifunction pattern recognition, as related to this project, are depicted in Figure 2.3 and explained in subsequent sections of this chapter.

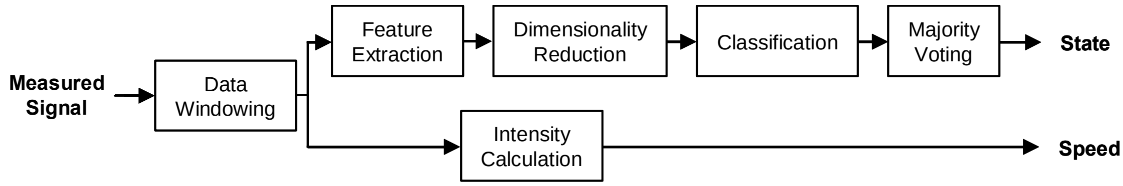


Figure 2.3 – Block diagram showing basic stages of multifunction pattern recognition

Pattern recognition based myoelectric control was first investigated in the late 1960s and early 1970s [11-13]. These early systems used amplitude coded features and a statistical classifier to achieve about 75% classification accuracy for a four class problem. Drawbacks included: a high number of MES channels, cumbersome equipment, and extensive processing times [14]. Beginning in the late 1970s and continuing today, autoregressive (AR) coefficients, supplemented with the RMS value of the signal, have been investigated as a feature set [15]. This approach has given approximately 85% accuracy in a three class problem while reducing the number of MES channels to 2 or 4 [10, 16]. Unfortunately, computing technologies of past years were unable to perform this classification in real-time.

In the early 1990s, Hudgins *et al.* [9] showed that the MES exhibited a deterministic structure during the initial phase of a muscle contraction. They proposed using a set of time domain (TD) statistics as a feature vector input to a two layer static artificial neural network (ANN) classifier. This system, using one channel of surface MES data, was able to classify four states with an average accuracy of 91.2%. These results represented a significant improvement in pattern recognition based systems, and a significant step toward an intuitive, independent, multifunction controller. Furthermore, an embedded controller was built to realize this control scheme, complete with an acceptable processing time delay of less than 300 ms. These described efforts rejuvenated research in pattern based control strategies for multifunction control.

More recently, effort has been devoted to investigating the effects of various feature sets and classifiers on the accuracy of MES pattern recognition. Feature sets formulated from TD statistics [9, 14], AR coefficients [15], and time-frequency information [17], have been shown to help classify MES measured from both continuous contractions and transient bursts. ANN's [9, 18, 19], genetic algorithms [14], linear discriminant analysis (LDA) [17], Gaussian mixture models (GMM) [15], and fuzzy logic [20] have all been shown to provide acceptable classification. However, it is found that classification performance is affected more by the choice of feature set than by the choice of the classifier [17].

The effect of increasing the number of surface MES data channels has also been investigated. Research has indicated that as the number of channels is increased the performance of the classifier improves, asymptotically approaching a maximum accuracy in each case. In an investigation of ten discrete motions, classification accuracies for 16 and 8 channels were not significantly different. Additionally, in an experiment with ten combined motions, differences between 4, 8, and 16 channels were statistically insignificant. [1]

Perhaps the newest contributor to the advancement of MES control is a surgical technique where residual nerves of amputees are reinnervated to spare regions of muscle. This targeted reinnervation provides independent MES sites which correlate physiologically to amputated degrees of freedom and can be used in state of the art multifunction myoelectric control. [21]

2.3 Feature Extraction

Feature extraction attempts to extract usable information from the MES through development of feature sets which are chosen to preserve class separability. Feature extraction generally reduces the dimensionality of the input space which is desirable for classification of patterns. Consider an amplified MES, (t), which is sampled at an interval T. This provides a discrete representation, $x(nT)$ for $n = (1...N)$, over the sample period NT. Typical sample rates are approximately 1 kHz, therefore using a 250 ms analysis window results in a 250 dimension input vector for each channel. Feature extraction reduces the dimensionality of the classification problem by replacing the discrete signal $x(nT)$ with a feature vector, $\beta = [\beta_1,...\beta_M]$ which contains M (usually $M << N$) representative features [9]. The experimentally proven TD, AR, and TDAR features will be used within this investigation and are described below in detail.

2.3.1 TD Features

The four TD features proposed by Hudgins [9] (MAV, number of zero crossings, number of slope sign changes, and waveform length) are described below in detail. For myoelectric control, these features are computed per each data analysis window for each MES input channel; resulting in a feature vector of dimension equal to number of channels times four.

Mean Absolute Value: An estimate of the mean absolute value of the signal, $\overline{X}_i$, in analysis window i, with N samples is given by

$$\overline{X}_i = \frac{1}{N}\sum_{n=1}^{N}|x_n| \ , \ i = (1,...,I)$$

where x_n is the n^{th} sample in analysis window i, and I is the total number of analysis windows over the entire sampled signal.

Number of Zero Crossings: This frequency measure is obtained by totaling the number of times the waveform, $x(t)$, crosses zero. Additionally, to reduce the number of noise-induced zero crossings, a threshold value of ε is included in the calculation. Given two consecutive values of the signal, x_n and x_{n+1}, the zero crossing count is incremented if

$$\{x_n > 0 \text{ and } x_{n+1} < 0\} \text{ or } \{x_n < 0 \text{ and } x_{n+1} > 0\}$$

and

$$\left|x_n - x_{n+1}\right| \geq \varepsilon$$

Slope Sign Changes: Another feature possibly providing a measure of frequency content is the number of times the slope of the waveform, $x(t)$, changes sign. Once again a threshold value, ε, must be incorporated for noise reduction. For three consecutive values of the signal x_{n-1}, x_n, and x_{n+1} the slope sign change count is incremented if

$$\{x_n > x_{n-1} \text{ and } x_n > x_{n+1}\} \text{ or } \{x_n < x_{n-1} \text{ and } x_n < x_{n+1}\}$$

and

$$\left|x_n - x_{n+1}\right| \geq \varepsilon \text{ or } \left|x_n - x_{n-1}\right| \geq \varepsilon$$

Waveform Length: This feature provides information on the complexity of the waveform in each analysis window; a measure of waveform amplitude, frequency, and duration all within a single parameter. It is the cumulative length of the waveform defined as

$$l_i = \sum_{n=1}^{N} \left|\Delta x_n\right|$$

where $\Delta x_n = x_n - x_{n-1}$ is the difference between consecutive signal samples.

2.3.2 AR Coefficients

For use as a feature set, AR coefficients are often supplemented with the RMS value of the signal [15]. In a linear autoregressive model of order R, a time series y_n is modeled as a linear combination of R earlier values in the time series and a signal correction term x_n

$$y_n^{predict} = x_n - \sum_{j=1}^{R} a_j y_{n-j}$$

The coefficients a_j, for $j = (1,..., R)$, are found by minimizing the mean squared error between $y_n^{predict}$ and y_n. The RMS value of the signal, r_i, is determined using

$$r_i = \sqrt{\frac{\sum_{n=1}^{N} x_n^2}{N}}$$

where x_n is the measured signal, and N is the length of the analysis window in samples. The AR coefficients and RMS value result in a $(R+1)$ dimension feature vector for each data window.

2.3.3 TDAR Features

A combination of TD, AR, and RMS value features is also employed to give the set of TDAR features. All features are computed as described above and simply concatenated to form a single, larger feature vector for each data analysis window.

2.4 Dimensionality Reduction

Given a set of multivariate data (the feature set), the role of dimensionality reduction is to find a smaller set of variables (features), having less redundancy, and yielding a near original representation of the data [22]. A classifier presented with fewer inputs (features) has fewer adaptive parameters to be determined, leading to better generalization properties. One method of dimensionality reduction, which has been shown to work well for myoelectric control, is feature projection performed using principal components analysis (PCA) [17]. In

PCA, redundancy in the data is measured by correlations between data elements. Given a n length vector, $\bar{v}$, the PCA transform is completed by subtracting the mean from the vector

$$\bar{\mathbf{x}} = \bar{v} - \mathrm{E}[\bar{v}]$$

The $n \times n$ covariance matrix, $\mathbf{C}_{\mathbf{x}}$ is then computed

$$\mathbf{C}_{\mathbf{x}} = \mathrm{E}[\bar{\mathbf{x}}\bar{\mathbf{x}}']$$

and the principal components of $\bar{\mathbf{x}}$ are given in terms of the unit-length eigenvectors, $(\bar{\mathbf{e}}_{\mathbf{1}},\ldots,\bar{\mathbf{e}}_{\mathbf{n}})$ where

$$y_j = \bar{\mathbf{e}}_{\mathbf{j}}\bar{\mathbf{x}}$$

PCA provides a means of unsupervised dimensionality reduction, as no class membership qualifies the data when specifying the eigenvectors of maximum variance.

2.5 Classification

Pattern classification processes attempt to categorize features (representing a dataset) into a finite number of output classes. There are three common approaches to pattern classification; the statistical approach, the structural (or syntactic) approach, and the learning (or neural) approach [23]. The statistical classification approach attempts to classify data using an estimate of the probability density functions of the data in an N-dimensional space and dividing the space into regions corresponding to each class [23]. The syntactic approach uses structural information to segment and classify the signal [24]. Learning approaches, commonly neural networks, learn the structure of the data for each class. A linear discriminant analysis (LDA) classifier, multilayer perceptron (MLP) artificial neural network (ANN) classifier, and a Gaussian mixture model (GMM) classifier are all employed in this study.

2.5.1 LDA

LDA classifiers are simplified Bayesian classifiers based on the Bayes classification rule: assign the N-length pattern $\mathbf{x}$ to the class, C_i, with the highest probability.

$$P(C_i \mid \mathbf{x}) > P(C_j \mid \mathbf{x}) \text{ for all } i \neq j$$

However, these *a posteriori* probabilities can not be directly measured. Instead, Bayes' Theorem

$$P(\mathbf{x} \mid C_i) = P(C_i)\, p(\mathbf{x} \mid C_i) = p(\mathbf{x}) P(C_i \mid \mathbf{x})$$

provides the solution by deriving the *a posteriori* probabilities from estimates of the *a priori* probabilities

$$P(C_i \mid \mathbf{x}) = \frac{P(C_i)\, p(\mathbf{x} \mid C_i)}{p(\mathbf{x})}$$

where $p(\mathbf{x} \mid C_i)$ is the probability density function for the samples within the i^{th} class, and $p(\mathbf{x})$ is the probability density function of the input space and is a constant over all the classes. Application of Bayes' classification rule now involves evaluating

$$d_i(\mathbf{x}) = P(C_i)\, p(\mathbf{x} \mid C_i)$$

for each class C_i and finding the maximum value.

The LDA implementation is a simplification of the Bayesian classifier where all probability density functions have a Gaussian distribution. The multivariate Gaussian probability density function for M classes of patterns can be expressed as

$$p(\mathbf{x} \mid C_i) = \frac{1}{(2\pi)^{N/2} \left|\mathbf{C}_i\right|^{1/2}} \exp\left[-\frac{1}{2} (\mathbf{x} - \mathbf{m}_i)^T \mathbf{C}_i^{-1} (\mathbf{x} - \mathbf{m}_i) \right],\ \mathrm{i} = 1,\ldots,M$$

where $\mathbf{m}_i$ is the N length mean vector for the i^{th} class and $\mathbf{C}_i$ is the $N \times N$ covariance matrix for the i^{th} class. Now,

$$d_i(\mathbf{x}) = \frac{P(C_i)}{(2\pi)^{N/2}|\mathbf{C}_i|^{1/2}} \exp\left[-\frac{1}{2}(\mathbf{x}-\mathbf{m}_i)^T \mathbf{C}_i^{-1}(\mathbf{x}-\mathbf{m}_i)\right]$$

Expressing this value in the natural logarithm form and canceling constant terms yields

$$d_i(\mathbf{x}) = \ln(P(C_i)) - \ln(\mathbf{C}_i) - (\mathbf{x}-\mathbf{m}_i)^T \mathbf{C}_i^{-1}(\mathbf{x}-\mathbf{m}_i)$$

Furthermore, by assuming that all the covariance matrices are equal, the set of discriminant functions becomes

$$d_i(\mathbf{x}) = \ln(P(C_i)) + \mathbf{x}^T \mathbf{C}^{-1}\mathbf{m}_i - \frac{1}{2}\mathbf{m}_i{}^T \mathbf{C}^{-1}\mathbf{m}_i$$

The classification now becomes a problem of M equations and N unknowns, where M is the number of classes and N is the length of the feature vector. $d(\mathbf{x})$ could also be expressed in terms of a $M \times N$ weight matrix and a $M \times 1$ offset array

$$\mathbf{W} = \mathbf{C}^{-1}\mathbf{m}_i$$

$$\mathbf{B} = -\frac{1}{2}\mathbf{m}_i^T \mathbf{C}^{-1}\mathbf{m}_i + \ln(P(C_i))$$

$$d(\mathbf{x}) = \mathbf{x}^T \mathbf{W} + \mathbf{B}$$

Clearly, after the weights and offset have been calculated from an appropriate set of training data, feed-forward classification using an LDA is computationally simple.

2.5.2 ANN

An ANN is an information processing system which mimics the learning capability and structure of biological neural networks; both are based on interconnected processing elements called neurons. Commonly in ANN design, a perceptron processing unit, as shown in Figure 2.4, constitutes the artificial neuron.

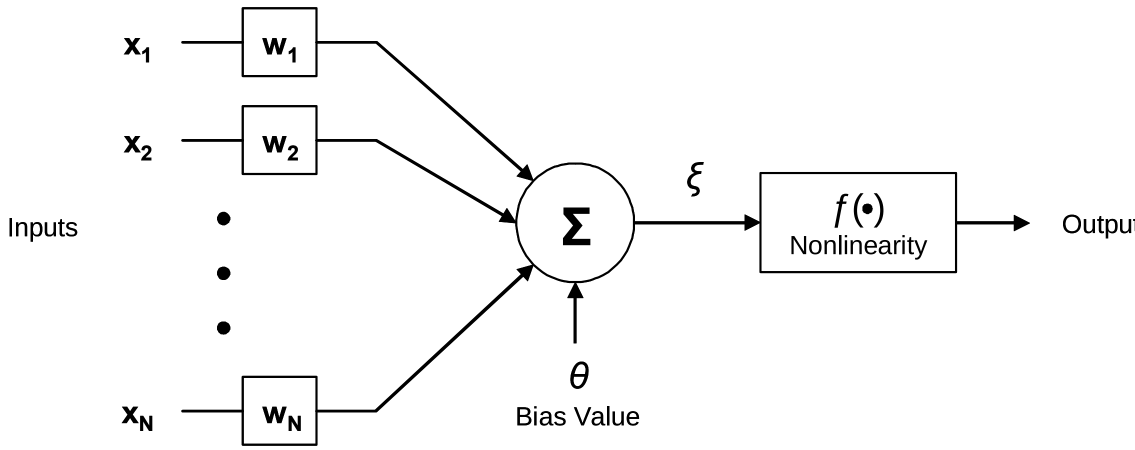


Figure 2.4 – Perceptron artificial neuron architecture

In each unit, the sum of weighted inputs $X \bullet W$ and bias value θ yield an activation ξ which is passed through a nonlinearity f to produce the neuron output. Three of the most common nonlinear activation functions used in ANNs are depicted in Figure 2.5.

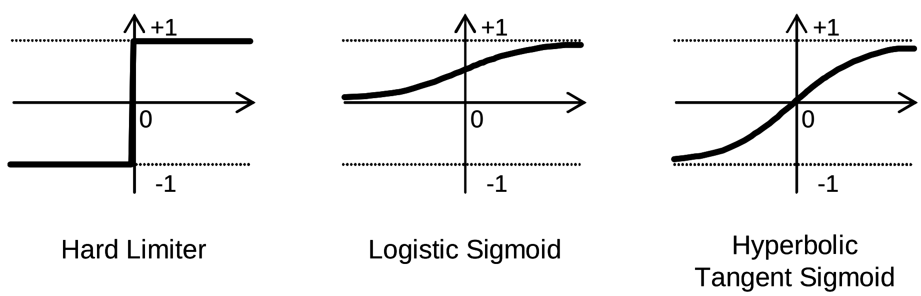


Figure 2.5 – Commonly used nonlinear activation functions

Two or more layers of single perceptrons, when cascaded together, form the MLP ANNs. These MLP networks allow the pattern space to be partitioned into arbitrarily complex, and nonlinear, decision boundaries; an advantage over the single perceptron. Choosing optimal number of layers for a MLP is a tradeoff between enough layers to form good class decision boundaries and as few as possible to eliminate poor estimates of the weights [25]. In describing the MLP architecture, the inputs are not typically included as a layer. Therefore, the MLP example of Figure 2.6 is considered a two layer network with five inputs, four hidden layer neurons, and two output layer neurons. The number of nodes in the output layer generally corresponds to the number of classes in the classification problem

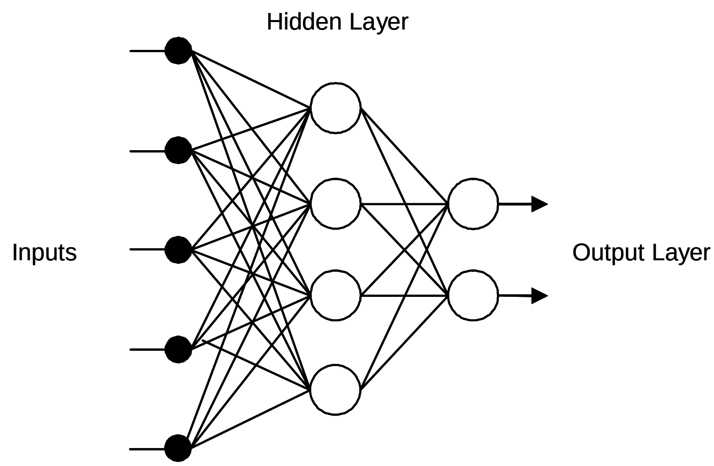


Figure 2.6 – Two layer MLP network with two output classes

Learning algorithms are required for ANNs and are either *supervised* or *unsupervised*. Supervised learning requires that desired outputs are available during training whereas with unsupervised learning, outputs are unknown and clusters are formed from the input patterns. For this work, outputs are known; these are the classes corresponding to patterns that represent the MES data. A common training algorithm for MLP networks is the backpropagation algorithm. This is an iterative gradient algorithm which minimizes a cost function, such as the mean squared error between the actual output of the network and the desired output of the network. During training, input patterns are presented to the network, the desired output is set to one, and all other outputs are set to negative one. The weights of the networks are adjusted using the backpropagation algorithm until an acceptable level of training is reached. An acceptable level of training occurs when the training error and the validation error begin to diverge. Once trained, feedforward classification from the network is computationally simple, fast, and can be completed in real-time.

2.5.3 GMM

A GMM has the ability to form smooth approximations for general probability density functions through the weighted sum of multiple Gaussian functions [26]. The GMM estimates the probability density function of the N-dimensional MES feature vector $\mathbf{x}$ using a Gaussian mixture density given by

$$p(\mathbf{x} \mid \lambda_i) = \sum_{m=1}^{M} w_m \lambda(\mathbf{x}, \mathbf{m}_m, \mathbf{C_m})$$

where M is the number of mixtures, w_i are the mixture weights which satisfy the constraints $\sum_{m=1}^{M} w_m = 1$, and $w_m \geq 0$, $\mathbf{m_m}$ is the N-length mean vector of the Gaussian densities, and $\mathbf{C_m}$ is the $N \times N$ dimension covariance matrix of the Gaussian densities.

A training set of data is used to estimate the parameters for each GMM and a model is constructed for each class of motion, $\lambda_1 ... \lambda_{10}$ [26]. After the parameters for each model have been determined, a data set can be presented for classification. Each pattern is provided to each of the models and the Gaussian density mixture is computed. The class associated with the model λ_i having the highest density mixture is chosen as the predicted class for that test pattern.

MES classification performance of GMMs is affected by some algorithmic issues, the most important of which is model order selection [26]. The objective is to choose the optimal number of mixture components that yields the highest discriminative accuracy for the test data set. Too few mixture components can produce a GMM which does not accurately model the probability density function of a motion's feature set probability distribution.

However, too many components can produce a model which has too many parameters to be accurately estimated from the training data.

2.6 Post Processing

It has been suggested that the response time of a prosthetic control system not exceed 300 ms in order suppress any perceivable delay by the user [14]. This real-time constraint generally encompasses both the length of analysis window (the data on which to base the decision) and associated processing delay τ. In this manner, windows of data presented to the continuous classifier are disjoint and adjacent as shown in Figure 2.6. Classification decisions occur τ seconds after each analysis window is acquired.

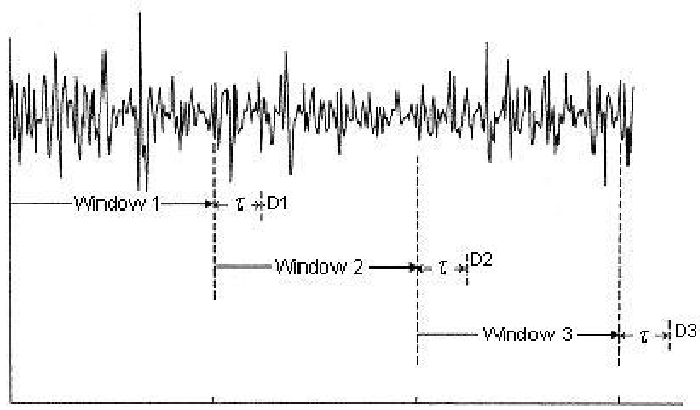


Figure 2.7 – Disjoint decision windows in a pattern based myoelectric control scheme [14]

It is clear from Figure 2.7 that if acquisition and processing can occur simultaneously, processing resources will be underutilized for a disjoint windowing scheme. As soon as a decision has been generated from a data window of N samples, processing for the next decision can begin using the N most recent samples. This overlapped-window approach, illustrated in Figure 2.8, yields a much more dense decision stream which may be subject to post processing in the form of majority voting. Majority voting considers the largest number of decisions, from the dense stream, that satisfy the real-time constraint. The majority vote decision is simply the class of greatest occurrence in the group. In real-time operation, majority voting provides a smoothing effect.

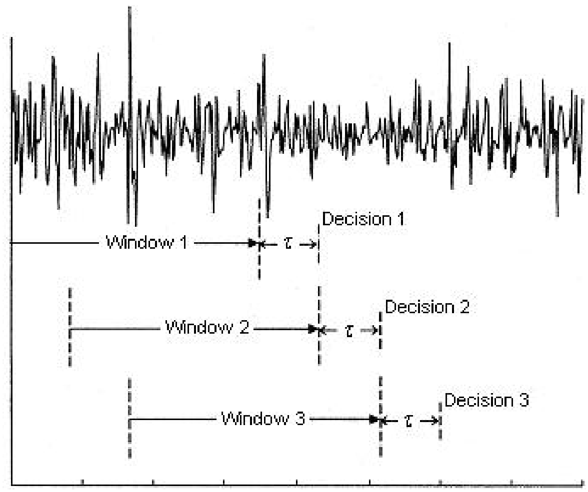


Figure 2.8 – Overlapped windowing scheme resulting in dense decision stream subject to majority voting [14]

2.7 Speed Control

As described above, some conventional myoelectric controllers compute RMS or MAV values for determining active/inactive state. For pattern recognition based control, class of motion and associated activations are found from MES features leaving RMS or MAV information as a possible input to proportional speed control [9]. Although Figure 2.3 illustrates the parallel nature of this processing concept, the same data that are subject to pattern classification are presented serially to an intensity calculation which determines real-time proportional contraction intensity as a percentage of the training intensity for that class of motion.

2.8 Virtual Environments

As discussed in Chapter 1, a virtual upper limb can provide great benefit to the study of multifunction MES control systems as multifunction electromechanical prostheses are not readily available. The economic and physical development limitations support the development of the virtual limb of this endeavor.

Proponents of virtual environments promote the economic benefits [27, 28], the manageable and rapid development [29], and availability of powerful computing and processing technologies [28-30] as driving factors to the recent successes and popularity of simulated clinical environments. Researchers and clinicians also enjoy many previously unattainable quantitative outputs when using virtual reality/environment tools [27, 30-32]. Common in today's practice, virtual environments help track rehabilitation progress and provide quick archiving of high volumes of useful data.

Virtual environments are inherently useful in many areas of Biomedical Engineering and rehabilitation since there exists a high level of human machine interaction. Virtual tools have been developed for a multitude of clinical and research applications including: stroke rehabilitation [33]; testing children with Cerebral Palsy [34]; assessments of Carpal Tunnel Syndrome [35]; other neuromuscular disorders [36] and; general physical therapy [27]. The focus of this work is the development of a virtual prosthetic environment for clinical and research uses.

Many who labor to develop state-of-the-art myoelectric control systems strongly support construction of virtual limbs [2, 14, 31, 37-39] to aid in research and clinical use. Central to both phases of this project, software development and functional assessment, is the successful development of a virtual limb interacting in real-time within a virtual environment.

Most documented virtual environments used for clinical and research purposes are accompanied by graphical user interfaces (GUIs) which permit easy setup, interaction, operation, data logging, etc. GUI-based systems remove a user from the developmental aspects of a virtual environment and are key in providing a high degree of usefulness. It is important that design and presentation of the GUI is clear, concise, and appropriate for the intended users' acceptance of the system [40].

Chapter 3: Software Implementation

Development of the virtual limb tool for functional assessment of multifunction myoelectric control has been designed to meet a number of objectives:

1) Realize a physiologically representative 3D virtual upper limb.
2) Achieve real-time operation of the virtual limb on a personal computer.
3) Package the system in a complete, intuitive GUI that includes MES acquisition and display, flexibility in MES control, and functional assessment via the virtual environment.
4) Incorporate all of the recent IBME advances in myoelectric signal processing for MES control.

The majority of recent IBME research and developments involve coding algorithms realized in Matlab® (The MathWorks, Inc. Natick, MA), written or modified by IBME personnel and researchers. Completing this project as a grouping of Matlab functions allows for future upgrades, additions, and maintenance of the system. The complete Matlab-based software suite, named CEVEN (Classifier Evaluation in a Virtual ENvironment), has been developed as a MES clinical and research tool. Specifically, the integrated system encompasses continuous, multifunction MES control and is highlighted by a real-time virtual arm environment.

CEVEN imparts itself naturally into three complementary sections: 1) acquisition; 2) control; and 3) graphical simulation. Success of the tool, and the project as a whole, was dependant on the creation and effective integration of these modules. The tool operates on any desktop or laptop personal computer equipped with Matlab software (must have Matlab's *Data Acquisition* toolbox). CEVEN is designed around an all inclusive, single GUI window, therefore appearing similar to many other computer programs that a user will be accustomed to. This main GUI has three tab-based panes (*Acquisition, Control, and Virtual Environment*), shown in Figure 3.1, which help to organize presentation of the large number of interface objects.

Figure 3.1 – Three tabs of CEVEN window; displayed with *Control* tab selected

When one tab is selected, its associated GUI controls are accessible while objects for the other two are hidden. On all three tabs of the CEVEN GUI, there are different types of interface controls, some of which are GUI buttons that spawn secondary GUI windows. All interface controls, the suite of GUI windows, and general program operation are detailed below.

3.1 Acquisition

At the forefront of MES control is the acquisition of myoelectric activity. At the IBME this is traditionally accomplished with the use of bipolar electrode pairs placed on the skin's surface, differential amplification to read the signal, anti-alias filtering, and analog-to-digital (A/D) conversion to digitize the signal for computer processing. The number of acquired

MES channels of data, type/vendor of A/D hardware, sampling rate, data windowing, and experimental protocol all vary among different IBME applications and/or experiments. The *Acquisition* tab of CEVEN permits tailoring of these parameters and directs data acquisition sessions.

3.1.1 Parameters

Figure 3.2 is a screenshot of the *Acquisition* tab illustrating how the parameters are appropriately grouped into three panes: Input Parameters, Recording Parameters, and Procedure Parameters.

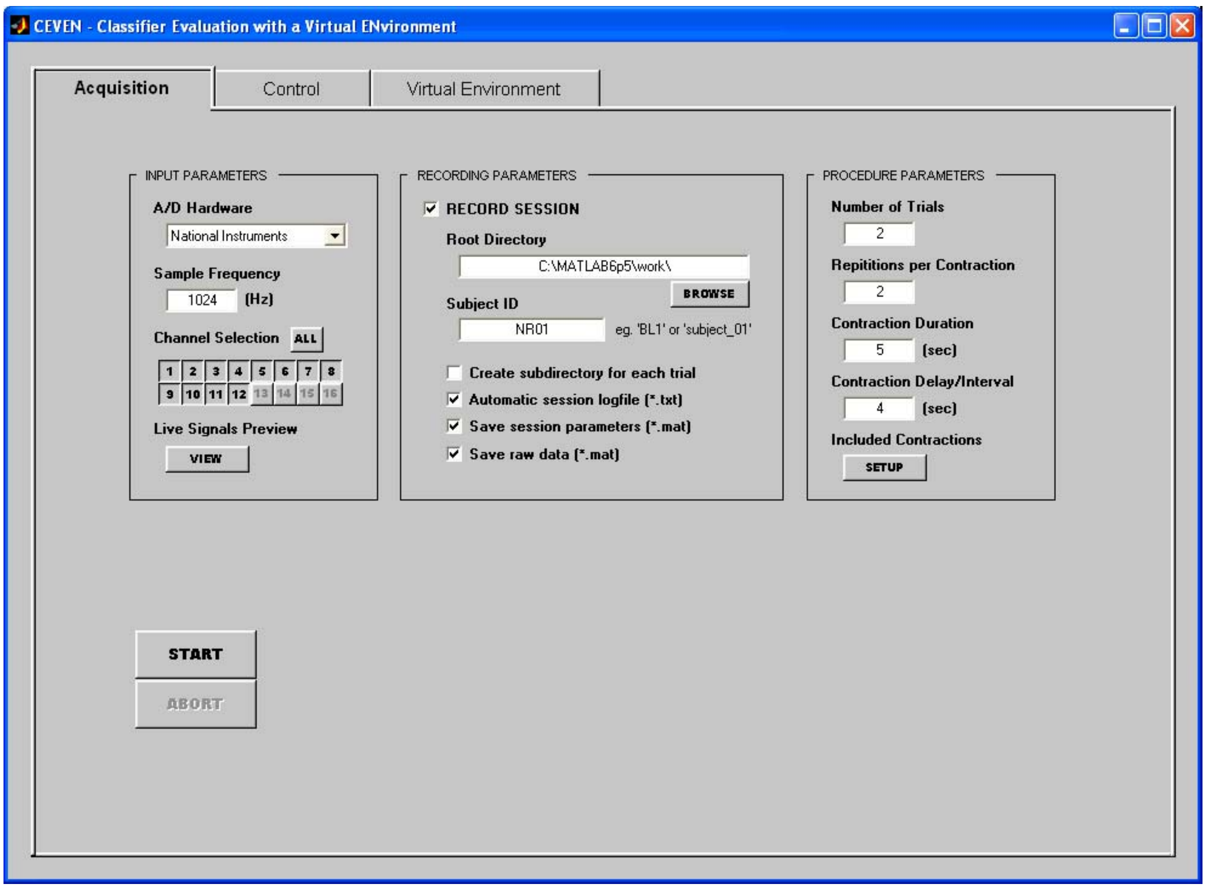


Figure 3.2 – Overview of *Acquisition* interface

Input Parameters

A/D Hardware – Upon startup of CEVEN, the host workstation is polled to determine all available data input/output devices which are then selectable from this pull-down list. CEVEN is designed to operate with various data acquisition hardware from National Instruments and Measurement Computing and also supports input from the host computer's sound card. Selecting one of the devices from the pull-down list presents the user with available channels for that device.

Sample Frequency – This editable text box displays the sample rate in Hertz (Hz) that will be used for data acquisition. Maximum and minimum allowable limits are automatically linked to A/D hardware selection and number of channels available; the software will restrict the sampling rate to an upper or lower bound when inappropriate values are entered. It should be noted that 8000 Hz is a common lower limit for most workstation sound cards. However, for MES applications, where sampling rates near 1000 Hz are common, CEVEN permits low sampling rates for sound cards – simulated by internal decimation of data acquired at a higher frequency.

Channel Selection – A section of numbered buttons represent the data input channels. CEVEN only displays those buttons which correspond to available channels for the type of A/D hardware selected. By default, no channels are selected; therefore, data acquisition will not be permitted until one or more channels are picked. An 'All' button provides quick means to select or de-select all of the available channels.

Live Signals Preview – When one or more channels are selected, a user is permitted to select hit the 'View' button to open a diagnostic window where real-time signals from each selected channel are viewed on an adjustable timebase. This secondary GUI window also permits viewing of the real-time spectral content of the input data. Viewing the unprocessed real-time signals can be essential in determining proper electrode contact and levels of electrical interference. Examples of both time-and frequency-based diagnostic windows appear in Appendix A.

Recording Parameters

Record Session – By default, CEVEN is setup to save raw data and experimental parameters for each acquisition session. De-selecting the record session box indicates the session will not be stored and therefore most of the other record parameters become irrelevant and are deactivated.

Root Directory – This text field displays the directory where session data and parameters will be saved. A ‘Browse’ button is available that leads the user to an interactive window to pick, or create, the destination directory.

Subject ID – Blank upon startup, this editable textbox is where a user must enter a subject and/or session label. The entered identification is used as a prefix to saved data, parameter, and log files. The *Subject ID* field is the one recording parameter that must be attended to even if *Record Session* is not selected. Also, data acquisition session will not be allowed to commence if *Subject ID* is left blank; a prompt is provided under this condition.

Create Subdirectory for Each Trial – When selected, data from numbered trials are saved in appropriately named subdirectories within the root directory.

Automatic Session Logfile – If selected (default), a text (*.txt) file will be saved in the root directory that contains useful information pertinent to the data acquisition session. “_log.txt” is appended to the *Subject ID* to from the filename.

Save Session Parameters – During any data acquisition session, internal parameters can be saved (default), which are later used in processing of control schemes and real-time operation. Automatically, naming convention places the *Subject ID* in front of “_params.mat” to form the filename.

Save Raw Data – In most cases, it is desired to save the myoelectric data in native acquired form. Choosing to save this data (default) allows for later processing of control and real-time operation using CEVEN, as well as availability of the data for any other offline uses. One file, containing the complete session data, is automatically named: *Subject ID* concatenated with "_Fulldata.mat". Data from each trail are also saved separately using: *Subject ID* joined to "_Trial_#_data.mat", where # represents the trial number.

Procedure Parameters

Number of Trials – Here, a CEVEN user enters the number of trails of data to be recorded during an acquisition session. If greater than one, the first trial is employed as a training set, while subsequent trails are used as separate testing sets. When one trial is specified, the single set of data is evenly divided into test and training records.

Repetitions per Contraction – For every acquisition session, a group of contractions (motions) are selected. The editable number in this text box determines how many times each contraction is performed/prompted during each trial of the session.

Contraction Duration – This number-of-seconds value represents the length of time for which data of each prompted contraction is recorded.

Contraction Delay/Interval – A value entered in seconds; the delay number sets the amount of 'rest' time between contractions. MES data is not recorded during these periods.

Included Contractions – Before any acquisition session is commenced, the set of contractions/motions intended for study must be selected. Pressing the 'Setup' button on CEVEN opens an interactive window (shown in Appendix A) which is designed around the list of chosen contractions. Initially blank, the list can be populated by adding or removing joint-based (hand, wrist, elbow, shoulder) groups of motions. Alternatively, contractions can be added separately from a list of all those available. A radio button is included on this GUI which, when selected, indicates the contractions will be presented in randomized order during the trials. When randomization is not selected, order of contractions appearing in the ‘selected’ list dictates the acquisition session; in this case, list order can be tailored with available GUI controls. A user is not permitted to close or ‘ok’ this window if the list of contractions remains blank. Finally, if a user omits to press the ‘Setup’ button and tries to start the acquisition session, the ‘Included Contractions’ GUI window will be automatically called.

3.1.2 Data Acquisition Session

After all appropriate setup, recording, and procedure parameters have been attended to, the automated data acquisition session can initiated with the ‘Start’ button. At this point, any appropriate errors or warnings are presented (examples of such are shown in Appendix A). The session begins as the GUI controls disappear in favor of large visual prompts aimed at the testing subject. A large picture (if available) and large, high-contrast text describe the contraction/motion to be performed. These prompts are displayed during the rest period (before the data for that contraction is to be recorded) and remain visible during the acquisition. The rest periods are animated with a red progress bar, growing left to right, and text that counts down the time: “Begin in __ second(s)…”; a screenshot of this is shown as Figure 3.3. When the rest period expires, the data sampling begins and the progress bar turns green and retracts to the left over the recording duration. The text during this time states: “Sampling”. A time-of-sampling screenshot is displayed in Figure 3.4.

Figure 3.3 – Screenshot of timed resting period before contraction; typical during acquisition session

Figure 3.4 – Screenshot of timed sampling period for contractions; typical during acquisition session

If at any time during the session a mistake is made (incorrect contraction, failure to start contraction, etc.) or a user wishes to cancel the automated procedure altogether, an 'Abort' button can be pressed. This action pauses the acquisition session and prompts the user (GUI shown in Appendix A) to either cancel the session, or repeat the most recent contraction. The abort capability helps to prevent having to redo or discard a complete session due to minor mistakes.

To aid both operator and testing subject, status information is shown in the CEVEN window during the acquisition session; current and total number of trials and current and total count of trail's contractions are displayed.

3.2 Control

Outlined in previous chapters of this document is how continuous multifunction MES control comprises several sequential control components and that recent efforts at the IBME have produced state-of-the-art algorithms for these components. Software suite CEVEN is designed to consolidate state-of-the-art control for both research and clinical uses. Described below is the design and operation of CEVEN's *Control* tab interface, illustrated in Figure 3.5. This GUI window is laid out in three sections: Control Parameters (configuration of control systems to be processed); Process Data (data source, channels, and processing start), and; Results/Output (processed systems' classification error, saving or loading control systems, and link to virtual environment).

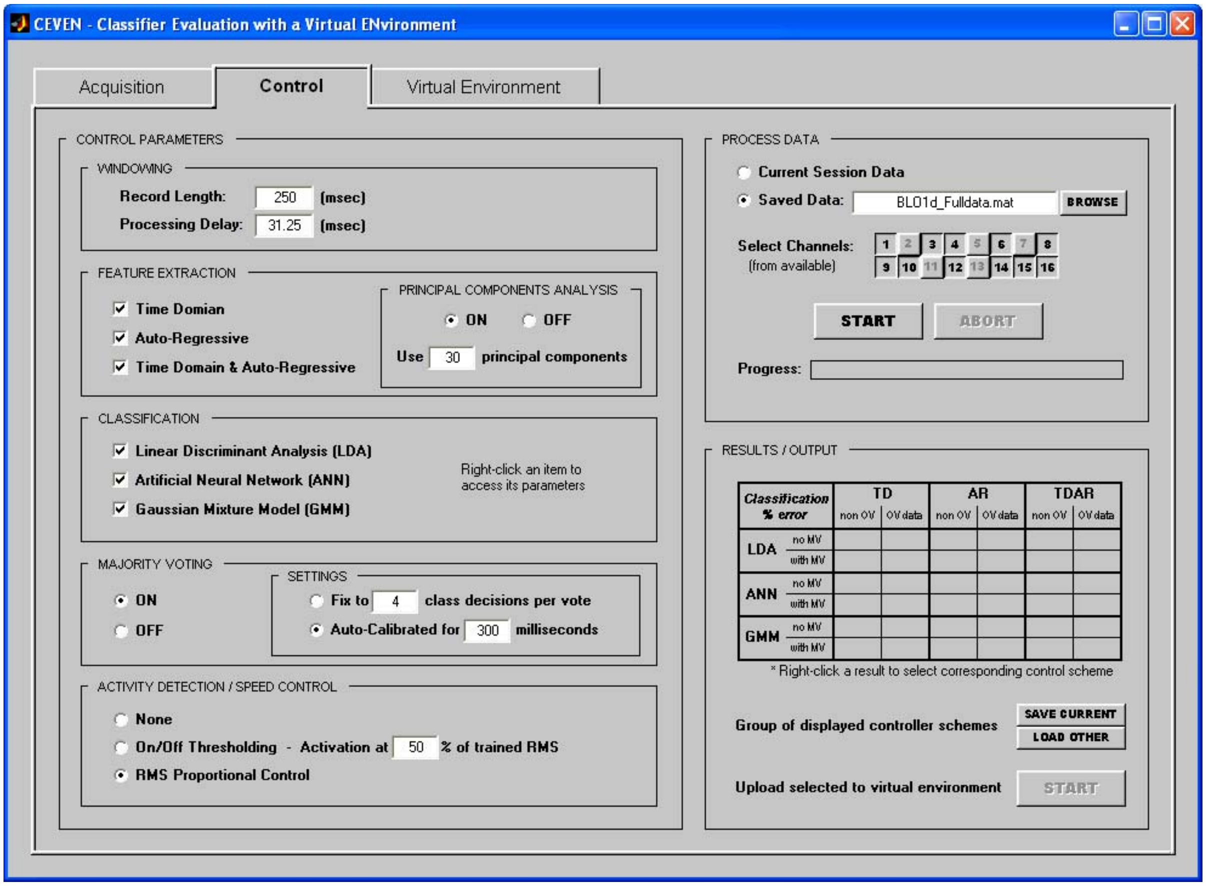


Figure 3.5 – Overview of *Control* interface

3.2.1 Control Parameters

The Control Parameters pane is organized into five subsections each representing a basic stage in multifunction pattern recognition control. The specifics and underlying algorithms of all represented control components have been detailed in Chapter 2, therefore, only the software interface is described below.

Windowing

Record Length – In this editable text box, a value in milliseconds is given which is the data window size to be classified (see Figure 2.7). A CEVEN user must caution that window size in number of samples is different and will depend on the recorded sample rate of data to be processed.

Processing Delay – As mentioned in Chapter 2, processing time may be significantly less than duration of data window in real-time situations, therefore, a large number windows of data can be used as they become ‘overlapped’. The value in this editable text box is the number of milliseconds between start of one data window and start of the next; see Figure 2.8.

Feature Extraction

Any combination of the three options for feature extraction (TD, AR, TDAR) can be selected for simultaneous processing on the same data. The auto-regression order (when AR and/or TDAR are used) can be changed from its default, 6, with a right mouse click over the word “Auto-Regressive” which initiates the GUI shown in Appendix A.

Principal Components Analysis – This form of dimensionality reduction can be turned on or off for processing. When PCA is selected ‘on’, a CEVEN user is permitted to set the number of principal components via the editable text box.

Classification

To classify the feature sets which represent the input MES data, the three pattern classifiers described in section 2.5 are available. Any selection combination is permitted as simultaneous processing of multiple classifiers is often desired. Both ANN and GMM systems are described by a number of settings, tailoring of each is accessible via a right mouse click over the associated classifier name (see Appendix A for these GUIs).

Majority Voting

Here, a CEVEN user can have post-processing, in the form of majority voting (section 2.6), turned on or off. If on, associated settings are accessible.

Settings – A user can choose between two forms of majority voting. For one, a set number of class decisions per vote are chosen while for the other, the most decisions possible within a specified time window are included in the vote. Depending on which is selected, number of votes or voting time window can be set using the appropriate text box.

Activity Detection/Speed Control

Although activity detection/speed control settings do not affect classification accuracies and are only applied during real-time control, a CEVEN user must choose between one of three options before processing data.

None – Selecting "None" skips any form of speed or activity control during real-time operation; a class decision will actuate the virtual limb a preset amount.

On/Off Thresholding – This can be chosen to supplement multifunction control as a form of activity detection. Under real-time control, RMS level is monitored and compared to a stored per-class RMS level determined during processing. The activation threshold, in percent of stored RMS value, is set via an editable text box.

Proportional Control – During real-time operation an RMS level is found for each classification window of data. This value, divided by the stored per-class RMS level determined during processing, estimates a level of contraction intensity related to training data. The percentage, which can be greater than 100, is applied to the preset movement amount for the classified motion yielding proportional velocity in the virtual environment.

3.2.2 Process Data

The Process Data pane provides the interface to load data for processing and controls to run the automatic procedure.

Loading Data

The GUI provides two choices for loading data: 1) data that were just acquired in an acquisition session can be selected (when available) by choosing ‘Current Session Data’; and 2) any previous CEVEN-acquired data sets can be investigated by selecting ‘Saved Data:’. An editable text field displaying the archived data to be used is activated with a ‘Saved Data:’ selection. To aid in locating a saved data file, the ‘Browse’ button is pressed which opens a file browse window intended specifically to find “*_Fulldata.mat” files (the CEVEN save format).

Select Channels

For either case, valid current or valid saved data, CEVEN determines which channels have been included in the record and displays corresponding numbered buttons. Control processing can be carried out using data from any subset of available recorded data channels by means of these channel buttons.

Start

Once data source has been chosen, channels are selected, and all control parameters are attended to, a CEVEN user initiates the control system processing with the ‘Start’ button. The first stage in the automated processing includes a series of internal checks to ensure all required data and parameters exist. If a problem is detected, the user is informed via error message boxes (examples shown in Appendix A) and the processing is cancelled.

Abort

Clicking on the 'Abort' button (available during control system processing) will pause the operation and prompt the CEVEN user to either continue or cancel the processing. The abort verification windows are shown in Appendix A.

Progress

Depending on size of data set and chosen control configurations, the automated process can become time intensive. A progress bar is employed to inform the user of processing state. Text appears below the bar noting stage of processing; e.g. "Extracting Features…", "Performing Classification…", "Majority Voting…", etc.

3.2.3 Results and Output

When control system processing of input data is complete, one or more multifunction pattern recognition classifiers have been constructed. To accomplish this, one set of data has been used to train and other data has been used to test the systems. Multiple control configurations can, at this point, be directly compared to each other and any one of these can be selected as the controller for the virtual environment.

Results

Tests during the processing determine the classification error of all developed control schemes; that is, number of misclassified decisions over total number of decisions for each controller. Classification error corresponding to each control configuration is displayed in the appropriate cell of the GUI results table. With three choices for feature extraction and three choices of classifier, nine basic controllers can be developed. Furthermore, these nine systems can be considered with or without overlapped window data and with or without majority voting, meaning four variations on each system, bringing the total number to thirty-six control systems. The table can, therefore, display from one to thirty-six results, depending on user setup. As a visual aid, cells of the results table containing a calculated error value are proportionally shaded in green to match their relative value within the results range. Figure 3.6 is a screen capture of the GUI table with classification results from thirty-six controllers; one system (TDAR and ANN with no overlapping and no majority voting) is shown selected.

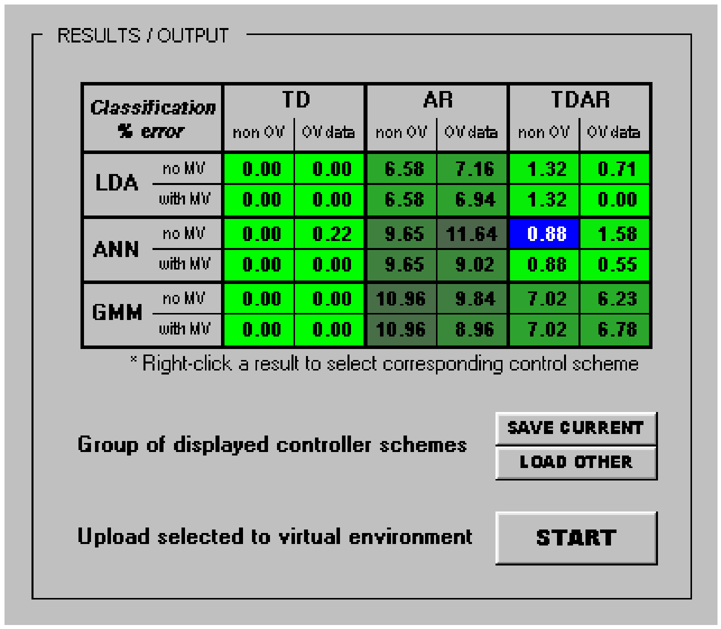


Figure 3.6 – Results table shown with thirty-six outcomes; one control scheme is selected

Group of displayed controller schemes

Two GUI buttons directly below the results table allow a CEVEN user to save or load a group of processed control systems. Clicking on 'Save Current', available when the results table is populated, prompts the user to enter a file identifier, adds "_Results.mat", and saves all controllers represented by values in the results table. Enough information and internal parameters are saved to permit use of the saved controllers in the virtual environment at a later date. 'Load Other', the button responsible for retrieving a previously saved group of control schemes, opens an interactive window designed to find "*_Results.mat" files and recover stored control systems

Upload selected to virtual environment

A right mouse click on any shaded green error value in the results table selects the associated control configuration, turns the table cell blue to indicate selection, and enables the ‘Start’ button. At this point, clicking on the ‘Start’ button uploads the selected controller to the virtual environment engine. The *Virtual Environment* tab is automatically selected and the virtual limb is commanded in real-time. To ensure proper operation, a series of internal verifications take place before activating the virtual environment. Some conditions will cause various warning and error messages to be displayed (shown in Appendix A).

3.3 Virtual Environment

To complement the GUI-based acquisition and control modules, CEVEN has a *Virtual Environment* tab which is a window dedicated to the real-time operation of a virtual arm. By default, the virtual arm is displayed alone and uncluttered, as shown in Figure 3.7, to support best possible interaction with a subject. However, the virtual arm and virtual environment can be affected in different ways via menu commands presented by a right-click anywhere within the virtual environment. The menu is depicted in Figure 3.8.

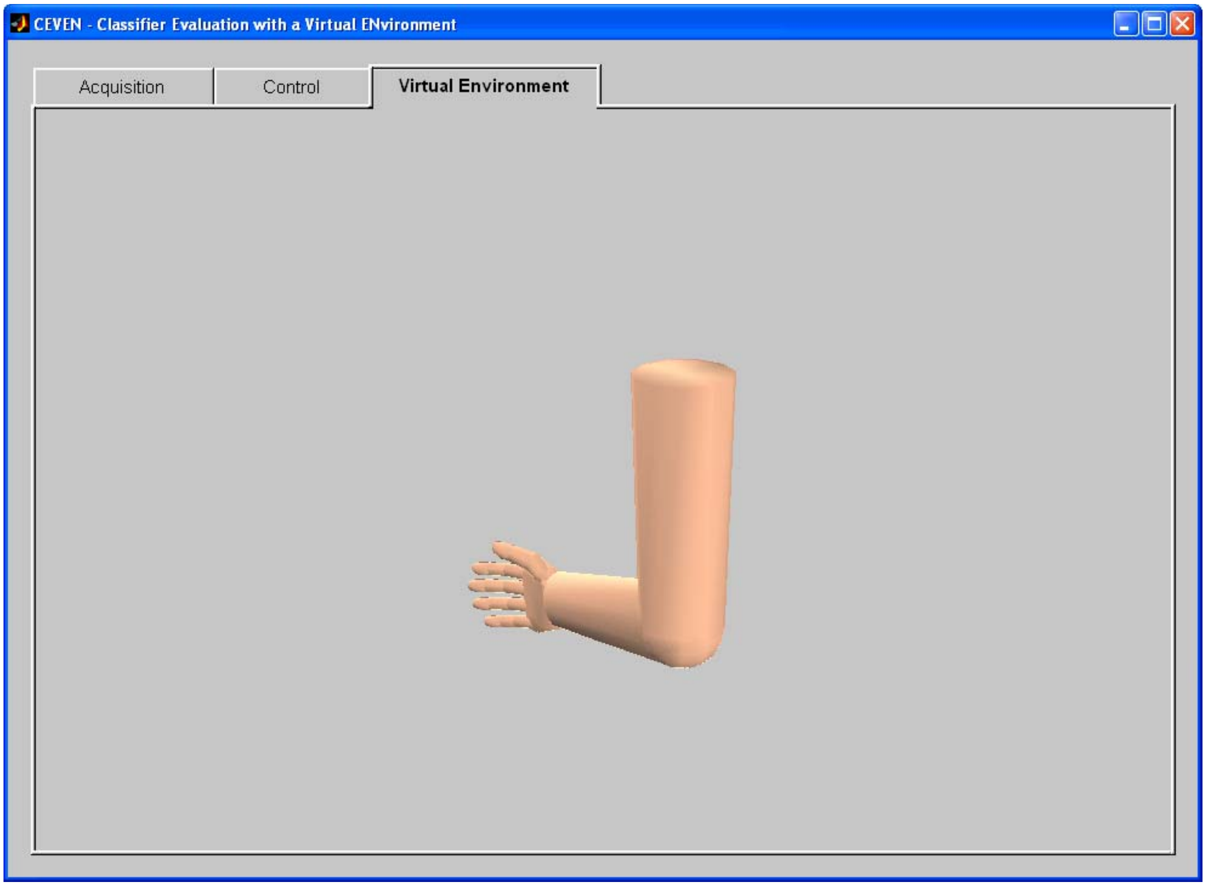


Figure 3.7 – Overview of the *Virtual Environment* interface

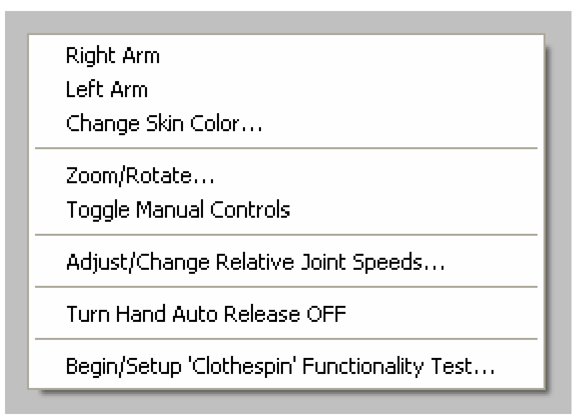


Figure 3.8 – *Virtual Environment* right-click menu

3.3.1 Virtual Arm

The virtual arm is designed to be a physiologically representative model of a human upper limb. For realization using Matlab, the arm is comprised of eighteen interacting 'surface' objects. The virtual arm is rendered with 'perspective' projection, directional lighting, and interpolated shading to help achieve a 3D scenario in 2D. Arm motions, with physiologically appropriate limits, are presently programmed; these include: all shoulder degrees of freedom excluding elevation; elbow flexion and extension; all wrist degrees of freedom; and three hand actions (chuck grip, kep grip, spreading of fingers).

3.3.2 Visualization

Many commands available from the menu shown in Figure 3.8 affect how a CEVEN user views the virtual arm and the virtual environment.

Right Arm/Left Arm

Since only one virtual arm is available in the environment, choice between left and right arm is available. Generally, a subject will prefer to use the same arm for which they are controlling the virtual limb in real-time.

Skin Color

A secondary GUI window, shown in Appendix A, is called and provides means to interactively select the overall skin color of the virtual arm.

Zoom/Rotate

An interactive GUI, shown in Appendix A, permits the CEVEN user to view the arm from any orientation and from closer or further away. For real-time control, the arm is best oriented the same as the arm of the controlling subject.

Manual Controls

For demonstration, investigation, or other purposes, the virtual arm can be manipulated by means of manual controls. When this is desired, a set of GUI sliders, each representing one joint/hand motion, appear next to the arm. Positioning the virtual arm is accomplished by adjusting the appropriate slider control. A ‘Home’ button is also included to reset the virtual arm position as desired. Slider control is not permitted during real-time operation. In Appendix A, one figure shows the virtual environment with the manual controls while another figure depicts the GUI allowing adjustment of the joint/motion limits.

Relative Joint Speeds

By default, any motion of the virtual limb will appear to operate with constant velocity. In real-time control this is sometimes altered by use of proportional control. In all cases, motion is based on a preset value representing constant velocity; similar to a real life actuator with an applied constant DC voltage. Default speeds of the virtual arm (hand, wrist, elbow, shoulder) can each be increased or decreased via a supplementary GUI, shown in Appendix A, in order to better represent a real life situation.

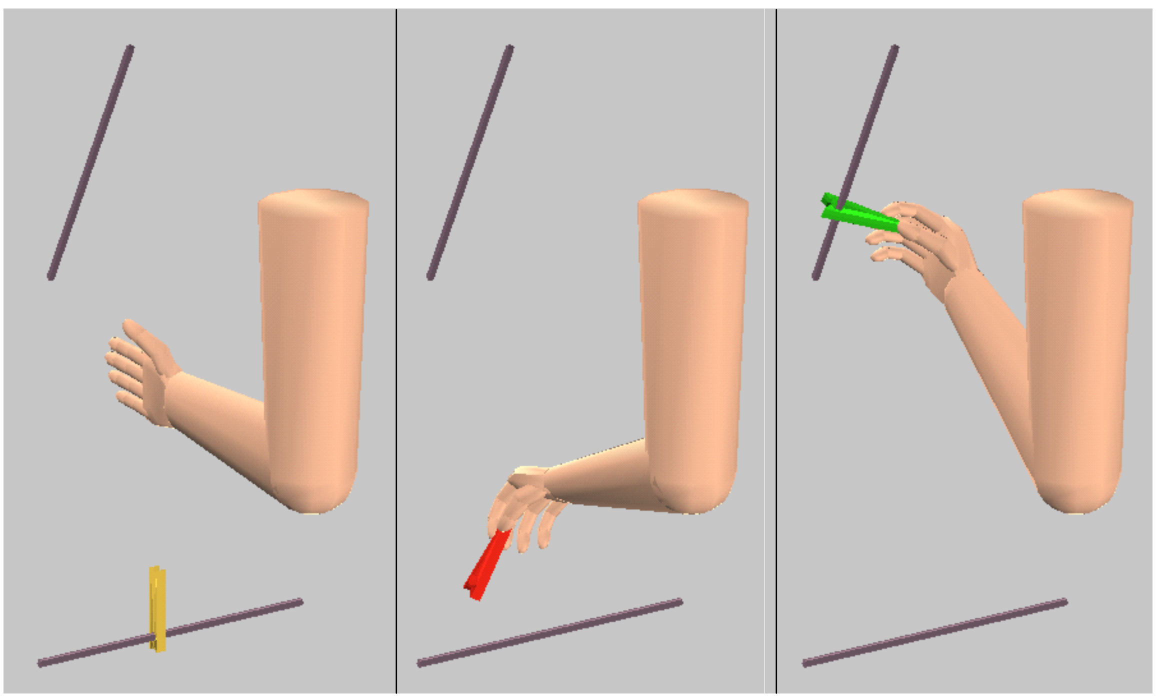
Hand Auto Release

The virtual arm of CEVEN performs motions associated with class decisions in real-time. In cases where classification does not meet activity threshold or a ‘no movement’ class is discerned, the virtual arm can be set to (the default) automatically and incrementally release any presently held hand grip. Selecting this menu option toggles said option between enabled and disabled states.

3.3.3 Clothes Pin Functional Task

As a test of function and usability, the virtual environment has been furnished with an emulation of a clothes pin test used in a real world assessment of multifunction MES control [21]. The test, initiated from the right-click menu, involves controlling the virtual arm to pick up a clothes pin from a horizontal bar and placing it on a vertical bar. This task requires the use of elbow flexion/extension, wrist pronation/supination, and hand grasp and release. Two modes of testing are available: 1) counting number of pins successfully placed in a set time; or 2) timing how long it takes a subject to place a chosen number of pins. Test setup is accomplished within a secondary GUI, shown in Appendix A, which is called at test commencement. Test timing, pin counting, and result logging are all automatic since the task exists in the virtual environment.

The virtual environment clothes pin test has visual aids not necessary or possible in the real world task; the clothes pin changes to a red color when the virtual arm is gripping or moving the pin and turns green in color when position and orientation are acceptable for placement of the clothes pin. Any clothes pin released prematurely or in an unacceptable position constitutes a ‘drop’ and a new pin appears (wooden color) clamped on the horizontal bar ready for retrieval. A screenshot compilation of clothes pin task positions is shown as Figure 3.9.



(a) (b) (c)

Figure 3.9 – Clothes pin task poses: (a) task starting position; (b) retrieved clothes pin being held/moved; (c) clothes pin held in a position acceptable for placement

Chapter 4: Assessment of Controllability

Previous studies have presented very good results for MES control but most have investigated performance when varying a small subset of control components. Because of this, results are presented and compared as classification accuracy percentage (or percentage error) without any measure of complete control system usability. Comparison of all possible control configurations has not yet been performed due to the intense programming effort and modularity of control system design. Additionally, the lack of physical devices capable of the multifunction commands generated by any state-of-the-art IBME control system has impeded any complete functional testing of multifunction MES control.

Using CEVEN, it is intended for this project to investigate how measures of classification accuracy relate to system usability for many possible configurations of multifunction control. That is, the experiment described below is specifically designed to provide two important metrics for any given control configuration: 1) classification accuracy; and 2) quantitative performance (an estimation of usability). It is hypothesized that usability is directly related to control system classification accuracy.

4.1 Method

4.1.1 Experimental Design

Although this experiment was designed as an investigation into multifunction MES control, the experimental protocol was only loosely based on a typical prosthetic application. This preliminary study intends to investigate a usability-accuracy relationship, not to promote transfer of technology as of yet.

The experiment as conducted consisted of sessions where a recruited subject would be fit with electrodes, train a set of multifunction MES controllers, and complete three, timed functional tests (clothes pin task [21]) using CEVEN. Isometric contractions were employed for testing in order to limit motion artifact and to maximize electrode contact that may become compromised with repeated and prolonged motions. Each subject would repeat a complete session five times on near-as-possible consecutive days. Each daily session required about one hour of the subject’s time seated in the Biosignals laboratory at the IBME. The author was present throughout all sessions to aid in electrode placement and apparatus, act as CEVEN operator, and address any questions/concerns.

4.1.2 Subject Recruitment

For this experiment, individuals from the local community were informed about and invited to participate in the testing. Volunteer subjects were required to read, understand, and endorse an informed consent document (see Appendix B) that outlined the minimal risk of research involving human subjects. This experiment enlisted the first twelve subjects who expressed interest. All twelve subjects were normally limbed, healthy, male individuals ranging in age from 23 to 44.

4.1.3 Apparatus

Because acquisition aids and the virtual environment were presented via CEVEN on a computer screen, it was decided that subjects were best situated facing the screen in a seated position. In this arrangement, the subject's dominant arm was placed in a custom built arm brace [41] which comfortably immobilized the forearm. The arm brace is shown below in Figure 4.1. Padded limits within the Plexiglas® brace provided a means for the subject to comfortably perform all isometric contractions required in this experiment.

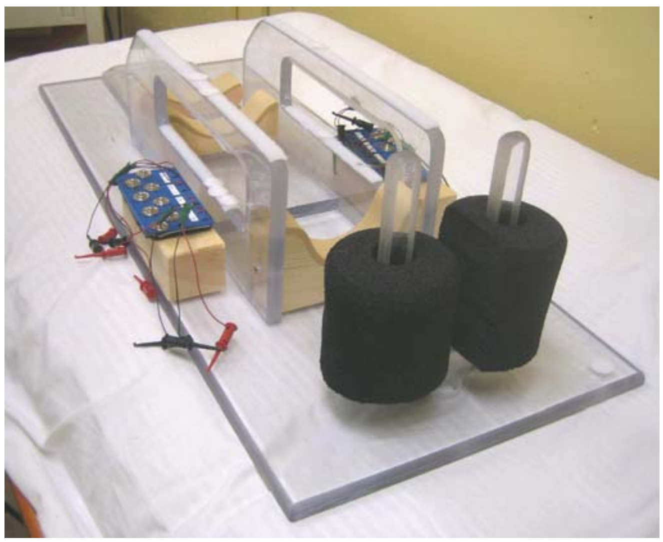


Figure 4.1 – Photograph of arm brace apparatus

Eight differential MES channels were used during each session. Four transhumeral sites, equally spaced around the circumference of the upper arm and equidistant from elbow and shoulder, comprised the first four channels. The remaining four channels were from sites equally spaced around the forearm at a distance approximately one third the length from elbow to wrist. Obviously, placement of electrodes on both forearm and upper arm is not practical in the context of an amputee; however, it has been assumed that targeted reinnervation (transferring the nerves innervating the hand/wrist muscles above the elbow)

[21] will accompany the realization of the real world multifunction limb. This assumption supports acquiring MES from these ‘direct’ control sites.

Disposable Duo-Trode® (Myotronics-Noromed, Inc. Tukwila, WA) bipolar electrode pairs were placed at all eight sites oriented in the direction of underlying muscle fibers. Care was taken to place the electrodes in near exact position on each subject for each daily session. One Red Dot™ electrode was placed behind the elbow on each subject to serve as the body potential reference. Skin preparation was minimal; each site was lightly rubbed with abrasive paper (to remove stratum corneum) and cleaned with alcohol swabs. The self-adhesive electrodes were placed on the skin when dry.

A custom cable was fabricated with sixteen numbered snaps (to attach to the electrodes) and an interface to a biomedical instrumentation amplifier. The amplifier used was a 16 channel surface EMG amplifier, *EMG 16*, which was developed by LISin Bioengineering Center in collaboration with Prima Biomedical & Sport. Amplified MES signals were input to the testing laptop computer via National Instrument’s *DAQCard 6024E* acquisition board placed in the laptop’s PCMCIA slot. When available, CEVEN was capable of automatically recognizing, communicating, and obtaining real-time data from the *DAQCard 6024E*.

4.1.4 Acquisition and Training Parameters

As descried in chapter 4, the developed software suite, CEVEN, allows for considerable flexibility in both data acquisition sessions and control system investigations. For this experiment, a set of acquisition and control configuration parameters were selected and kept consistent over each subject and each session.

Acquisition

The eight channels of differential MES were sampled and recorded at 1024 Hz to capture data for six different classes (elbow flexion, elbow extension, wrist pronation, wrist supination, hand grasp, and no movement). These six classes of motion, shown in Figure 4.2, comprise the set required to complete the clothes pin functional task and emulate three-function actuation (elbow, wrist, hand).

(a) (b) (c) (d) (e) (f)

Figure 4.2 – Set of six classes used: (a) elbow flexion; (b) elbow extension; (c) wrist pronation; (d) wrist supination; (e) hand grasp; (f) no movement

Each acquisition session consisted of two sequential trials during which each of six contractions were performed twice. Contractions against the padded constraints of the arm brace were held isometrically for five seconds and separated by four-second rest periods. Order of presented contractions was randomized by CEVEN to help prevent any subject anticipation or learning effects.

Training

Using each two-trial set of data recorded during the acquisition session, CEVEN trained control systems while the subject kept their arm and electrodes in place. Typical processing took between two and three minutes and gave each individual time to relax before undertaking the clothes pin tests. For processing, data were separated into 250 ms records (corresponding to 256 samples) and considered with overlap delays of 31.25 ms (corresponding to 32 samples). Two sets of data, overlapped and disjoint records, were then subject to all available forms of feature extraction (TD, AR, TDAR) and limited to thirty principal components. An auto regression order of six was employed. Sets of determined features were conveniently divided by trial: data from the first trial to train classifiers and the second trial to test. All three classifiers available in CEVEN (LDA, ANN, GMM) were processed. Classifier outputs were subject to majority voting that would consider the set of all decisions made within 300 ms. This training setup resulted in thirty-six complete control schemes, represented by percent classification error, presented in CEVEN's results table. The full set of processed controllers and associated classification errors were saved for each session.

4.1.5 Clothes Pin Testing

For each session, a subject was tasked to undertake three separate clothes pin tests, each timing the successful placement of three virtual clothes pins (section 3.3.3). The subject, for each of the three tests, controlled the virtual arm in real-time via one of the thirty-six implemented controllers. With all thirty-six control schemes presented in the results table, the principal investigator would note the 'best' (lowest classification error), the 'worst' (highest classification error), and the 'moderate' (classification error closest to average of best and worst) classifiers. These three selections comprised the control schemes to be employed for the three clothes pin tests of each session. It is noted that no selection criteria were employed to utilize similar schemes inter- and intra-subject, however, in cases where multiple classification errors were the same in the table, care was taken to enlist control systems of different nature where possible (i.e. alternate classifier or alternate feature extraction). The order of tests performed was randomized by the investigator and blind to the subject; during virtual arm operation the subject had no knowledge as to which configuration of multifunction MES control they were using.

Each clothes pin test was commenced without giving the subject extensive practice time in order to better investigate any inter-session learning effects. The tests were carried out as described in section 3.3.3. After each three-pin test, the investigator would record the timing results, similar to those depicted in Figure 4.3.

(a) (b)

Figure 4.3 – Clothes pin test results: (a) General output window; (b) Detailed time results shown in Matlab Command Window

4.2 Results

Ideally, each of the twelve subjects participating in this study were to complete five consecutive-day sessions within each they would be able to place nine clothes pins – three pins for each of three different multifunction control schemes. In a few cases, sessions were not fully completed for various reasons common to this form of data collection, such as: equipment/apparatus failure and gross operator error. Five instances saw the subject complete two of the three tests and in two other sessions one of the three tests were successful. Personal scheduling issues forced one subject to leave the study after two of the five sessions were completed.

Table 4.1 shows the subset of collected data used for the principal investigation of this endeavor; the mean pin time (time take to place three clothes pins divided by three) and associated classification error from each completed test. The data of Table 4.1 is matched with a number of other important metrics, including test order and controller configuration, all tabulated separately in Appendix C.

The real-world clothes pin experiments by Kuiken *et al*. [21] involved two amputee subjects. Using their conventional prostheses, the subjects had mean pin placement times of 45.7 and 20.9 seconds which improved to 33.7 and 11.3 using their experimental prostheses. Many of the test results from the present work (Table 4.1) are comparable with the results from [21].

It is noted that CEVEN describes control schemes by percent classification *error*, therefore promoting data to be recorded in terms of error. However, it is commonplace in multifunction MES control literature and data analysis to use percent classification *accuracy*. For purposes of discussion below, percent classification *accuracy* (100-*error*) is used.

SUBJECT	CONTROLLER TYPE	SESSION 1		SESSION 2		SESSION 3		SESSION 4		SESSION 5	
		Classification Error (%)	Average Pin Time (sec)	Classification Error (%)	Average Pin Time (sec)	Classification Error (%)	Average Pin Time (sec)	Classification Error (%)	Average Pin Time (sec)	Classification Error (%)	Average Pin Time (sec)
1	Best	0.00	31.1	0.00	31.8	0.00	47.2	0.00	64.7	0.00	27.7
	Moderate	0.83	27.4	7.29	49.5	3.04	25.7	2.50	66.4	5.42	74.2
	Worst	2.50	43.2	15.42	137.6	6.55	28.1	7.50	26.4	13.33	25.5
2	Best	0.00	35.6	0.00	84.2	0.00	43.8	0.00	17.4	0.00	18.1
	Moderate	2.29	66.7	6.28	24.7	5.32	21.8	2.29	18.2	0.85	52.6
	Worst	5.83	35.5	13.75	55.6			5.75	63.8	1.70	19.7
3	Best	4.90	30.8	0.00	26.8	4.17	37.8	14.91	39.0	0.00	25.0
	Moderate	16.67	59.7	0.21	30.4	11.50	24.0	21.51	23.3	1.25	30.3
	Worst			0.59	54.1	19.81	179.3	29.02	76.0	5.00	35.5
4	Best	1.28	110.9	17.08	109.2	4.63	112.1	0.00	39.5	0.00	35.1
	Moderate	12.25	117.2			7.45	36.6	6.25	27.3	0.83	30.3
	Worst	24.17	220.9			18.42	42.4	12.41	32.8	9.58	75.9
5	Best	0.00	25.6	0.00	32.5	0.00	26.1	0.00	70.1	0.00	15.3
	Moderate	6.23	57.9	7.87	19.7	10.89	63.0	2.20	37.7	1.67	17.3
	Worst	11.64	53.0	13.60	32.1	21.49	75.6	5.01	35.2	3.33	51.5
6	Best	4.39	38.6	3.08	31.1	13.16	108.0	2.79	95.4	0.77	88.8
	Moderate	12.38	39.7	12.93	33.0	21.16	84.3	4.59	13.4	5.21	14.1
	Worst	25.25	124.3	17.99	86.2			9.17	90.2	9.17	35.1
7	Best	0.00	25.6	0.48	52.3	0.00	44.3	0.27	35.8	0.00	13.3
	Moderate	4.26	89.8	7.29	30.0	7.08	25.7	1.67	14.5	3.33	20.9
	Worst	10.54	50.9	15.00	36.6	17.50	47.5	3.33	21.7	12.08	34.2
8	Best	9.58	59.3	0.53	36.8	2.50	36.1	11.55	40.1	0.37	35.9
	Moderate	14.58	133.7	5.00	26.9			16.67	60.8	7.77	158.4
	Worst			9.17	95.3			18.33	38.0	15.42	38.5
9	Best	0.00	271.0	3.14	32.1						
	Moderate	5.42	40.1	6.25	41.4						
	Worst			9.58	57.4						
10	Best	0.00	18.7	16.25	26.2	4.15	42.0	0.00	39.9	1.76	55.9
	Moderate	3.75	133.9	19.65	54.7	13.79	40.2	9.64	32.4	11.93	28.9
	Worst	7.61	80.1	27.50	49.3	29.50	42.1	20.83	56.4	23.33	43.6
11	Best	17.92	37.0	5.54	46.2	0.83	36.0	0.32	54.5	6.50	74.7
	Moderate	21.09	44.3	11.40	96.7	11.13	32.8	7.08	55.3	11.55	40.2
	Worst	25.51	58.3	16.25	36.8	20.71	32.8	15.00	39.2	15.71	32.1
12	Best	1.21	40.5	0.00	20.2	3.69	72.4	5.33	45.4	8.20	24.0
	Moderate	15.79	24.2	0.00	55.7	10.73	66.5	17.04	35.0	15.76	24.0
	Worst	25.14	58.3	1.52	75.4	31.14	37.4	25.77	112.3	25.08	44.7

Table 4.1 – Clothes pin experiment results (percent classification error and average pin placement time) by subject and session

Not only did the clothes pin testing provide a useful, multi-dimension data set, but a number of qualitative observations were made throughout the process. These observations, discussed below where appropriate, are valued since real-time multifunction control is novel and experiences are limited.

4.2.1 Usability versus Classification Accuracy

The principal investigation of this work was to obtain quantitative outcomes from the virtual clothes pin tests to expose any ‘usability’ versus ‘accuracy’ relationship. The basic theory, that classification accuracy of a multifunction controller is directly related to the usability of a multifunction device employing said controller, was to be tested.

The scatterplot of Figure 4.4 shows the complete set of outcomes from the clothes pin functionality testing. Each plotted point matches the mean time, in seconds, taken to place a clothes pin against the percent classification accuracy representative of the multifunction controller used for that test. Points are only included for completed tests, therefore, timing metric is the average of the three pin placement times in each test. Using accuracy data to predict usability (task timing), a linear, best fit is determined and also found on the plot of Figure 4.4. It is clear that the data are not significantly related. The high degree of scatter shows a minimal correlation between classification accuracy and usability as investigated by this experiment. Correlation coefficient, R, verifies this observation with an extremely low value of 0.238.

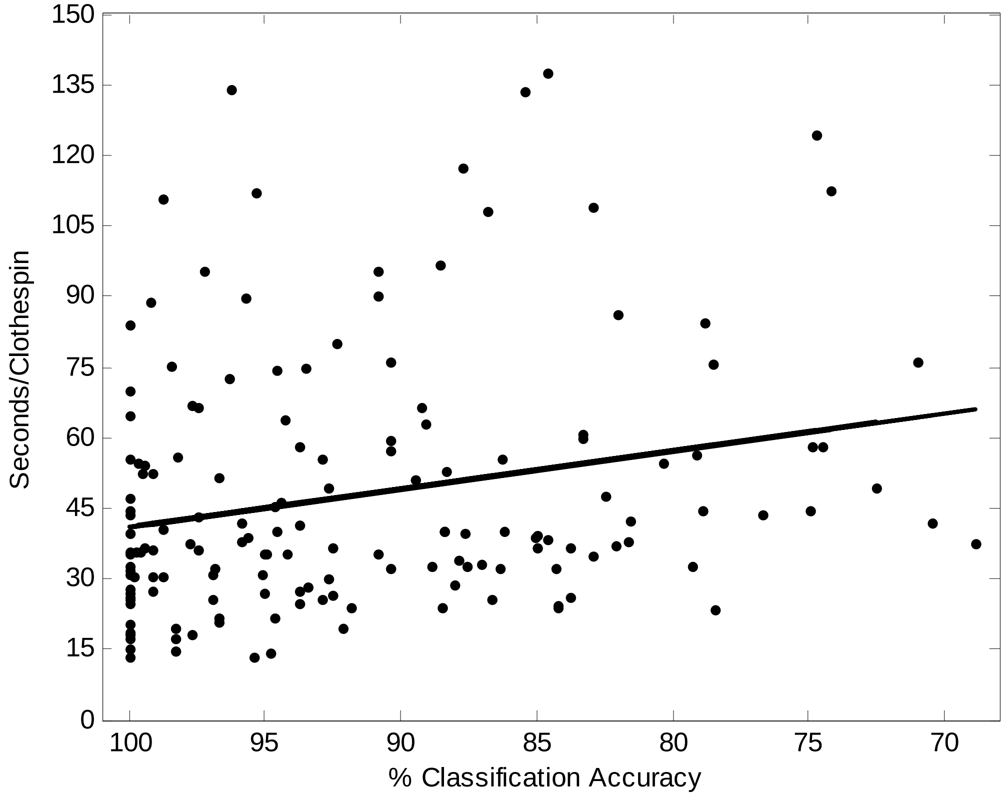


Figure 4.4 – Scatterplot: Clothes pin test measure of usability (sec/pin) versus percent classification accuracy

Results from this work do not support using the classification accuracy of a controller to estimate usability. This observation is limited, of course, using a virtual multifunction limb in place of a physical device and a single virtual task instead of real world tests.

4.2.2 Classification Accuracy by Class

Multifunction control schemes, like those investigated here, are dependent on algorithms which can discern a period of MES activity into one of a number of possible classes. The term ‘classification accuracy’, commonly used in investigations of pattern classification for MES control, generally indicates a global measure of accuracy of classification for all included classes. That is, the accuracy represents the number of correct classifications taking into account all classes. The contribution from each class is not indicated and can be widely spread in many cases. If each class is considered separately, performance of a controller on a per-class basis is available.

It is hypothesized in this work that, since there is limited relationship between global classification accuracy and usability, functionality may be more related to classification on a class-by-class basis. Since proficient usability depends on accurate control of all included motions, and all of these motions are represented by a class, it is easily understood how poor classification in one class can affect the overall usability. Under this premise, a new subset of data is compiled – each completed clothes pin test (usability score) is paired with a new percent classification accuracy that is the worst accuracy among the six classes. These data are plotted as a scatterplot in Figure 4.5 along with a first order best fit.

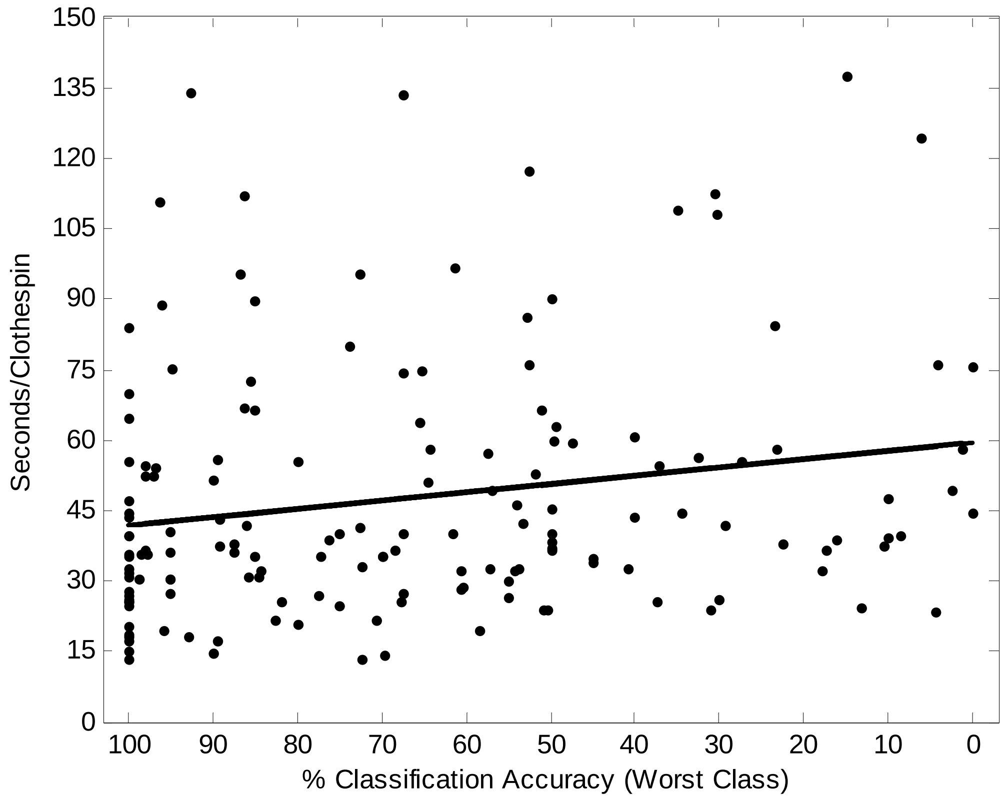


Figure 4.5 – Scatterplot: Clothes pin test measure of usability (sec/pin) versus the worst percent classification accuracy among the six employed classes

Similar to the case of global classification accuracy, the healthy degree of scatter exhibited in Figure 4.5 does not support the hypothesis. A very weak relationship (R = 0.195) is shown to exist between usability and a measure of classification accuracy from the 'worst' class.

The effect of per-class classification performance on usability is further investigated in Figure 4.6 where mean per-class classification accuracy for each subject is shown. Included in each average are all per-class accuracies for all control schemes used for virtual clothes pin tests. The bold line depicts the mean across all subjects with error bars showing plus and minus one standard deviation. This depiction exposes and compares the per-class accuracy profile of each subject; useful in understanding if multiple subjects classify low for similar classes

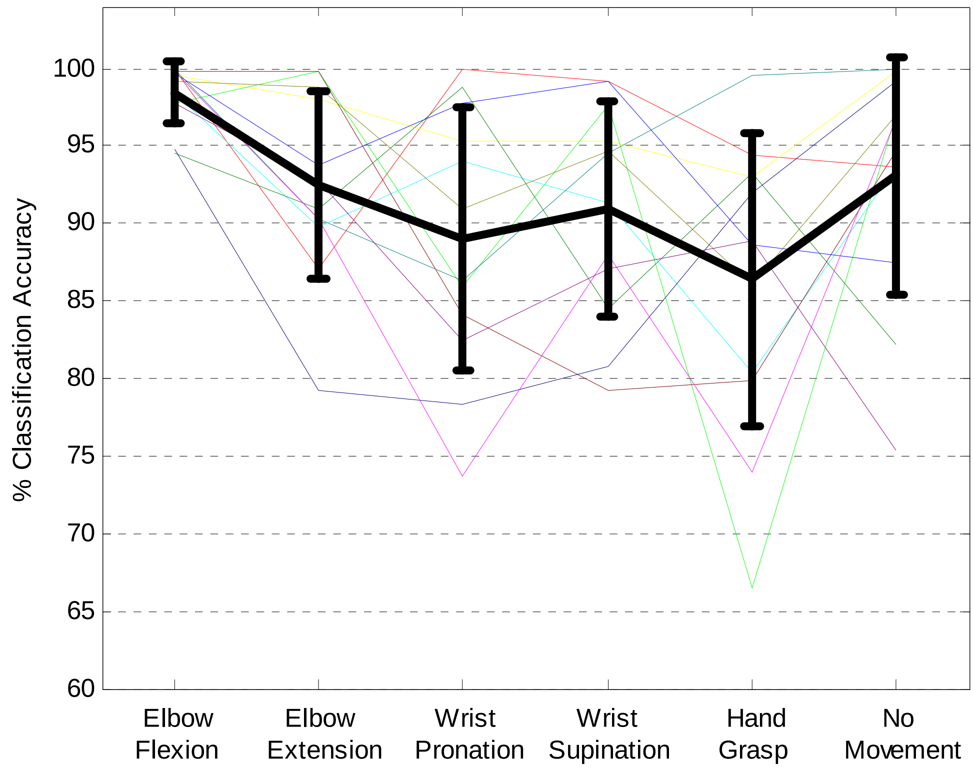


Figure 4.6 – Classification accuracy per class

These data were subject to a two-way analysis of variance (ANOVA) to investigate statistical significance. A p value of 0.002 indicates significant differences do exist among the mean accuracies for the six classes. Specifically, analysis highlights the only significantly different group: average accuracy for elbow flexion differs significantly from both wrist pronation and hand grasp. The second p value, 0.14, indicates no subject effect for this investigation.

Since differences among inter-class accuracies are significant, an alternate look into per-class accuracy contribution is presented. Figure 4.7 shows six plots, one corresponding to each class used in clothes pin testing. Each of these plots, on identical axes, is a scatterplot similar to that of Figure 4.4 showing clothes pin usability score versus percent classification accuracy. In this case, percent accuracies correspond to the depicted class; showing the relationship of each motion's classification accuracy on usability.

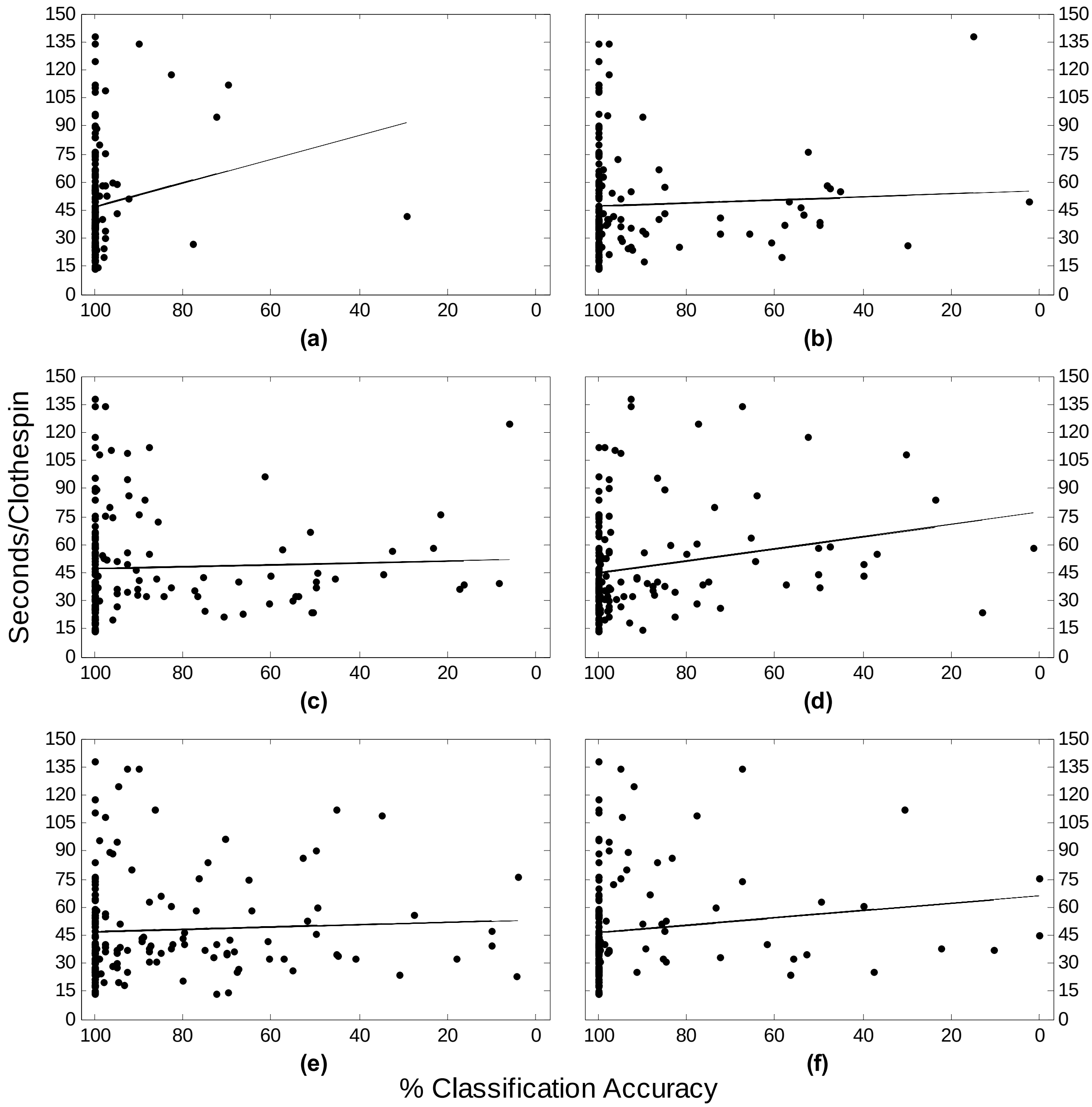


Figure 4.7 – Scatterplots: Clothes pin test measure of usability (sec/pin) versus percent classification accuracy by class: (a) elbow flexion; (b) elbow extension; (c) wrist pronation; (d) wrist supination; (e) hand grasp; (f) no movement

Unfortunately, a high degree of scatter remains for all classes indicating class accuracy of any class cannot support usability. Again, however, this observation is limited as a virtual multifunction limb is used in place of a physical device and ideal world tests are replaced by a single virtual task.

Low correlation coefficient (R) values from all six classes support the observed high degree of scatter: $R_{\text{ELBOW FLEXION}} = 0.162$; $R_{\text{ELBOW EXTESION}} = 0.051$; $R_{\text{WRIST PRONATION}} = 0.039$; $R_{\text{WRIST SUPINATION}} = 0.221$; $R_{\text{HAND GRASP}} = 0.054$; $R_{\text{NO MOVEMENT}} = 0.138$.

4.2.3 Training Effect on Usability Score

Achieving proficiency in the virtual clothes pin placement task is most dependent on two factors: (1) acceptance and perception of the visual feedback provided by the virtual environment; and (2) achieving dexterous command of a multifunction MES control system through practice.

All subjects participating in this study expressed satisfaction with the virtual environment and, when asked, indicated no problems understanding what was visualized (orientation and the virtual images). Many of the tested individuals felt that use of this virtual environment had no negative or limiting effects on their task performance. Practice of the task was, therefore, taken as the stronger component of training during this experiment.

To investigate the training effect, usability scores were monitored over five discrete days' sessions. If task training and practice had an effect over the five sessions, subjects would likely become more proficient with the clothes pin task; that is, taking less time to place the virtual clothes pins. Figure 4.8 shows the measured performance (mean of pin placement times) for each subject over the five sessions. Also plotted is the subject-mean performance by session, complete with indicators of standard deviation.

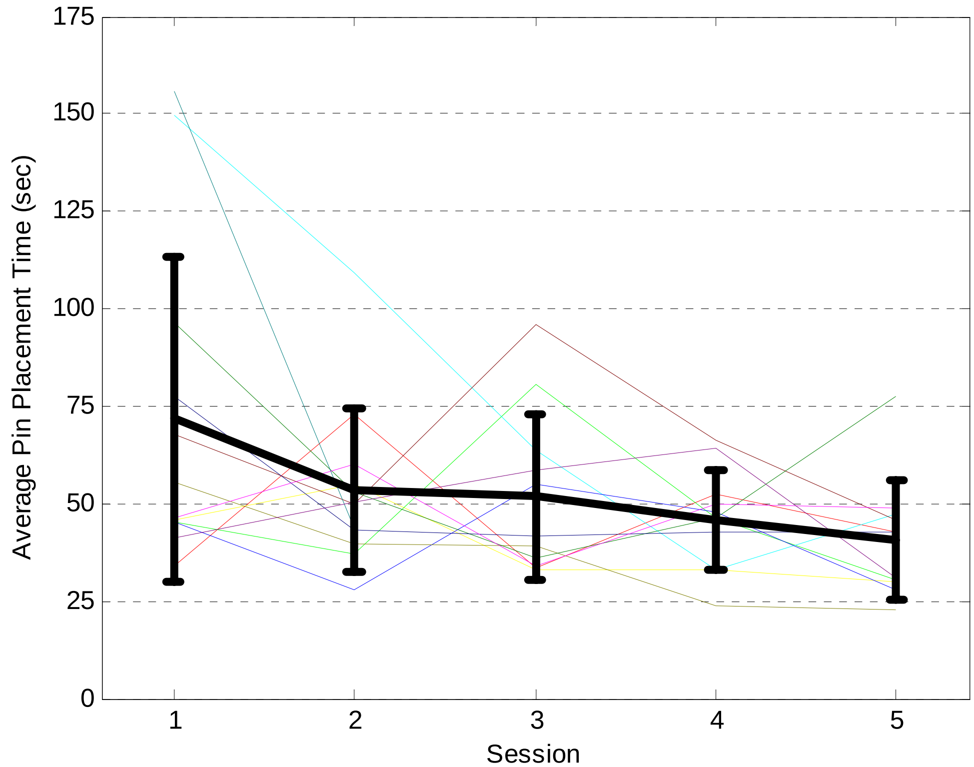


Figure 4.8 – Clothes pin placement performance by session

A two-way ANOVA was used to assess the effect of subject and session on clothes pin task performance. A p value of 0.05 for subject-effect suggests significant difference between individuals who performed the testing; a perceivable result. The second p value, 0.09 for session effect, just exceeds the 0.05 level of statistical significance. Although this cannot be statistically accepted, it indicates that five days of testing has a weak effect on usability.

Inspection of Figure 4.8 supports the ANOVA outcomes: only slight improvement in task completion speed (mean for all subjects) is evident. More apparent is the greater variance in performance between subjects for the initial session.

4.2.4 Session Effect on Classification Accuracy

The multiple-day testing setup of this work also promoted investigation into day-to-day effect on classification accuracy. Since the accuracy of a processed controller is related to the MES training data, and each daily session saw new acquisition of these data, it was perceived that a subject would ‘learn’ to better train the system over the five sessions. Subjects having difficulties performing the virtual clothes pin task could often indicate which classes of motion were non-responsive, being confused by the controller, or too specific to activate. These users would relate their limiting experiences from a previous session and seek to better train the systems on subsequent sessions.

As the subjects tuned their training contractions based on experience, the associated classification accuracies would be affected. Shown in Figure 4.9 are the session-mean classification accuracies for each subject. That is, an average of the three classification accuracies used for clothes pin testing each session. The thick line shows the average across subjects with error bars indicating the standard deviation. By inspection, no increase in classification accuracy over the five sessions is evident. This indicates subjects’ day-to-day adjustments in training had little or no effect on processed controllers.

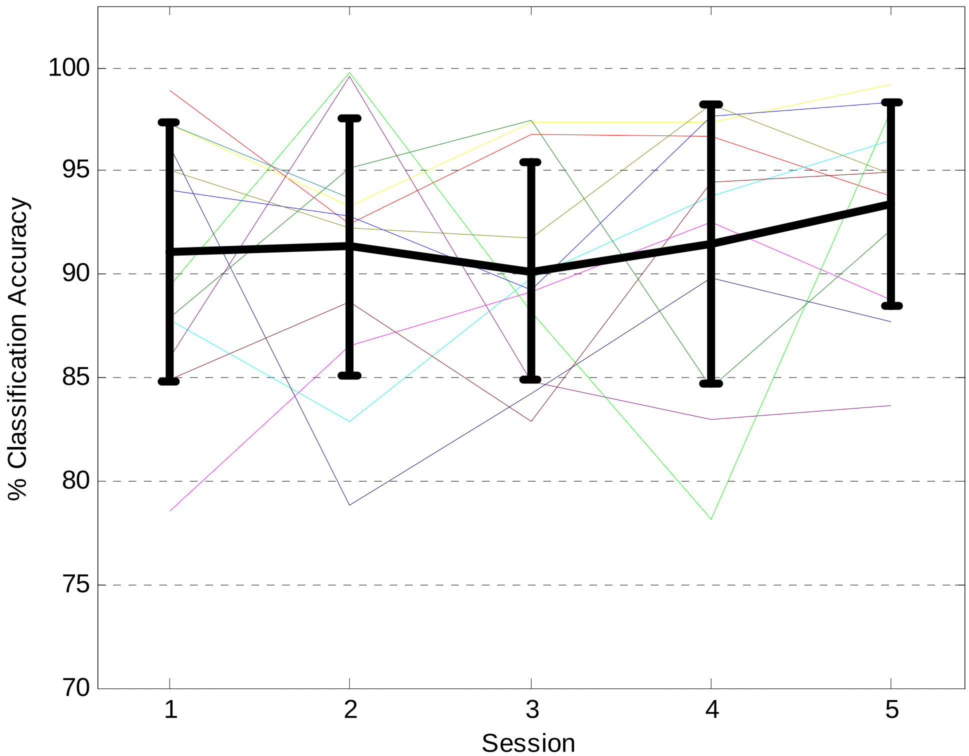


Figure 4.9 – Classification accuracy of employed controllers by session

A two-way ANOVA test investigates the significance of subject and session on classification accuracy. A p value of 0.04 for subjects suggests a slight significant difference between individuals but a p value of 0.66 for session indicates five days of testing has no effect on classification accuracy.

4.2.5 Classification Performance of Control Configurations

Proponents of multifunction MES control for everyday use in upper-extremity prosthetics understand the requirement for system training and are often interested in day-to-day performance and usability effects. Current state-of-the-art classifiers included in the development of CEVEN all represent good choices for a controller that would be used daily. For a physical multifunction device, an embedded processor would be programmed with the best suited algorithm for the given application; however, for each day of prosthetic use, it is possible that a different control configuration may perform the best. Thus, the five session design of this experiment was intended to test subjects over discrete days in order to investigate any day-to-day effect of control configuration. With a large number of suitable multifunction controllers available, it was to be determined if subjects show consistency of control configuration for sessions on different days. Furthermore, the complete set of processed controllers' classification accuracies was investigated in order to uncover any standout multifunction MES configurations.

Each data acquisition/control processing session produced a set of nine basic controllers (three forms of feature extraction with three forms of classification). The nine systems were subject to supplementary processing giving four variations on each; thirty-six in total. However, for this analysis, the most typical of these variations (overlapped data windowing and majority vote post processing) were considered for each of the feature set and classifier combinations. The classification accuracies of each of these nine configurations were ranked for each session, with the lowest accuracy given a zero and the highest accuracy assigned an eight. The session rankings were summed for each subject yielding an additive score for each of the nine configurations. In this manner, any configuration consistently ranking high would have a large score and, conversely, a consistently poor-performing controller would expose a low score. Highest possible score (ranked best for five sessions) produces a score of forty; however, scores were normalized within a zero to one range for analysis.

In Figure 4.10, nine shaded regions represent the scores corresponding to the control configurations for one of the tested subjects where degree of shading is relative to configuration score. The region of lightest shading highlights the control configuration which provided the worst classification performance for subject 4: AR feature extraction and GMM classifier. The control combination of TDAR features and LDA classifier is shown to be the best since its corresponding region is of darkest shade. The results depicted in Figure 4.10 are annotated with a color-range index bar and arrows showing the relative score of best and worst results. The extremes of the shade indicator represent the best- and worst-possible scores; that is, respectively, a controller ranking highest or lowest for each and every session.

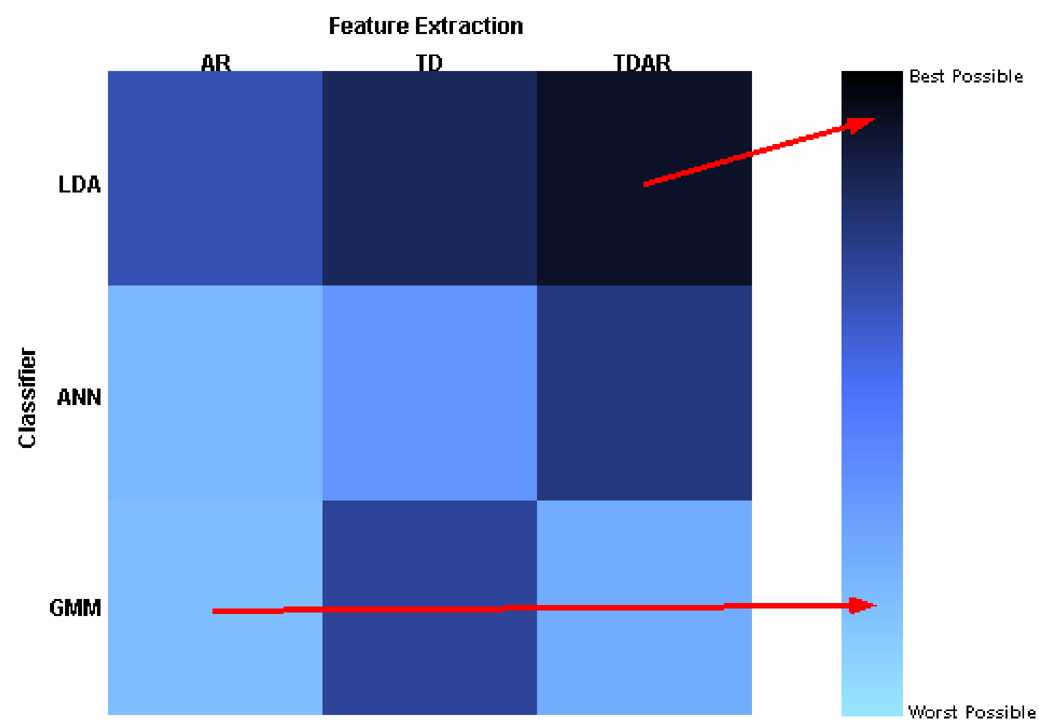


Figure 4.10 – Graphical representation of controller performance for subject 4

Similar diagrams showing the results for the remaining eleven tested subjects are included in Appendix D. With all subjects' outputs considered together, inter-subject controller performance can be investigated. Figure 4.11 displays the overall averaged outcomes. Akin to the results of subject 4 (Figure 4.10) and some of the depictions in Appendix D, the TDAR-LDA combination has shown the most positive consistency while the AR-GMM configuration scores lowest.

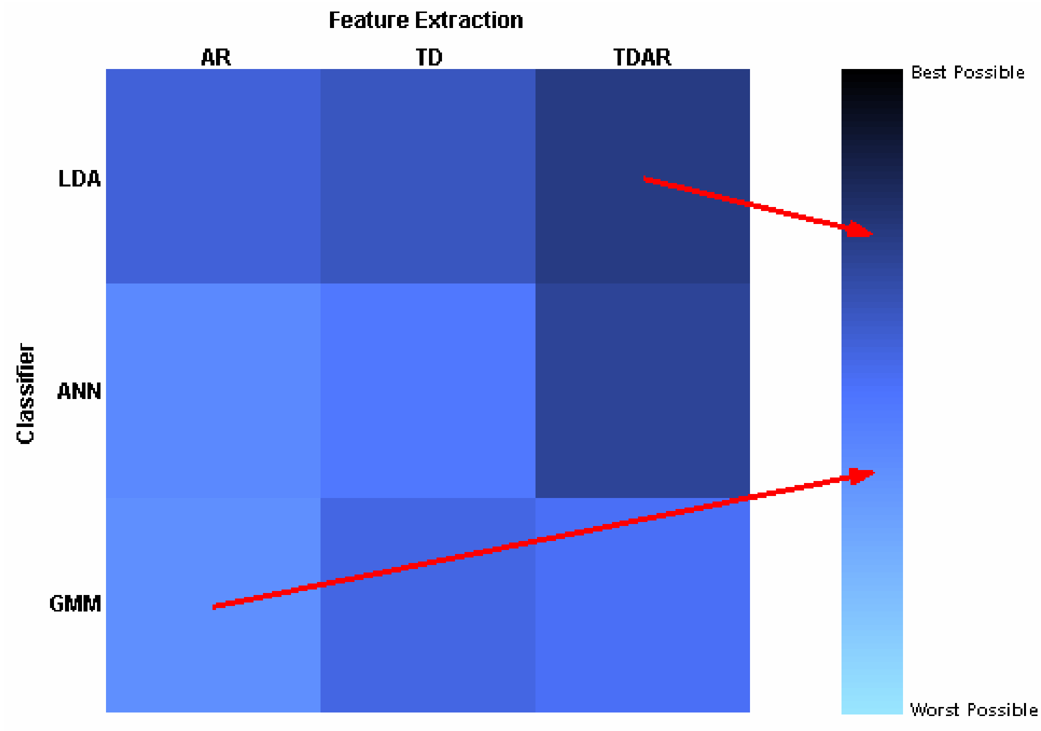


Figure 4.11 – Graphical representation of controller performance (average for all subjects)

The plots of Figure 4.10, Figure 4.11, and Appendix D suggest similar trends in the classification performance for configurations of feature set and classifier. Inspection of these figures indicates TDAR performs slightly better than TD, which, in turn, gives superior results over AR. For classifiers, the best to worst performing order is: LDA, ANN, GMM. Because these performance tendencies have only been visually exposed, a two-way ANOVA was used to investigate any statistical significance. Resulting p values of 0.059 and 0.096 indicate no significant relevance for choice of feature set and classifier respectfully.

Chapter 5: Conclusion

5.1 Summary

This work has been motivated by a number of issues in multifunction MES control. In recent years, many developments have been made at the IBME where researchers have approached the improvement of the myoelectric prosthetic controller by enhancing each of its components: feature extraction, movement intent, pattern classification, proportional control, post processing, etc. These advancements have not been consolidated to form a single state-of-the-art MES controller nor has an economically viable multifunction device been available to evaluate the controller.

It has been a chief objective of this project to develop a complete research tool incorporating all the recent advancements in multifunction MES control. The developed system was to provide GUI-based means of investigating various configurations of control and include a virtual multifunction limb to mimic the real-time operation of a physical prosthetic device.

An additional purpose of this work was to employ the developed virtual limb in a functionality experiment intending to explore the usability and classification accuracy relationship.

5.2 Contribution

The efforts during the course of this project have contributed two discrete yet related bodies of work. One component is the software suite, named CEVEN, while the second is the assessment study made possible with use of the developed software. Not only has this project added to the specific research area of multifunction MES control but it has produced a research tool for continued use and development in both clinical and research settings.

Because of what functionality it encompasses, CEVEN can be considered complete and successful. The Matlab-based software tool is GUI controlled and provides means for flexible data acquisition and archiving. CEVEN has been endowed with state-of-the-art continuous multifunction classification components and permits simultaneous investigations into a large number of control configurations. To complement the acquisition and control components, the software suite has been developed with a complete, physiologically appropriate virtual arm which can be controlled in real-time by classified MES. Naturally, this arrangement has lent itself to quantitative investigations of multifunction MES control. The virtual environment has also been promoted as an economically viable tool in prosthetics fitting and training.

A number of IBME researchers have found great use in CEVEN. Two current studies employ the data acquisition and control processing functionality while another pending project seeks to further develop and utilize the real-time virtual arm.

Following the development of CEVEN, this project employed the virtual arm in a lab assessment of multifunction MES control. The research has related classification accuracy of multiple control configurations to performance measures of usability and, in doing so, made a number of contributions:

- Results have shown minimal correlation between classification accuracy and usability of controllers. This suggests heeding caution in future acceptance of multifunction classifiers by way of accuracy only.
- Effects of per-class classification accuracies, hypothesized as more intuitive predictors of usability, have been discredited. Weak correlation was shown between usability score and the accuracy of the worst performing class and also between the usability and each class considered separately. Statistical significance was however, promoting differences between the degree of accuracy contribution from each class.
- Data collected over five discrete-day sessions were analyzed to investigate training and learning effects. For the data acquired, no statistically significant improvement in task completion times or classification accuracies was uncovered. It is common understanding that training and practice will provide quantitative benefits, suggesting more data must be acquired to further investigate this observation. Pattern recognition based control schemes may indeed possess unique characteristics that make training effects different than conventional schemes.
- Consistencies in classification accuracy performance of control configurations, both positive and negative, were evident. Accuracy results from multiple sessions exposed the TDAR and LDA combination as the ‘best’ while AR and GMM combined as the ‘worst’. However, for these data, the trends were unconvincing as no choice of feature set or classifier was statistically significant.

5.3 Future Work

Although this work has both produced a complete MES research tool and contributed to multifunction control research, the efforts can be considered preliminary. The software suite has been fully developed from scratch, not an alteration of an existing system. This implies that future efforts are well suited to add to and improve CEVEN. Additionally, CEVEN has been developed in a modular style using Matlab – a scripting platform familiar to many researchers. A list of suggested future enhancements to CEVEN includes:

- Inclusion of conventional amplitude threshold-based MES control as a choice for control of the virtual limb.
- Improved means of saving and loading user and testing profiles.
- Addition of more functional tasks to accompany clothes pin test. Tests such as: box and blocks, pegboard, ball tracking, etc. would be feasible and beneficial for advanced testing.
- Supplementing the virtual arm with appropriate dynamics; the intent would be to mimic a physical device as closely as possible.

Since the research component of this work has also been a pilot effort, many suggestions for future investigations can be based on these findings:

- Most importantly, the relationship between classification accuracy and usability of multifunction MES classifiers must be further investigated. Results from this work are not sufficient on their own to discredit classification accuracy as an indicator of performance. Subsequent studies should incorporate additional functional tasks and multiple measures of usability.
- Any additional factors affecting the accuracy and usability relationship should be sought out by means of further testing, observation, and data analysis.

- System training and learning effects must be investigated using larger, more complete sets of data.
- To uncover best and worst overall classifier configurations included in CEVEN, in depth testing would have to involve variations of: number of principal components, auto-regression order, GMM and ANN parameters, etc. This would prove to be a time consuming and specific task.
- To accommodate variations in classifier performance between subjects, and between days, a possible solution would be to fuse the results of all classifiers (or a selected subset of the consistently best). This would require parallel execution of each controller, and a fusion algorithm at the output to select the "best" classifier, such as that proposed by Chan *et al* [42].

Finally, clinical applications of the software should be tested for both proof of product and clinical relevance. Repeating this research with limb deficient individuals, who would greatly benefit from a multifunction artificial limb, may better expose the accuracy and usability relationship and provide valuable direction to CEVEN enhancement.

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Appendix A: Supplementary CEVEN GUIs

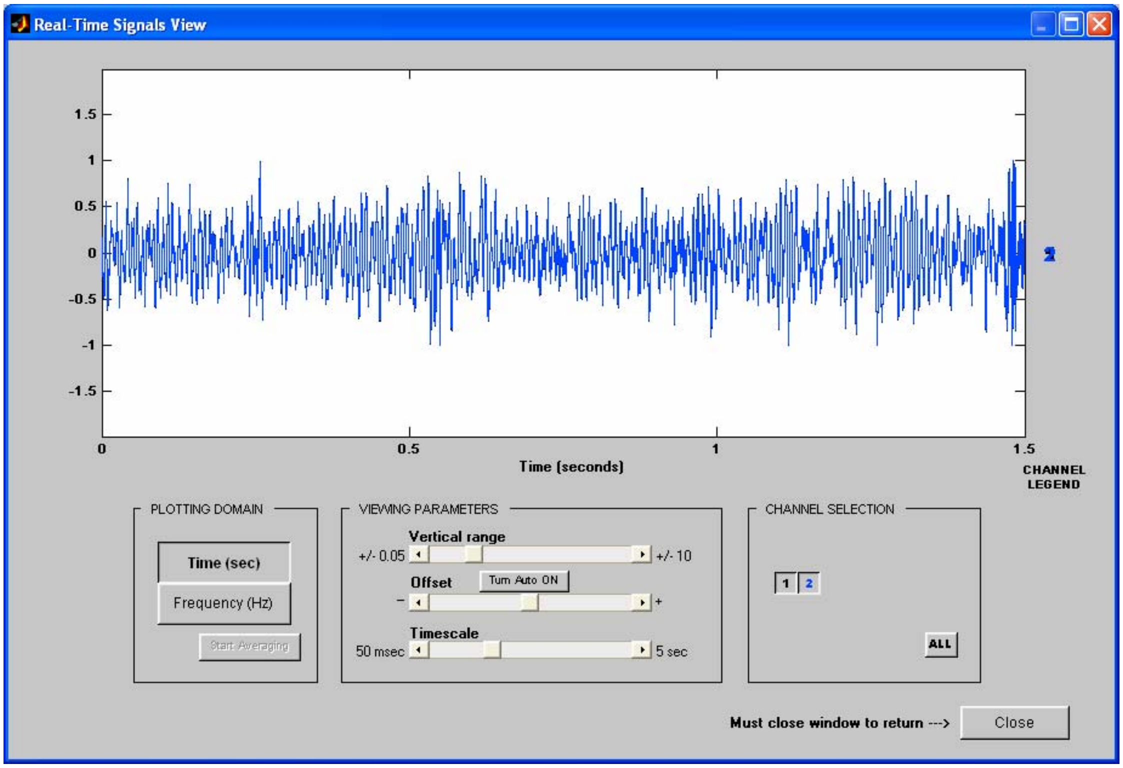

Figure A.1 – Real-time display of input signals (time domain representation)

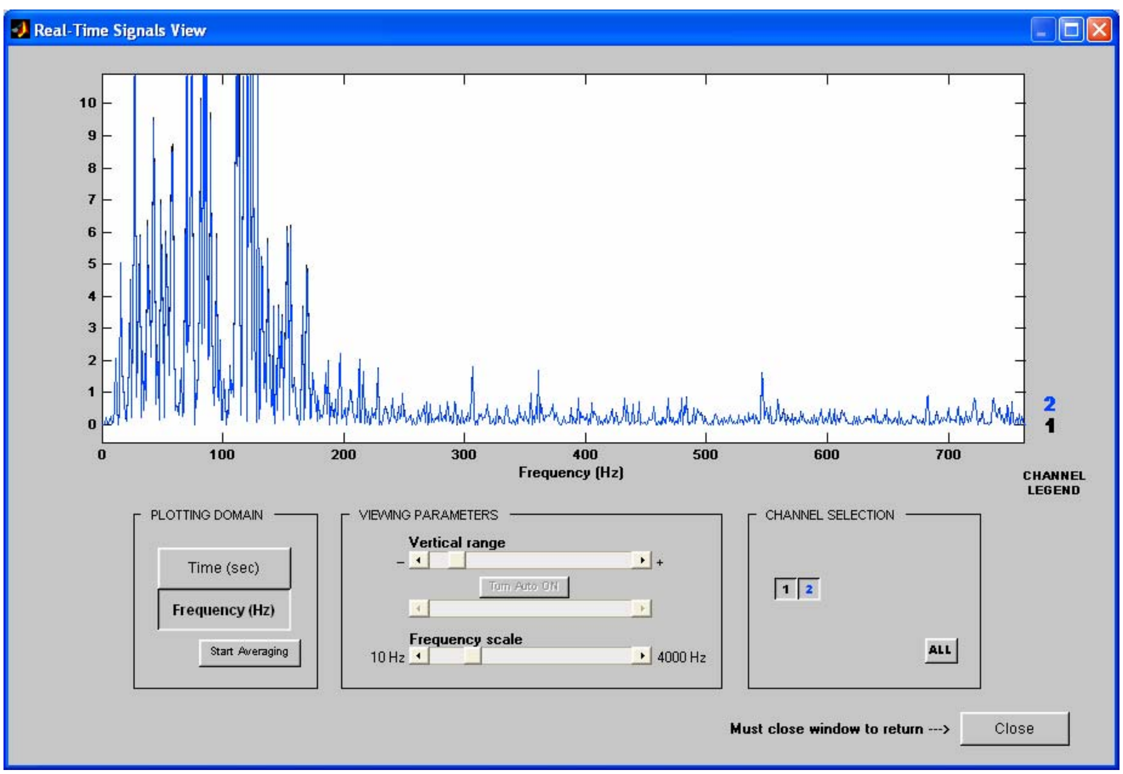

Figure A.2 – Real-time display of input signals (spectral representation)

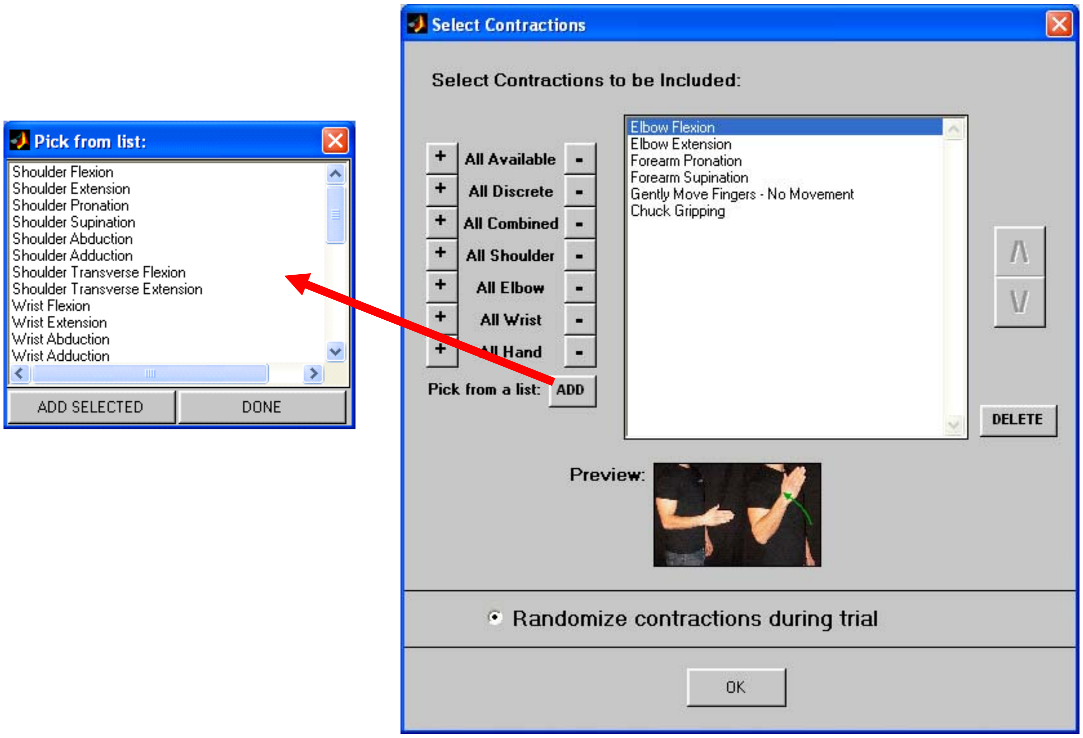

Figure A.3 – Contraction selection GUI shown with list of selectable items

Figure A.4 – Examples of error messages possible at the start of data processing

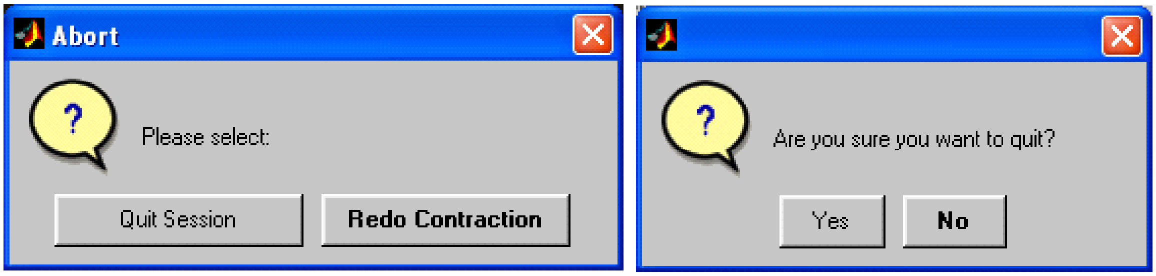

Figure A.5 – Abort verification GUIs; for canceling data acquisition or repeating most recent contraction

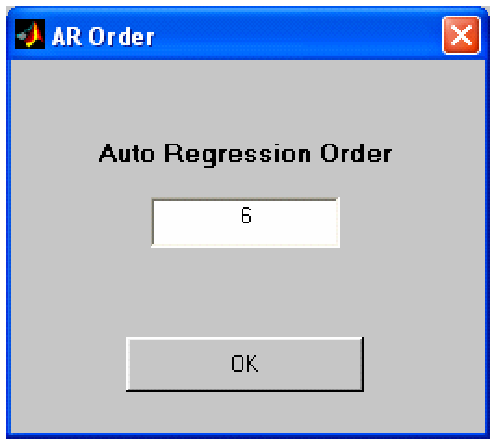

Figure A.6 – GUI window for setting auto regression order

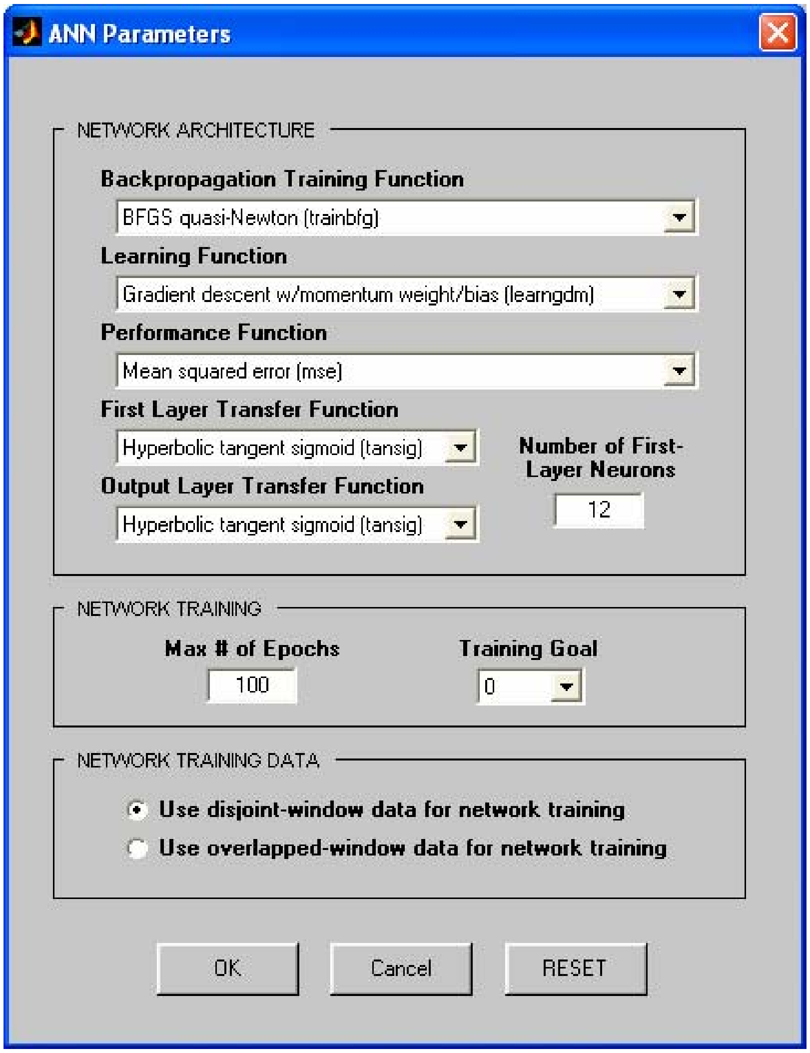

Figure A.7 – ANN parameters GUI

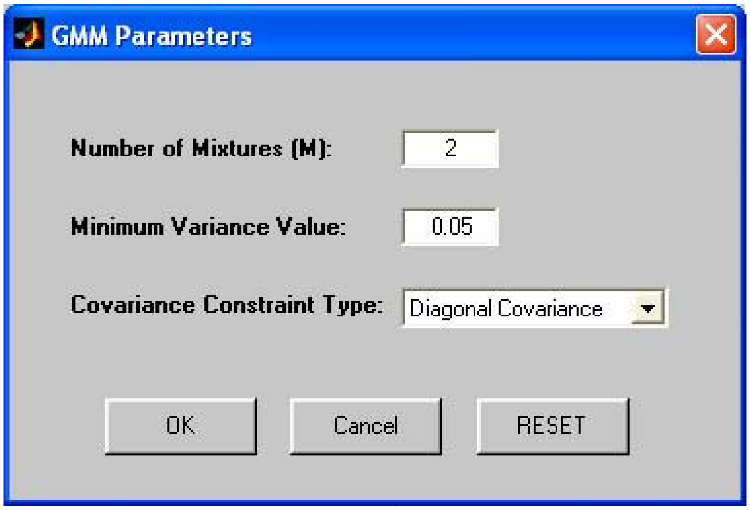

Figure A.8 – GMM parameters GUI

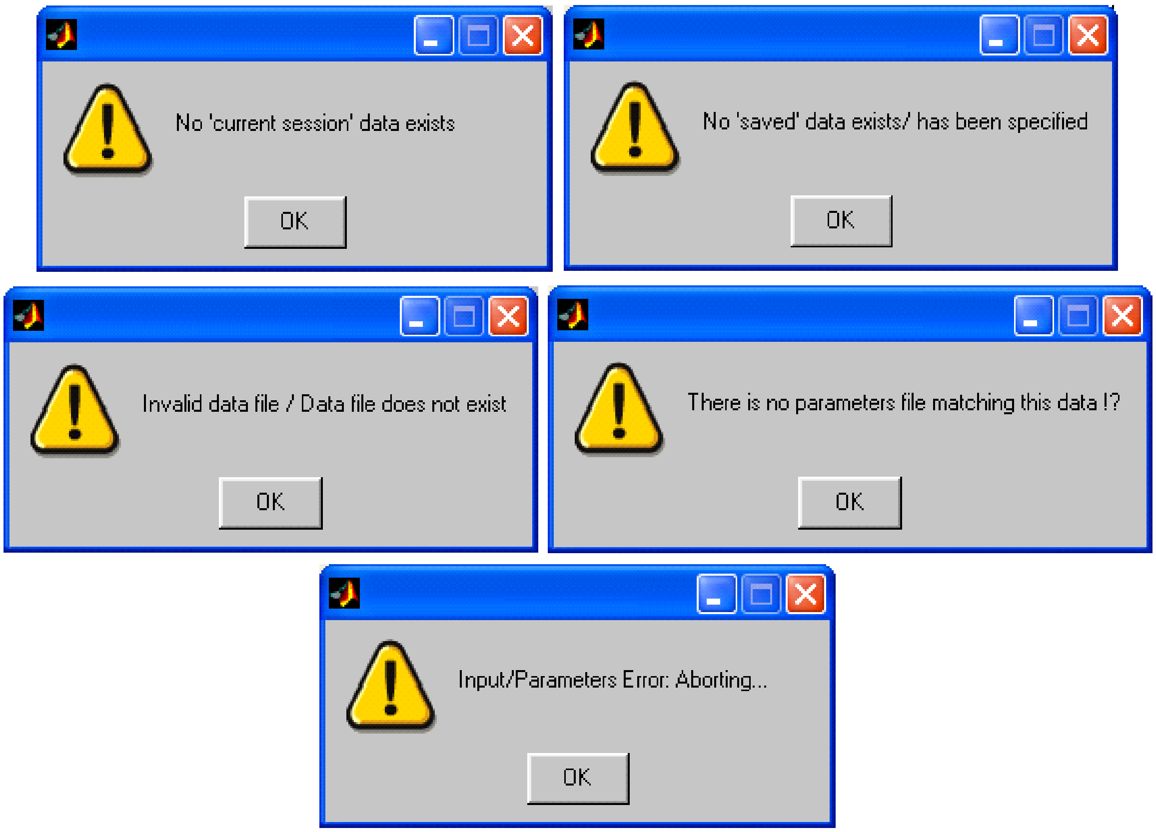

Figure A.9 – Suite of error messages possible at the start of data processing

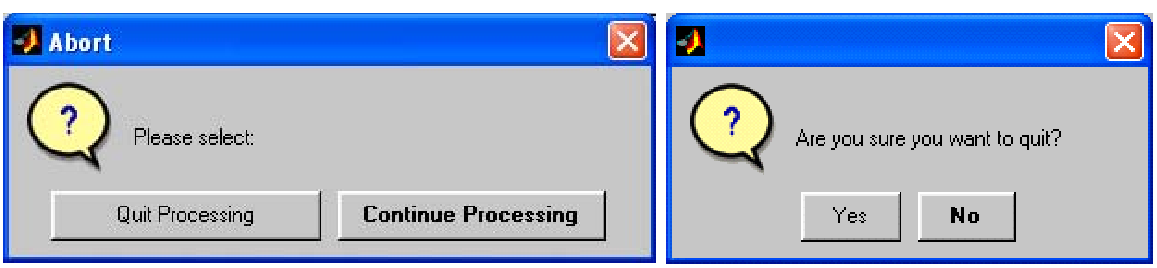

Figure A.10 – Abort verification GUIs; for canceling controls processing

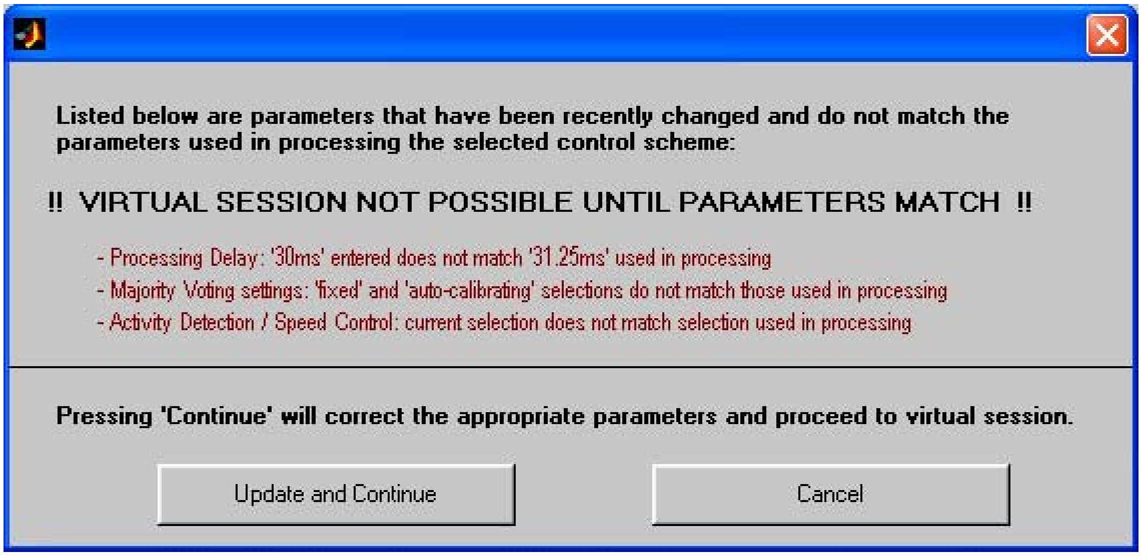

Figure A.11 – Warning at initialization of virtual session describing control parameters mismatch

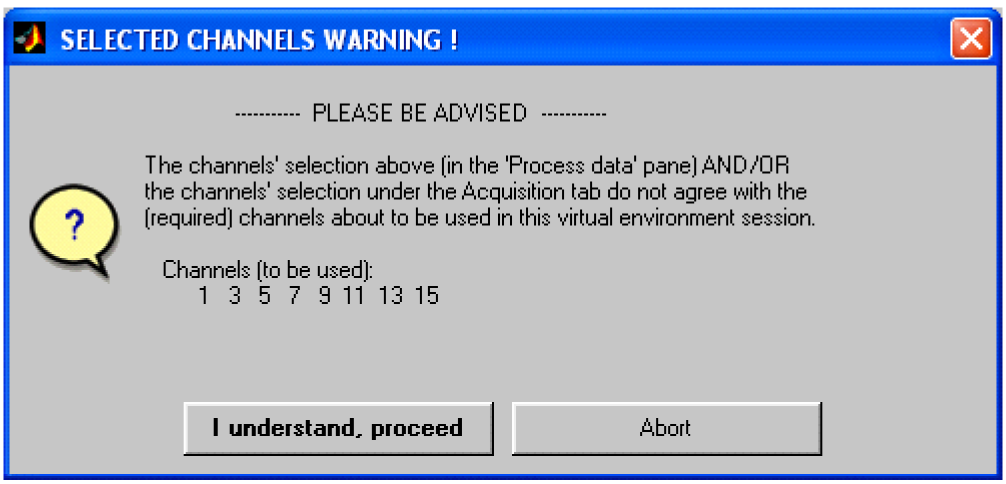

Figure A.12 – Warning at initialization of virtual session to informing of selected channels mismatch

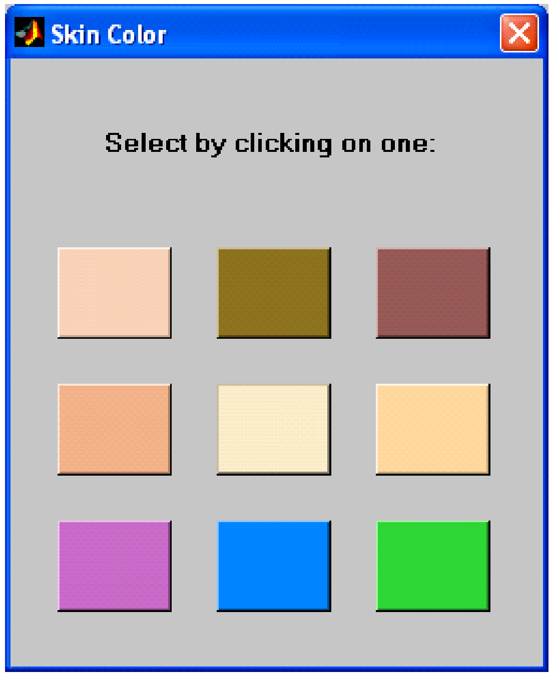

Figure A.13 – GUI window for selecting color of virtual arm

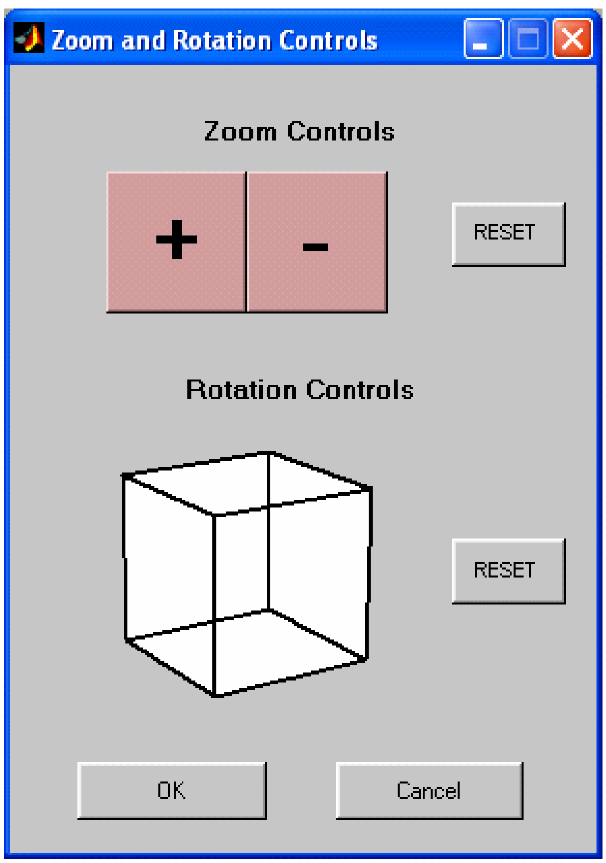

Figure A.14 – GUI window to interactively adjust viewing distance and orientation

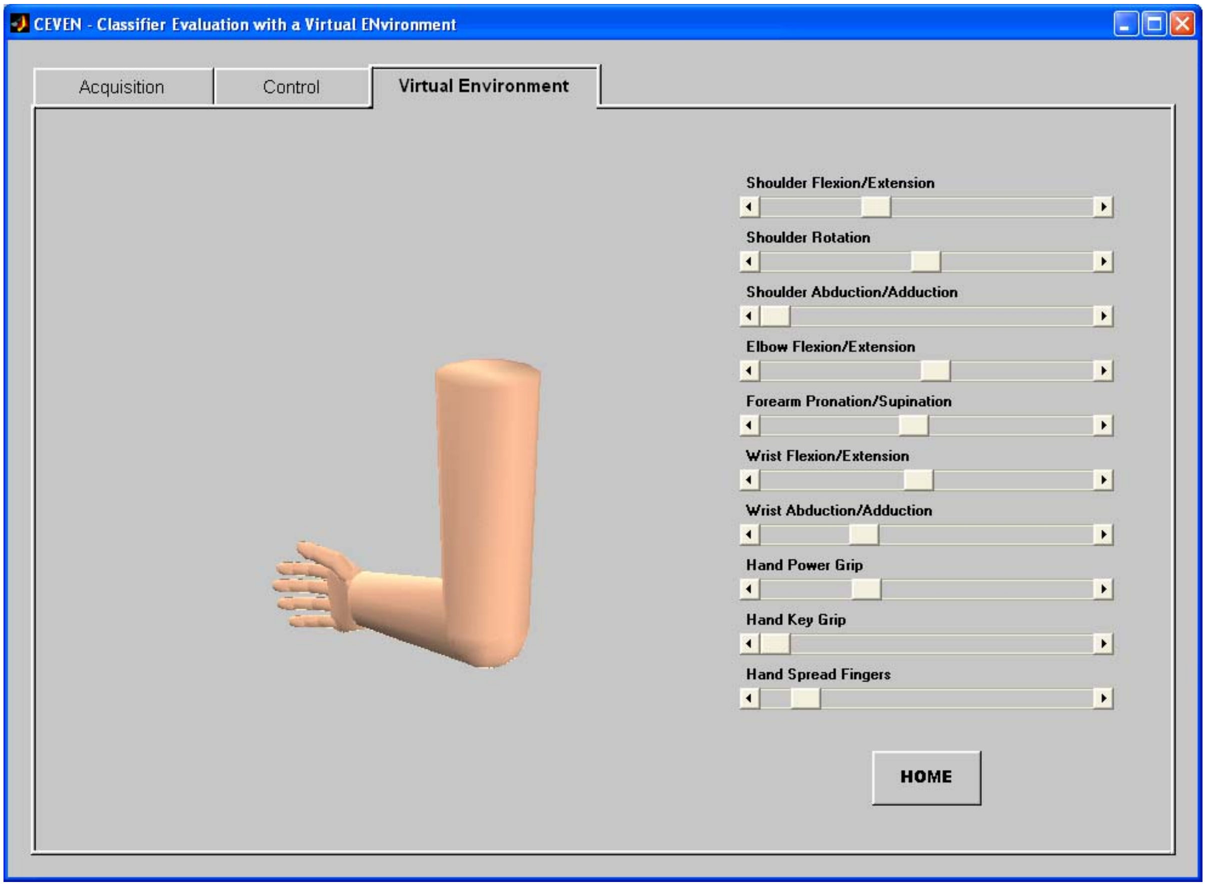

Figure A.15 – Virtual environment shown with manual controls present

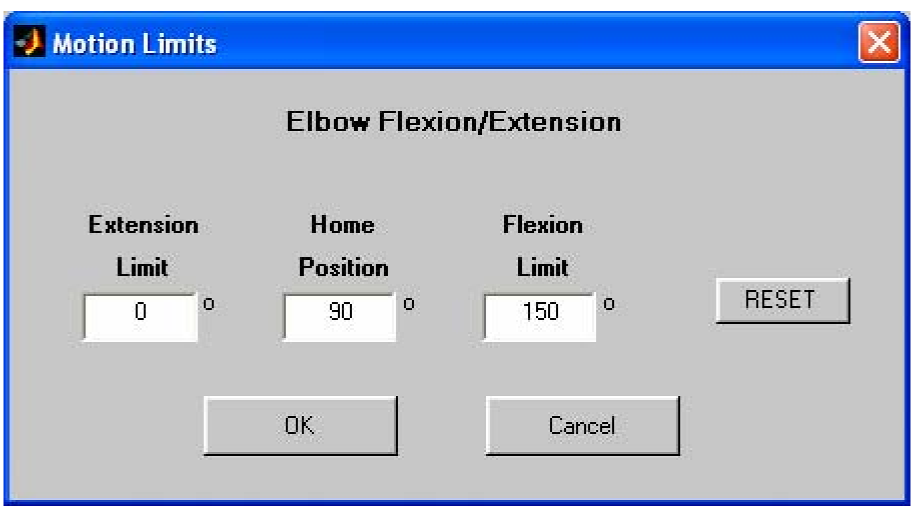

Figure A.16 – GUI window for setting motion limits

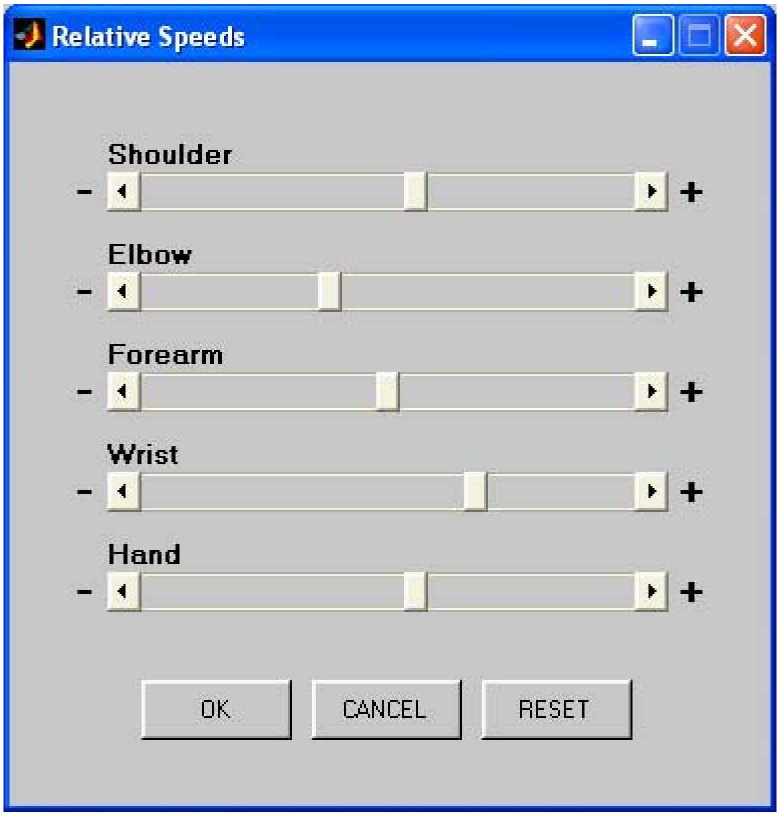

Figure A.17 – GUI window for adjustment of relative velocities of joints/motions

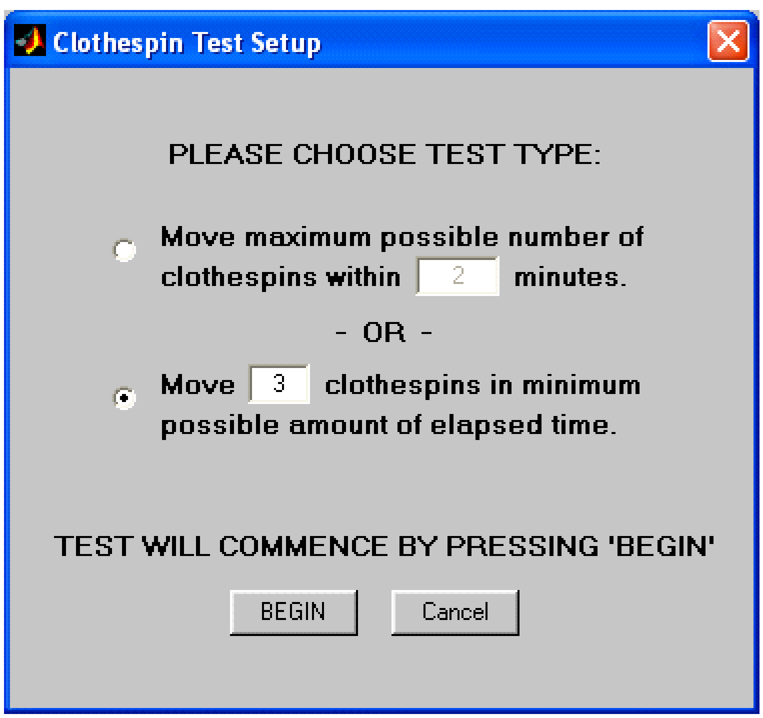

Figure A.18 – Clothes pin task setup window

Appendix B: Informed Consent Form

UNIVERSITY OF NEW BRUNSWICK – INSTITUTE OF BIOMEDICAL ENGINEERING

INFORMED CONSENT

REAL-TIME MYOELECTRIC CONTROL IN A VIRTUAL ENVIROMENT TO RELATE USABILITY AND CLASSIFICATION ACCURACY

Location:	Institute of Biomedical Engineering - University of New Brunswick 25 Dineen Drive PO Box 4400 Fredericton, NB, E3B 5A3	
Investigators:	Blair Lock, Institute of Biomedical Engineering Tel. 458-7032 (o), 454-4801 (h) blair.lock@unb.ca	(Principal)
	Dr. K. Englehart, Institute of Biomedical Engineering Tel. 458-7020 kengleha@unb.ca Dr. B. Hudgins, Institute of Biomedical Engineering Tel. 443-4966 hudgins@unb.ca	(Supervisors)

Invitation
You are invited to participate in the research project titled “Real-Time Myoelectric Control in a Virtual Environment to Relate Usability and Classification Accuracy”.

Purpose
The proposed work seeks to expose the relationship between classification accuracy (how well myoelectric signals are classified by the controller) and usability (how well the device driven by the controller can be used). Control research has previously presented results with little measure of usability. Additionally, this study will investigate any learning and repeatability effects.

Procedure
This experiment will be conducted in five sessions on consecutive days. Each daily session, lasting approximately one hour, will consist of two stages: acquisition and testing. During each session, 8 channels of myoelectric signal (MES) data will be recorded, 4 from surface electrodes around the upper arm and 4 from surface electrodes around the forearm. Each acquisition stage will consist of two trials, each prompting the subject to hold muscle contractions for 5 seconds. There will be 6 different contractions used, performed twice randomly for each trial, and the subject will be instructed on their specifics before acquisition is started. After the data are acquired in each stage, the computer will quickly process 36 control schemes and present the classification accuracies. Three schemes will be chosen (the ‘best’, ’worst’, and ‘moderate’) and set to control the movements of the virtual limb on the screen. Once for each classifier (3 times) the subject will participate in a virtual clothespin test. Here, a horizontal and a vertical bar appear in the virtual space and a clothespin appears clamped onto the horizontal bar. The test has the subject drive the virtual limb to appropriate position, grasp the clothespin (which will then change color), and move to put it onto the vertical bar. Scores will be displayed at the end of each test; number of clothespins successfully moved in a set time, or, time needed to move a set number of clothespins. A total of 3 clothespin tests are performed each testing day.

Withdrawal
Participation in this study is strictly voluntary. Participants are free to withdraw from the experiment at any time and without any consequences.

Feedback
At the end of this project, a summary of the results and copies of any publications will be provided to you if desired. If you have any concerns about this research, you are encouraged to speak with the researcher or supervisors identified at the beginning of this document.

Participants may also contact Dr. P. Kyberd, who is not directly involved with this study but is knowledgeable in the field, to express any additional concerns.
Tel: 458-7025
pkyberd@unb.ca

Risks
With the application of surface electrodes, there is a minor risk of skin irritation similar to that of obtaining an ECG (cardiac) record. There are no invasive procedures as part of these tests and there is no associated discomfort.

Potential Benefits
There are no direct benefits to participants in this study.

Consent
I hereby agree to participate in this study and consent to the use of this research data in scientific reports, presentations, and publications with the understanding that my identity will remain confidential. I have read and understand the above explanation of the research procedure and all my questions have been answered to my satisfaction. I understand that I am free to withdraw from this research at any time and without any consequence.

Participant: ________________ Signature: _______________________ Date: _____________

Investigator: _______________ Signature: _______________________ Date: _____________

This project has been approved by the University of New Brunswick Research Ethics Board (REB File# 2005-053)

Appendix C: Experimental Data

SUBJECT	CONTROLLER TYPE	SESSION 1 Classification Error (%)	SESSION 2 Classification Error (%)	SESSION 3 Classification Error (%)	SESSION 4 Classification Error (%)	SESSION 5 Classification Error (%)
1	Best	0.00	0.00	0.00	0.00	0.00
	Moderate	0.83	7.29	3.04	2.50	5.42
	Worst	2.50	15.42	6.55	7.50	13.33
2	Best	0.00	0.00	0.00	0.00	0.00
	Moderate	2.29	6.28	5.32	2.29	0.85
	Worst	5.83	13.75		5.75	1.70
3	Best	4.90	0.00	4.17	14.91	0.00
	Moderate	16.67	0.21	11.50	21.51	1.25
	Worst		0.59	19.81	29.02	5.00
4	Best	1.28	17.08	4.63	0.00	0.00
	Moderate	12.25		7.45	6.25	0.83
	Worst	24.17		18.42	12.41	9.58
5	Best	0.00	0.00	0.00	0.00	0.00
	Moderate	6.23	7.87	10.89	2.20	1.67
	Worst	11.64	13.60	21.49	5.01	3.33
6	Best	4.39	3.08	13.16	2.79	0.77
	Moderate	12.38	12.93	21.16	4.59	5.21
	Worst	25.25	17.99		9.17	9.17
7	Best	0.00	0.48	0.00	0.27	0.00
	Moderate	4.26	7.29	7.08	1.67	3.33
	Worst	10.54	15.00	17.50	3.33	12.08
8	Best	9.58	0.53	2.50	11.55	0.37
	Moderate	14.58	5.00		16.67	7.77
	Worst		9.17		18.33	15.42
9	Best	0.00	3.14			
	Moderate	5.42	6.25			
	Worst		9.58			
10	Best	0.00	16.25	4.15	0.00	1.76
	Moderate	3.75	19.65	13.79	9.64	11.93
	Worst	7.61	27.50	29.50	20.83	23.33
11	Best	17.92	5.54	0.83	0.32	6.50
	Moderate	21.09	11.40	11.13	7.08	11.55
	Worst	25.51	16.25	20.71	15.00	15.71
12	Best	1.21	0.00	3.69	5.33	8.20
	Moderate	15.79	0.00	10.73	17.04	15.76
	Worst	25.14	1.52	31.14	25.77	25.08

Table C.1 – Classification error of control configurations used for clothes pin testing

SUBJECT	CONTROLLER TYPE	SESSION 1 Average Pin Time (sec)	SESSION 2 Average Pin Time (sec)	SESSION 3 Average Pin Time (sec)	SESSION 4 Average Pin Time (sec)	SESSION 5 Average Pin Time (sec)
1	Best	31.1	31.8	47.2	64.7	27.7
	Moderate	27.4	49.5	25.7	66.4	74.2
	Worst	43.2	137.6	28.1	26.4	25.5
2	Best	35.6	84.2	43.8	17.4	18.1
	Moderate	66.7	24.7	21.8	18.2	52.6
	Worst	35.5	55.6		63.8	19.7
3	Best	30.8	26.8	37.8	39.0	25.0
	Moderate	59.7	30.4	24.0	23.3	30.3
	Worst		54.1	179.3	76.0	35.5
4	Best	110.9	109.2	112.1	39.5	35.1
	Moderate	117.2		36.6	27.3	30.3
	Worst	220.9		42.4	32.8	75.9
5	Best	25.6	32.5	26.1	70.1	15.3
	Moderate	57.9	19.7	63.0	37.7	17.3
	Worst	53.0	32.1	75.6	35.2	51.5
6	Best	38.6	31.1	108.0	95.4	88.8
	Moderate	39.7	33.0	84.3	13.4	14.1
	Worst	124.3	86.2		90.2	35.1
7	Best	25.6	52.3	44.3	35.8	13.3
	Moderate	89.8	30.0	25.7	14.5	20.9
	Worst	50.9	36.6	47.5	21.7	34.2
8	Best	59.3	36.8	36.1	40.1	35.9
	Moderate	133.7	26.9		60.8	158.4
	Worst		95.3		38.0	38.5
9	Best	271.0	32.1			
	Moderate	40.1	41.4			
	Worst		57.4			
10	Best	18.7	26.2	42.0	39.9	55.9
	Moderate	133.9	54.7	40.2	32.4	28.9
	Worst	80.1	49.3	42.1	56.4	43.6
11	Best	37.0	46.2	36.0	54.5	74.7
	Moderate	44.3	96.7	32.8	55.3	40.2
	Worst	58.3	36.8	32.8	39.2	32.1
12	Best	40.5	20.2	72.4	45.4	24.0
	Moderate	24.2	55.7	66.5	35.0	24.0
	Worst	58.3	75.4	37.4	112.3	44.7

Table C.2 – Results from clothes pin testing: average of three pin placement times

SUBJECT	CONTROLLER TYPE	SESSION 1 Testing Order	SESSION 2 Testing Order	SESSION 3 Testing Order	SESSION 4 Testing Order	SESSION 5 Testing Order
1	Best	3	2	1	1	2
	Moderate	2	1	3	2	3
	Worst	1	3	2	3	1
2	Best	3	3	2	2	2
	Moderate	2	2	3	1	3
	Worst	1	1		3	1
3	Best	1	3	3	1	3
	Moderate	3	2	1	3	2
	Worst		1	2	2	1
4	Best	3	1	1	2	2
	Moderate	1		3	1	1
	Worst	2		2	3	3
5	Best	2	1	1	2	3
	Moderate	1	2	3	3	1
	Worst	3	3	2	1	2
6	Best	2	2	2	3	3
	Moderate	3	1	1	2	2
	Worst	1	3		1	1
7	Best	3	3	1	1	3
	Moderate	1	2	3	3	1
	Worst	2	1	2	2	2
8	Best	1	2	1	2	3
	Moderate	3	1		1	1
	Worst		3		3	2
9	Best	3	2			
	Moderate	2	1			
	Worst		1			
10	Best	2	3	3	2	1
	Moderate	1	1	2	1	3
	Worst	3	2	1	3	2
11	Best	3	1	2	2	3
	Moderate	1	2	3	1	2
	Worst	2	3	1	3	1
12	Best	1	3	2	3	1
	Moderate	3	2	1	1	2
	Worst	2	1	3	2	3

Table C.3 – Session testing order employed for clothes pin testing

SUBJECT	CONTROLLER TYPE	SESSION 1 Control Configuration	SESSION 2 Control Configuration	SESSION 3 Control Configuration	SESSION 4 Control Configuration	SESSION 5 Control Configuration
1	Best	LDA,TDAR,MV	LDA,TD,MV	GMM,TDAR,MV	GMM,TD,MV,OV	LDA,TD,MV,OV
	Moderate	ANN,AR	GMM,TDAR,OV	LDA,TD,OV	ANN,AR,MV	GMM,TDAR
	Worst	GMM,AR,OV	GMM,AR,MV	ANN,TD,MV,OV	LDA,AR	GMM,AR,MV
2	Best	GMM,TDAR,MV	ANN,TDAR,MV,OV	ANN,TDAR,MV,OV	LDA,TDAR,MV	LDA,TDAR,MV,OV
	Moderate	LDA,TD,MV,OV	ANN,TD,OV	LDA,AR,OV	GMM,TDAR,OV	ANN,AR,OV
	Worst	GMM,AR	GMM,AR,MV		GMM,TD,MV,OV	GMM,AR,OV
3	Best	ANN,AR,MV,OV	GMM,TD,MV,OV	GMM,TD,MV	GMM,TDAR,MV,OV	LDA,TDAR
	Moderate	ANN,TDAR,OV	LDA,AR,OV	ANN,TDAR,OV	GMM,TD,OV	GMM,AR,MV
	Worst		ANN,AR,OV	ANN,TD,MV,OV	LDA,AR,MV,OV	ANN,AR,MV
4	Best	LDA,TD,MV,OV	LDA,TD,MV	LDA,TDAR,MV,OV	LDA,TDAR,MV,OV	ANN,TDAR,MV,OV
	Moderate	ANN,TD		LDA,TD,OV	ANN,TD,MV	LDA,AR
	Worst	GMM,AR		ANN,TD,OV	GMM,AR,OV	GMM,TDAR,MV
5	Best	LDA,TD	LDA,TDAR,MV	LDA,TDAR	LDA,AR,MV,OV	LDA,TDAR,OV
	Moderate	GMM,TDAR,OV	ANN,TD,OV	GMM,AR,MV,OV	GMM,AR,OV	LDA,AR,OV
	Worst	ANN,AR,OV	GMM,AR	ANN,AR	ANN,TDAR,OV	GMM,AR
6	Best	LDA,TD,MV	LDA,TDAR,MV,OV	LDA,TDAR,OV	ANN,TD,MV,OV	ANN,TDAR,MV,OV
	Moderate	ANN,TD,OV	ANN,TDAR,OV	ANN,AR,MV,OV	ANN,TDAR,OV	LDA,TD,OV
	Worst	GMM,AR,OV	LDA,AR,MV,OV		GMM,AR,MV	GMM,AR,MV
7	Best	LDA,TD,MV	ANN,TDAR,MV,OV	ANN,TD,MV	GMM,TD,MV,OV	LDA,TD,OV
	Moderate	GMM,AR,MV,OV	GMM,TD,MV	LDA,AR,OV	LDA,TDAR	GMM,TDAR,MV
	Worst	ANN,AR,OV	GMM,AR	GMM,TDAR	GMM,AR,MV	GMM,AR
8	Best	LDA,TD,MV	ANN,TDAR,MV,OV	ANN,TDAR	LDA,AR,MV,OV	ANN,TDAR,MV,OV
	Moderate	ANN,AR,MV	LDA,AR,MV		ANN,TDAR,MV	GMM,TDAR,OV
	Worst		GMM,AR,MV		LDA,TDAR,MV	ANN,TD
9	Best	ANN,TD,MV,OV	ANN,TDAR,OV			
	Moderate	LDA,AR,MV	LDA,TD,MV			
	Worst		ANN,AR,MV			
10	Best	LDA,TD,MV	LDA,TDAR,MV	GMM,AR,MV,OV	GMM,TD,MV,OV	LDA,TD,MV,OV
	Moderate	ANN,AR	ANN,TDAR,MV,OV	ANN,TD,OV	GMM,TDAR,OV	GMM,AR,MV,OV
	Worst	GMM,AR,OV	GMM,TDAR	ANN,AR,OV	ANN,AR	ANN,AR
11	Best	LDA,TD,MV	ANN,AR,MV,OV	LDA,TDAR,MV	LDA,AR,MV,OV	ANN,TD,MV,OV
	Moderate	GMM,TDAR,OV	GMM,TDAR,MV,OV	GMM,TD,OV	ANN,TDAR	GMM,AR,OV
	Worst	ANN,AR,OV	ANN,AR	ANN,TD,OV	GMM,TD,MV	LDA,TDAR,MV,OV
12	Best	ANN,AR,MV,OV	ANN,TDAR	ANN,TDAR,MV,OV	GMM,TD	LDA,AR,MV,OV
	Moderate	LDA,AR	LDA,TD	GMM,AR,MV,OV	LDA,TD,OV	GMM,AR,OV
	Worst	GMM,TDAR,OV	GMM,AR	LDA,TD	ANN,TDAR,MV,OV	LDA,TD,MV,OV

Table C.4 – Control configurations used for clothes pin testing

Appendix D: Subject Classification Trends

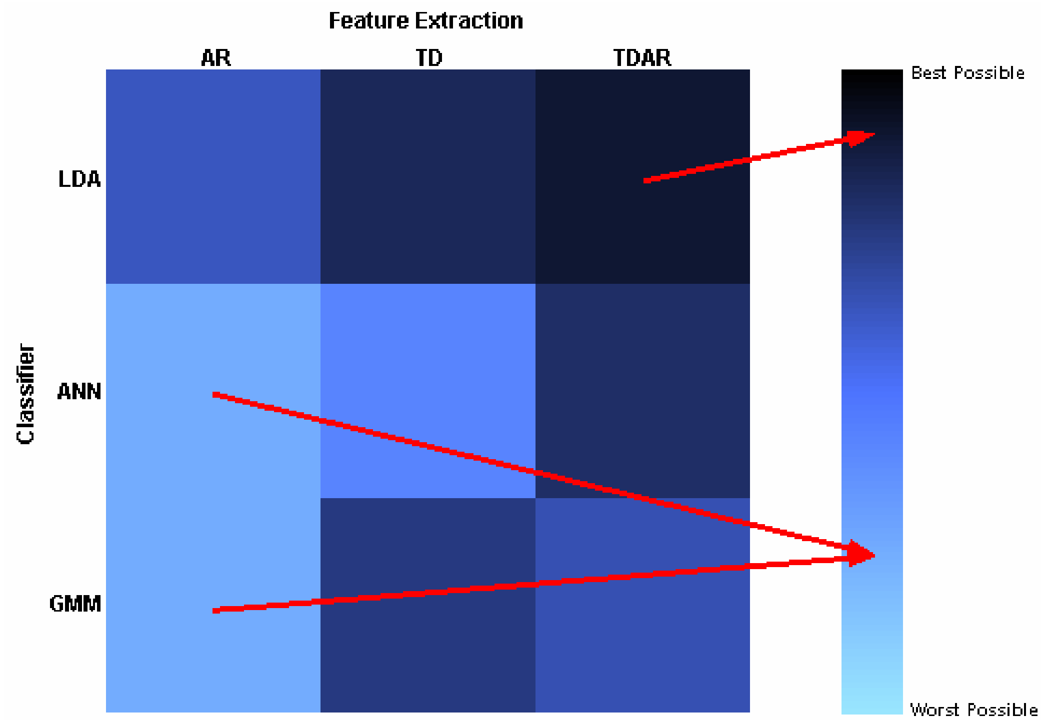

Figure D.1 – Graphical representation of controller performance for subject 1

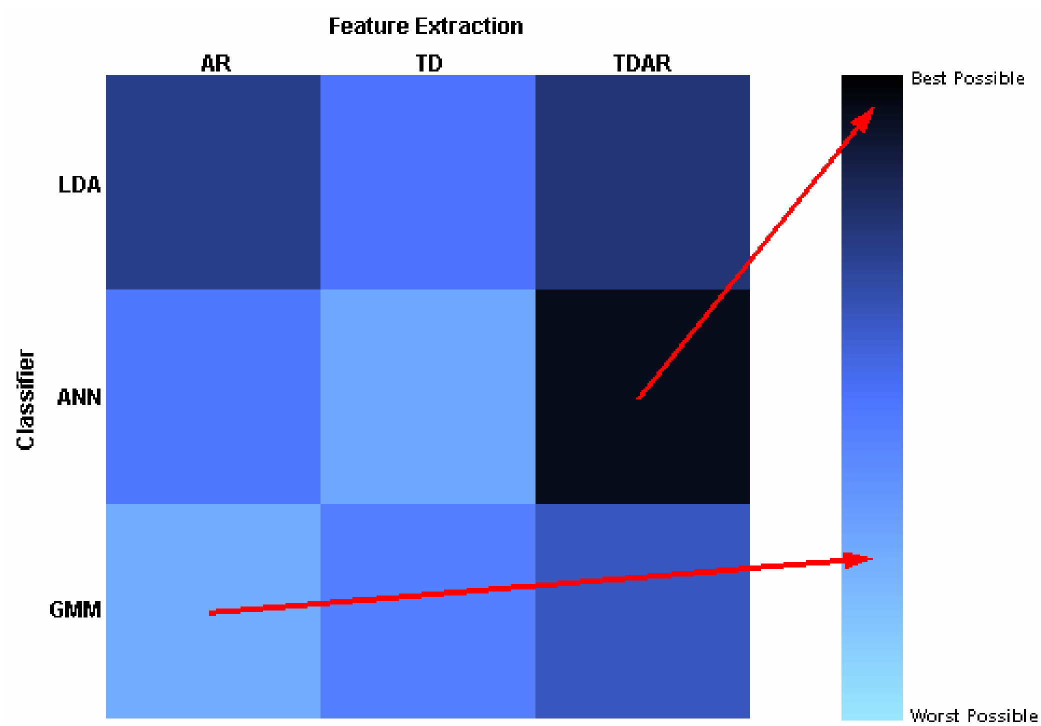

Figure D.2 – Graphical representation of controller performance for subject 2

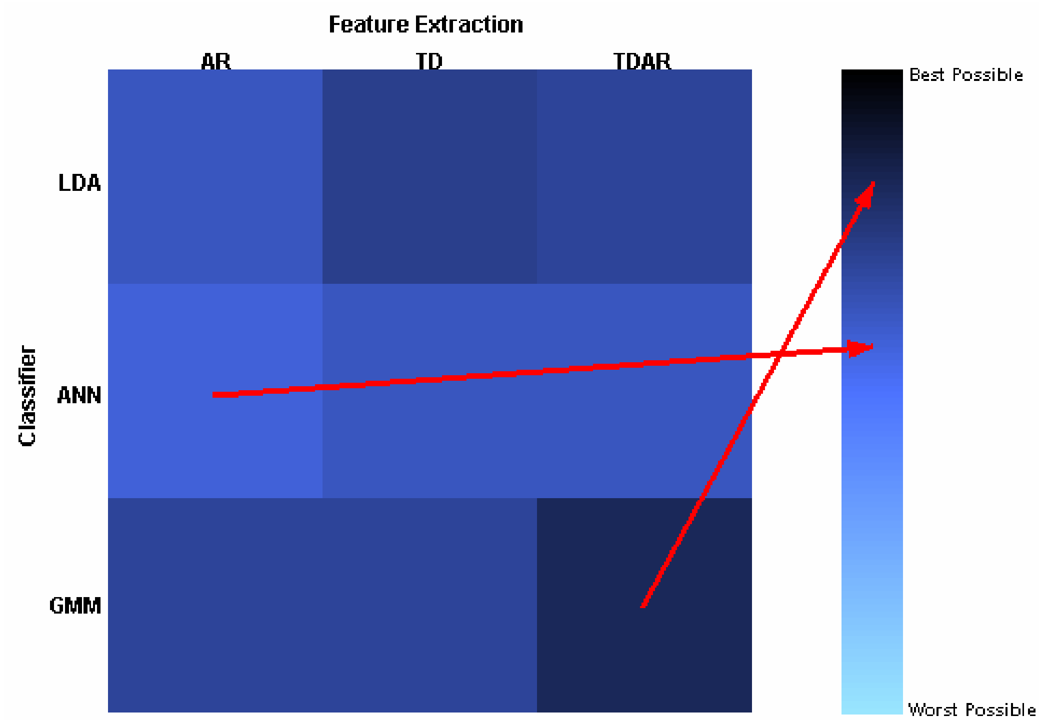

Figure D.3 – Graphical representation of controller performance for subject 3

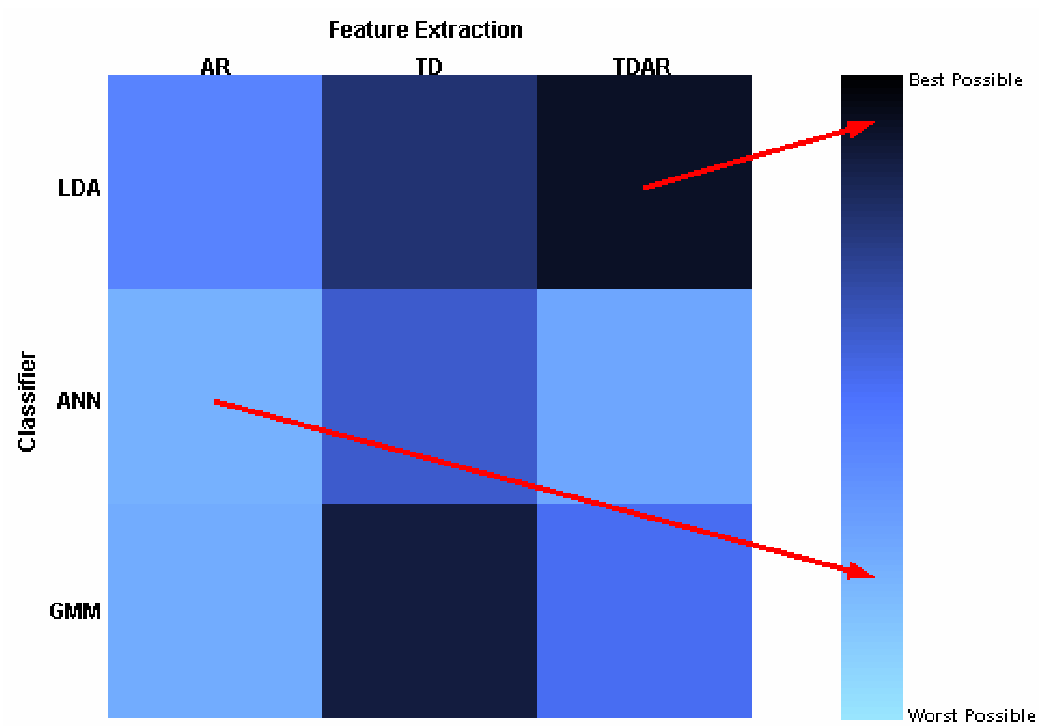

Figure D.4 – Graphical representation of controller performance for subject 5

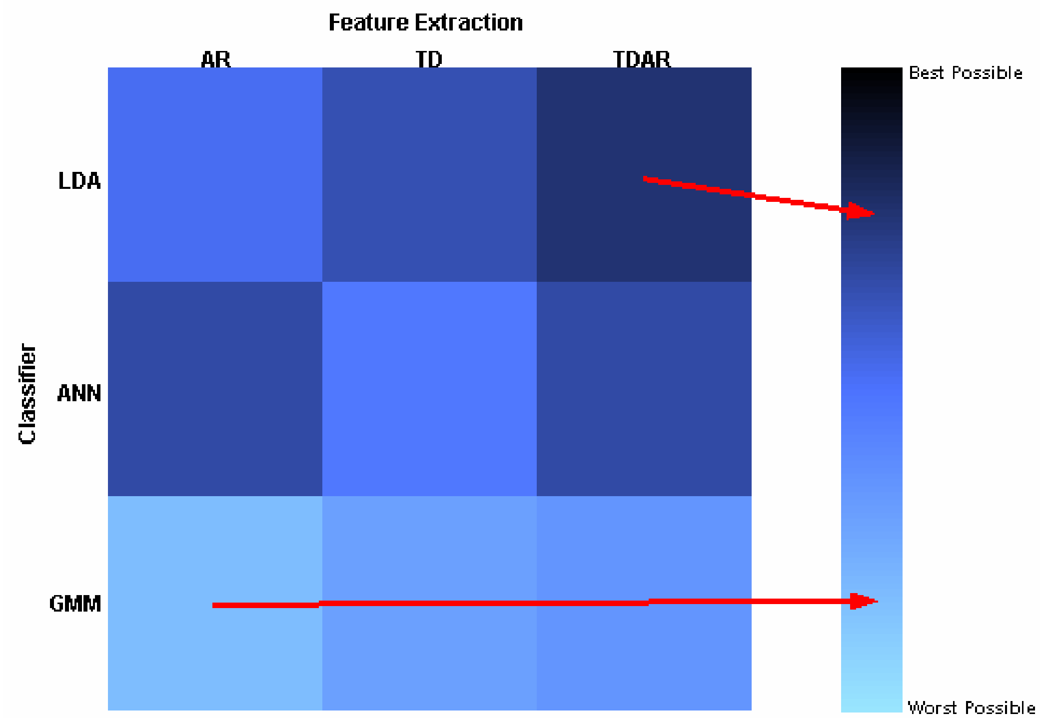

Figure D.5 – Graphical representation of controller performance for subject 6

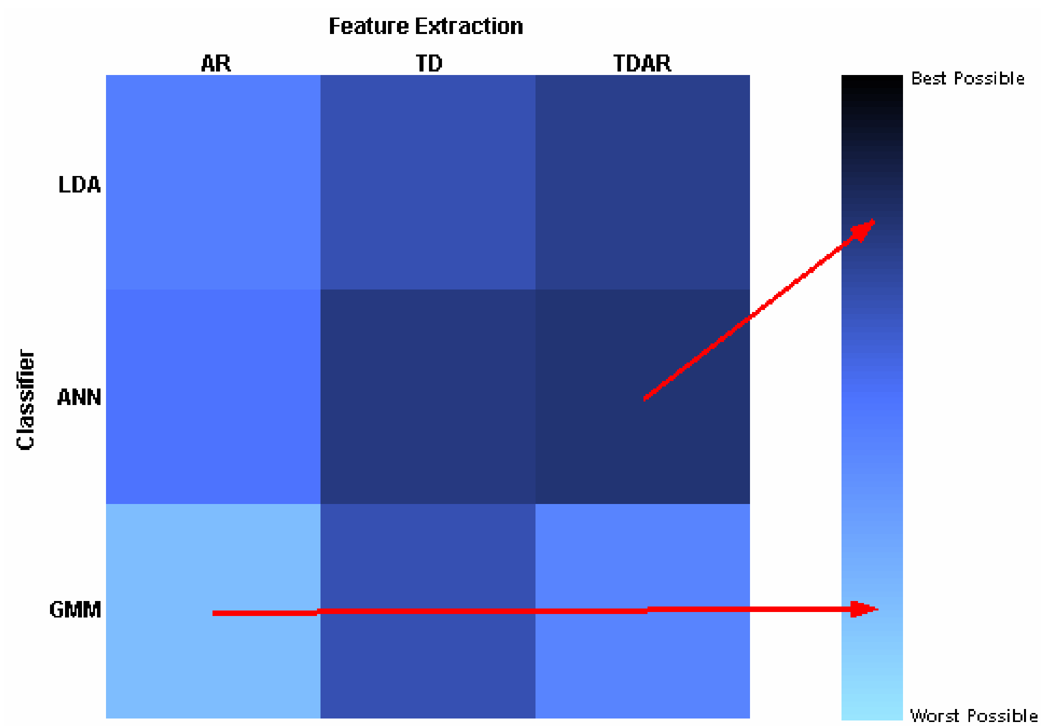

Figure D.6 – Graphical representation of controller performance for subject 7

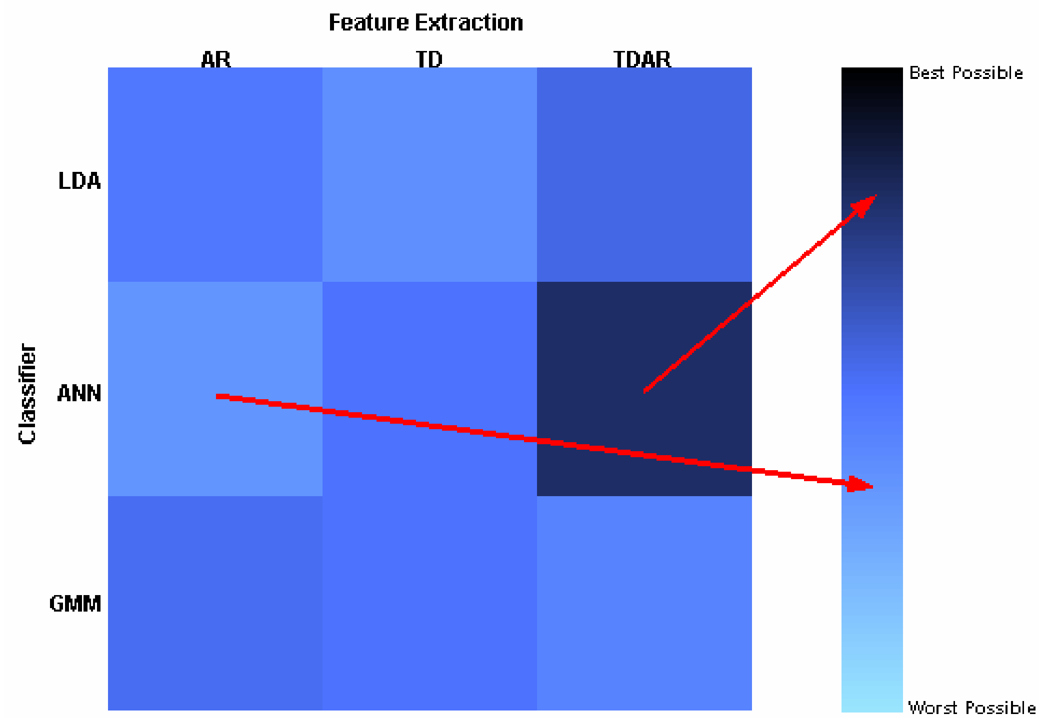

Figure D.7 – Graphical representation of controller performance for subject 8

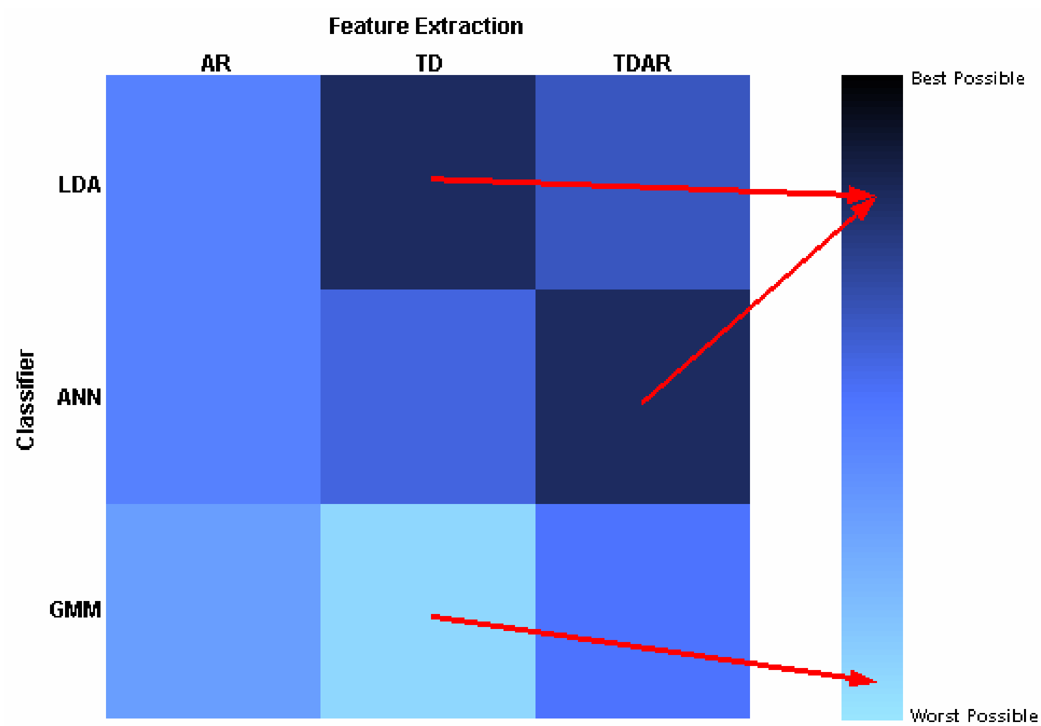

Figure D.8 – Graphical representation of controller performance for subject 9

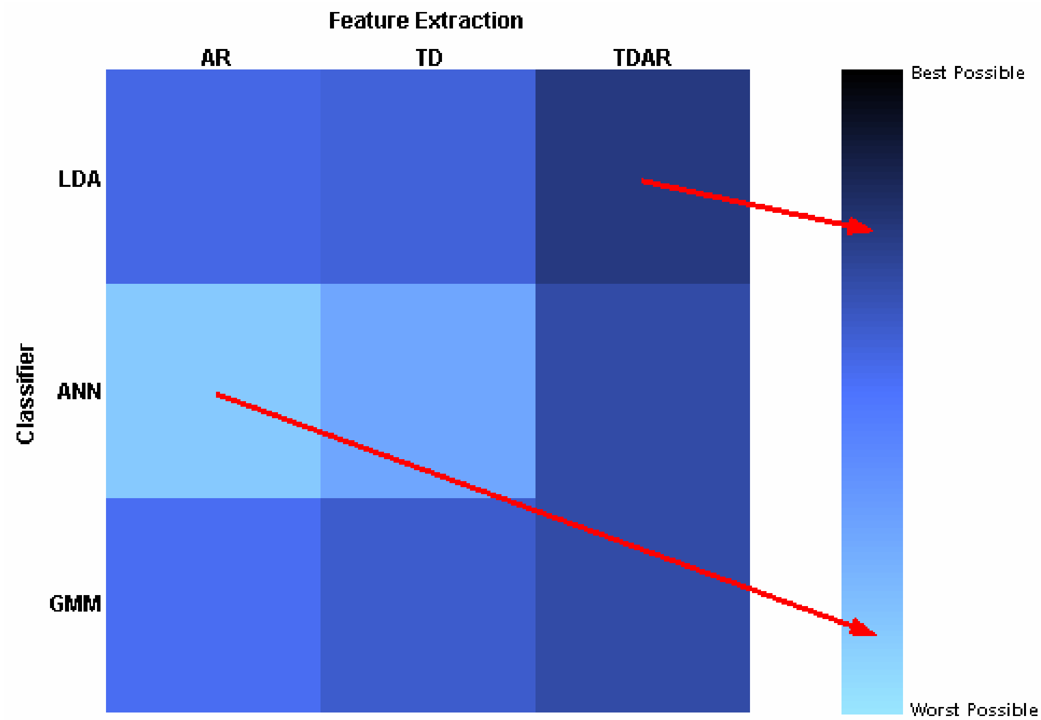

Figure D.9 – Graphical representation of controller performance for subject 10

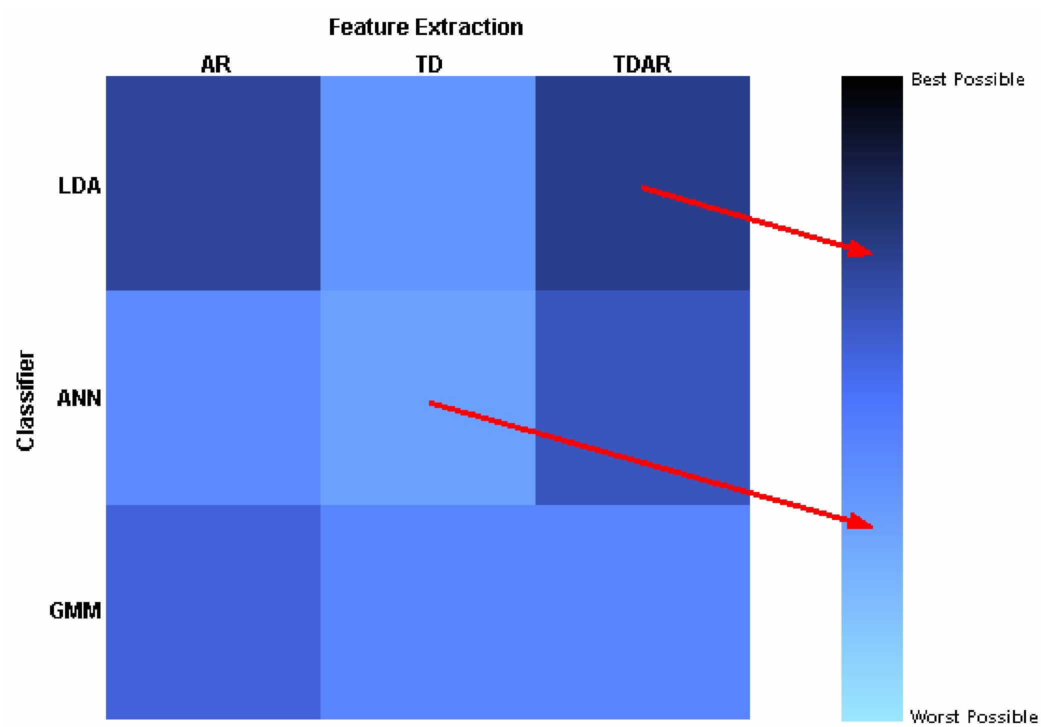

Figure D.10 – Graphical representation of controller performance for subject 11

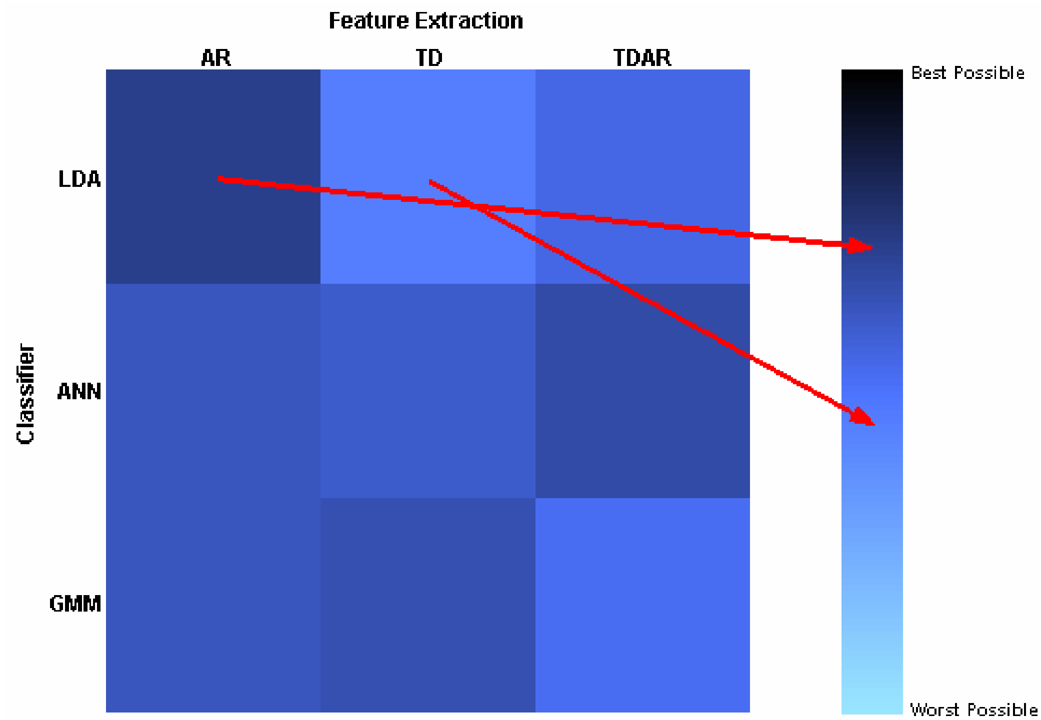

Figure D.11 – Graphical representation of controller performance for subject 12

Vita

Candidate's full name: Blair Andrew Lock

Universities attended: University of New Brunswick, 2003, B.Sc.E. (EE)

Publications:

B. A. Lock, and D. J. MacDougald, ”Active Feedback Suppression,” B.Sc.E. Thesis, University of New Brunswick, April, 2003

B. A. Lock, K. Englehart, and B. Hudgins, ”Real-time myoelectric control in a virtual environment to relate usability vs. accuracy,” in Proceedings of the Myoelectric Controls Sysposium (MEC'05), Fredericton, NB, August, 2005.

Conference Presentations:

“Wide Angle Reflection and Bottom Loss and Time-Dependant Transmission Loss,” Defence Research and Development Canada – Atlantic Technical Conference, Dartmouth, Canada, August, 2002.

“Virtual Fitting Clinic for Prosthetics,” 10th Annual Nursing Research Day, Fredericton, Canada, May, 2005.

“Real-time Myoelectric Control in a Virtual Environment to Relate Usability and Accuracy,” Dalhousie University School of Biomedical Engineering Research Day, Halifax, Canada, May, 2005.

“Real-time Myoelectric Control in a Virtual Environment to Relate Usability and Accuracy,” Myoelectric Controls Symposium (MEC'05), Fredericton, Canada, August, 2005.