Shoulder Complex Motion Based Input Strategies for Prosthetic Limb Control

by

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Dedication

To my family, Chantal, Simon, and Alexa.

Abstract

The work presented in this thesis outlines several new input strategies aimed at providing intuitive and robust signals for the control of a prosthetic limb in cases of high-level amputation. It was demonstrated that various input sources could be exploited to produce effective adapting strategies that provide a means of automatically calibrating and optimizing the control system schemes.

The thesis describes myoelectric signal-based (MES) classification strategies that utilizes contractions originating from the shoulder complex (shoulder elevation, protraction, depression, and retraction) and humeral rotation. Experimental data collected from one amputee and six able bodied individuals revealed that high offline classification accuracy could be achieved with these MES-based strategies.

This work also resulted in the development of a novel shoulder position-based input strategy, termed vector projection. The new control scheme focused on the position of the shoulder rather than interpreting the MES originating from the shoulder complex musculature. The algorithm also adapted to several user and input sensor variables based on a short data collection protocol performed prior to the use of the prosthetic limb.

An investigation of the functional usability of the devised strategies revealed that the vector projection method outperformed the MES-based schemes. The reaction tests showed that all strategies added little increase in the mental burden load demanded from the user.

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Chapter 1 – Introduction

1.1 Research Objectives and Motivation

Significant research has occurred in the past several decades to achieve a suitable solution for the control of upper extremity prosthetic limbs [1]. Although the development of advanced and sophisticated strategies has progressed steadily for more distal amputation cases, very limited improvements have taken place for more proximal amputation levels. This may be, in part, caused by the simple fact that the majority of cases are below elbow amputees while higher level amputations, such as shoulder disarticulation, are less common. “The functionality requirement of the prosthesis increases with the level of amputation, which leads to a paradox” for any control strategy of the prosthetic limb as the number of available input sources inversely decreases [1]. As a result, the need for a robust and intuitive strategy is most critical for high level amputation cases in order to regain some acceptable level of functionality with the artificial limb.

Under ideal conditions, a synergistic relationship could be developed between the amputee’s neural activity and associated missing degrees of freedom (DOF). Unfortunately, this correlation cannot be utilized since no such interface is readily available for practical purposes. There are, however, non-invasive alternatives that have existed for several decades. These alternatives include the monitoring of either the movement of a residual limb (or of another part of the body) or the electrical activity accompanying voluntary contraction of one or multiple muscles.

It can be said that most natural arm trajectories require coordinated and simultaneous movements of several independent joints [2]. Previous research has shown that these complex movements only require a limited amount of user input while the majority of the control and coordination of the DOF are determined by the lower levels of the musculoskeletal system and central nervous system. As a result, very little conscious effort is required from an able bodied individual when performing upper extremity motions. Many researchers have devoted their research to modeling and describing the means by which an individual processes and executes a desired motion via the nervous, muscular and skeletal systems.

Although research has been ongoing in these outlined areas, very few advancements have been devoted to providing new and more effective solutions for high level upper extremity amputees. The purpose of the work described in the following chapters does not attempt to develop a control system to replace the complex control loops found within the body. The work, rather, focuses on exploiting the residual input sources available to produce the most effective non-invasive input strategy that will provide the user with the maximum amount of controllability while imposing the least amount of mental burden. More specifically, this work's motivation was on investigating more efficient use of the available control sources in high-level amputation cases. The relationship between various input sources, user intent, and the control strategies employed must be better understood in order for the prosthetic limb's control system to effectively exploit the available information.

1.2 The Control of Artificial Limbs in High Level Amputation Cases

The gross movement of a prosthetic arm, in above elbow up to forequarter cases, has relied heavily on the use of residual motions in order to allow the user to control several DOF. Body powered motion has indeed been successfully used as an input source to control all the available prosthesis movements since the *19th* century [3,4]. Externally powered prostheses were first attempted in Germany shortly after the First World War [5]. In this case, electromagnets were used in an effort to drive a prosthetic hand. The first myoelectric signal-based (MES) prosthesis was developed later in 1948 [6] while pneumatic prostheses were developed in the early 1950s. Various input sources and control schemes for these devices have been investigated and are continually evolving to this day.

The most common form of input source and control scheme, for high-level upper extremity amputation, is the use of residual movements to drive cable-operated joints. This body-powered method has been in use for several decades and is the most clinically available option at this point in time. Externally powered systems do exist where sensors, such as force sensing resistors, joysticks, and rocker switches, are activated by the user's residual motion or single or dual site MES originating from the residual limb and shoulder complex [7-9] have been used to control some functions of the prosthetic limb.

To this day, the commercially available control algorithms used in conjunction with these input sources have been simplistic in nature. Often, the limited number of residual DOF and/or independent MES electrode sites available for present schemes restricts the controllability of the user's prosthesis. It may also require considerable training in order to achieve an acceptable level of control over these residual DOF and MES input sources. In some cases, users may require extensive iterative socket customization. Amputees frequently favor the cable-operated system for gross movements of their prosthesis since it offers simpler operation of the prosthesis' DOF, even more so when the potential implementation of a single or dual site MES control paradigm is limited. Other promising, and possibly more sophisticated control schemes have yet to present themselves as viable and effective alternatives that yield better results for proximal DOF control. This may help explain why there are currently no commercially available electric-powered mechanisms for positioning any shoulder DOF of a prosthetic limb [10].

The use of MES has, however, proven itself to be a useful input source to control the more dexterous distal DOF of the prosthesis for below elbow amputation cases. Over the past several decades the University of New Brunswick's (UNB) Institute of Biomedical Engineering (IBME), along with several other research groups, have been developing various MES strategies that provide control of prosthetic limb functions. The UNB one-site three-state control system was first clinically used in 1965 [6] and the algorithm was then published a year later [11]. The system simplified the control problem since only one controllable MES site was needed. Furthermore, the user could enter one of three different states based on the rectified measured MES amplitude. The 'open hand', 'close hand', and 'no movement/rest' states were typically employed with this strategy (Figure 1.1). This approach was widely accepted as a clinically implementable solution since hardware could be easily designed with the available technology, it was simple for the user to learn and only demanded a low mental burden to operate. Attempts at expanding this approach to a one-site five-state myoelectric control system have been investigated [12] but were found not to be suitable for clinical implementation due to high error rates.

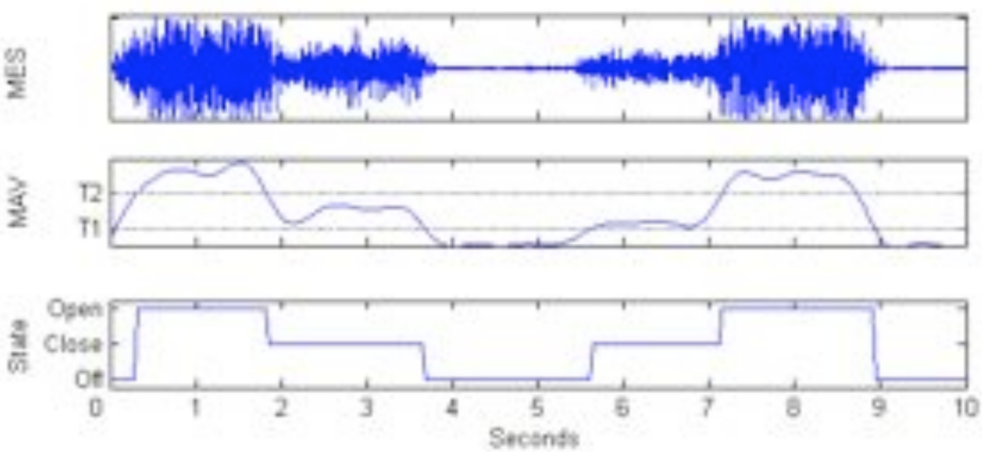

Figure 1.1 – One-site three-state controller system diagram. The mean absolute value (MAV) of the MES is thresholded to provide state control.

During that time, several research groups started focusing on pattern recognition techniques that could potentially achieve multifunction control [32] while reducing the number of control sites required to attain such a goal. These techniques shifted the focus from solely using amplitude measures (MAV or root mean square – RMS) to extracting several new features from the MES. In fact, these new strategies evolved from the assumption that, for a specific state of muscle activation, the MES feature set would be repeatable and would differ from feature sets obtained during different state muscle activations [13].

The feature sets used in the early pattern recognition-based myoelectric control systems consisted of amplitude coded features and were classified with a statistical-based classifier. Studies showed that the classification rate for a four-class problem was roughly 75%. These early systems suffered from several limitations (e.g. bulky instrumentation and limited control system processing power) and required a large number of MES sites [14].

Further advancements in myoelectric pattern recognition, during the following decade, introduced the use of autoregressive (AR) coefficients as part of the feature set [15]. These increased classification accuracy by approximately 10% for a 3 class problem, when compared to previous classifiers, and used as few as 4 or 2 MES sites [13, 16]. These classifiers were, however, clinically not implementable due to the computational complexity of the AR algorithms, and insufficient computing capacity of the day.

During the early 1990s, research conducted at the IBME demonstrated that the MES showed a deterministic structure at the onset of muscle contractions [17]. The feature set used was composed of time domain (TD) characteristics of the MES; these TD features were provided to a two-layer artificial neural network (ANN) classifier. The scheme provided classification accuracy above 90% for a four state system using only one MES electrode site. The results from this work demonstrated a new control system with an enhanced capacity for discriminating multiple classes of motion. Furthermore, the algorithm was implemented on a microprocessor-based system to control a bench mounted electric elbow and hand prosthesis. It was also determined that defining an appropriate training procedure for the pattern recognition control system was not trivial, and required further investigation. This work also generated much work to follow in identifying other possibly useful features extracted from the MES signal.

In recent years, considerable efforts in this field have yielded systems that use new feature sets based not only on TD statistics [14, 17] but also AR coefficients [15] and time-frequency information [18]. The system classification schemes investigated vary from ANN [17, 19, 20], genetic algorithms [21], fuzzy logic [22], Gaussian mixture models (GMM) [15], to linear discriminant analysis-based (LDA) algorithms [18]. All have been shown to achieve high classification accuracy. Figure 1.2 illustrates the common components found in many of these multifunction control approaches.

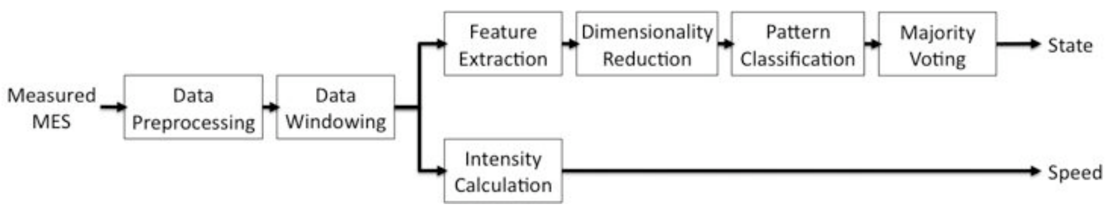

Figure 1.2 – A block diagram showing basic stages of current multifunction pattern recognition system.

Throughout the development of all these schemes, the primary objectives have remained the same: to provide functional operability of the device while simultaneously reducing the conscious effort demanded from the user to operate the limb. Many other factors, such as ease of use, number of drivable actuators, and sensor fittings also has to be considered when developing new control strategies, as they will inherently be linked to the overall performance and user acceptance of the prosthesis.

1.3 Thesis Outline

Chapter 1 has discussed the research advancements that have been aimed at producing viable control solutions for the prosthetic limbs of upper extremity amputees. The limited improvements to the control system options for high level upper extremity amputation case, over the past few decades, was highlighted as the main motivation for the work presented in this thesis.

Chapter 2 presents the background information relating to the obstacles and limitations faced when developing a new control system for a prosthetic limb. A thorough review of previous control philosophies and designed control systems are also included to present some of the key considerations required when attempting to enhance the robustness and intuitiveness of a new control strategy while also struggling to reduce the mental burden imposed on the user.

Chapter 3 describes the shoulder electrophysiology associated with various movements of the shoulder complex. This chapter also introduces several new multifunction myoelectric control strategies based on the muscle synergies affecting shoulder movement. Data are presented to outline the ability of each strategy to accurately classify the user's intent for both able-bodied and amputee subjects.

Chapter 4 presents a novel shoulder position-based algorithm that automatically tailors the input strategy parameters in order to eliminate many of the issues associated with the design, fabrication, and fitting of a prosthetic limb. A detailed explanation of the algorithm is presented along with qualitative results from several case studies using different input sensors.

Chapter 5 discusses the current lack of functional tests to investigate new input strategies for the prosthesis' control system. The chapter describes the design and fabrication of a new usability test aimed at providing qualitative and quantitative results of various shoulder-based input strategies. A devised experimental protocol is also detailed and was used for the data collection sessions.

Chapter 6 details the analysis of the results obtained from the qualitative and quantitative usability test performed using the designed experimental functional testing apparatus described in Chapter 5. The data presented demonstrates the effectiveness of the proposed input strategies in addressing the objectives outlined in Chapter 1. Chapter 7 summarizes the original contributions of this thesis while also proposing future research considerations for improving the devised input strategies.

Chapter 2 – Literature Review

2.1 Introduction

A person's ability to achieve simultaneous and independent control of multiple upper extremity DOF is influenced by several factors. Clearly the control scheme employed along with the actuator strategy will heavily influence the overall performance of the system. It must be kept in mind that choosing to control each individual DOF independently will exhibit a very different behavior from trying to control multiple DOF as a synergetic group. The former would require a different form of input data from the latter as well as a much larger quantity of input sources. These distinctions can be directly attributed to the implemented control scheme and must be evaluated in the context of available input sites and the number of DOF to be controlled.

The type of data acquired from the input sources also has to be considered as a significant attributing feature within the system. Several different data acquisition methods have been investigated in previous research studies and some have been implemented within the clinical setting. Each approach has advantages along with some drawbacks or limitations. As previously mentioned, the most commonly used are MES and some form of residual limb motion. Both of these input sources along with several control philosophies are presented in greater detail in the remainder of this chapter.

2.2 User-Based Prosthetic Input Sources

2.2.1. Myoelectric Signals

The MES occurs during muscular contractions as a result of the depolarization and repolarization of the cell membrane of the muscle fibers. The electric currents associated with the ionic displacements produce measurable action potentials in the body [23]. The propagation of these potentials can be non-invasively measured on the skin surface using surface electrodes.

Myoelectric signals allow for the partial interpretation of the intent of the user. This limited view is because the MES does not indicate what the desired motion is but rather whether this muscle is an active participant within that intended motion. This can be thought of as being a noisy input to a multi-dimensional dynamic system. It has been shown that it is possible to train the amputee user to use alternate muscles to control prosthetic DOF. In many instances, such an approach will unfortunately increase the mental burden (level of concentration) required of the amputee to control these ‘reconfigured’ DOF [24].

There are a limited number of ways that one could feasibly control multiple DOF simultaneously in an independent manner solely using MES or in combination with other non-invasive sensor technology as input data sources. The most obvious would be to have the ability to directly map the muscle activity to the missing DOF. In order to achieve such controllability, the muscles targeted by this approach would need to be

those that are naturally involved in the movement of the DOF in question. Such an approach would allow the user of a prosthetic limb to intuitively contract the DOF related muscles in order to control it. The intuitiveness would come from the fact that "coordinated movements are not represented in the higher levels of the central nervous
hukommelsesspor
systems as joint-muscle schemata, but rather exist as topologically oriented engrams that can be translated into different joint-muscle sets" [25]. Additional research also seems to be in agreement with such a statement [26, 27]. As a result, the user would not need to think of controlling each DOF individually, which would be a tremendous mental burden in itself, but rather naturally perform a desired motion. The muscles necessary to control all the intended DOF would be recruited to perform the desired motion. Unfortunately, it is impossible to use such an approach on all DOF as their associated muscles groups may also be missing. The possibility of targeted reinnervation may increase the total number of controllable DOF with the use of this method [28]. This innovative approach consists of surgically deinnervating some functioning muscle(s) and reinnervating it with nerves
avstumpe
that were truncated due to the amputation. The elicited contractions of the reinnervated muscle(s) now represent the user's intended activation of muscles groups that are missing as a result of the amputation.

The use of physiologically appropriate muscle activity to control a DOF may be termed *direct control.* Direct control theory is certainly not a recent breakthrough in prosthetic limb research. Many early control strategies were developed during the 50s, 60s and 70s and can often be found within papers from the Dubrovnik conferences. It has been stated that "communication between the patient and his assistive device should be established through preserved neuromuscular complexes rather than through isolated muscles in order to use efficiently higher levels of natural neuromuscular hierarchy" [29]. Such a scheme should be used whenever possible as it currently allows for the nearest direct interface between user intent and DOF activation (with the use of surface EMG). The shoulder joint may have the greatest potential reward for such an approach especially in the case of shoulder disarticulation (SD) amputees. The elbow DOF could also utilize this methodology for above elbow amputees provided there is a suitable amount of agonist/antagonist musculature remaining within the residual limb (or, again, in the case of successful targeted reinnervation). The remaining proximal segments are more involved in the gross movement of the upper extremity and are not actively involved in finely coordinated motor activities. As a result, the control of such fine motions may be incredibly difficult if based solely on the remaining muscle sites from the shoulder area.

As previously mentioned, muscle activity may also be used to predict the intent of the user by extracting feature sets from the muscle group. These sets can then be used to estimate the user's intent by means of pattern classifiers. Once again, this concept is by no means new; multiple pattern recognition algorithms have been used within various control schemes since the late 1960s [30]. Considerable advancements in this field [17, 31] have yielded systems that can be tailored to individual users and achieve high classification accuracy [14].

Previous research has also investigated the use of the MES to estimate the torque values used as input for a prosthetic control system. Indeed, an elegant control theory, which attempts to estimate the desired limb motion using a mathematical formulation of musculo-skeletal dynamics, was developed in the early 1970s [33]. The strategy, termed *postulate-based theory*, attempted to control the prosthetic joints by using the residual limb MES to describe the dynamic characteristics of the intact arm and prosthetic device. Unfortunately, the method by which the joint moments were estimated required that a new dynamic model be developed on a subject-by-subject basis and that inter-subject variability was such that generalization was not feasible while maintaining an accurate model [33]. As a result, the clinical evaluation of the system demonstrated that joint control was possible but required considerable effort and that other control methods concurrently investigated showed superior performance [34, 35].

Many of the obstacles faced by previous research groups come back to the issue of information transmission. How much user intent information can be extracted from the MES? Also, what is this information saying? Most current clinical myoelectric control systems utilize the MES to interpret some low level of user intent along with the intensity level of activity. This information is then used to actuate the DOF in question. In terms of control theory, this method is nothing more than an open loop control system. Kinematic and dynamic feedback[1] are rarely considered in the controllability of the prosthesis.

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[1] The term *feedback* here relates solely to the prosthetic control system and not to user sensory/proprioceptive feedback which is another issue altogether.

2.2.2. Body Movement

Total/brutto

Gross body movement as a control input has been around since the design of early prostheses [3]. Reasonable performance of these devices was achieved by directly linking the prosthesis joint motion to the back, shoulder and residual limb movements. Although, in many cases, this proved to be non-intuitive in nature, it was deemed successful since amputees regained a certain level of mobility from their residual limb.

In 1974, a new concept, termed extended physiological proprioception (EPP), was developed which states that the body's own natural physiological sensors can be used to relate the state of the prosthetic arm to the operator [36]. It can be thought of as the

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extension of one's proprioceptive feedback into an intimately linked inanimate object [37].

This concept was applied to a pneumatically-powered prosthesis where the positions of

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the two clavicles controlled four DOF [38-40]. Three of these specified the endpoint position of the device while the fourth characterized the orientation of the terminal device. It should be noted that the clavicle movements were restrained when the movement actuators were restricted thereby allowing proprioceptive information of the current state of the prosthesis to be transmitted to the user at all times. The results demonstrated that a high level of subconscious control could be attained given the continuous awareness of the current position of the prosthesis.

Another research group also applied the EPP concept by linearly controlling a prosthetic elbow using the humeral flexion angle of an above-elbow amputee [41] and went on to develop another controller for an electric elbow which was driven by biscapular abduction motion [42, 43]. They reported achieving excellent results during laboratory tests of these systems.

The feasibility of using shoulder elevation-depression and protraction-retraction to control elbow flexion and wrist rotation was also investigated [37]. The research initially consisted of analyzing normal subjects' physiological control of these two joint motions in one-dimensional and two-dimensional tracking experiments. The motions were then used as inputs in combination with an experimental prosthesis to implement the EPP control of the prosthesis elbow flexion and wrist rotation. They reported having more potential for providing effective control as compared to velocity-based control.

Research conducted at Southampton University also investigated the possibility of using body motions as inputs to control a prosthetic limb in three-dimensional space. An end point strategy was integrated within the control system using three input sources originating from the user's body movements [44]. This work continued by incorporating additional DOF and adding an additional MES input source [45]. The resulting eleven DOF hand/arm prosthesis was shown to be controllable with some difficulty as a result of the limitations of the processing technology available at the time of the research.

Other researchers also went on to develop a prosthetic controller based on the shoulder flexion angle during specific motion trajectories, which they termed *linkages* [46]. The shoulder flexion angle was measured using an electrogoniometer that would be attached to the chest and residual limb of the subject. The controller output was based on mapped motion angles stored in the controller's memory. These output angles would determine how the prosthetic elbow joint was controlled. Their research differed from previous work [37] since this new research attempted to incorporate the control of several different linkages as an open-loop system. It was felt that only having one fixed linkage between the controller's input and output signals was very constraining on the number of tasks that could be performed [46]. Therefore, an increase in performance would be achieved by allowing the control of several different input-output relationships. A selector switch was used within their experimental system to choose the desired task.

Including the shoulder abduction/adduction as an input to the controller [47] to previous research efforts [46] was also investigated. The control system determined which linkage was to be selected by using several different kinematic features of the shoulder joint as inputs to a nearest neighbor classification scheme. They reported having successful experimental results using a subject with an intact limb doing three different tasks.

It should be noted that the later mentioned controllers [46, 47] provided the user with the ability to choose from multiple different tasks (linkages). Although this provided a less constraining control system, it also resulted in a reduction in the level of proprioception that would be delivered to the user, since the direct one-to-one mapping of the input and output was partially lost.

The use of gross body movements yields different information content as it has the ability to show the current position, velocity, and acceleration of the limb, which differs from the information that MES data is able to provide. This type of information is more often used to determine the 'current' desired state of the missing DOF in terms of some predefined correlation between the input data and/or residual joint being used. The use of such input sources should be strongly considered during the development of new control strategies.

2.3 Control Strategies

The EPP principle had a profound impact on the way some researchers approached prosthesis and orthosis control issues. However, several years prior to the EPP paradigm, researchers recognized the need for the implementation of control systems that were more intuitive. These researchers developed the basis of many of the control strategies that have been attempted by various research groups in the past several decades as well as some concepts that have yet to be successfully implemented.

It has been stated that "All or part of the information provided by sensory elements must not go to the central or conscious control place for processing, but should be directly used for servomotor control. Such loops are called local feedback loops and their existence greatly reduces the information content of conscious signal sources without affecting the artificial hand performance. The best way to achieve improved prosthesis performance is to give the problem of control signal sources full consideration. In our opinion it is not wise to rely only on conscious signals in the prosthesis design." [48].

Two things can be drawn from this statement. The first observation is that reducing the conscious effort demanded from the user may increase intuitiveness and operability of the device. Second, not all control input parameters need to originate from the user. The degree to which research groups, through the years, have applied both these statements has varied [44, 45, 73]. Any new control strategies will need a careful consideration of these factors as they are inherently linked to the overall performance and acceptance of the prosthesis by the user. It should be noted however that the acceptance of a system by the user does not necessarily require it to be intuitive. Other factors, such as motivation and ease of use, also need to be considered.

It is also worth noting that not all researchers are in agreement that some level of feedback will be necessary in order to achieve a successful control system. Some researchers have stated "that many movements can be performed in the complete absence of sensory feedback [49-53] even in the presence of external mechanical disturbances [50, 53-57]. Thus, the amputee's need for direct feedback from an artificial limb may be more due to poor controller architecture than to loss of proprioception." [58]. They postulated that the observed dependence on feedback information could be reduced provided the control system could accurately interpret the intention of the user [51, 59-61].

In light of this, it is believed that difficulties experienced by EMG-based control research may be alleviated if better control strategies could be developed to improve the overall performance. Investigating the possible use of more than one type of EMG control approach (hybrid systems) may yield some interesting and fruitful results. The same could be said of also integrating residual limb motion information within the conventional EMG control systems with the use of a multi-expert system. Although numerous research groups have been investigating both approaches (EMG and residual limb motion), very few have evaluated the effectiveness of combining both strategies within the same system. Pattern recognition could also be used to determine the user intent based on residual movements at the shoulder and associate that intent with a specific linkage/task from a given list. The amplitude of the EMG activity, from selected sites, could be used to scale the intensity/speed at which the recognized task is performed as well as, possibly, to adjust the endpoint condition.

Depending on the control approach, there may be issues when implementing gross upper-extremity movements using two separate control schemes. Several research groups [35, 47] have cited that some correlation exists between the shoulder and elbow kinematics during various tasks. Since there may be a need for some level of communication between both schemes, it may be difficult to implement kinematic characteristics within the control system. Other approaches would utilize pattern recognition in order to implement and expand upon trajectory task-based motion control. Many of the possible implementations could benefit from the addition of the shoulder motion along with the MES from residual limb. Residual motion may include clavicular motion, shoulder elevation-depression, flexion/extension, and/or abduction/adduction. Such motions, however, may be limited by the techniques used to suspend the prosthetic limb. Investigation of new materials used to measure body movement have been ongoing [62] and the addition of such technology could also be beneficial if additional shoulder motion information is shown to be valuable for the control system.

2.4 Modular Control System Approach

It is evident that there is a need to step back and look at the different levels of upper extremity amputation. It is clear that every user will have different input sources associated with their amputation and also variable level of control on those inputs. It is important to try to develop several different strategies that can be applied, in one form or another, to each subject. It will be important to avoid assumptions as to the type and number of input sources a particular subject has available when developing these schemes. The design of such a system must also be investigated in a somewhat modular fashion. Improvements in different areas should ideally allow researchers to implement advancements within the system without significant modifications to its overall architecture.

In terms of control strategies, the number of DOF of a particular system reveals no real indication of its movement performance and characteristics. Rather it roughly outlines the boundaries in which the system may operate. Although it is true that any control system will be limited by the physical and mechanical characteristics of the prosthesis in question, these constraints should not be considered metrics used to evaluate the system's controllability. The control scheme employed within the system will be much more indicative of the prosthesis behavior. It is important to make such distinctions as, inevitably, the development of control strategies should not be restricted solely to a specific prosthetic system but, to a certain extent, be able to be applied to several different devices with varying physical and electrical characteristics. Although the implementation of any designed system will always require a thorough examination of the necessary interconnection between the input sources and the control system layers, it is also important to consider the control strategy as an independent component in itself. Making such differentiation potentially eliminates any possible restrictions associated with the future advancement of the control system with respect to input source limitations. Finally, it is important to make a distinction between the control and actuator driver systems. This separation between control intent and motor signal function modularizes the entire system such that improvements may be independently implemented to specific components. Using such an approach inherently results in a higher level of execution flexibility.

Using the term ‘control’ for the interpretation of information content in the MES and actuating the prosthetic devices accordingly is, although correct, a fairly generalized statement. It is beneficial to refine and classify such assertion into the major components required to develop a successful prosthetic control strategy. The suggestion of using multiple layers (e.g. user intent, prediction, kinematic, dynamic, actuation, etc) within the control scheme (Figure 2.1) definitely has merit and can be used to integrate various control philosophies.

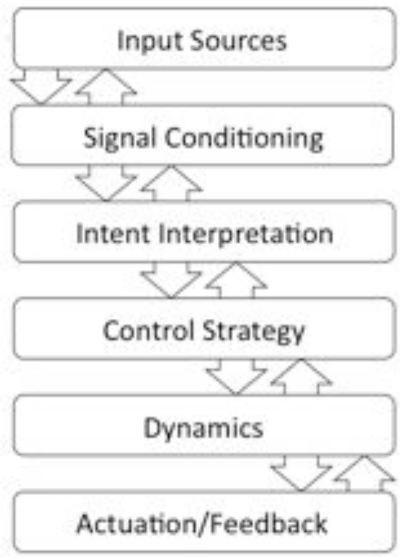

Figure 2.1 – Layered control system diagram.

2.5 Mental Burden Considerations

Some of the described approaches are intended to partly move the control issues away from the user and instead put that burden on the control system itself. The concept would basically reduce the information content required from the residual limb and EMG sites but at the expense of removing some level of control from the user. This raises several issues that must be resolved during the design of any system using both user and embedded control. How much control is given to the control system? What kind of information is needed to control the system? Is it robust? Is it continuously adaptable or predefined in its control strategy? How does it relate in terms of dynamically controlling the multiple DOF of the prosthesis?

It is clear that the user should always be the "driving force" behind the control system. It will undoubtedly be necessary to allow the system to take control of some of the coordination issues associated with multiple DOF whether it is through the use of linkages, heuristic rules, or both. To achieve this goal, the control system will require a large amount of information from various sources, including many from the prosthesis itself. To put such burden on the user would simply not be feasible or realistic. Feedback loops originating from the prosthesis will provide the system with its present characteristics while other inputs may be acquired from classifiers of the user intent layer.

Concentrated efforts should be invested into determining exploitable relationships that could be used in the embedded control development. Some researchers have found potentially useful upper extremity behaviors in their work but few have implemented these into a useful control scheme. An example of such correlation would be from Lacquaniti and Soechting who stated that "the ratio between the angular acceleration (*sic*) is the parameter which is invariant of target location" with respect to the shoulder and elbow joint [63]. Using this information could reduce the overall complexity of trajectory planning and generation as the dimensionality of the problem is decreased.

2.6 Concluding Remarks

The background information presented in this chapter describes many issues associated with the development of a robust and practical control system for a prosthetic limb. Although user intent interpretation and control signal sources were clearly identified as important considerations nearly fifty years ago, very little advancements have been made for shoulder disarticulation and forequarter amputation cases when compared to more distal amputation situations.

Several new MES-based pattern classification strategies are presented in Chapter 3 that have been designed to provide improved control solutions for high level amputation cases. These approaches are based on the notion that reducing the mental burden of the user and simplifying the control requirements will lead to a more effective and intuitive control strategy.

Chapter 3 – MES Classification of Shoulder Complex Motions

3.1 Introduction

Pattern classification has been described, in the previous chapters, as an effective method of interpreting user intent based on myoelectric data. Most research efforts have been devoted to the classification of hand, wrist and elbow movements. The work presented in this chapter expands the use of pattern classification schemes to the shoulder complex to provide new input strategies for high level amputation cases.

Understanding the available musculature of the residual limb is an important first step in determining the potentially accessible input signal sites for the control of a prosthetic limb. Since this research concentrates on the potential input sources for high level amputation cases, this section will concentrate on the musculature that may or may not be available in a transhumeral, shoulder disarticulate and/or forequarter amputee. It should also be noted that, due to the high synergistic muscle activity in these areas, the amputee might not be able to activate all of the remaining musculature in a controllable fashion. As a result, a careful examination of the muscle activations during common shoulder motions is also presented as to provide a better understanding of these muscle synergies.

3.2 Shoulder Physiology and Electrophysiology

The shoulder is one of the most sophisticated and complex joints in the human body. Unlike the knee and elbow, which can be defined as a hinged joint, the shoulder is best described as a ball and socket joint capable of a series of motions with a wide range of mobility. These movements are caused by a large array of muscles that act upon and displace the humerus, clavicle and scapula. Figure 3.1 specifies all the major muscles that are active in the shoulder complex area.

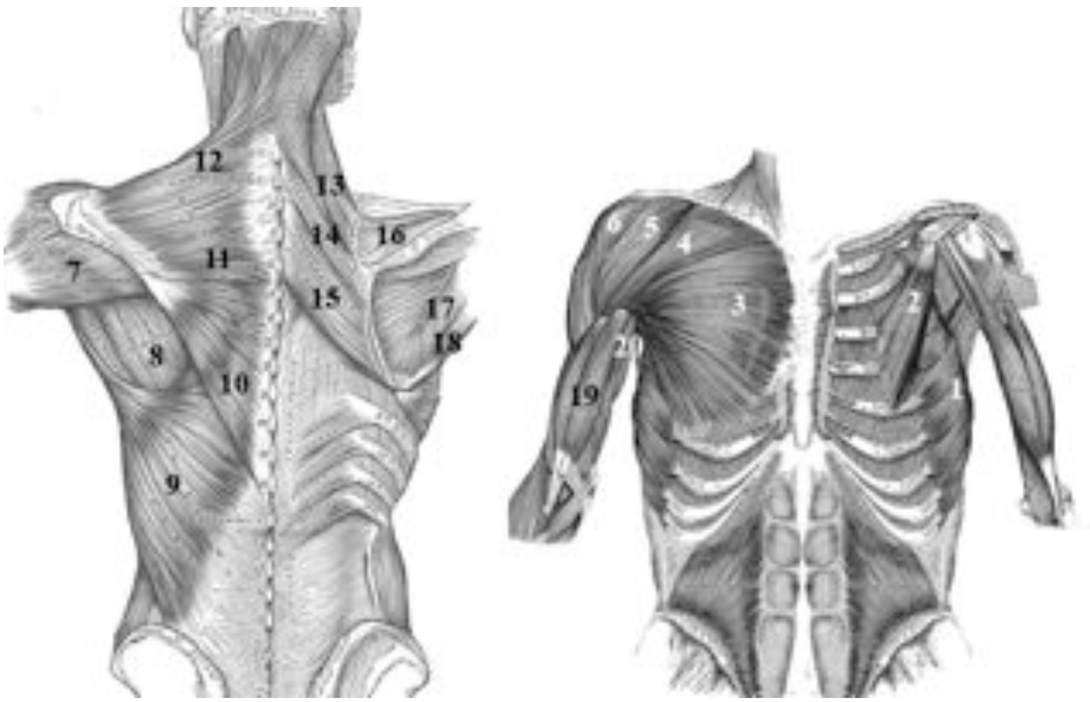

Figure 3.1 – Shoulder/Humeral Area Musculature (Note: Images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918 were used in this figure)

1. Serratus Anterior
2. Pectoralis Minor
3. Pectoralis Major (Sternal Head)
4. Pectoralis Major (Clavicular Head)
5. Anterior Deltoid
6. Lateral Deltoid
7. Posterior Deltoid
8. Infraspinatus
9. Latissimus Dorsi
10. Lower Trapezius
11. Middle Trapezius
12. Upper Trapezius
13. Levator Scapulae
14. Rhomboid Minor
15. Rhomboid Major
16. Supraspinatus
17. Teres Minor
18. Teres Major
19. Biceps Brachii
20. Coracobrachialis

Some of the shoulder motions consist of the displacement of the shoulder socket itself (Table 3.1 a-d) while others also result in the movement of the humeral bone (Table 3.1 e-l).

	Shoulder Motions
a	Shoulder Elevation
b	Shoulder Depression
c	Shoulder Protraction
d	Shoulder Retraction
e	Shoulder Flexion
f	Shoulder Extension
g	Shoulder Abduction
h	Shoulder Adduction
i	Transverse Flexion
j	Transverse Extension
k	Medial Humeral Rotation
l	Lateral Humeral Rotation

Table 3.1 – List of Relevant Shoulder Motions

Most studies found in the literature outline which muscles' associated MES were recorded when performing various motions with an intact arm [65-67]. The main goals of these studies vary but can generally be categorized in the following groups: 1) Investigation of MES/kinematic relationship during intact limb motion, 2) Development of musculoskeletal system models, 3) Motor control theory studies. For the purpose of the work outlined in this thesis, it would be beneficial to not only highlight which muscles are elicited during the various motions of interest but also map their spatial/MES characteristics. This information would provide a visual guide as to optimally select the electrode site locations. The IBME signals lab is equipped with a multi-channel amplifier system (Figure 3.2) manufactured by TMS International (www.tmsi.com). This system is capable of capturing high density MES allowing the simultaneous recording of up to 128 monopolar electrodes at a sampling frequency of 2KHz.

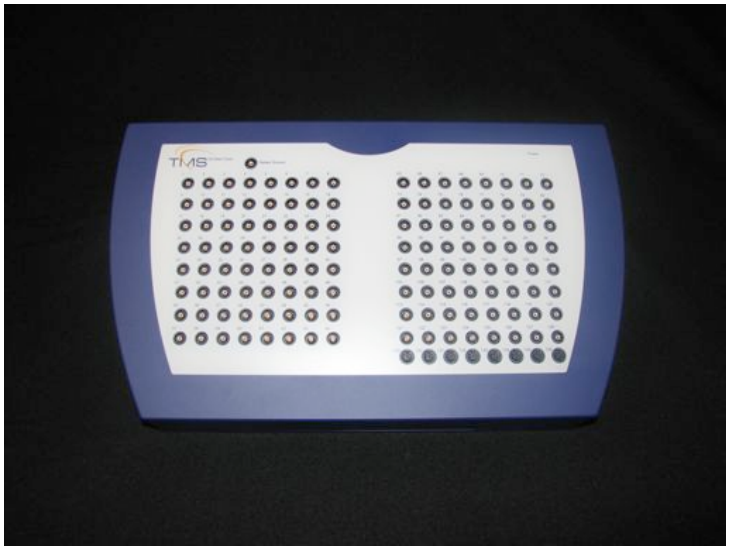

Figure 3.2 – REFA™ Multi Channel Data Collection System

Following a comparable protocol to previous work found in literature [68], a pilot study to investigate the mapping of the elicited MES was performed on one able-bodied subject (Figure 3.3) performing the motions found in Table 3.1. Figures 3.4 and 3.5 illustrate typical high-density color maps obtained from the pilot data collection. The numbered electrode locations and the remaining map associated with each motion can be found in Appendix A.

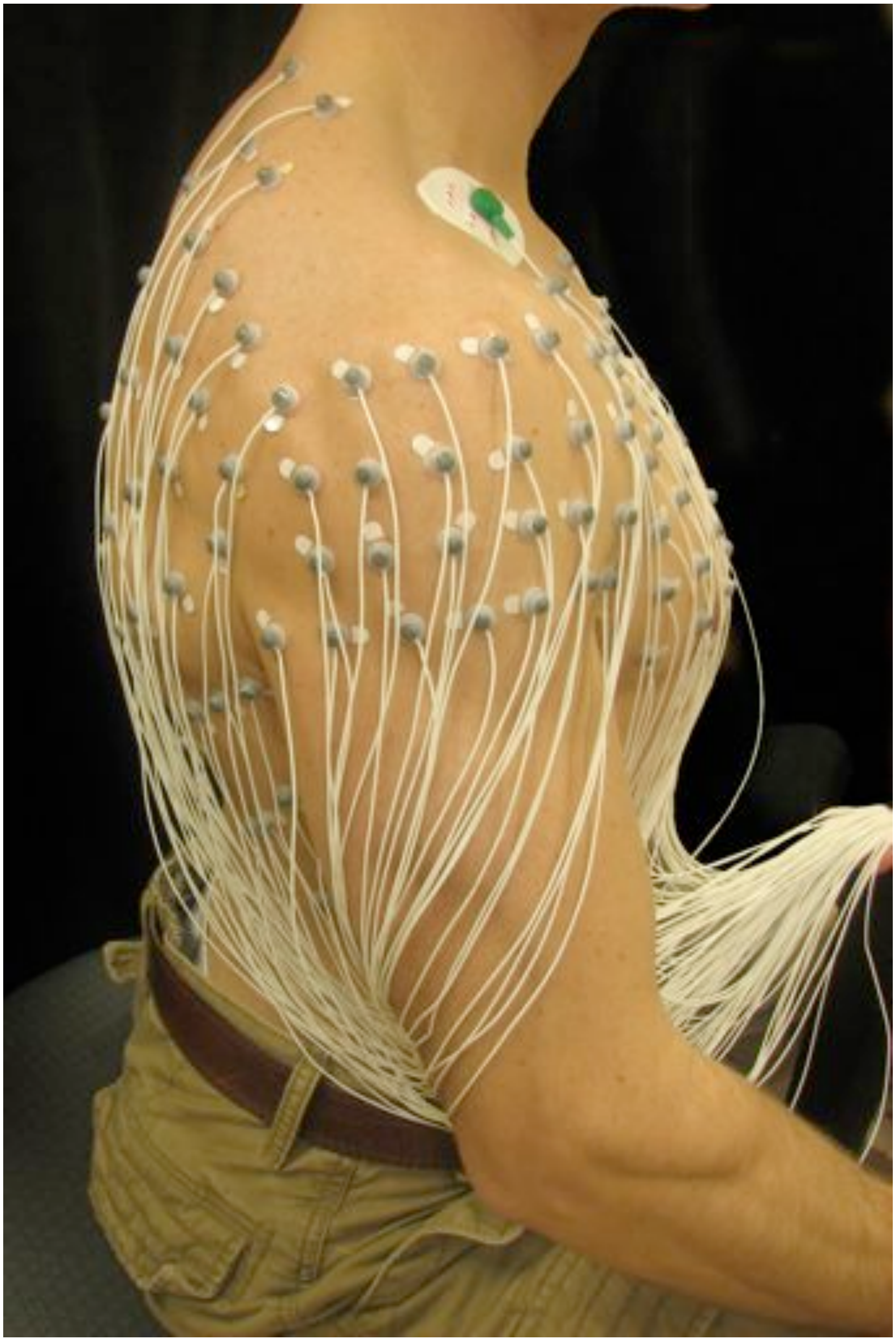

Figure 3.3 – High Density MES Data Collection Setup

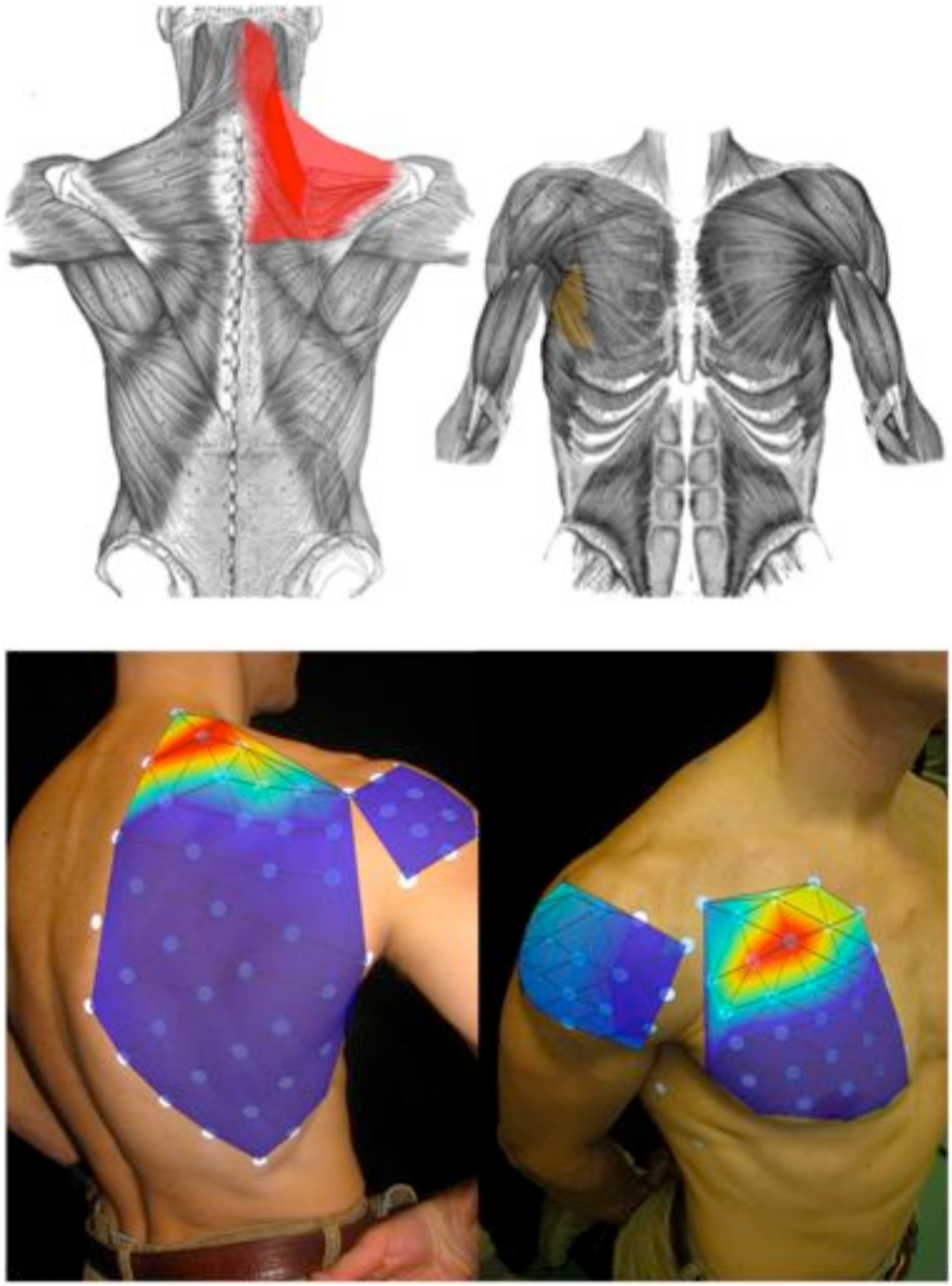

Figure 3.4 - Shoulder elevation motion muscle activity diagram. The highlighted muscles in the upper diagram illustrate the expected active muscles while the color mapped diagram indicate the observed muscle activity during the contraction. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

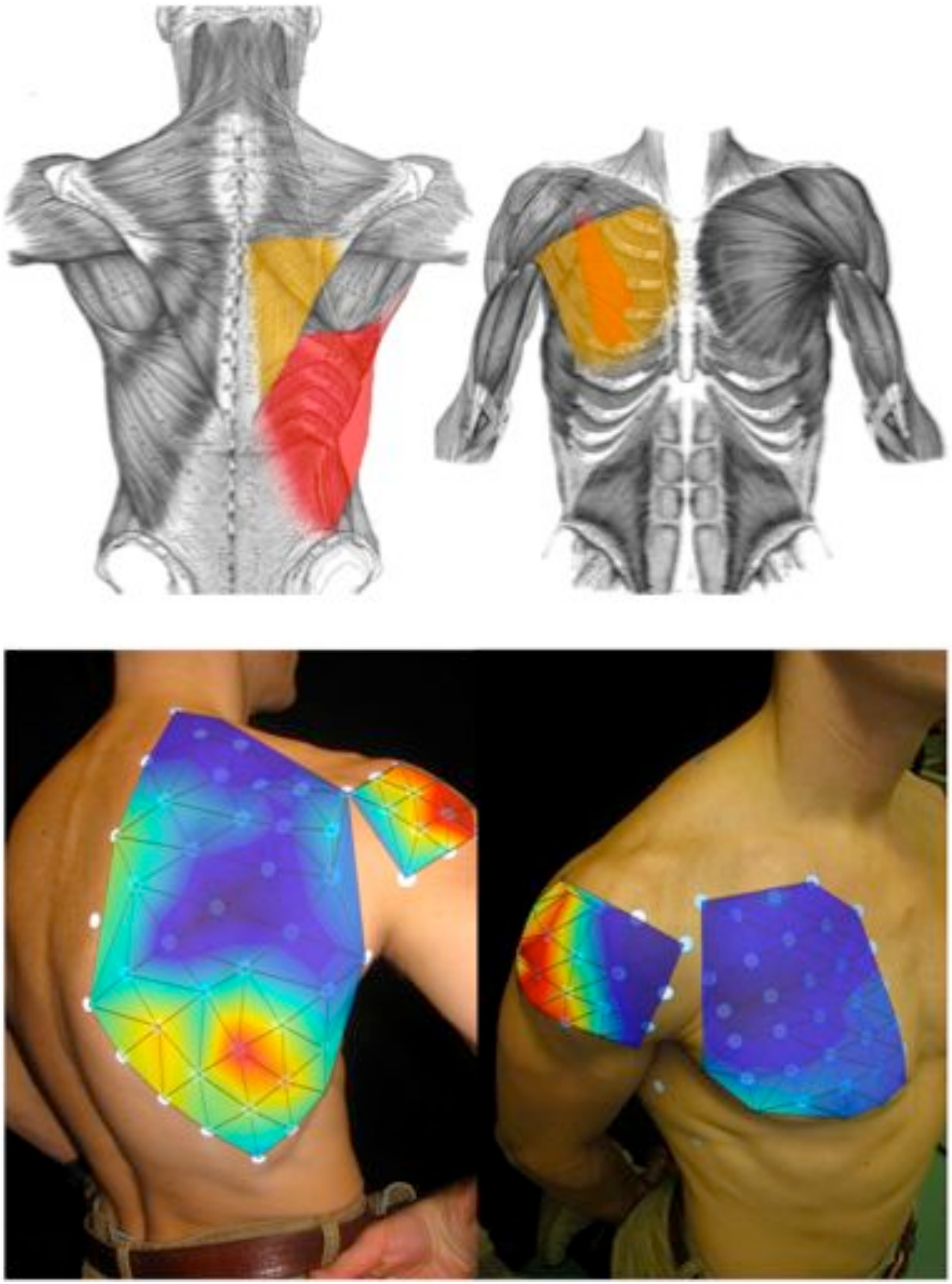

Figure 3.5 - Shoulder depression motion muscle activity diagram. The highlighted muscles in the upper diagram illustrate the expected active muscles while the color mapped diagram indicate the observed muscle activity during the contraction. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

The MES maps seem to indicate distinct activation patterns for the various motions performed. Some variability was observed when comparing the results with reference literature. This can be attributed to method which was used to perform the desired motions as defined by the experimental protocol. Any slight difference in performing a given motion, if compared to the protocols used in the reference literature, may elicit other muscle contractions which would result in the variations seen in the intensity mapping.

It has been hypothesized that a pattern classification scheme could be used rather than employing a conventional direct control strategy for the shoulder. Previous shoulder control research carried out at the IBME has had limited success [69]. Although clearly illustrating the ability to achieve high accuracy with various classification algorithms and a specific subset of the motions listed in Table 3.1, the work could not be implemented into a usable and intuitive control output to drive the system's virtual actuators. It was apparent that "alternative methods of representing shoulder motion are necessary for intuitive and natural control of an artificial shoulder" [69]. The mental burden associated with mapping multi-articulated user intent directly to the available DOF was found to be too high for the successful implementation of the pattern classification scheme. The task of controlling each DOF individually and sequentially is not an intuitive approach and confuses the user. The work presented in the remainder of this chapter attempts to overcome these obstacles by investigating the use of more physiologically relevant shoulder characteristics to allow more intuitive shoulder classification scheme implementations.

3.3 MES Classification for User Intent Interpretation

An LDA classification scheme has been chosen for the user intent interpretation layer because it has proven itself as a simple robust MES pattern recognition strategy for the control of prosthetic limbs [14]. A feature set based on TD statistics was also selected based on prior pilot data, collected by the author, that showed no significant performance improvements when using an AR-based feature set or a feature set which combined both TD and AR coefficients when classifying shoulder motions.

3.3.1 Linear Discriminant Analysis Classification Scheme[2]

Linear discriminant analysis classification schemes are based on Bayes' classification rule that estimates the *a posteriori* probability of a pattern belonging to a given class using a *priori probabilities* of the system. The scheme assumes that all the probability density functions have a Gaussian distribution and that all covariance matrices are equal. As a result, the classification calculations are simplified to a feed forward function based on the current input feature vector as well as weight and offset matrices defined using MES pattern data collected during a prior training session.

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[2] A complete mathematical explanation of the system can be found in [70]. Only a very short summary of the referenced literature has been included in this section.

3.3.2 Time Domain Feature Set

A feature set consisting of TD statistics, used previously in real time MES control schemes [14, 17, 71] was selected as part of the signal representation layer of the input strategy. Included in the TD set are the number of zero crossings, the waveform length, the number of slope sign changes and the mean absolute value for a given data window. The data from each channel were segmented into window frames of 250ms[3] from which these features were computed. The features from each channel were then concatenated into an aggregate feature vector and used as inputs to the LDA classifier.

3.4 Previous Work on Shoulder Motion Classification

As stated in Section 3.1, previous research conducted at the IBME investigated the ability of able-bodied users to elicit repeatable patterns from the shoulder complex musculature that could accurately be interpreted by several experimental classification schemes used in myoelectric pattern recognition systems for the control of prosthetic limbs. The motions used for this research concentrated on humeral movements which are created by the various synergistic relationships of the shoulder musculature. Fairly accurate offline results were reported with the use of several classification algorithms [69]. Results from real time usability experiments in a virtual environment did not, however, indicate usable and intuitive control. It was concluded that the humeral-based motions chosen, although highly repeatable, might not necessarily lend themselves as ideal movements for eliciting

[3] Window length was selected based on pilot work aimed at calculating optimal classification accuracy results. It should be noted that an optimal window length, aimed at obtaining the smallest user error, would be of shorter duration.

MES for the control of a prosthetic limb in terms of reaching tasks involving multiple DOF.

3.5 Discrete Shoulder Contraction Classification

Based on the results from the previous outlined research, it was felt that attempting to solely classify a large number of humeral segment motions might not result in the most reliable or robust input strategy for high-level amputation cases. The need to use simple contractions, which would be intuitive for users to produce, would most likely improve the chances of developing a practical MES-based input strategy option. As a result, contractions that were physically achievable for high-level amputees were chosen as potential candidates for the classification scheme. Four different discrete shoulder girdle contractions were selected: elevation, protraction, depression, and retraction. In addition, both medial and lateral humeral rotations were included in the motion subset along with a no movement class.

3.5.1 Experimental Protocol

The MES data corresponding to seven classes of contraction were collected from six healthy subjects and one bilateral shoulder disarticulated (SD) amputee who has had targeted muscle reinnervation (TMR) surgery[4] on the left pectoralis area of the body. Eight Ag-AgCl Duotrode electrodes (Myotronics, 6140) were placed at physiologically relevant locations for shoulder girdle motions for the able bodied group (Figure 3.6). A total of sixteen electrodes were used with the amputee subject (Figure 3.7) although 4

[4] Details concerning TMR surgery and patient can be found in [89].

electrodes were purposely placed in the TMR region (reinnervated by the nerves which would normally control the elbow, wrist and hand) and were not used in the analysis of the data collected. The UNB Research Ethics Board approved the experimental procedure used for this research and each subject provided informed consent prior to participating in the experiment.

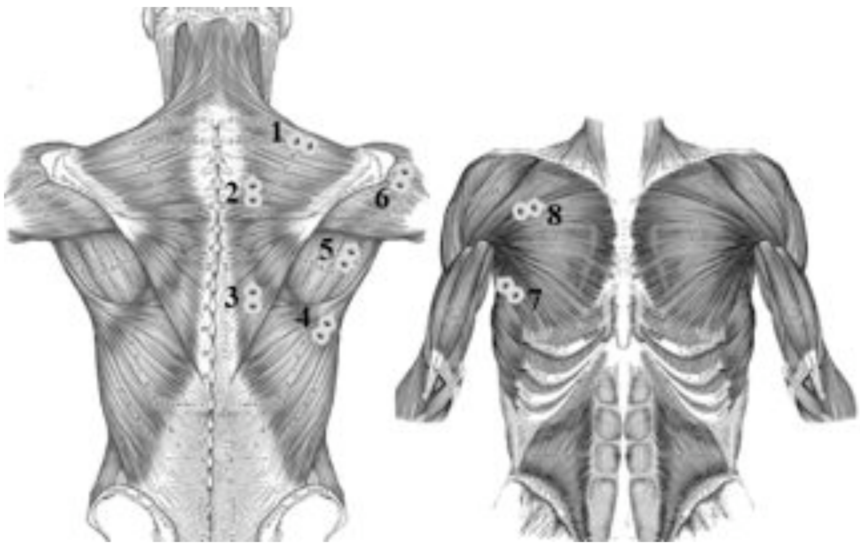

Figure 3.6 – Electrode Placement Locations (Able-Bodied Users Group). (Note: Images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918 were used in this figure)

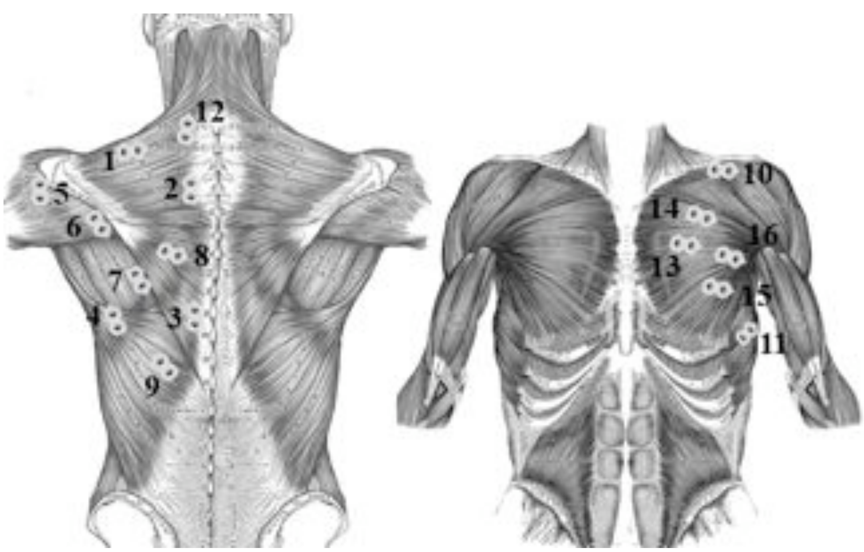

Figure 3.7 – Electrode Placement Locations (SD/TMR Amputee). (Note: Images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918 were used in this figure)

Subjects were instructed to complete seven isometric contractions associated with the following shoulder girdle motions: elevation, protraction, depression, retraction, medial humeral rotation, lateral humeral rotation, and a no movement/rest class. Each contraction was held for four seconds and the entire set was repeated six times. The first three repetitions were used as training data, and the remaining data were used for testing. The data were amplified using a gain of 20000, low pass filtered at 500 Hz, and acquired at 1 kHz using a 16-bit analog-to-digital converter.

3.5.2 Data Processing

The optimal number of channels used to extract the features, train and test the classifiers was investigated. Classifiers based on all possible channel combinations were trained and evaluated. The classifiers were then ranked, for the able-bodied group, on a subject-by-subject basis in terms of their classification accuracy. The process was repeated for i channel data sets (where i=1:8). The classification accuracy of the optimal channel combination (the best i of 8 channels) was recorded on a subject-wise basis. It should be noted that although 12 electrodes were used with the SD/TMR amputee subject only the results for up to 8 optimal channels were reported in this section in order to coincide with the able-bodied group's maximum number of electrodes available.

3.5.3 Classification Results

The classification results of both the able-bodied group and the SD/TMR amputee are presented in Figure 3.8. Error bars of one standard deviation are shown for the able-bodied group. It can be seen that, for both cases, significant classification improvements occur when initially increasing the number of electrodes. It should be mentioned however, that increasing the number of channels beyond five produced only minor improvements to the classifiers' performance. Furthermore, the optimal electrode subset varied across subjects without providing any clear indication of any electrode location whose inclusion in the subset would provide only limited classification improvement. The results from the single TMR subject indicate very similar performance when compared to the able-bodied group.

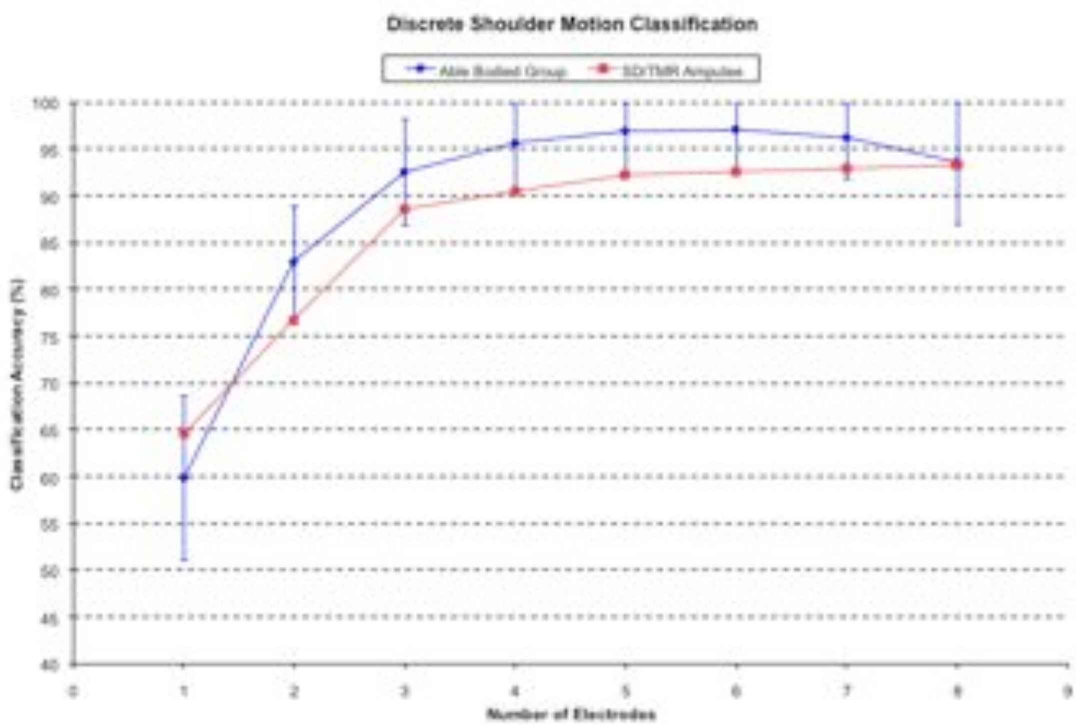

Figure 3.8 – Accuracy Results for Discrete Motion Classification

3.6 Combined Shoulder Contraction Classification

The previous section illustrated how highly accurate classification of discrete contractions could be achieved through the use of a pattern classification scheme. The shoulder girdle is, however, not only limited to these discrete contractions. In fact, it is possible to move the shoulder in various ways that simultaneously combines two of the discrete motions previously presented. Eliciting these motions with the discrete classifier presented in Section 3.4 would not generate a combined output since the pattern classifier can only output one discrete class. As a result, it was felt that adding additional combined contraction classes might produce a more reliable scheme for the interpretation of the user's intent.

3.6.1 Experimental Protocol

Additional combined contraction data were collected from the same subjects outlined in the discrete shoulder motion classification study. Subjects were asked to complete four combined motions originating from the shoulder girdle: elevation/protraction, depression/protraction, depression/retraction, and elevation/retraction. Similarly to the discrete motions described in the previous section, these contractions were held for four seconds and repeated six times. The first three repetitions were used as training data, and the remaining data were used for testing. The combined shoulder contraction classification evaluation used an identical data processing approach as described in the previous section.

3.6.2 Classification Results

The overall classification accuracy of both the able-bodied group and the SD/TMR amputee are presented in Figure 3.9. Similarly to the discrete classification section, error bars of one standard deviation are shown for the able-bodied group. The results also seem to indicate similar performance behavior as a function of the number of electrodes used by the classifier. A drop in classification accuracy was, however, observed for all optimal electrode subsets when compared to the discrete shoulder motion classification case.

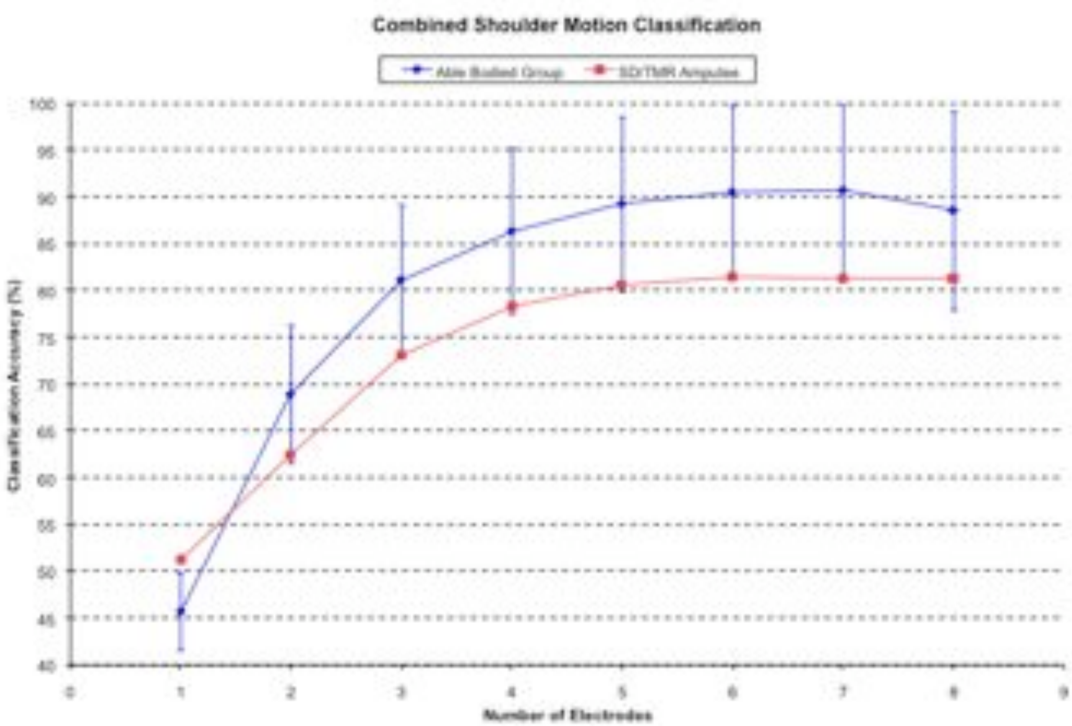

Figure 3.9 – Accuracy Results for Combined Motion Classification

A confusion matrix table (Table 3.2) was additionally calculated for the eight-channel classification performance. The results were averaged across all subjects and illustrate the classifier's ability to accurately identify each of the desired motions. The dark shaded areas represent accurate motion classification while the results found within the lightly shaded areas represent adjacent misclassification during combined motion performance. The remainder of the respective column represents incorrect classification for the given motion.

The overall classification accuracy, for the able-bodied group using eight electrodes, was found to be 88.5%. Another classification measure, termed *adjacent classification*, was also used to underscore the misclassifications, which were one of the discrete motions used in the combined motion classes. Its value was found to be 3.6%; indicating that 7.9% of the misclassifications were from unrelated contractions.

The performance results of the classifiers seem to indicate that the protraction and depression motions as well as the retraction and elevation motions pair are major contributors to classification error. This may be explained by the highly correlated actuation of synergistic shoulder muscles used for these movements.

	Elevation	Elevation/ Protraction	Protraction	Depression/ Protraction	Depression	Depression/ Retraction	Retraction	Elevation/ Retraction	Medial Rotation	Lateral Rotation	Rest
Elevation	91.36	2.23	0.00	0.00	0.00	0.16	0.98	8.97	0.00	0.00	0.00
Elevation/Protraction	7.83	83.86	2.88	0.00	0.00	0.00	0.00	0.00	1.36	0.00	0.00
Protraction	0.00	3.64	68.42	10.38	2.01	1.74	0.11	0.98	0.00	0.00	1.20
Depression/Protraction	0.00	0.00	14.67	78.64	7.61	0.00	0.00	0.00	0.00	0.00	0.00
Depression	0.00	0.05	13.26	10.98	89.95	1.03	0.00	0.00	0.00	0.00	0.00
Depression/Retraction	0.43	0.00	0.00	0.00	0.00	95.11	2.77	0.00	0.00	0.00	0.00
Retraction	0.00	0.00	0.00	0.00	0.00	1.79	88.15	0.00	0.00	0.00	0.00
Elevation/Retraction	0.38	0.00	0.00	0.00	0.00	0.00	7.93	89.84	0.00	0.00	0.00
Medial Rotation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	98.42	8.75	0.00
Lateral Rotation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	91.25	0.00
Rest	0.00	10.22	0.76	0.00	0.43	0.16	0.05	0.00	0.22	0.00	98.80

Table 3.2 – Classification Confusion Matrix Table for Combined Motion Classification, Averaged Across Alls Subjects, using eight electrodes

3.7 Humeral Rotation Classification

The residual shoulder contractions, utilized in the previous sections of this chapter, displaced the shoulder girdle when the shoulder musculature was activated. An alternate input strategy, based on the shoulder position measurements, is presented in the following chapter. In an attempt to utilize both positional information and MES information, it was deemed beneficial to further investigate an additional MES-based classification option that would focus solely on the musculature responsible for movements that could not be measured by means of inputs based on shoulder position. As a result, this classifier could be combined with a positional-based scheme to increase the number of input sources for the control strategy layer. The medial and lateral humeral rotations movements were selected for this new classifier.

3.7.1 Data Processing

The humeral rotation motion classification evaluation used an identical data processing approach as described in the two previous sections. It should be noted, however, that all other motion (discrete or combined) data trials were used as part of the no movement class.

3.7.2 Classification Results

The overall multi-channel classification accuracy of both the able-bodied group and the SD/TMR amputee are presented in Figure 3.10. Error bars of one standard deviation are shown for the able-bodied group. Minimal classification performance variance can be observed when using a different number of MES channels. The optimal channel subset varied between subjects. Decreasing the number of channels produced only minor degradations to the classifier performance. Furthermore, the performance of the humeral rotation classifier shows its ability to separate the EMG elicited during normal shoulder and humeral rotation movements.

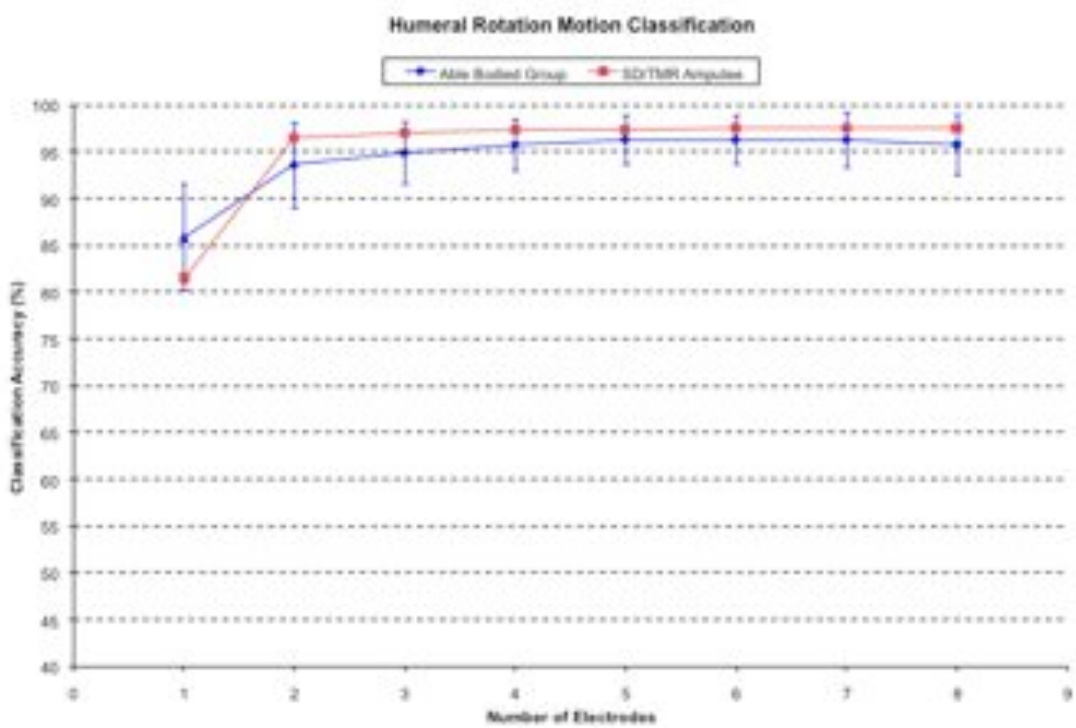

Figure 3.10 – Accuracy Results for Humeral Rotation Motion Classification

3.8 Concluding Remarks

The results presented in this chapter demonstrate how the devised strategies allow for reliable interpretation of the user's intended motions by using MES originating from the shoulder musculature. These intuitive schemes represent significant new options for the development of robust control systems for the control of a prosthetic limb in high-level amputation cases.

As mentioned in Chapter 2, the advancements in the use of residual limb position for high-level amputation control strategies have progressed at a much slower rate than for their distal counterparts. The following chapter seeks to investigate the ability to interpret the motion intent using positional information of the shoulder instead of the associated MES. This is done in an innovative way that removes many of the complexities often associated with motion-based solutions.

Chapter 4 – Residual Shoulder Motion Vector Projection

4.1 Introduction

Residual shoulder motion has been shown to be a useful input source for various prosthetic control strategies [37, 40, 44, 72, 73]. Each research group illustrated various methods in which this type of input source could be implemented. Its importance is often amplified for high-level amputation cases where the availability of robust input control sources is often limited. The selection of sensors and the control scheme by the clinical team will depend heavily on the consideration of several design factors (patient's musculature condition, range of motion, learning ability, etc.) in order to obtain an appropriate prosthetic rehabilitation plan [9]. Other design issues such as sensor orientation and output range also require some consideration prior to the fabrication of the prosthesis.

Some level of final adjustments and modifications are often required with any devised solution. Ideally, it would be beneficial to have an initialization protocol by which some of these factors would be taken into consideration and their associated implementation complexity removed from the prosthetic design stages. Automatic tailoring of the system for factors such as the user's range of motion, the sensor type, positioning and output range would also speed up the setup time required within a clinical fitting and/or system retraining setting.

This type of approach has been successfully implemented in MES pattern recognition systems where the location of the electrodes and the elicited MES patterns for each motion class will certainly vary for each person. To accommodate for this variability, a user is required to perform a short training session where class specific contractions are performed as prompted by a training software program. Following the completion of the training session, the information collected is used to train a user specific pattern classification system that will respond to repeatable MES contraction patterns elicited by the user, which are comparable with the patterns observed during the training session.

It may also occur that the electrode locations found within the socket of the prosthesis may be misaligned with respect to the residual limb as a result of removing and re-donning the prosthesis. In the occurrence of such event, the control system performance may degrade if the MES captured by the electrodes on the new residual limb locations are significantly different when compared to the original data from the training session. If this does occur, a new training session can be carried out such that the pattern classification system recognizes the new patterns. Recent work has also demonstrated the possibility of incorporating the MES data found within close proximity of the electrode locations into the training protocol in an attempt to account for possible pattern variability, thereby eliminating the need for a new training session and thus increasing the overall robustness of the system [74]. Although mostly utilized for MES based schemes, these adapting strategies could also be used with other input sources. The incorporation of such components would provide a means of automatically calibrating and optimizing motion-based control strategies.

4.2 Vector Projection Algorithm

The algorithm presented in this chapter addresses the issue of automatic calibration and control using residual shoulder motion by adapting the actuator output calculations based upon data collected during a short training session. The fundamental basis of the algorithm consists of three stages: 1) creating *class specific* vectors based on training data, 2) determining the projected[1] interim class values by relating a real time input signals based vector to these class vectors, and 3) calculating the class outputs by adjusting these values using algorithm parameters. The first stage is performed automatically immediately following the training session while the latter two stages are executed in real time.

4.2.1 Class Centroids and Vectors

The data collected during the training session provide the information necessary to determine the average position of each class (including the rest class), termed *class centroids*, within the input signal space. The centroids are treated as localized vectors (Figure 4.1) to produce *class specific* vectors (Figure 4.2). These class vectors are created using the rest class as the origin where X denotes the vector class:

$$\vec{V}_{Rest\,X} = \vec{V}_{O\,X} - \vec{V}_{O\,Rest} \tag{4.1}$$

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[1] The term *projection* used in this chapter does not refer to the common angle projection methods used in various fields of study. It rather refers to the comparison of the real time input vector with respect to the adjacent class vectors.

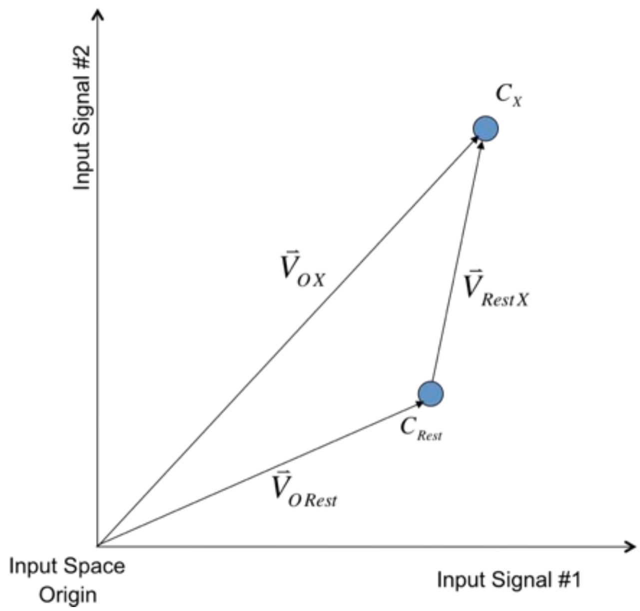

Figure 4.1 – Class centroids and vector diagram within input space

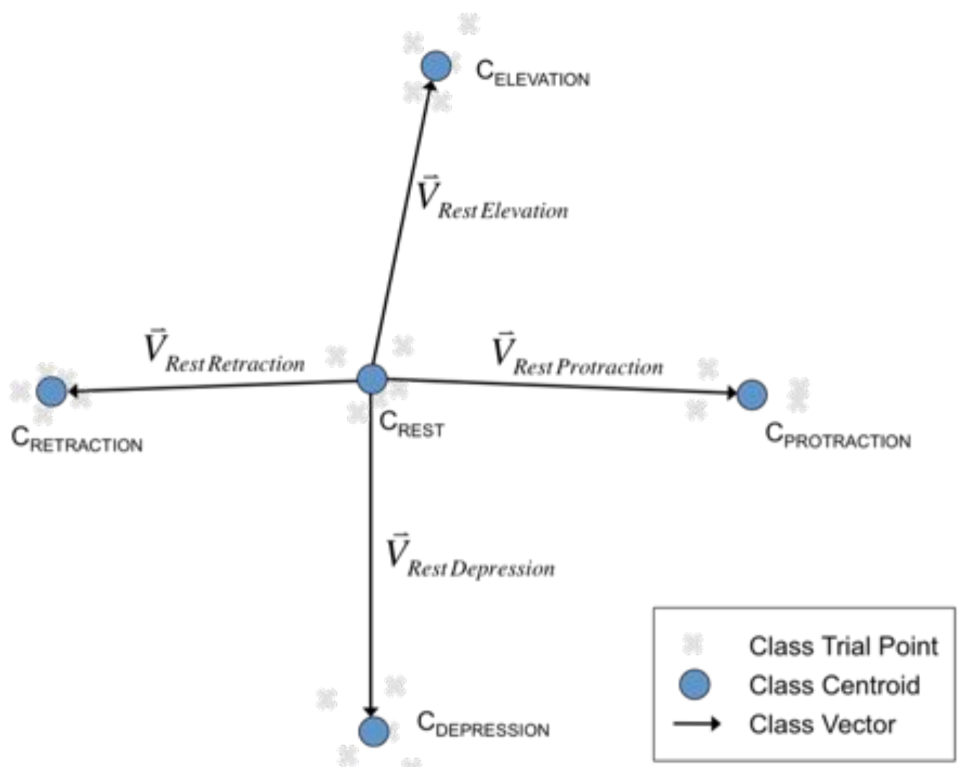

Figure 4.2 – Class specific vector diagram for the vector projection algorithm

The use of a rest state is a common occurrence in most control systems. Some systems have used the rest state/class as the starting point (i.e. origin) by which a classification decision could be made [17]. A variation of this concept was utilized for this scheme as the foundation upon which to relate all other classes in order to remove some of the dependencies associated with the input sensor type, orientation and range. By specifying the centroid of the rest class as the reference point, the scheme effectively eliminates any need for the actual origin of the input signals.

The newly calculated class vectors for every desired class in the system also encompass several noteworthy characteristics. The range of motion for each class has been integrated into the magnitude of its associated vector. As described below, this information will be invaluable in determining the amplitude of the output signals. The orientation of these vectors also removes the complexities normally associated with sensor placement and alignment. The importance of the orientation of the input signals axis has been negated since all future calculations are performed solely with the use of these centroids and vectors.

Having created the class vectors with the training data, it is now possible to calculate both the magnitude component of each class vector along with the angle between two adjacent vectors:

$$\left|\vec{V}_{Rest\,X}\right| = \sqrt{\sum_{i=1}^{N}\left(C_X - C_{Rest}\right)_i^2} \tag{4.2}$$

where N = input space dimension

$$\Delta\theta = \cos^{-1}\left(\frac{\vec{V}_{Rest\,X1} \cdot \vec{V}_{Rest\,X2}}{\left|\vec{V}_{Rest\,X1}\right|\left|\vec{V}_{Rest\,X2}\right|}\right) \tag{4.3}$$

4.2.2 Input Signal Projection onto Class Vectors

In terms of real time implementation, the current input signals can also be used in order to form a final vector, termed the *input vector*, using Equation (4.4).

$$\vec{V}_{Rest\,Current} = \vec{V}_{O\,Current} - \vec{V}_{O\,Rest} \tag{4.4}$$

Similarly, its magnitude and the angles between it and the adjacent class vectors can also be calculated using Equations (4.2) and (4.3) respectively. The input vector can also be projected onto any of the class vectors:

$$d_X = \frac{\left|\vec{V}_{Rest\,Current}\right|}{\left|\vec{V}_{Rest\,X}\right|} \tag{4.5}$$

This projected value, termed d_X, represents the normalized input vector magnitude for class X. More than one projected value is calculated at this stage since one can be calculated for each class vector defined in the algorithm (Figure 4.3).

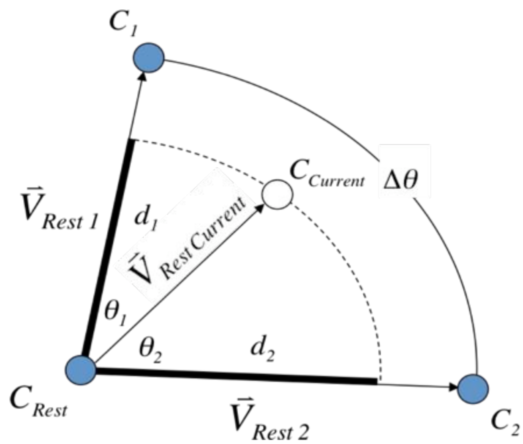

Figure 4.3 – Simultaneous projection of input vector onto adjacent class vectors

4.2.3 Projection Algorithm Coefficient Equations and Tuning Parameters

The final stage of the algorithm uses the previously calculated values along with tunable parameters to determine each of the class output strength. The coefficients and tuning parameters used in the class output strength equations are described individually below.

Threshold Factor, TF:

The threshold factor, TF, creates a region of inactivity for any amplitude below the threshold value. The TF ensures that a given class output is inactive for the specified area.

Amplitude Factor, AF:

The amplitude factor, AF, allows the clinician to adjust the position at which the projected value will saturate to unity. It should be noted that the class output saturation would occur at the centroid location if a unity AF were used.

Spread Factor, SF:

The spread factor, SF, dictates how quickly the offset coefficient value (described below) will diminish as the angle between the input signal and class vectors increases.

Magnitude Coefficient, α:

The magnitude coefficient, α, represents the adjusted input signal's projected value, d_X, based on both the threshold factor, TF, and amplitude factor, AF. It is required to provide a region of no activity near the rest class centroid as well as adjust the amplitude value associated with the given class centroid. It should also be noted that the current implementation of the magnitude coefficient ensures that no discontinuities will occur when crossing the boundary between the rest and active regions.

$$\alpha = \begin{cases} 0 & , \quad d_X < TF \\ \dfrac{d_X - TF}{\dfrac{1}{AF} - TF} & , \quad TF < d_X < \dfrac{1}{AF} \\ 1 & , \quad d_X > \dfrac{1}{AF} \end{cases} \tag{4.6}$$

Offset Coefficient, δ:

The offset coefficient, δ, reduces the effective output strength of a given class as the angle between the input signal and class vectors increases.

The spread factor, SF, dictates how quickly the value will diminish as the angle increases (Figure 4.4).

$$\delta = \frac{\cos\left(\frac{\theta_X}{\Delta\theta} SF\ \pi\right) + 1}{2} \tag{4.7}$$

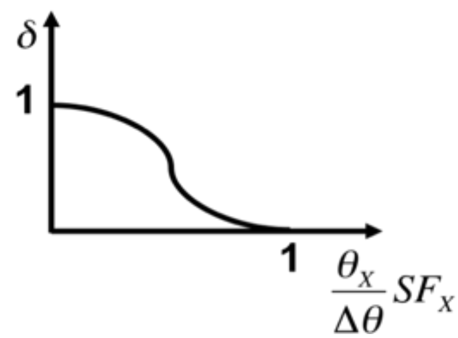

Figure 4.4 – Offset coefficient transfer function

The described components are used in the class output strength equation (4.8) to determine the magnitude of each class output.

$$\omega_X = \alpha\left(d_X, TF_X, AF_X\right)\delta\left(\theta_X, SF_X\right) \tag{4.8}$$

These values can now be used as inputs to the control strategy layer of the control system as defined in Figure 2.1.

To help illustrate the effect of each tuning parameter, class output colormaps were created which illustrate how adjusting the parameters will affect the output strength. Figures 4.5, 4.6, and 4.7 demonstrate the output behavior that occurs when modifying the TF, SF, and AF respectively.

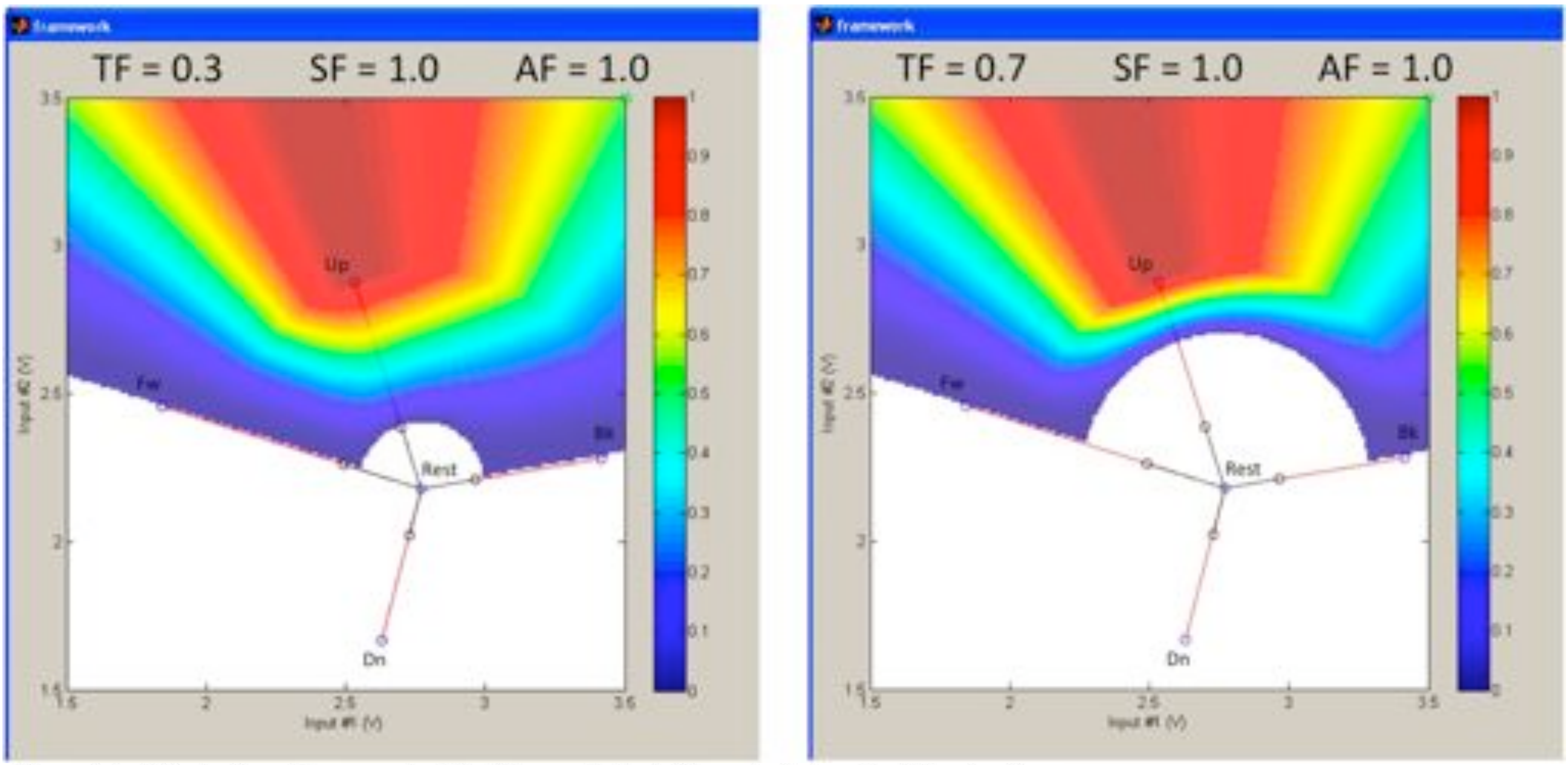

Figure 4.5 – Effect of tunable parameter TF. The panels depict the output strength of the elevation (i.e. up) class when using a TF value of either 0.3 or 0.7.

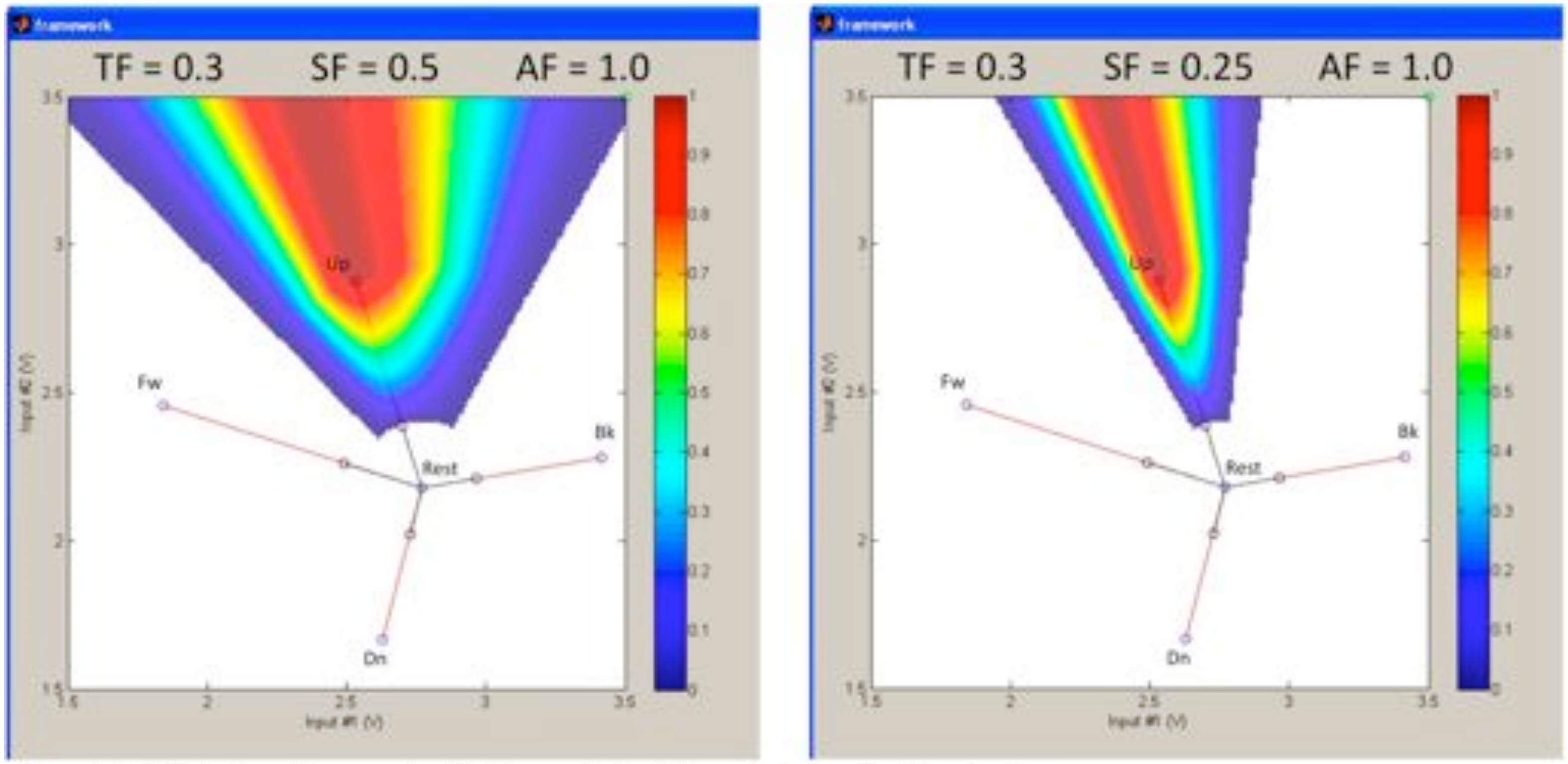

Figure 4.6 – Effect of tunable parameter SF. The panels depict the output strength of the elevation (i.e. up) class when using a SF value of either 0.5 or 0.25.

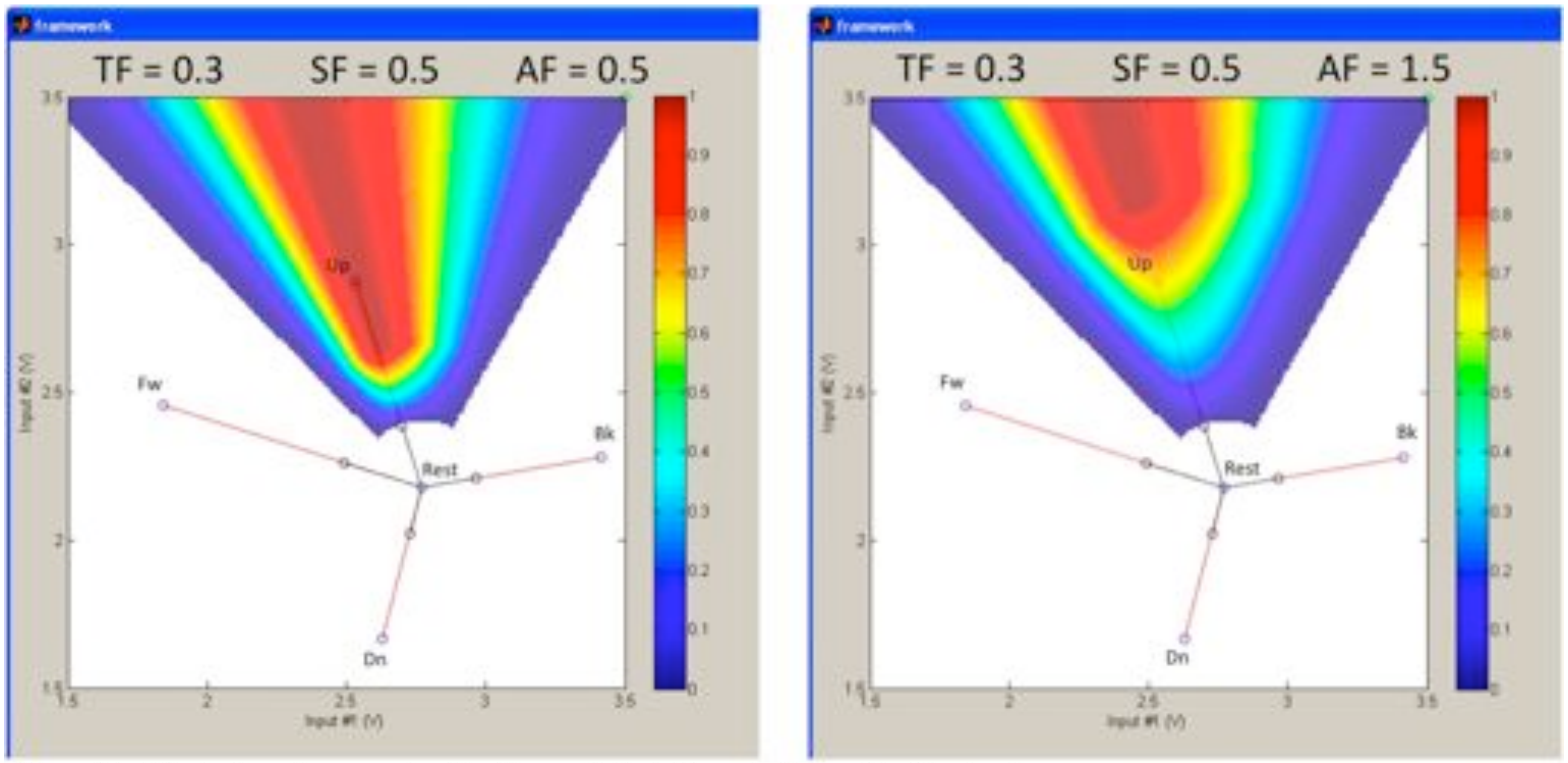

Figure 4.7 – Effect of tunable parameter AF. The panels depict the output strength of the elevation (i.e. up) class when using an AF value of either 0.5 or 1.5.

4.3 Training Data Collection Protocol

The vector projection algorithm requires very little data to properly calculate the class centroids. It was empirically determined that, unlike certain MES classification systems, repetitive trials of very short duration provide ample data to reliably calculate the class centroids. The data collection protocol designed for the preliminary case studies of the algorithm instructed users to complete five shoulder motions: elevation, protraction, depression, retraction, and a rest class. Each motion was held for one second and the entire set was repeated five times. The one second duration was arbitrarily chosen and shorter durations are acceptable since the algorithm only requires one instantaneous time sample for each motion in the set. Subsequent experiments prompted the user to only repeat the entire set three times. There were no apparent detrimental effects as a result of the reduction of trial repetitions. The entire data collection can be completed in approximately one minute if a three second delay is used in between motion recordings.

4.4 Vector Projection Algorithm Case Studies

The development of the vector projection algorithm greatly benefited from four separate case studies that permitted the evaluation of the effectiveness, reliability and versatility of the system. Rather than solely relying on the offline results obtained during the development stages, the real-time implementation and user feedback allowed for quick corrections and modifications to be made in order to improve the input strategy. Three case studies consisted of using a two-axis joystick as the input source while the final case study used two linear transducers mounted on an experimental bypass socket. Each case study is described below.

4.4.1 Case Study #1: Experimental Joystick in Laboratory Setting

The first study consisted of orienting the joystick such that one of its axes was vertical while the other horizontal. The subject performed the training protocol and qualitatively assessed the performance of the algorithm. Some issues were experienced as a result of having the joystick positioned on an experimental stand (Figure 4.8). The rest position drifted occasionally since the subject's body position, relative to the joystick, could be drastically altered during the experiment. This problem was easily corrected by ensuring a chair with a backrest supported the subject's torso.

Figure 4.8 –Experimental joystick apparatus used for the evaluation of the vector projection algorithm

4.4.2 Case Study #2: Offset Experimental Joystick in Laboratory Setting

The second case study used the same joystick employed in the first study but rotated by 45 degrees (counter clockwise) such that the new axes were now oriented halfway in between the original vertical and horizontal axes. This was done in an attempt to evaluate the algorithm's ability to automatically calibrate itself regardless of sensor orientation. The same training protocol was used and similar performance was observed.

4.4.3 Case Study #3: Experimental Joystick on a Shoulder Disarticulation Amputee's Socket

Having observed promising results from the first two case studies, it was felt that the algorithm should be tested with a socket such that the sensor would be more realistically positioned as compared to the experimental apparatus used in the previous studies. Access to a shoulder disarticulation amputee's socket (Figure 4.9) was provided by the Neural Engineering Center for Artificial Limbs (NECAL) group at the Rehabilitation Institute of Chicago (RIC) during a visit to their research facility. The algorithm used a custom two-axis joystick as the input source and the amputee qualitatively assessed its performance. The results did coincide with the elicited shoulder movements and seem to corroborate the previously observed performance with the experimental joystick apparatus.

Figure 4.9 – Shoulder disarticulation amputee's socket with a two-axis joystick for the evaluation of the vector projection algorithm

4.4.4 Case Study #4: Linear Transducers on Bypass Shoulder Socket

The final case study used an experimental bypass shoulder socket that used two linear transducers as the input source to monitor shoulder movement (Figure 4.10). The UNB clinical fitting team fabricated this socket and Dr. Peter Kyberd of the IBME provided access to the socket. Testing the algorithm with the socket outlined some algorithm implementation errors that were easily corrected. The algorithm was tested and found to work well once some of the parameters were tuned based on user feedback. The socket was also removed and re-donned during the course of the experiment. The system was qualitatively reassessed without any retraining once the socket was reattached and was found to operate with similar performance.

Figure 4.10 – Experimental bypass socket with linear transducer inputs used for the evaluation of the vector projection algorithm

4.5 Concluding Remarks

A mathematical algorithm has been described which attempts to eliminate some implementation complexities associated with sensor characteristics and possible user physiological constraints. The use of a short preliminary training session allows the algorithm to automatically tailor itself to both the prosthesis setup and user. Several case studies were used during the development phase of the algorithm and they have showcased the benefits of using such a system.

All of the classification results, from Chapter 3, along with the qualitative results presented in this chapter, although promising, are not indicative of actual functional usability when combined with various control strategies (e.g. endpoint, joint position/velocity, torque-based control schemes). Previous research has shown that usability may vary significantly when compared to classifier performance [75, 76]. To appropriately evaluate these classification schemes, the use of an appropriate qualitative and quantitative experimental test was required to further investigate their efficacy. Since no such test was available, an experimental testing apparatus and protocol was developed by the author and is presented in Chapter 5.

Chapter 5 – Experimental Functional Test

5.1 Introduction

Several different input strategies have been introduced in the previous chapters. Although the vector projection algorithm was qualitatively tested to assess its performance, the MES classification strategies have only been evaluated using classification accuracy results from data collected during experiments. Additionally, the vector projection algorithm was never evaluated in combination with the humeral rotation MES classifier. In order to properly assess these strategies, it would be beneficial to use some form of gross movement functional test in order to determine the efficacy of each strategy as well as evaluate the performance with respect to each other in three-dimensional space.

5.2 Specifying the Remaining Layers of the Control System Architecture

To use the input strategies within a functional test, the remaining layers found in the control system architecture must be specified in order to have a complete control solution (Figure 5.1). Since all three input strategies are able to provide six control signals to the control strategy layer, a three dimensional endpoint control scheme was chosen. The control strategy's output signals were transmitted to a servo motor-based manipulator which was used during the course of the experiment. Protraction and retraction motions were used to control the forward and backward motion. Elevation and depression motions were correlated to the upward and downward movement of the manipulator's endpoint. Finally, the medial and lateral humeral rotations were used to control the left and right movement.

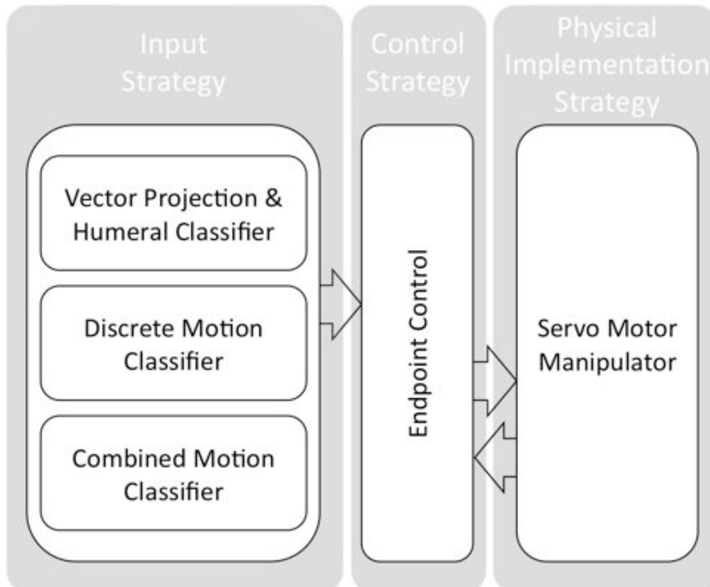

Figure 5.1 – Experimental control system

5.3 Endpoint Control Strategy

Literature has suggested that a MES-based input strategy could potentially be used in conjunction with an endpoint control strategy in order to provide multifunctional control of prostheses [77]. Using endpoint control would help alleviate some of the user's mental burden by significantly reducing the dimensionality of the control problem. Kinematic functions are required to implement such a scheme since they are used to infer the appropriate angular displacements necessary for multi-joint control of the prosthetic limb.

5.3.1 Forward Kinematics

The term forward kinematics refers to the mathematical process by which the endpoint Cartesian position of an articulated limb is calculated using the angular position of every joint. The articulated limb's mechanical characteristics are represented in a mathematical form using coordinate transforms:

$$T_{4x4} = \begin{bmatrix} R_{3x3} & P_{3x1} \\ 0_{1x3} & 1_{1x1} \end{bmatrix} \tag{5.1}$$

Here, R denotes the rotation matrix for a specified axis while P represents the translation component of the coordinate transform. For the purpose of the servo arm described in the following section, the transformation matrix derivation can be found in Appendix B. The resulting matrix can be used as a function, *f*, to calculate the Cartesian position of the manipulator's endpoint given the angular position of every servo motor:

$$P = f(\theta_1, \theta_2, \theta_3, \theta_4) \tag{5.2}$$

5.3.2 Inverse Kinematics

Inverse kinematics (IK) refers to the process by which a manipulator's joint angles are calculated given a desired position of the manipulator's endpoint in Cartesian space. It is often considered a more difficult problem since many possible solutions may exist for a given position. Several techniques exist for solving the IK problem including various iterative approaches. For the purpose of this experimental control system, the transformation function, *f*, was differentiated to obtain the Jacobian matrix, *J*:

$$\mathrm{d}P = J\,\mathrm{d}\theta \tag{5.3}$$

$$J = \begin{bmatrix} \frac{\partial x}{\partial \theta_1} & \frac{\partial x}{\partial \theta_2} & \frac{\partial x}{\partial \theta_3} & \frac{\partial x}{\partial \theta_4} \\ \frac{\partial y}{\partial \theta_1} & \frac{\partial y}{\partial \theta_2} & \frac{\partial y}{\partial \theta_3} & \frac{\partial y}{\partial \theta_4} \\ \frac{\partial z}{\partial \theta_1} & \frac{\partial z}{\partial \theta_2} & \frac{\partial z}{\partial \theta_3} & \frac{\partial z}{\partial \theta_4} \end{bmatrix} \tag{5.4}$$

Since J is nonsingular, the following equation can be used with an iterative technique in order to solve the inverse kinematics problem for small changes in position:

$$d\theta = J^{-1}\, dP \tag{5.5}$$

The iterative solution requires that the Jacobian inverse be calculated and used with the small change in endpoint position, dP, in order to calculate the change in theta, $d\theta$. This value is added to the current θ vector and the process is repeated until the system converges to the desired solution.

5.4 Servo Motor-Based Manipulator

The endpoint control strategy requires that the angular position of each joint of the device is known at any given point in time. Furthermore, the device also requires a minimum of three DOF in order to functionally move the endpoint in three-dimensional space. Since no prosthesis was available that met such requirements, a servo motor-based manipulator was designed and fabricated (Figure 5.2). The length of both the upper arm and forearm segments were selected based on previous literature [78]. As seen in Figure 5.2, the manipulator does not have the 'conventional' flexion/extension, abduction/adduction, and humeral rotation joints. The two most proximal joints have instead been arranged in a spherical coordinate representation. It should be noted that, for endpoint control, the actual mechanical joint composition of the device is irrelevant in terms of the control input signals required from the user. Having the weight of the manipulator being countered by a thrust bearing[3] rather than the joint's servo motor torque is the most significant benefit of using a transverse flexion/extension joint rather than an abduction/adduction joint for this experimental setup.

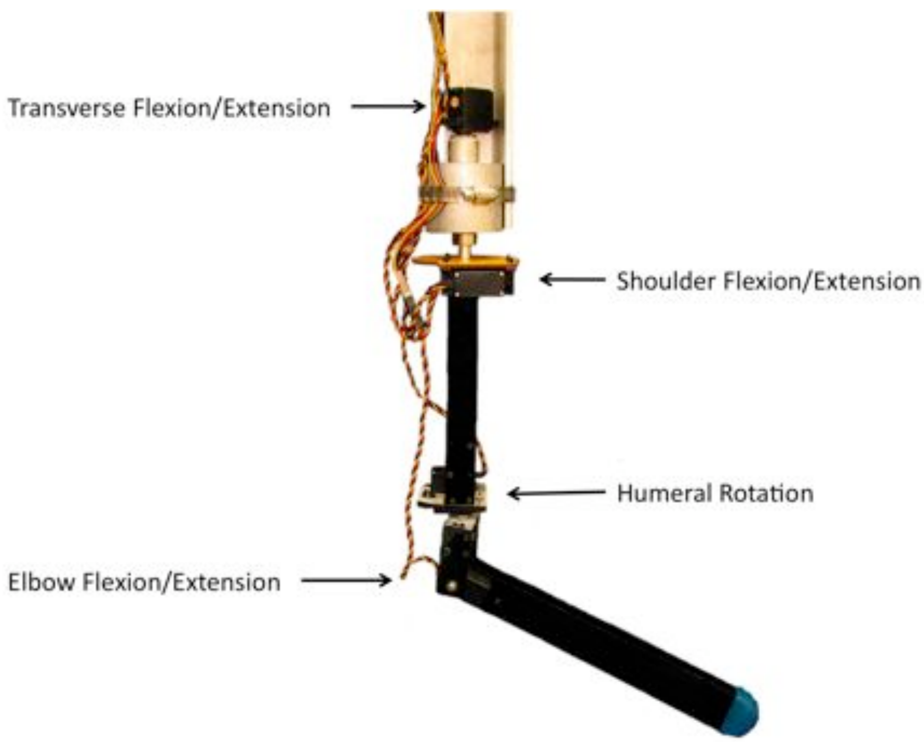

Figure 5.2 – Servo motor manipulator

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[3] Thrust bearings differ from common radial bearings since they are designed to support loads along the axis of rotation rather than perpendicularly.

5.5 Experimental Objectives

Several assessment methods and tools exist for the evaluation of prosthetic limb systems [73, 79-84] and the outcome measure of each of these methods will vary [85]. This variation can best be described by the intended purpose of the outlined method. Like many other fields, the qualitative and quantitative goals will differ depending on whether the device is, for example, in an early development, prototype form, or final product stages. Leading researchers[4] in the prosthetic field have attempted to best describe the involvement of various groups within this development cycle through the use of a diagram (Figure 5.3) that is based on the International Classification of Function health framework [86]. This figure illustrates how early outcome measures typically require the involvement of technical, often engineering, expertise to help with the development, prototyping and refinement of a control scheme. Their involvement decreases as the outcome measures move away from functionality tests to more activity-based tests where the use of a clinical staff and expertise is expanded. Finally, the user's involvement increases dramatically when the outcome measures focus on actual participation and use of the prosthesis by the user.

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[4] Dr Peter Kyberd developed the figure based on the discussions from the 'Outcome Measures in an Upper-Limb R&D Context' workshop in Trondheim, Norway (March 1-2, 2007). No publication references were available at the time of the thesis submission but the author obtained approval, from Dr Kyberd, to present the diagram in this document.

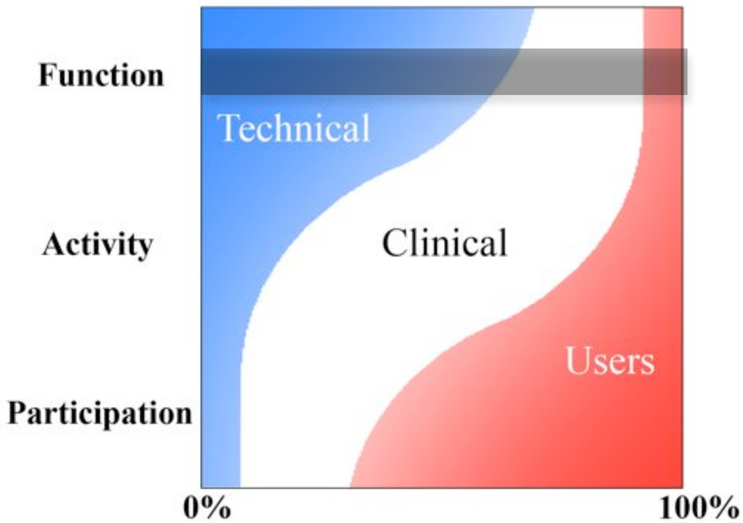


Figure 5.3 – Stakeholders' contribution to assessment domain diagram. The shaded area roughly represents the corresponding location of the functional test described in this chapter.

The intended purpose of the functional test for this project was to evaluate the input strategies' ability to produce accurate and robust signals to be used by the control system layer. The goal of the experiment was to effectively evaluate the strategies' performance while minimizing the effects of possible highly variable factors within the control system. As a result, it was felt that it would be preferable to solely concentrate on evaluating the gross movement of the manipulator rather than focusing on fine manipulation displacement, which would normally be linked to the DOF of the hand and wrist components. This approach was discussed with two occupational therapists[5] in the prosthetic field and both concluded that this approach seemed to appropriately coincide with the evaluation objective diagram (Figure 5.3) as the current development of these

[5] Kathy Stubblefield, OTR/L, is a member of the Neural Engineering Center for Artificial Limbs at the Rehabilitation Institute of Chicago.
Wendy Hill, BSCOT, is a member of the IBME clinical prosthetic team at the University of New Brunswick.

control strategies is still attempting to evaluate functional benefit rather than assess a complete prosthetic solution for various activities of daily living. The test also attempted to record a measure of mental burden associated with each input strategy. A dual task paradigm was chosen in order to provide possible insight as to how much effort and concentration was required to effectively use these input strategies. This approach has been used as a method of quantitavily assess the mental load associated with a performed task [73, 87, 88]. The cognitive load associated with an individual task performance (i.e. reaction test) can be compared with the performance of the same task when combined with an additional task (i.e. usability test) in order to calculate a measure of the associated mental burden imposed on the user.

5.6 Experimental Setup

The experimental appartus was designed and fabricated with the intended purpose of:

- Acquiring both shoulder position and MES originating from the shoulder complex
- Providing a manipulator device capable of handling endpoint control
- Quantitatively measuring the input strategy performance for gross movement tasks
- Quantitatively capturing some form of mental burden measure

The experimental setup is illustrated in Figures 5.4 and 5.5 while a brief description of the major components is included in the following subsections.

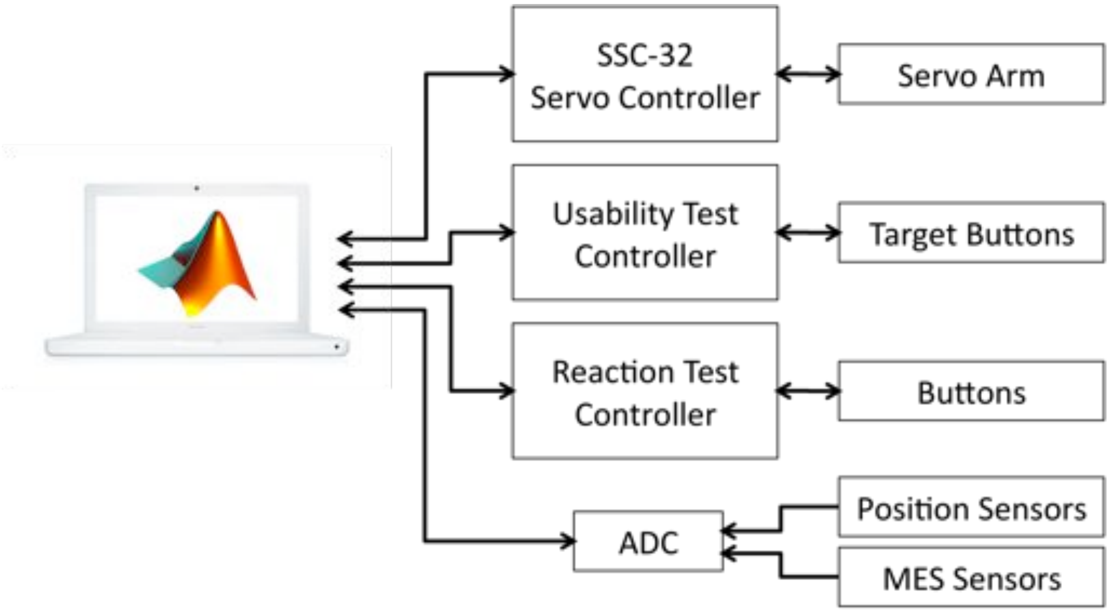


Figure 5.4 – Experimental apparatus diagram

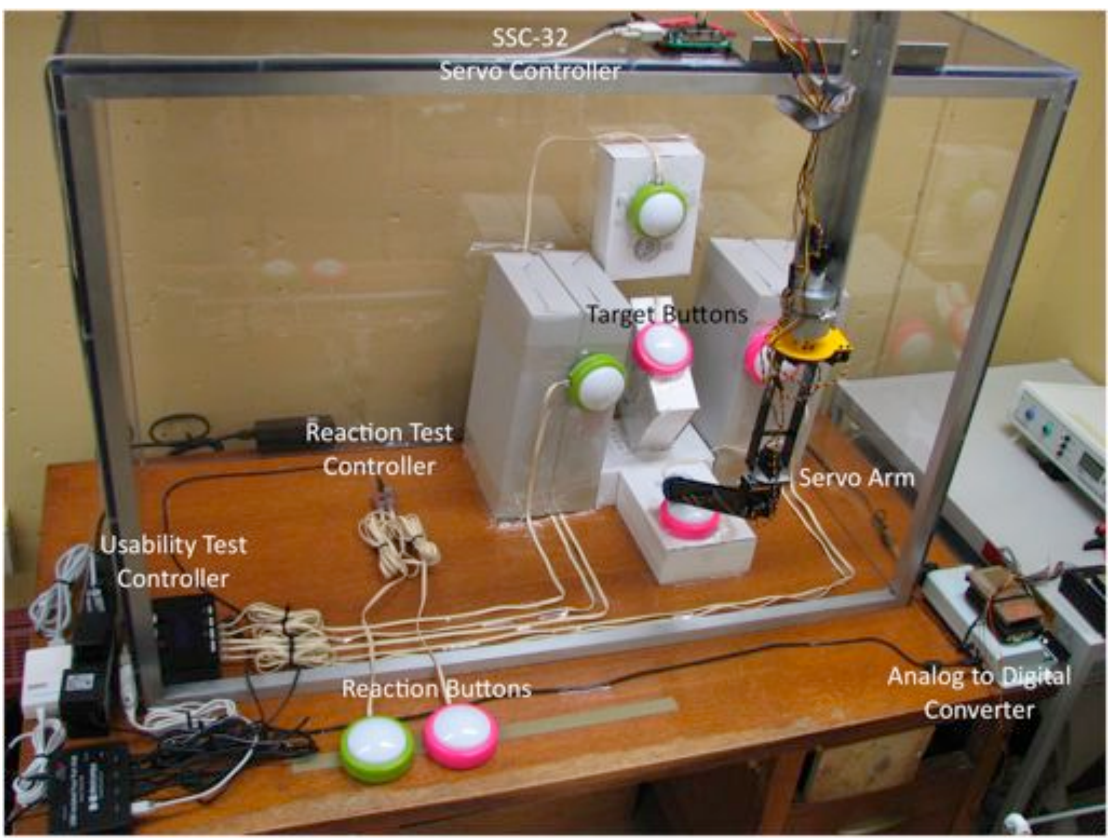


Figure 5.5 – Experimental apparatus setup

5.6.1 Usability Test Apparatus

The usability test apparatus consisted of a central controller and several pushbuttons. The controller would instruct which pushbutton should be illuminated while the pushbuttons would alert the controller when pressed. The sequence in which the buttons were pressed was specified in a MATLAB GUI-based program specifically designed for this experiment.

Figure 5.6 – Usability test system

5.6.2 Reaction Test Apparatus

The reaction test used two pushbuttons similar to the ones found in the usability test apparatus. The controller for the reaction test included a buzzer which would instruct the user when to perform the test. The buttons would alert the controller when either the primary button was released (i.e. reaction time) or the secondary button was pressed. The purpose of both these buttons is explained in the following section of this chapter. The time at which the test would be initiated was selected through the same GUI-based MATLAB software.

5.7 Experimental Protocol

The experiment consisted of one session where subjects were fitted with eight Ag-AgCl Duotrode electrodes (Myotronics^{TM}, 6140) placed at physiologically relevant locations (Figure 5.7) for the desired shoulder movements. A reference ground electrode (3M Health Care^{TM} RedDot, 2259) was placed on the clavicular bone region midway between the sternum and acromium. A second similar electrode was place on the acromium bone landmark and was used to attach the joystick connector.

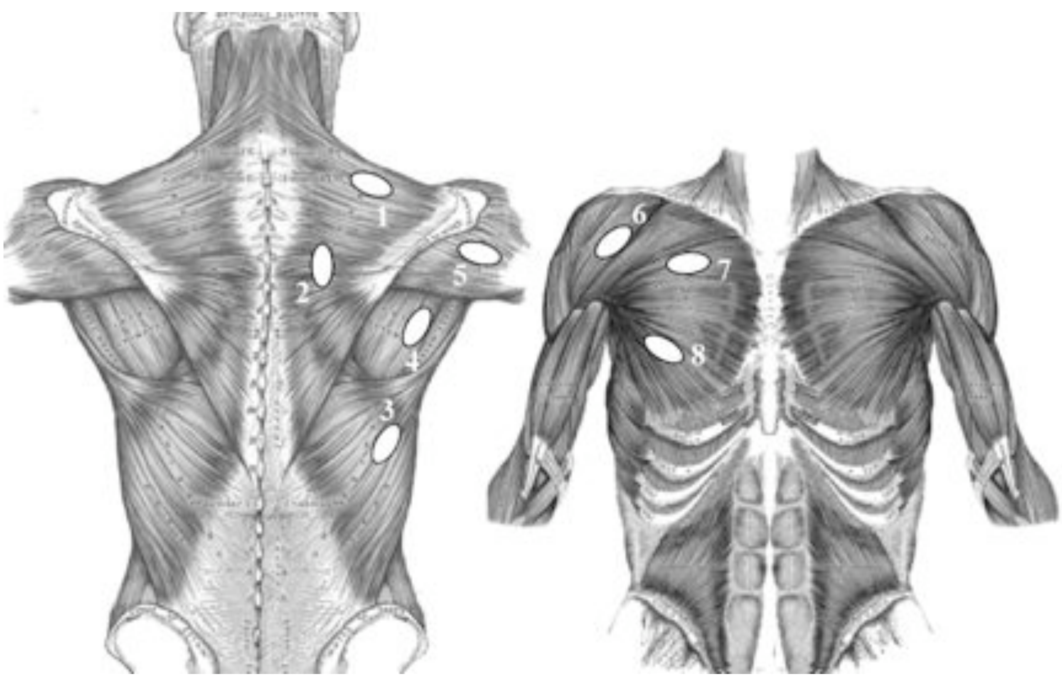


Figure 5.7 – Electrode placement diagram. (Note: Images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918 were used in this figure)

1 – Upper Trapezius / Supraspinatus
2 – Mid Trapezius / Rhomboid
3 – Lattissimus Dorsi
4 – Teres Major / Minor
5 – Posterior Deltoid
6 – Anterior Deltoid
7 – Pectoralis Major (Clavicular Head)
8 – Pectoralis Major (Sternal Head)

Subjects were seated and their right hand secured in order to allow for isometric humeral rotation contractions (Figure 5.8). The users were required to rest their left hand by pressing the primary reaction button located in front of them (Figure 5.8).

Figure 5.8 – Subject setup diagram

Twelve normally limbed, healthy, male individuals ranging in age from 25 to 33 were recruited to participate in this experiment. Each subject was required to provide informed consent (Appendix C) prior to participating in the experiment. The UNB Research Ethics Board approved the experimental procedure used for this research.

Each subject was given a general overview of the purpose of the experiment. The data collection process was also described in detail since most subjects had no prior experience with MES data collection. Four consecutive reaction test trials were performed at the beginning of the experiment.

Each input strategy required a different data collection protocol as outlined in Table 5.1. Every LDA classifier used the training data from all 8 MES channels to calculate their weight and offset matrices. The testing data were not used during the experiment and were collected for classification accuracy comparisons, which are detailed in a later section in this chapter. It should be noted that the amplitude value for MES-based classifiers was calculated as the average of the mean absolute value from each channel that was then amplified by a gain factor.

The testing of a given input strategy was performed immediately following its associated data collection session. The participants were given the opportunity to practice moving the manipulator with the implemented input strategy until such point that the researcher felt the user had reached an acceptable level of controllability. Furthermore, the researcher, at his discretion, adjusted the amplitude gain of any given class output to ensure that the entire control system was operating at an acceptable and controllable speed. The order in which the input strategies were presented was randomized in order to negate any learning effects associated with the experiment.

	Discrete Motion Classification	Combined Motion Classification	Humeral Motion Classification	Vector Projection
Number of Training Repetitions	3	3	3	3
Number of Testing Repetitions	3	3	3	3
Contraction duration (sec)	4	4	4	1
Delay duration (sec)	3	3	3	3
Elicited Motions	Elevation Protraction Depression Retraction Lateral Humeral Rotation Medial Humeral Rotation No Motion	Elevation Elevation/Protraction Protraction Depression/Protraction Depression Depression/Retraction Retraction Elevation/Retraction Lateral Humeral Rotation Medial Humeral Rotation No Motion	Lateral Humeral Rotation Medial Humeral Rotation No Motion NOTE: No motion also included an additional 6 secs where the user was instructed to move shoulder around without rotating the humerus.	Elevation Protraction Depression Retraction No Motion

Table 5.1 – Data collection parameters

A total of three trials were completed for each input strategy. A trial consisted of moving the manipulator to 1) press the illuminated start button, 2) press the randomly selected illuminated target button, and 3) repeat the process until instructed otherwise. Unbeknownst to the user, each target was illuminated twice during each trial and the reaction test was performed once for each target. The order in which the reaction test was performed was also randomized in an attempt to avoid any user anticipation of the reaction test prompting. During the course of the trial, the buzzer from the reaction test controller would activate and the user was required, with their left hand, to release the primary reaction button, press the secondary reaction button, and return their hand back to a resting position by pressing the primary reaction button. A time delay was added for each reaction test at the onset of the reaching task of the newly illuminated target and was varied between 0 and 2 s. The purpose of this delay was to reduce the user's ability to anticipate the commencement of the reaction test. All of these parameters were specified through the MATLAB GUI software (Figure 5.10). Once a trial was completed, the results were displayed in the GUI for recording purposes.

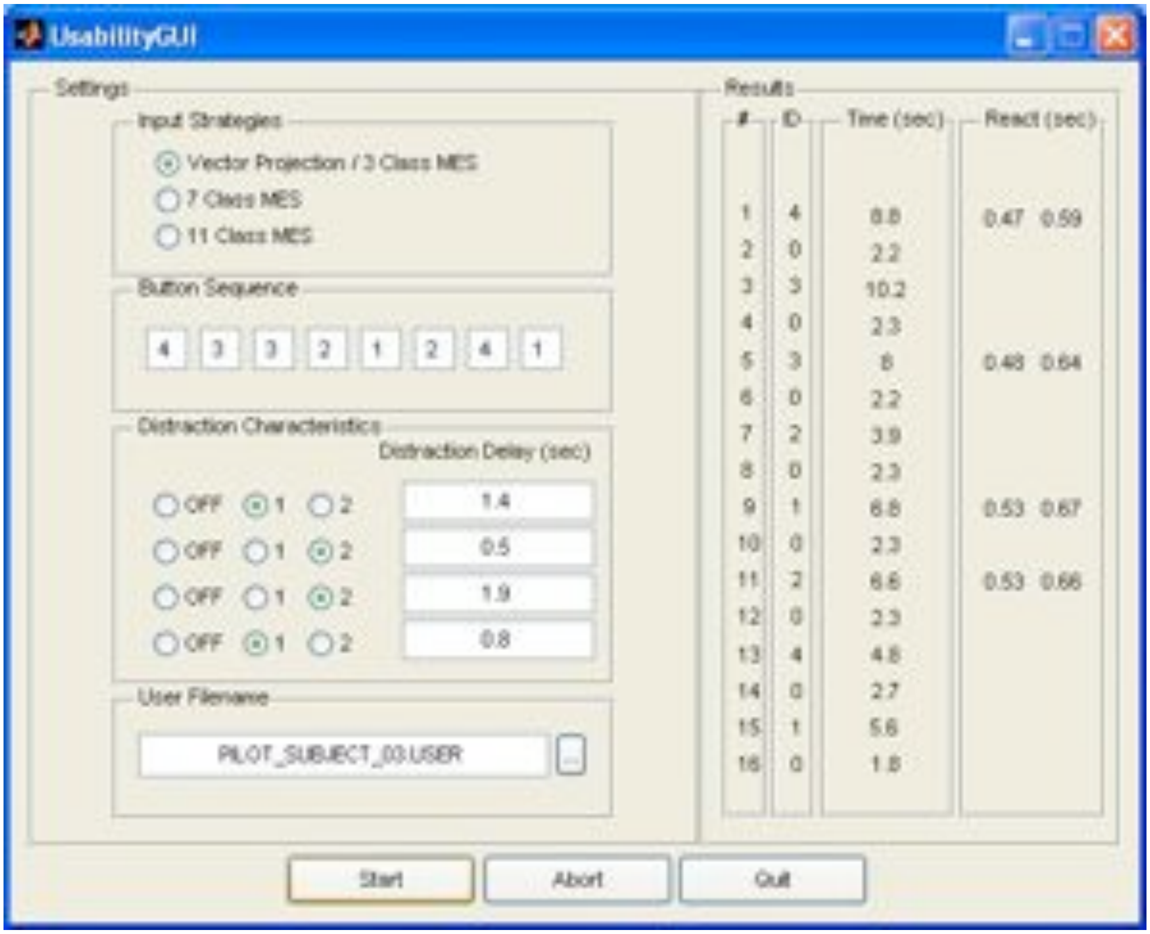


Figure 5.9 – MATLAB graphical user interface screen capture

5.8 Concluding Remarks

An experimental functional test was described and implemented to evaluate the three input strategies described in the previous chapters. This new test was required since no currently available tests are capable of producing results to compare the different user intent interpretation strategies developed through the course of this research. The control system was completed with the selection of an endpoint control strategy and servo-based manipulator. Several additional components were designed and fabricated as part of the experimental apparatus. A total of twelve subjects participated in the study. The analyzed results can be found in the following chapter.

Chapter 6 – Experimental Results Analysis

6.1 Introduction

The experimental test described in the previous chapter was implemented in an attempt to quantitatively and qualitatively assess the functional characteristics of the input strategies. This chapter will focus on presenting the input strategies' performance and associated mental burden. It should be noted that the vector projection/humeral rotation MES based classifier input strategy is simply termed as the vector projection strategy throughout this chapter.

The strategy performance metric used for the data analysis is the average time required to reach a given button, μ_{Time}. The mental burden metric used for the data analysis is expressed as the difference between the time to depress the primary button when performing both the reaction and usability tests and the time to depress the same button when solely performing the reaction test (6.1).

$$\Delta_{REACTION} = T_{REACTION\ DURING\ USABILITY\ TEST} - T_{REACTION\ ONLY} \tag{6.1}$$

The relationship between offline classification error and functional usability is also covered in this chapter. The analysis of the data set out to answer the null hypotheses outlined in Table 6.1 and are described as follows:

1. The average time to press a usability test button was the same for all input strategies.

2. The average time to press a usability test button remained the same during the entire experiment.
3. The average time to press a usability test button remained the same during the usability testing of a given input strategy.
4. The average reaction time difference (Eq. 6.1) was the same for all input strategies.
5. The average reaction time difference remained the same during the course of the entire experiment.
6. The average reaction time difference remained the same during the usability testing of a given input strategy.

1-a) H_o: $\mu_{projection} = \mu_{discrete} = \mu_{combined}$
1-b) H_o: $\mu_{projection} = \mu_{discrete}$
1-c) H_o: $\mu_{projection} = \mu_{combined}$
1-d) H_o: $\mu_{discrete} = \mu_{combined}$

2) H_o: $\mu_{trial\ \#1} = \mu_{trial\ \#2} = \ldots = \mu_{trial\ \#9}$

3-a) H_o: $\mu_{projection\ trial\ \#1} = \mu_{projection\ trial\ \#2} = \mu_{projection\ trial\ \#3}$
3-b) H_o: $\mu_{discrete\ trial\ \#1} = \mu_{discrete\ trial\ \#2} = \mu_{discrete\ trial\ \#3}$
3-c) H_o: $\mu_{combined\ trial\ \#1} = \mu_{combined\ trial\ \#2} = \mu_{combined\ trial\ \#3}$

4-a) H_o: $\Delta_{projection} = \Delta_{discrete} = \Delta_{combined}$
4-b) H_o: $\Delta_{projection} = \Delta_{discrete}$
4-c) H_o: $\Delta_{projection} = \Delta_{combined}$
4-d) H_o: $\Delta_{discrete} = \Delta_{combined}$

5) H_o: $\Delta_{trial\ \#1} = \Delta_{trial\ \#2} = \ldots = \Delta_{trial\ \#9}$

6-a) H_o: $\Delta_{projection\ trial\ \#1} = \Delta_{projection\ trial\ \#2} = \Delta_{projection\ trial\ \#3}$
6-b) H_o: $\Delta_{discrete\ trial\ \#1} = \Delta_{discrete\ trial\ \#2} = \Delta_{discrete\ trial\ \#3}$
6-c) H_o: $\Delta_{combined\ trial\ \#1} = \Delta_{combined\ trial\ \#2} = \Delta_{combined\ trial\ \#3}$

Table 6.1 – Investigated null hypotheses for input strategies performance test

6.2 Functional Performance Assessment

6.2.1 Input Strategy Effect on Usability Performance

The principal objective of this experimental test was to obtain quantitative and qualitative outcomes from the implemented input strategies. Figure 6.1 shows the averaged usability test outcomes for each subject where button time refers to the average time required to reach the buttons during the usability test. The data were subjected to a one-way analysis of variance (ANOVA) to investigate statistical significance. A p value of less than 0.001 was found, indicating that the input strategies' performance were not similar. The results also indicate that the vector projection input strategy was significantly better than the other two MES-only based strategies ($p < 0.001$ for both combinations).

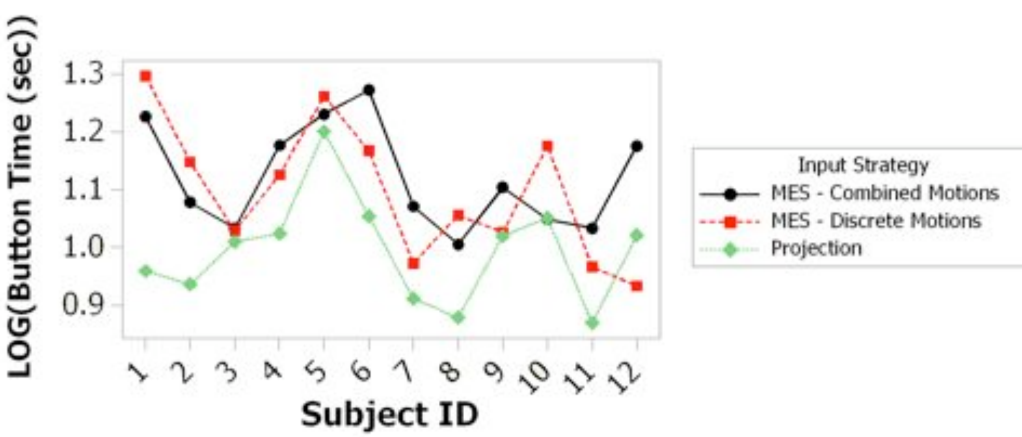


Figure 6.1 – Usability performance of input strategies on a per subject basis

No significant difference, p=0.228, was found between the two MES strategies (Figure 6.2). Further investigation attempted to regroup the MES data based on the order in which the MES strategies were presented (i.e. 1st and 2nd implemented MES based strategy in experiment). It was hypothesized that usability performance may have improved based on the amount of time exposed to MES-only based control systems as opposed to the specific input strategies themselves.

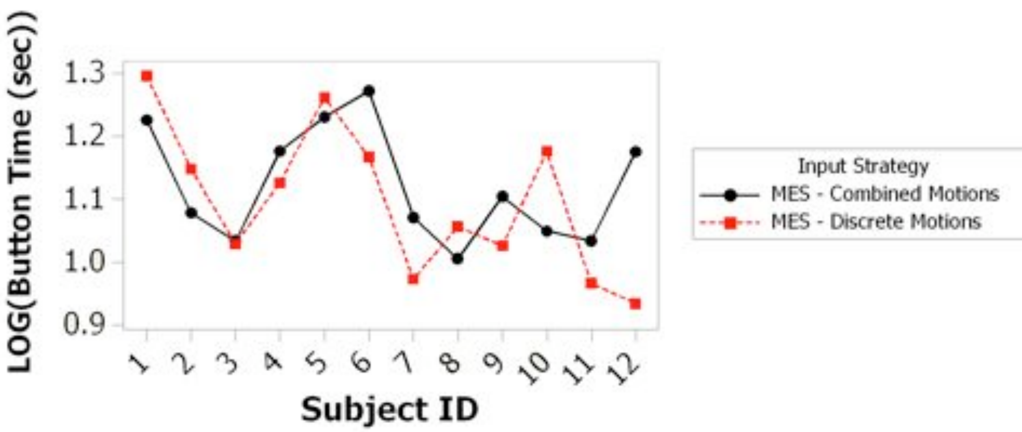


Figure 6.2 – Usability performance of MES input strategies on a per subject basis

Statistical analysis of the regrouped data failed to show significance, *p* = 0.073, although the regrouped data do appear to suggest that a possible weak learning affect may be present (Figure 6.3). The short exposure to each control strategy may have been a contributing factor to the lack of statistical significance between the two groups.

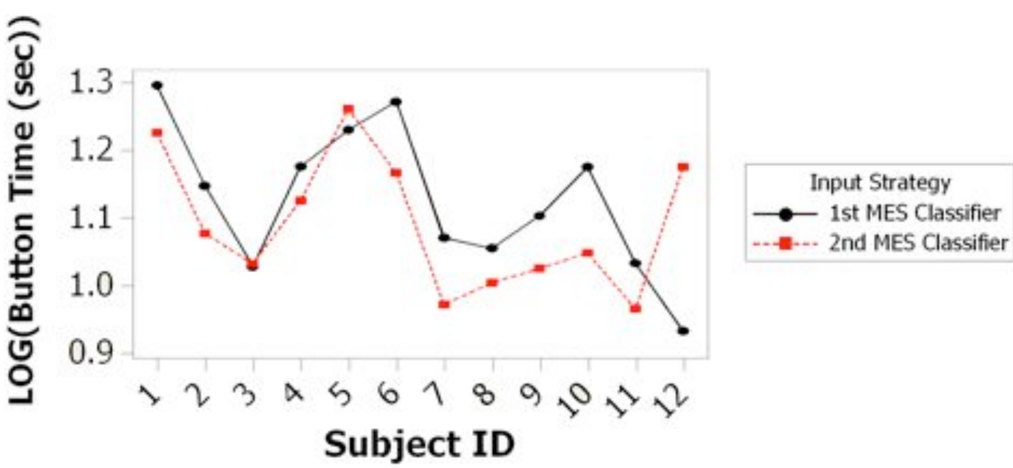


Figure 6.3 – Usability performance of regrouped MES input strategies on a per subject basis

6.2.2 Experiment Trial Effect on Usability Performance

While the purpose of the functional test was to evaluate the developed input strategies presented in this thesis, the collected data could also be used to evaluate any possible learning effect that would have occurred during the course of the experiment regardless of the order in which the strategies were presented. These data yield $p = 0.055$, indicating that no significant improvements occurred during the experiment (Figure 6.4).

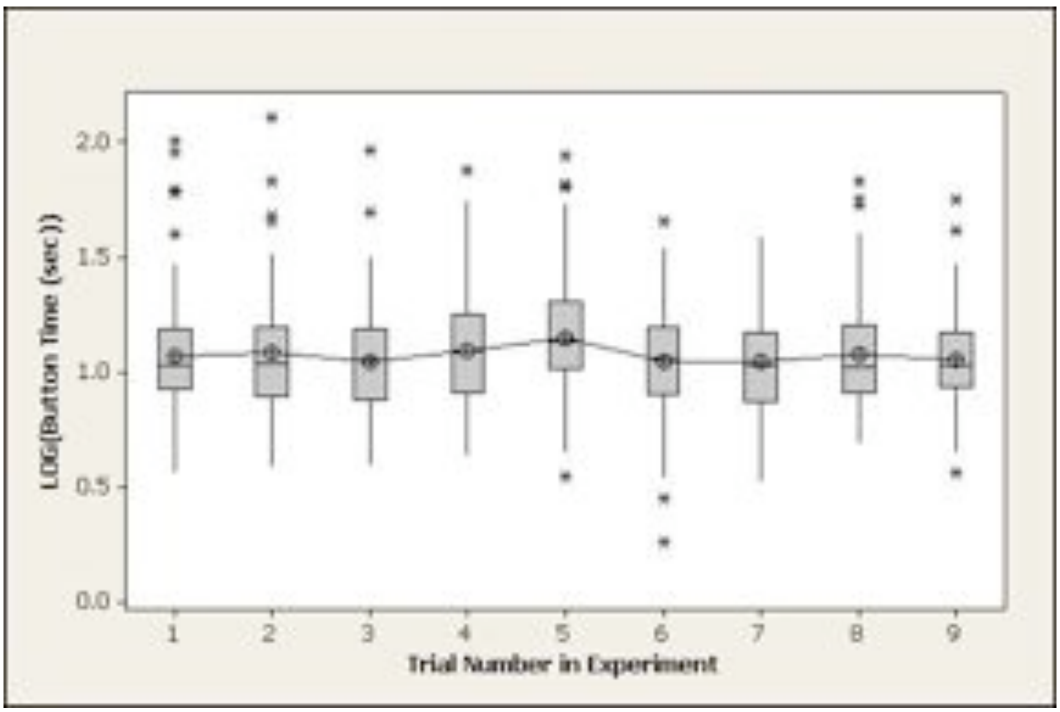


Figure 6.4 – Button time versus experiment trial number diagram

6.2.3 Strategy Specific Trial Effect on Usability Performance

The effect of trial performance for a given input strategy was further investigated (Figures 6.5-6.7). No significant differences were found for the vector projection, discrete MES motions classifier, and combined MES motions classifier strategies (p = 0.086, 0.427, 0.257 respectively). As previously stated, the relatively short duration of the experiment, both in terms of familiarization and testing, would inhibit the manifestation of such improvements. The results may have varied if users were given additional time to use the device and further familiarize themselves with the control systems' characteristics.

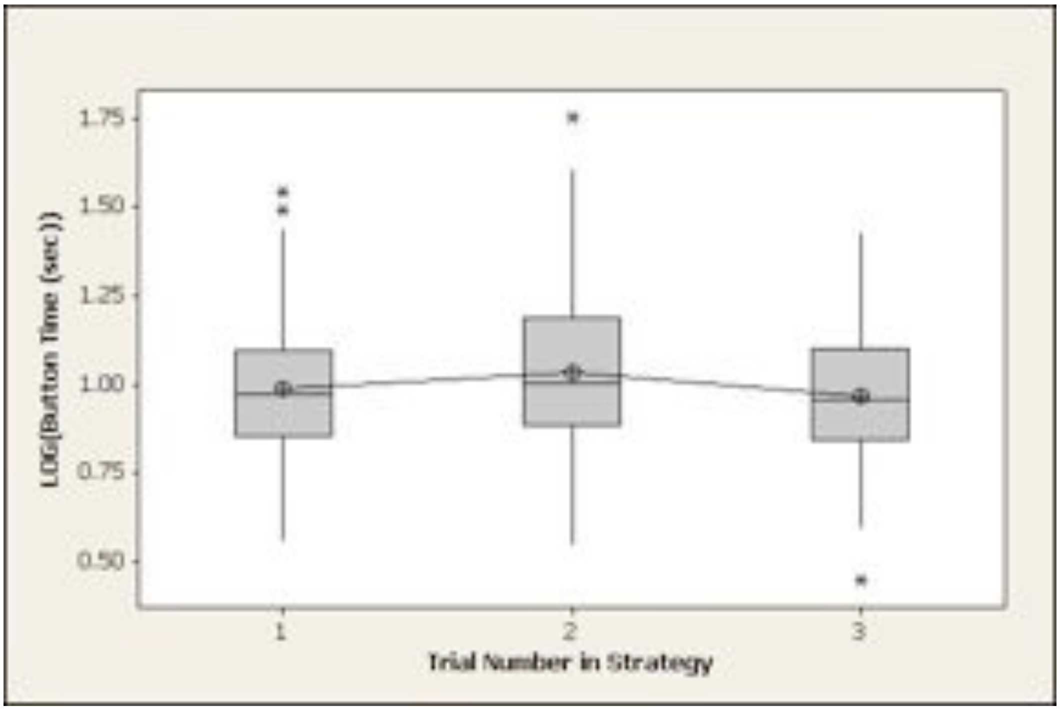


Figure 6.5 – Button time versus vector projection strategy trial number diagram

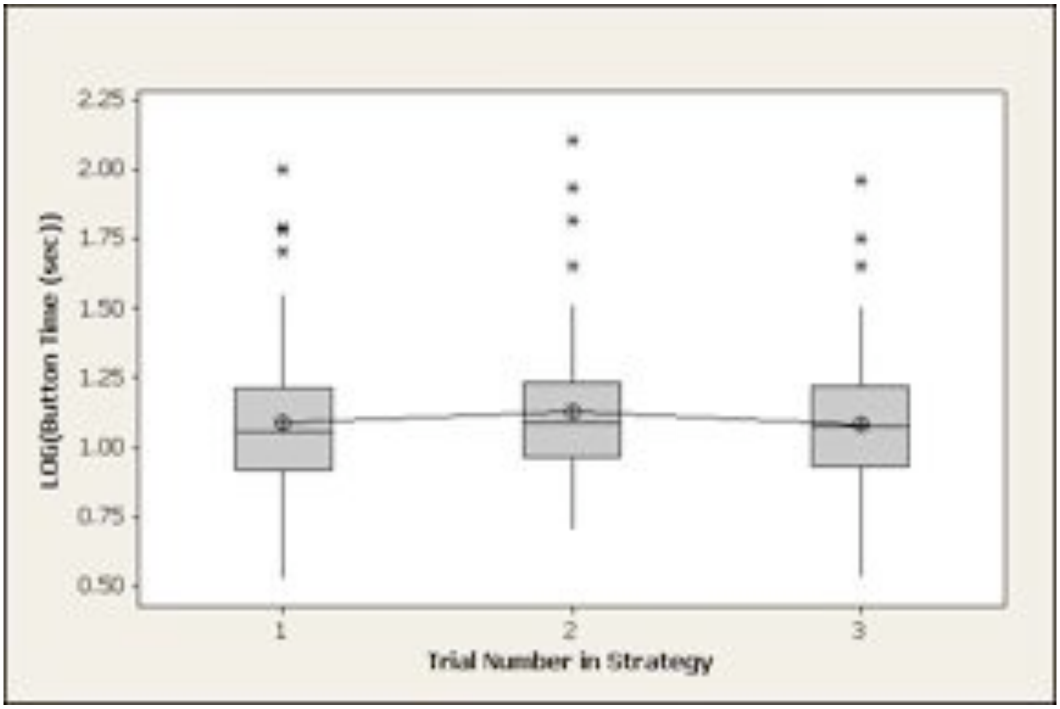


Figure 6.6 – Button time versus discrete strategy trial number diagram

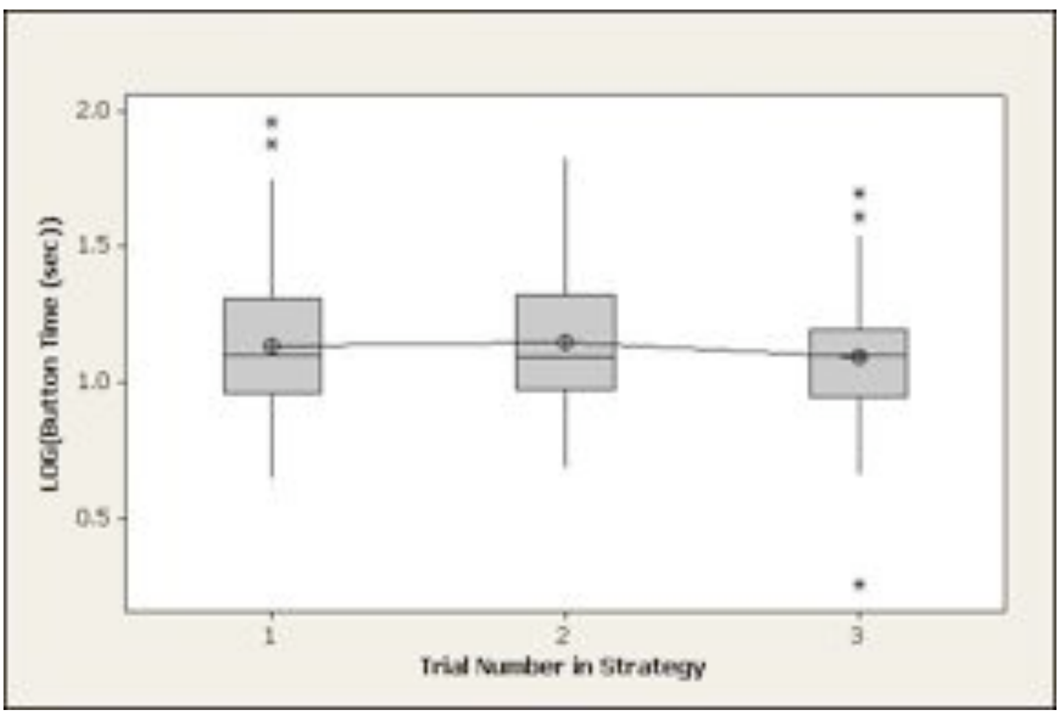


Figure 6.7 – Button time versus combined strategy trial number diagram

6.3 Mental Burden Assessment

6.3.1 Input Strategy Effect on Reaction Time

The purpose of evaluating the reaction test outcomes was to measure the additional mental load associated when performing the functional test. Previous research has used secondary tasks as a means of increasing the mental burden when performing a usability task [73, 87, 88]. Using this method provides a measure of the mental load associated with the primary task. Any sizeable mental burden difference between the input strategies could possibly suggest the elimination of the higher mental burdened strategy in favor of the others. The experimental results showed a significant difference between the strategies ($p = 0.008$, Figure 6.8). Specifically, the difference was found to be between the vector projection and the combined motion MES-only classifier strategies ($p = 0.006$). It should, however, be taken into consideration that the analysis did not find any significant difference between the discrete MES-only classifier strategy when paired with one of the two other strategies ($p = 0.287$ and 0.033 for projection/discrete and discrete/combined respectively).

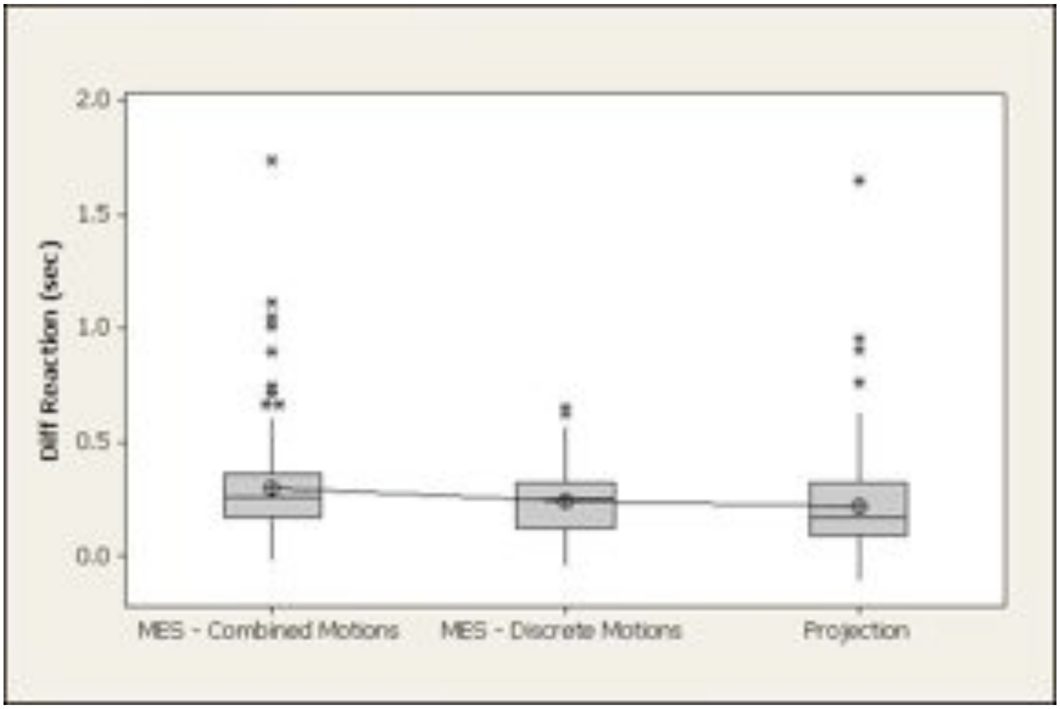


Figure 6.8 – Reaction time versus input strategy diagram

6.3.2 Experiment Trial Effect on Reaction Time

The mental burden associated with a specified control system cannot be fully associated with the chosen input strategy. The control strategy used along with the device dynamics may also contribute to the added mental load. It was hypothesized that there would be no reduction in reaction time, due to increased exposure to the endpoint control strategy from trial to trial during the experiment (Figure 6.9). A $p = 0.174$ for trial effect, over the course of the experiment, suggests that there was no significant reduction in the added mental burden over the course of the experiment. The amount did decrease, however, by approximately 100 ms when comparing the mean reaction times of the first and last trials in the experiment.

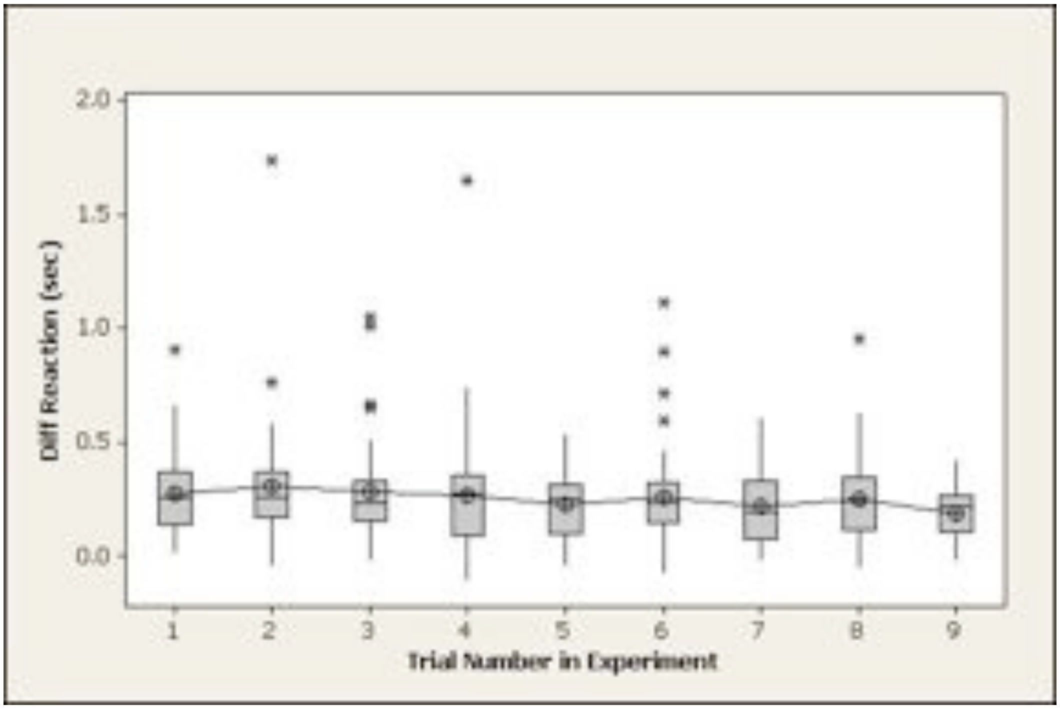


Figure 6.9 – Reaction time versus experiment trial number diagram

6.3.3 Strategy Specific Trial Effect on Reaction Time

The trial effect for a given input strategy was further investigated (Figures 6.10-6.12). No significant differences in added cognitive burden were found for the vector projection, discrete MES motions classifier, and combined MES motions classifier strategies (p = 0.406, 0.627, and 0.670 respectively). It should be noted that the data were highly variable and additional reaction test results may be desirable to provide better statistical power to the evaluation of trial effect for the given strategies.

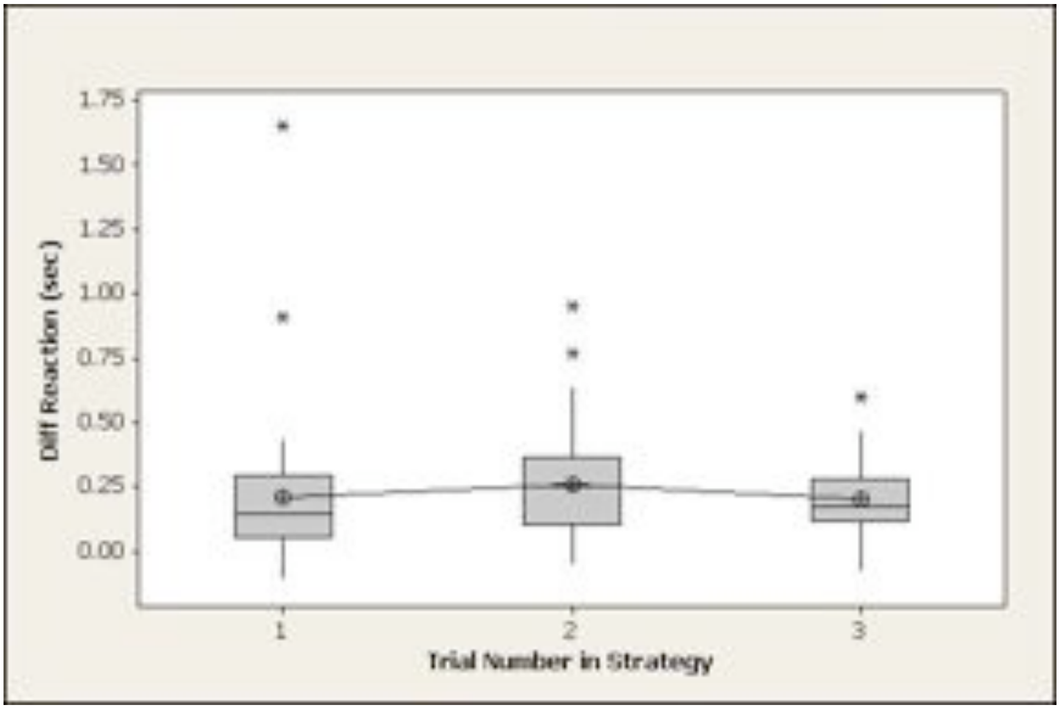


Figure 6.10 – Reaction time versus projection strategy trial number diagram

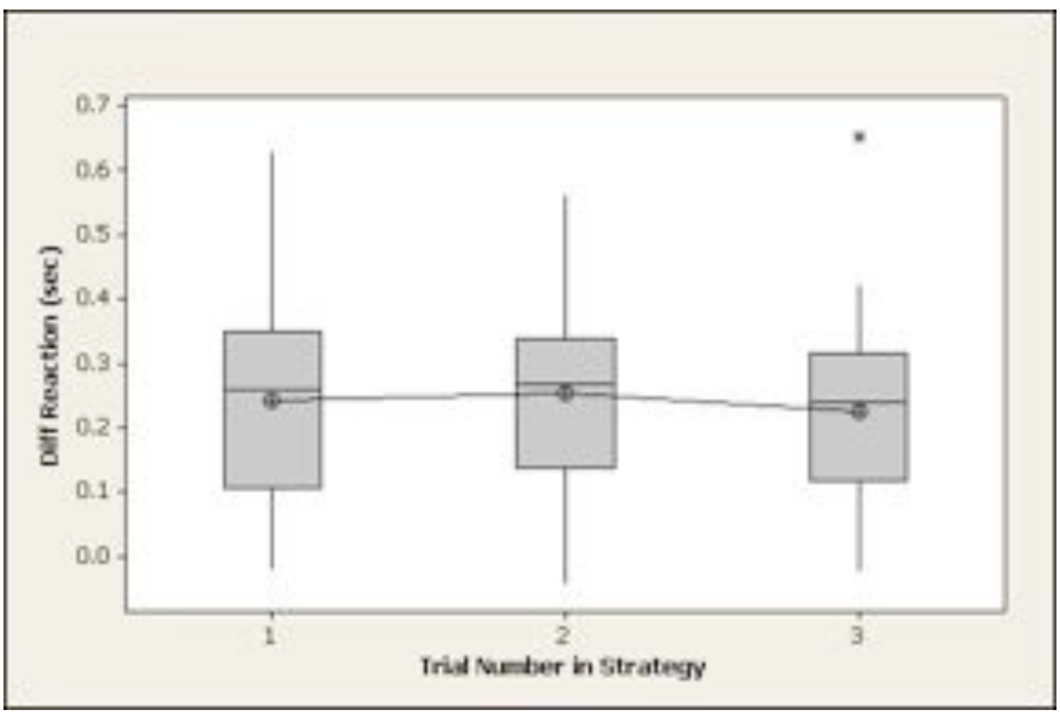


Figure 6.11 – Reaction time versus discrete strategy trial number diagram

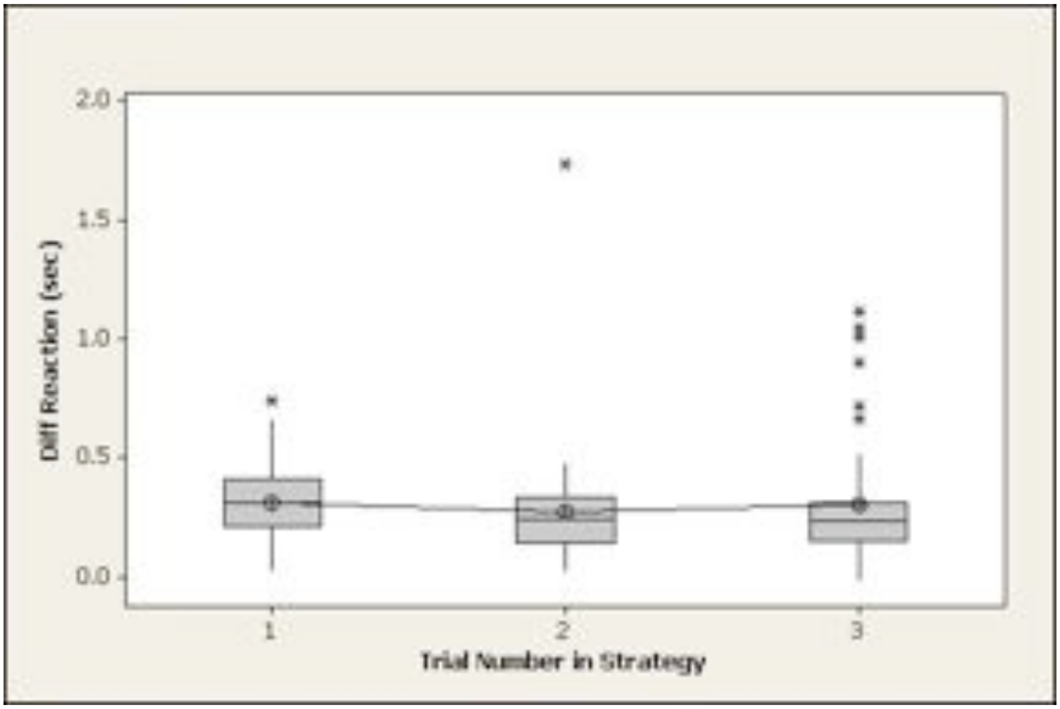


Figure 6.12 – Reaction time versus combined strategy trial number diagram

6.4 Qualitative Assessment of Input Strategies

The results presented in the previous sections of this chapter focused on providing a quantitative assessment of the investigated input strategies. Qualitative results, obtained through a short series of questions to the user, were also recorded upon the completion of the experiment. Additionally, the primary researcher recorded a number of qualitative observations throughout the data collection process. Users were asked to rate the input strategies, from most controllable to least controllable, after completing the entire experiment (Table 6.1).

Input Strategy ID	Input Strategy Name
1	Vector Projection
2	Discrete MES
3	Combined MES

		User Rated Input Strategies		
sub ID	Presented Order	Best	Middle	Worst
01	231	Projection	Discrete	Combined
02	123	Combined	Projection	Discrete
03	213	Projection	Discrete	Combined
04	321	Discrete	Projection	Combined
05	321	Projection	Discrete	Combined
06	132	Projection	Discrete	Combined
07	312	Projection	Discrete	Combined
08	123	Projection	Combined	Discrete
09	312	Discrete	Projection	Combined
10	231	Combined	Projection	Discrete
11	132	Projection	Discrete	Combined
12	213	Projection	Discrete	Combined

Table 6.2 – Qualitative input strategy user rating

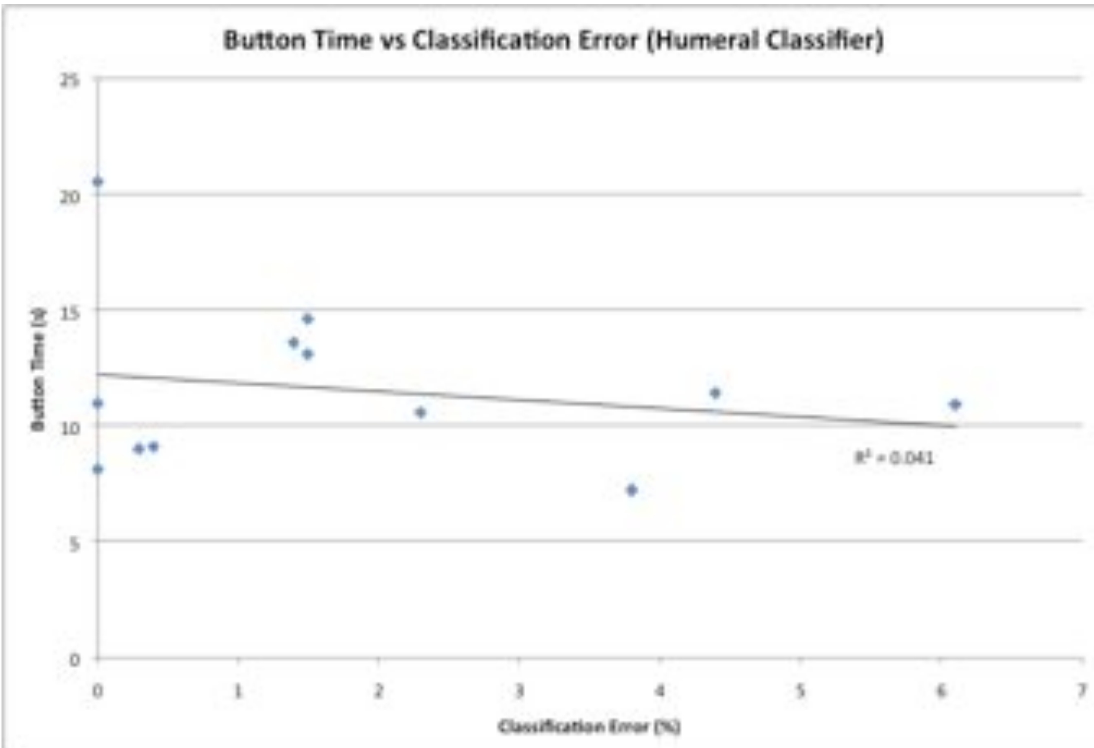
From these ratings, it can be seen that the user group mainly favored the use of the vector projection method over the two MES based classifier input strategies. These findings seem to corroborate the experiment's quantitative results. It should also be noted that the discrete MES motion classifier strategy was frequently preferred over the combined MES motion classifier strategy. Interestingly, in the three other cases, the combined classifier was seen after the discrete classifier strategy. Although no conclusions can be made from this observation, the possibility of the order influencing qualitative results does indicate the need for further investigation.

Users were also asked if any of the strategies enabled them to proportionally control the speed of the device. Most subjects identified some proportional control capabilities with the vector projection method while few felt any proportional amplitude using the MES-only based strategies. This lack of output variation has been a known issue for IBME researchers and is currently the subject of ongoing research.

On a final note, the primary researcher observed simultaneous control of two different DOF for every subject while using each strategy. This was to be expected of both the vector projection and combined motion strategies but was not, however, deemed possible by the discrete motion classifier prior to the experiment. This classifier can indeed only activate one DOF at any point in time. This apparent simultaneous control of two degrees of freedom can most likely be explained by rapid variation of the classifier outputs between two different motions (most commonly elevation and protraction).

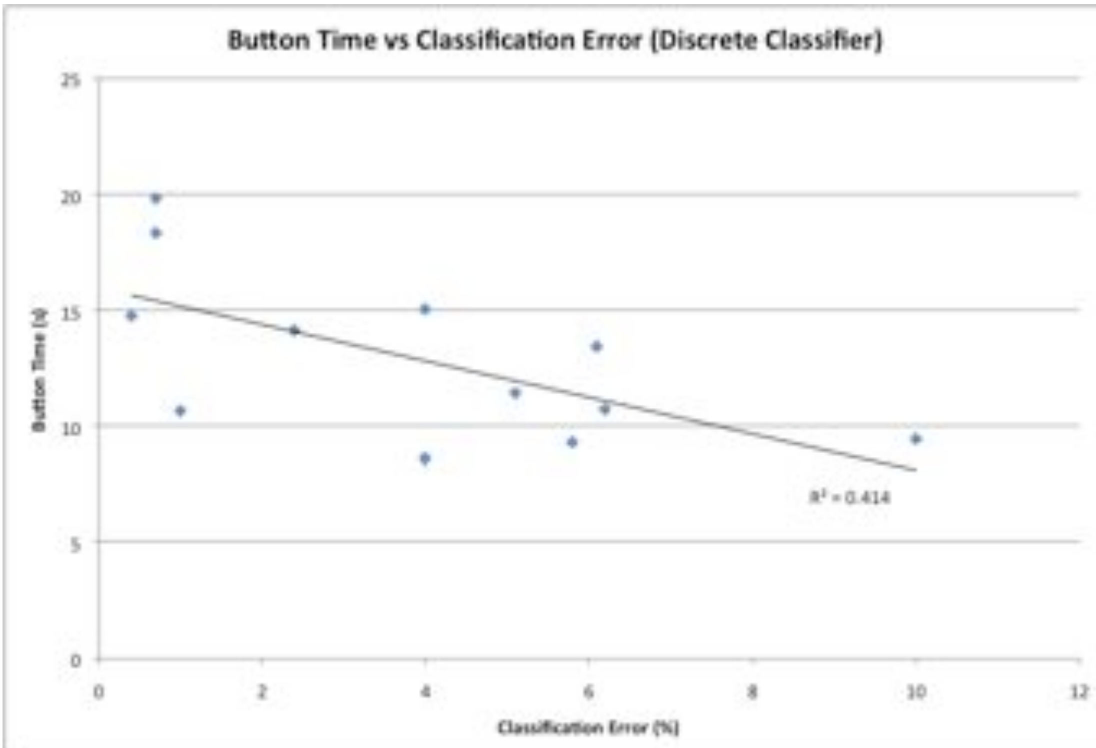
6.5 Classification Accuracy and Usability Comparison

Previous work has suggested that the often-presumed direct relationship between classification accuracy and usability performance may be affected by several other factors [75]. This conclusion was based on the results of a virtual environment clothespin usability test. Since the protocol of the usability test described in this document included the classification accuracy calculation of the MES-based classifiers, the accuracy/performance relationship was investigated.

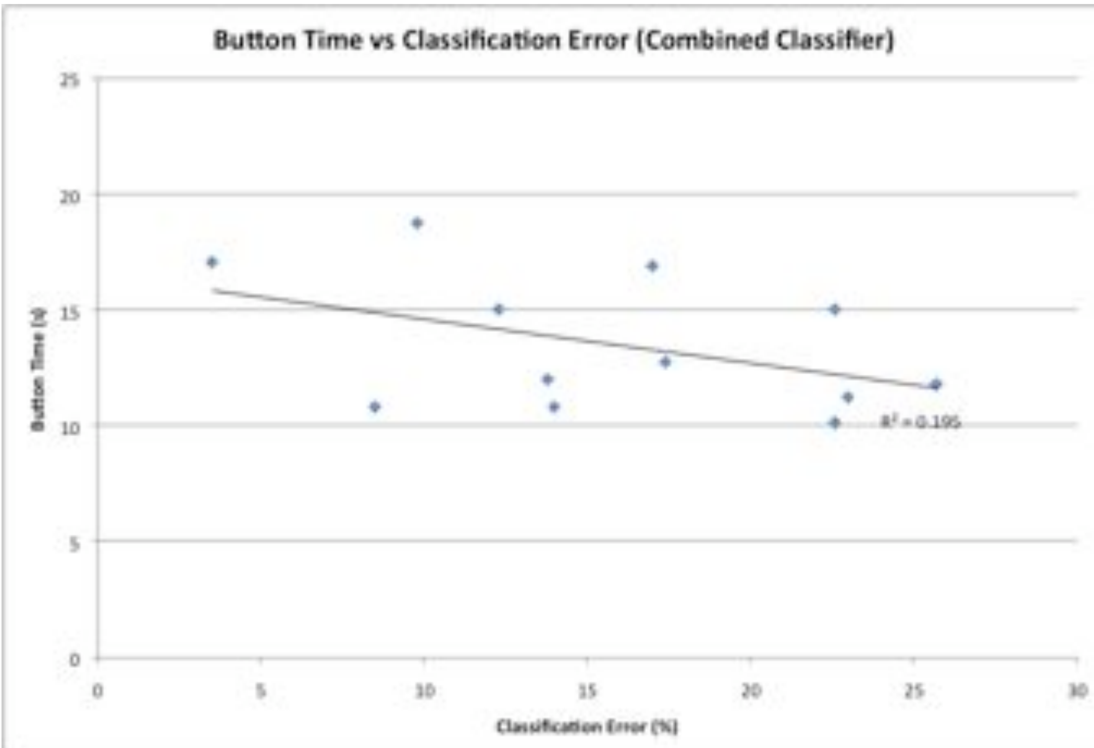


6.13 Humeral rotation (projection strategy) classification error and usability performance comparison

The humeral rotation classifier's offline error rate was compared with the usability button time results for the vector projection strategy (Figure 6.13). It can be seen that no clear relationship may be drawn from these results. Similar comparisons were performed for both MES-only based discrete and combined motions classifiers (Figures 6.14. 6.15). In both cases, there appears to be a downward trend which would indicate that a worst performance may occur when a low error rate (i.e. high classification accuracy) is achieved during offline training of the classifier. Clearly, more data would be required to further investigate these possible trends. It is of the author's opinion that the usability button time would start increasing as the error rate further increased. Unfortunately, none of the users error rates were significantly large enough to corroborate this suggestion. It is also believed that the higher usability button times for highly accurate classifiers may be the result of the users being capable of eliciting highly repeatable contraction patterns during the training session but not producing similar patterns during the actual usability test.



6.14 Discrete classification error and usability performance comparison



6.15 Combined classification error and usability performance comparison

6.6 Concluding Remarks

The usability results presented in this chapter indicate that the vector projection method was significantly better than both MES strategies. No significant difference was found between the two MES system although regrouping the data into the order in which they were presented did seem to suggest a possible learning effect. There were no apparent improvements over the course of the experiment although it was stated that the user's limited 'wear time' and familiarization might have greatly impacted the results.

Furthermore, the reaction test results did not see a highly significant difference between all the strategies.   The results were found to be highly variable and no improvements over the course of a given strategy or entire experiment were observed. This might, again, be explained by the relatively short duration of the experiment and lack of considerable practice time with the device.

The qualitative assessment demonstrated that the vector projection strategy was clearly the favored input strategy. From an observer's perspective, the discrete motions and projection methods seemed to be more robust. Most users found the discrete method to be the second best. Three users identified preferring the combined MES strategy to the discrete MES method. It was noted that these users used the combined classifier at some point after the discrete strategy.

The classification accuracy and usability performance comparison seems to be in agreement with previous research that suggests that their relationship is more complex than previously reported in literature. The results also seemed to indicate that highly accurate classifiers may have a decrease in performance when compared to a slightly less accurate classification system.

The results presented in this chapter were never meant to eliminate any of the three options but rather ensure that all could be reliably used. Some users faired better than others with the MES classifiers. Most users were able to seemingly elicit some level of simultaneous control of two DOF with the use of the discrete motion classifier. Most users reported a small learning and familiarizing curve with respect to the control systems while many reported intuitive use of the shoulder for endpoint control.

Proportional speed control was only apparent to users with the vector projection method. MES based system have often been known for their lack of proportional amplitude control and it was not unexpected to see similar results with this functional test. The evaluation of learning effects was inconclusive due to the limited scope of the functional test. It is felt that a more involved training and evaluation protocol would be necessary to properly evaluate any improvements in usability or decreased mental load.

A new non-virtual environment based usability test was performed to investigate the performance of several different control strategies aimed at high-level amputation cases. The MES based strategies are typically used in distal amputation cases and this work has shown that they are quite capable of being transferred to more proximal amputation cases. However, the projection-based method offered the best performance of the control strategies tested.

Chapter 7 – Conclusions

7.1 Summary

The intended purpose of this thesis was to exploit the input source potential found at the shoulder complex for the control of prosthetic limbs for high-level amputation cases. Chapter 2 described several key components of control systems for prosthetic applications. The information content in various input sources and its correlation to user intent was discussed. A review of the literature relating to prosthetic limb control theory and developed strategies was presented. This chapter suggested the need to modularize the control system into a series of layered components to allow focused research in developing/improving/testing specific elements of the control system as opposed to a complete control system solution.

In Chapter 3, the shoulder physiology was introduced with an emphasis on the relevant musculature used in various shoulder motions. An experimental protocol aimed at highlighting the elicited myoelectric signal activity was used and the resulting amplitude data was superimposed on their respective musculature with the use of amplitude-based colormaps. The experimental data corroborated reference literature in terms of specific elicited muscles during various upper extremity motions. Past work, which focused on humeral motion classification, was presented and its limitations were outlined. Three new classification schemes based on experimental data collected from one amputee and six able bodied individuals was described. The classifiers were based on movements originating from the shoulder complex (shoulder elevation, protraction, depression, and retraction) and humeral rotation motions. The results revealed that high offline classification accuracy could be achieved using these classification systems for the user intent interpretation layer. Furthermore, the amputee results were found to be comparable to those from the able bodied group.

A new shoulder position-based input strategy, termed vector projection, was introduced in Chapter 4. This novel mathematical framework addresses sensor installation issues related to its type, output range, and orientation while simultaneously adjusting its output signals based on the user's range of motion. These adjustments are based on a short and simple training data collection protocol performed prior to using the prosthetic device. Several adjustable parameters were outlined and their characteristics were presented. Vector Projection focused on the actual position of the shoulder rather than interpreting the MES originating from the shoulder complex musculature. Several case studies were utilized to verify its potential use and to ensure proper functionality.

Chapter 5 introduced a newly devised functional test aimed at evaluating the performance of the three input strategies presented in the previous chapters. A reaction test was also developed in an attempt to measure the added mental burden associated with the implemented schemes. These new tests were created since no currently available performance tests were capable of both quantitatively and qualitatively measure the effectiveness of the newly developed input strategies. The complete control system was formed by using an endpoint control strategy along with a servo motor-based manipulator. Users were required to press target buttons by controlling the manipulator using one of the three input strategies. The reaction test apparatus periodically prompted users to release a primary button and press a secondary button during the course of the usability test.

The analysis of the experimental results was presented in Chapter 6. The data revealed a significant improvement between the performance of the vector projection method and the two MES-based input strategies. User feedback also corroborated these findings. The reaction test results indicate that all strategies were intuitive doing little, if any, increase in mental burden. The vector projection method had consistently lower mental burden over the combined MES method and was similar in mental burden to the discrete MES method. No improvements, in either usability performance or reaction times, were observed over the course of a given strategy or the entire experiment. The experiment's relatively short duration and the user's lack of training with the device and input strategies may have reduced the ability of detecting any significant improvements or the task may have been simple enough that there was no learning necessary for accurate use due to the intuitive nature of the control strategies.

7.2 Original Contributions

In the author's opinion, several components of this research are to be considered original contributions:

1. The implementation of several new pattern classification schemes using the MES elicited during shoulder motions typically remaining for high-level amputation

cases. These schemes were shown to be intuitively controlled in a robust manner by solely using shoulder motions.

2. The development of a novel mathematical framework that eliminates some prosthesis fabrication issues related to the sensor installation, type, and range while also considering the user's range of motion. This is done, in part, by using a short preliminary data collection session to train the algorithm for the intended user and prosthesis.

3. Expanded vector projection algorithm to provide configurable parameters capable of adjusting the projection method's characteristics to suit the user's needs.

4. Successfully integrated a shoulder position-based scheme with a MES-based classifier for a new input strategy layer option.

5. Designed and implemented a new real-time functional test capable of producing quantitative and qualitative results to assess both user's performance and imposed mental burden.

7.3 Future Work

There remain several points that would benefit from additional investigation efforts:

1. Expand vector projection to include more than 2 sensors. Although the algorithm can, theoretically, be expanded into a higher dimensional input space, its actual implementation and consequent robustness remains to be seen.

2. Implement vector projection input strategy within the control system of an experimental prosthesis.

3. Investigate using vector projection with other control strategies. This may allow users to robustly incorporate EPP functionality within the overall control system with minimal setup time and effort.

4. Attempt an MES-based vector projection input strategy by linearly discriminating the input signals to provide a successful implementation.

5. Investigate the effect of the number of electrodes on usability performance of the MES-based input strategies. The investigation of the number electrodes presented in this thesis only examined offline classification accuracy results.

6. Study the effect of shoulder socket movement constriction on the performance of MES-based systems.

7. Attempt to provide proportional amplitude control for MES-based systems. The addition of proportional control would increase the usability of the MES schemes. Although this goal has eluded most distal amputation research cases, it is unclear how amplitude control will be affected by the shoulder muscle synergies.

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Appendix A – High Density MES Colormaps

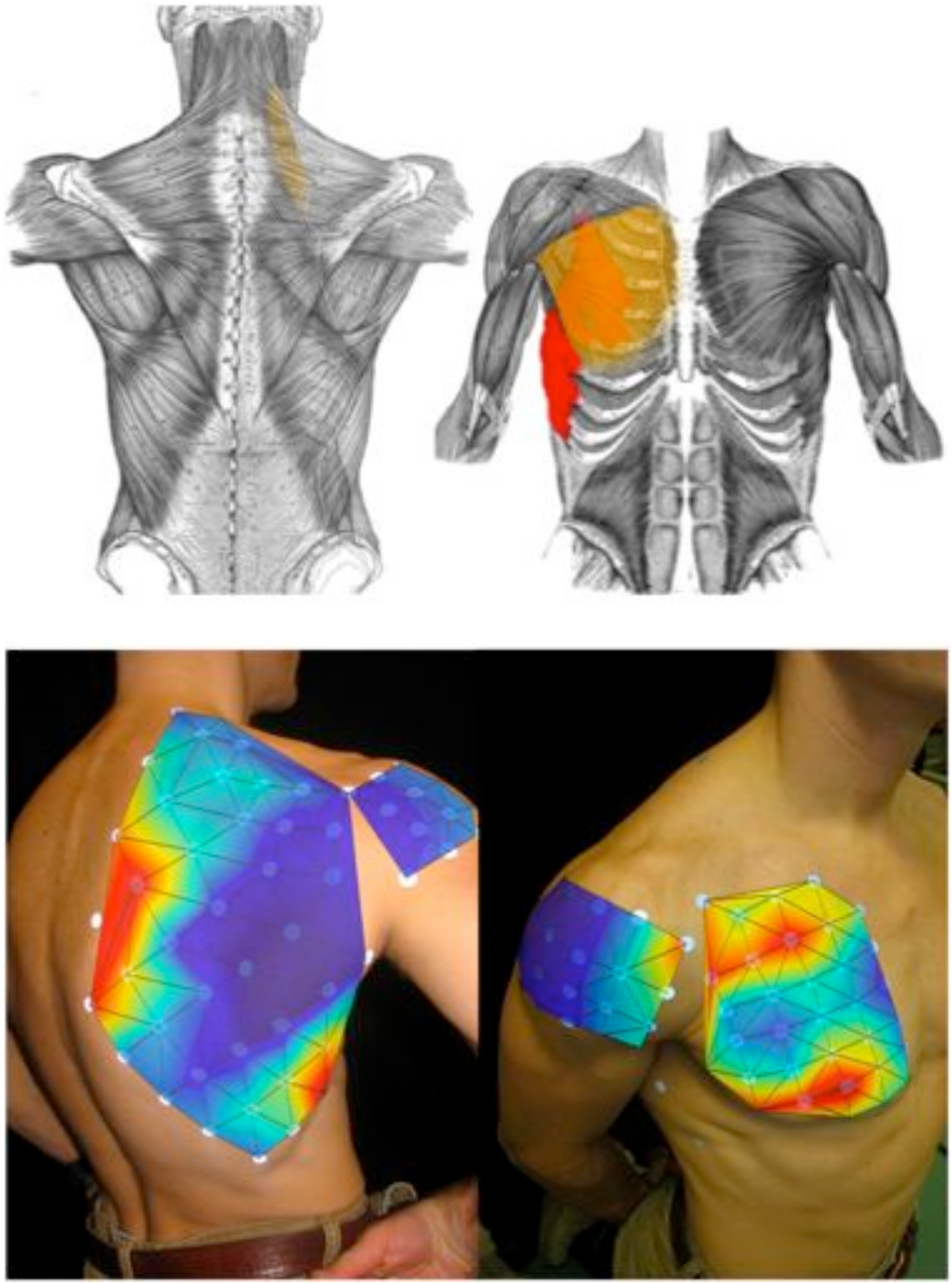

Figure A.1 - Shoulder Protraction Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

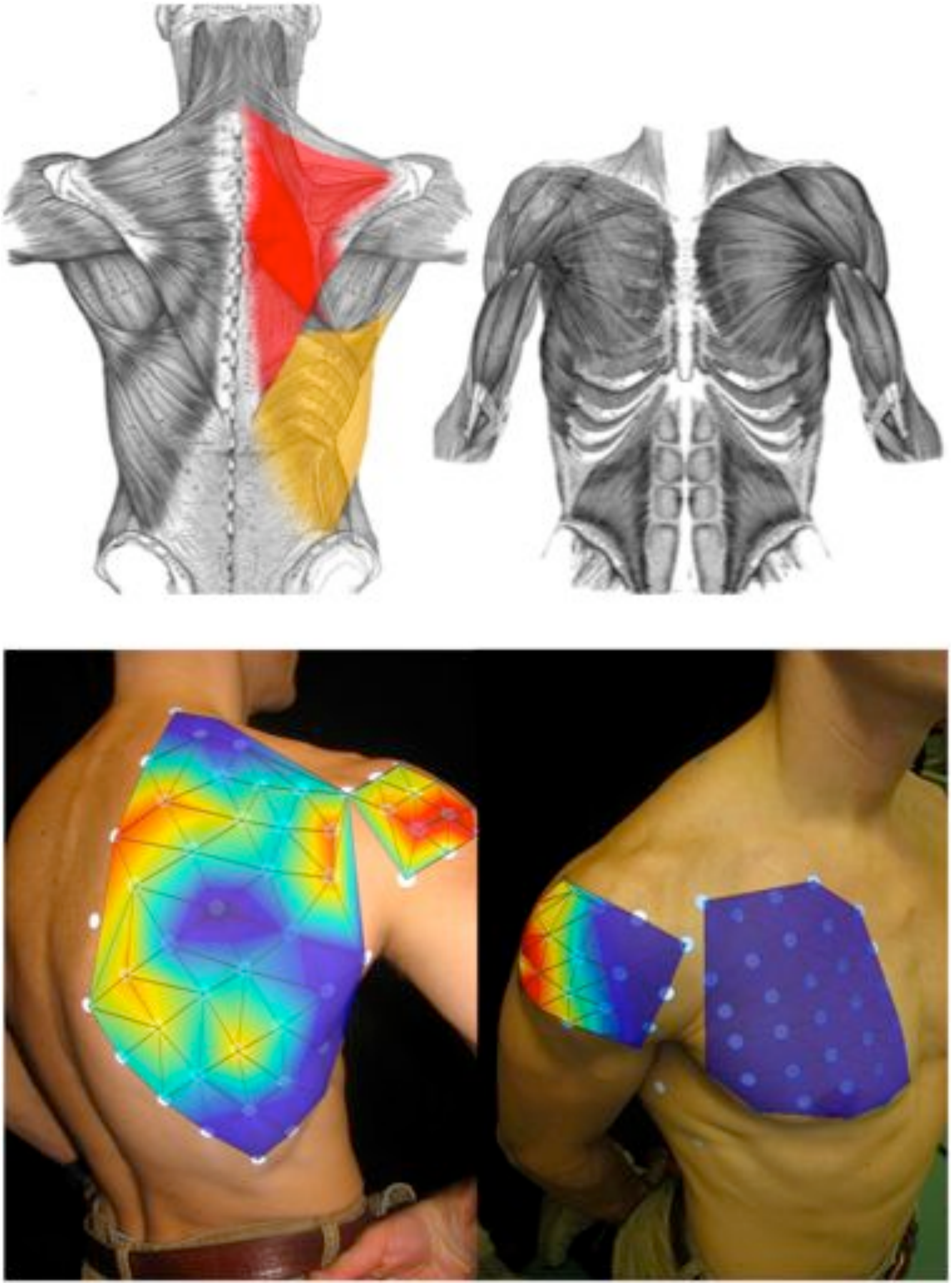

Figure A.2 - Shoulder Retraction Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

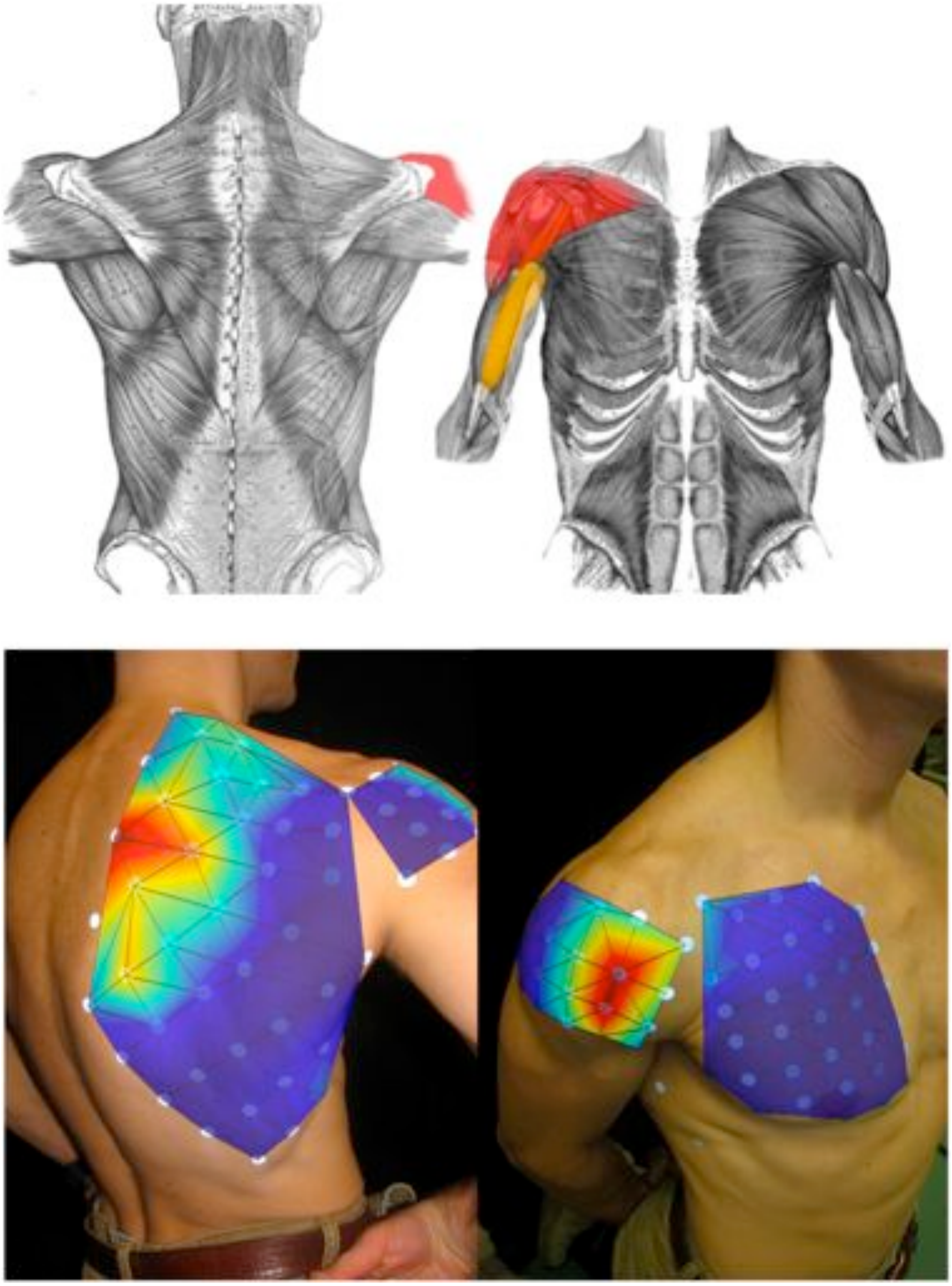

Figure A.3 - Shoulder Flexion Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

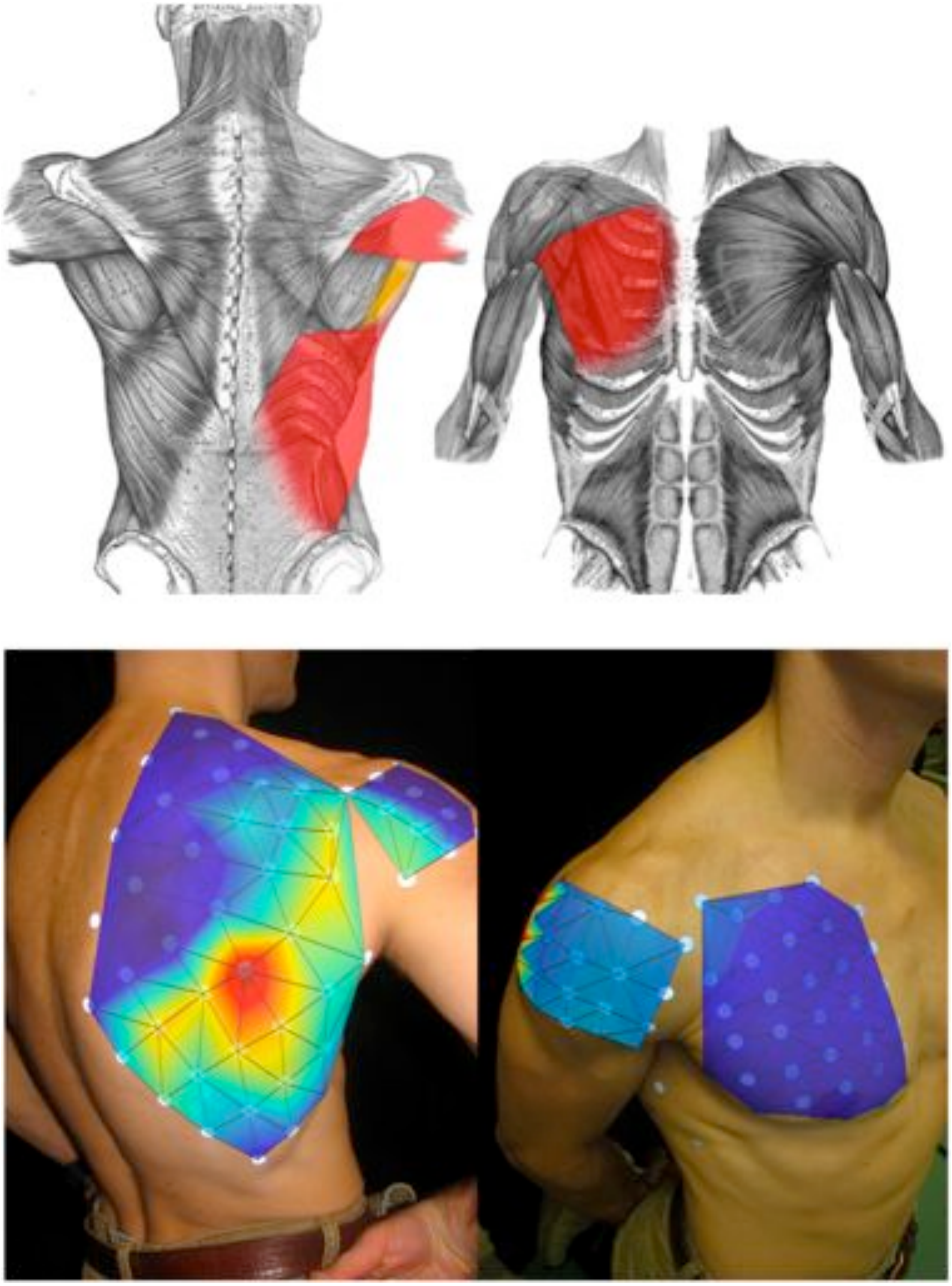

Figure A.4 - Shoulder Extension Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

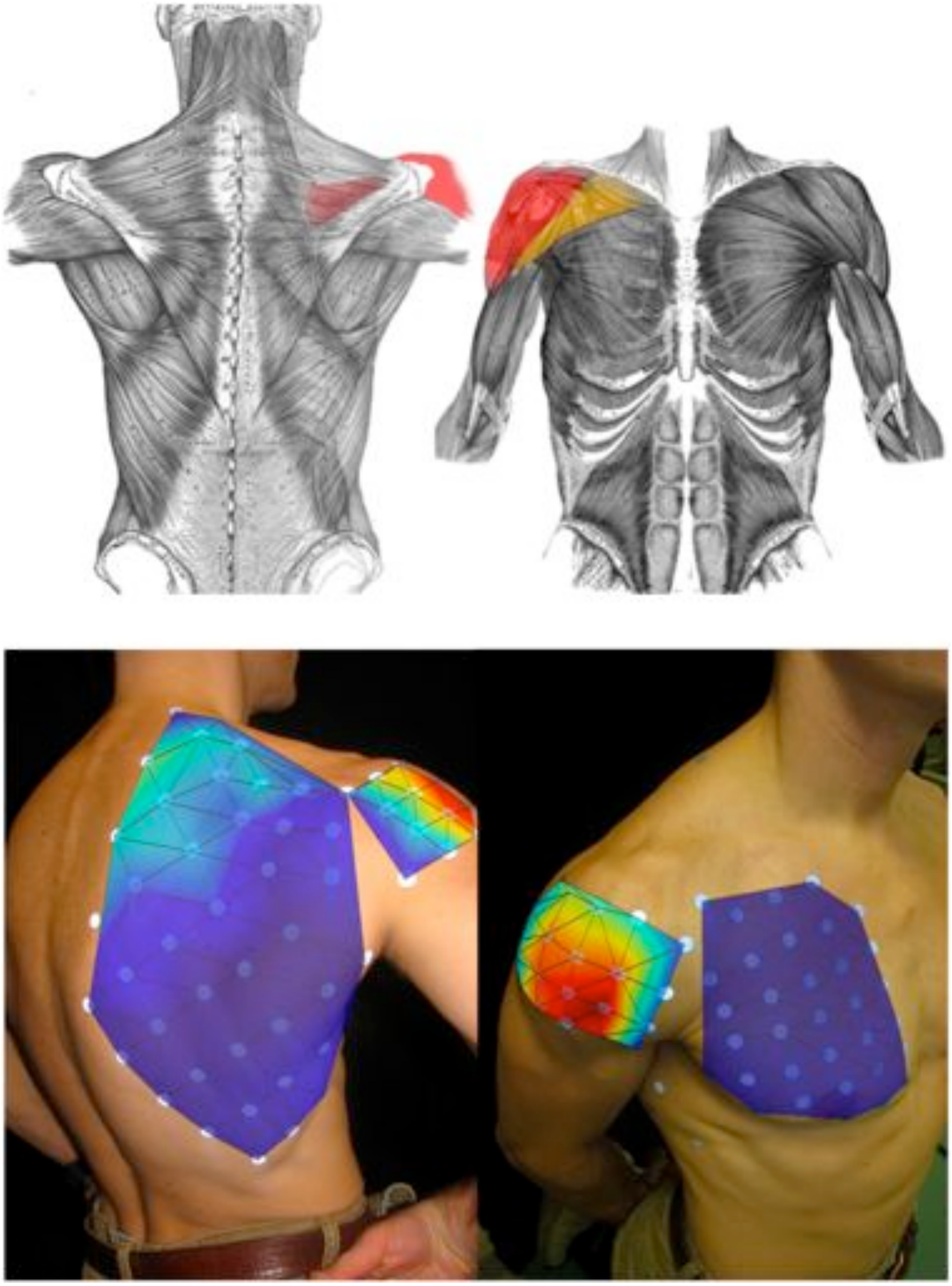

Figure A.5 - Shoulder Abduction Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

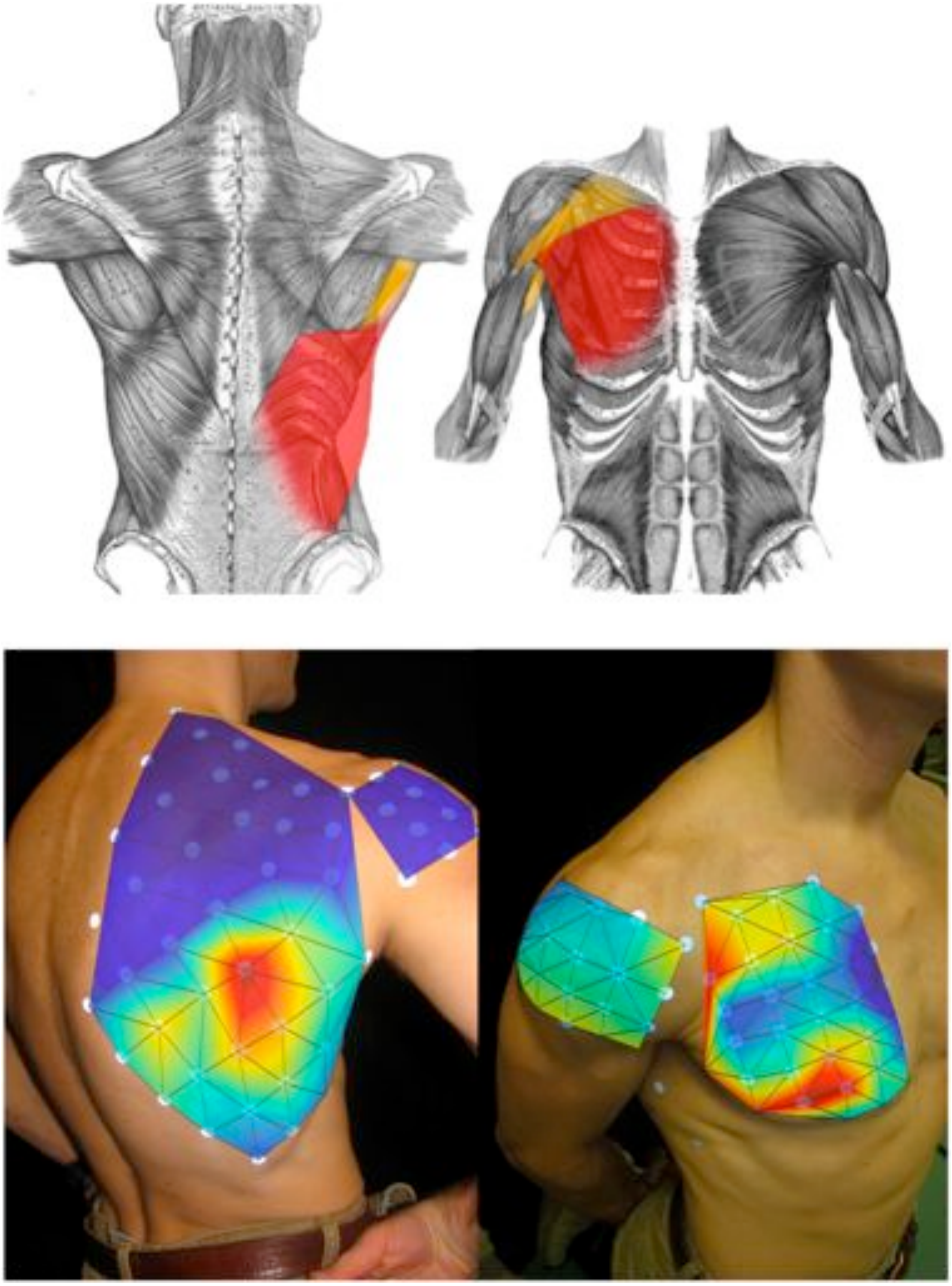

Figure A.6 - Shoulder Adduction Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

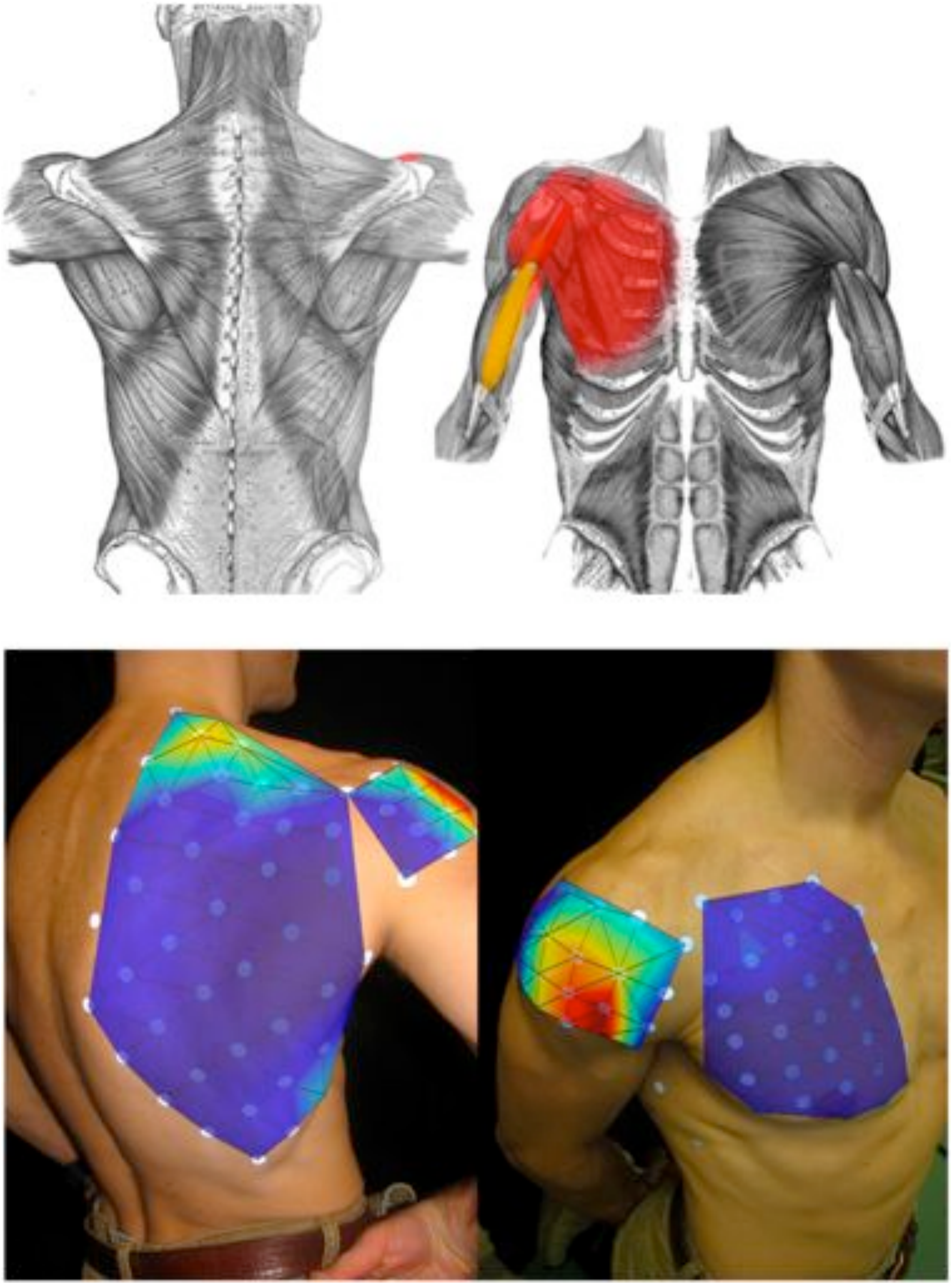

Figure A.7 - Transverse Flexion Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

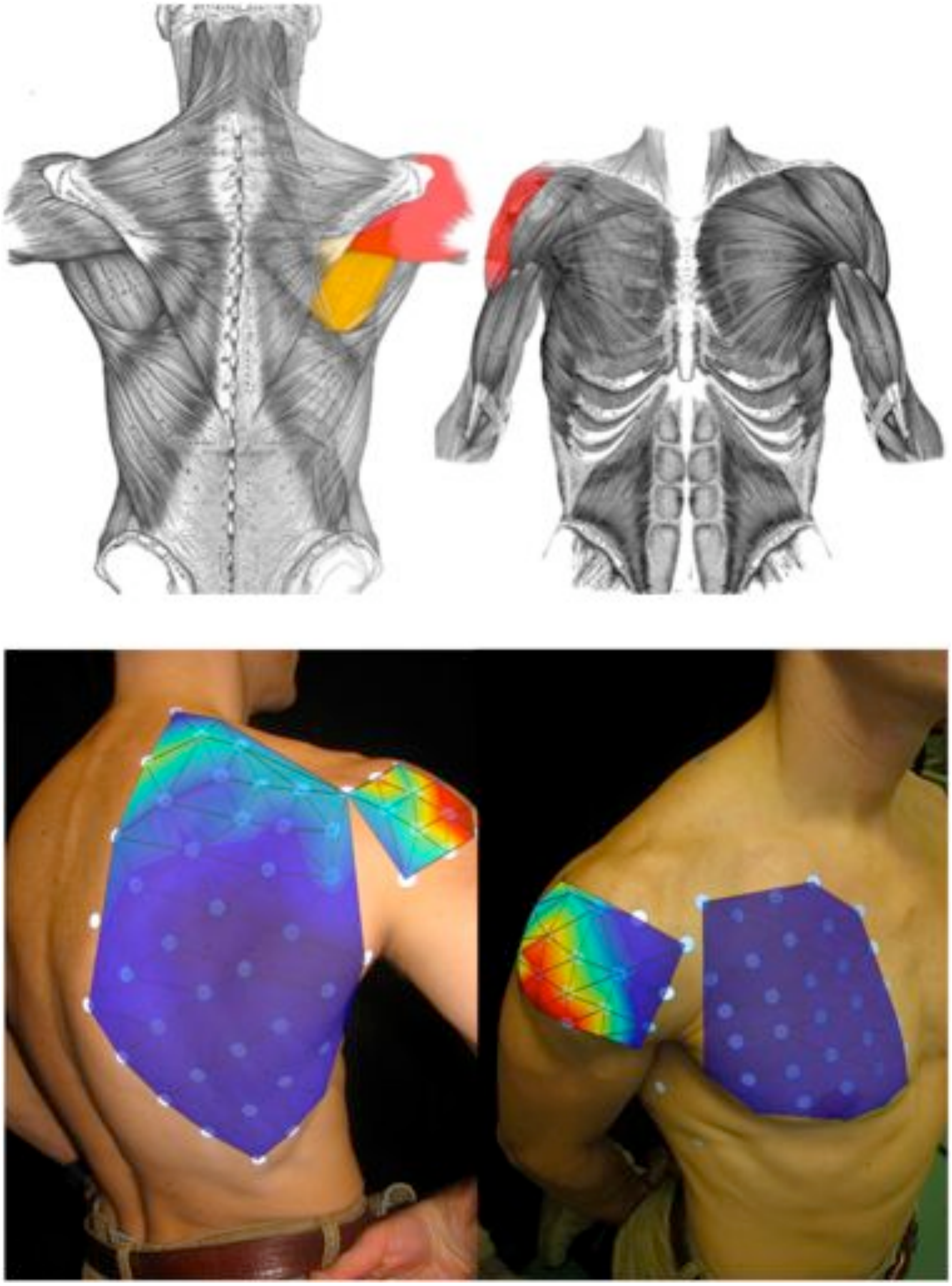

Figure A.8 - Transverse Extension Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

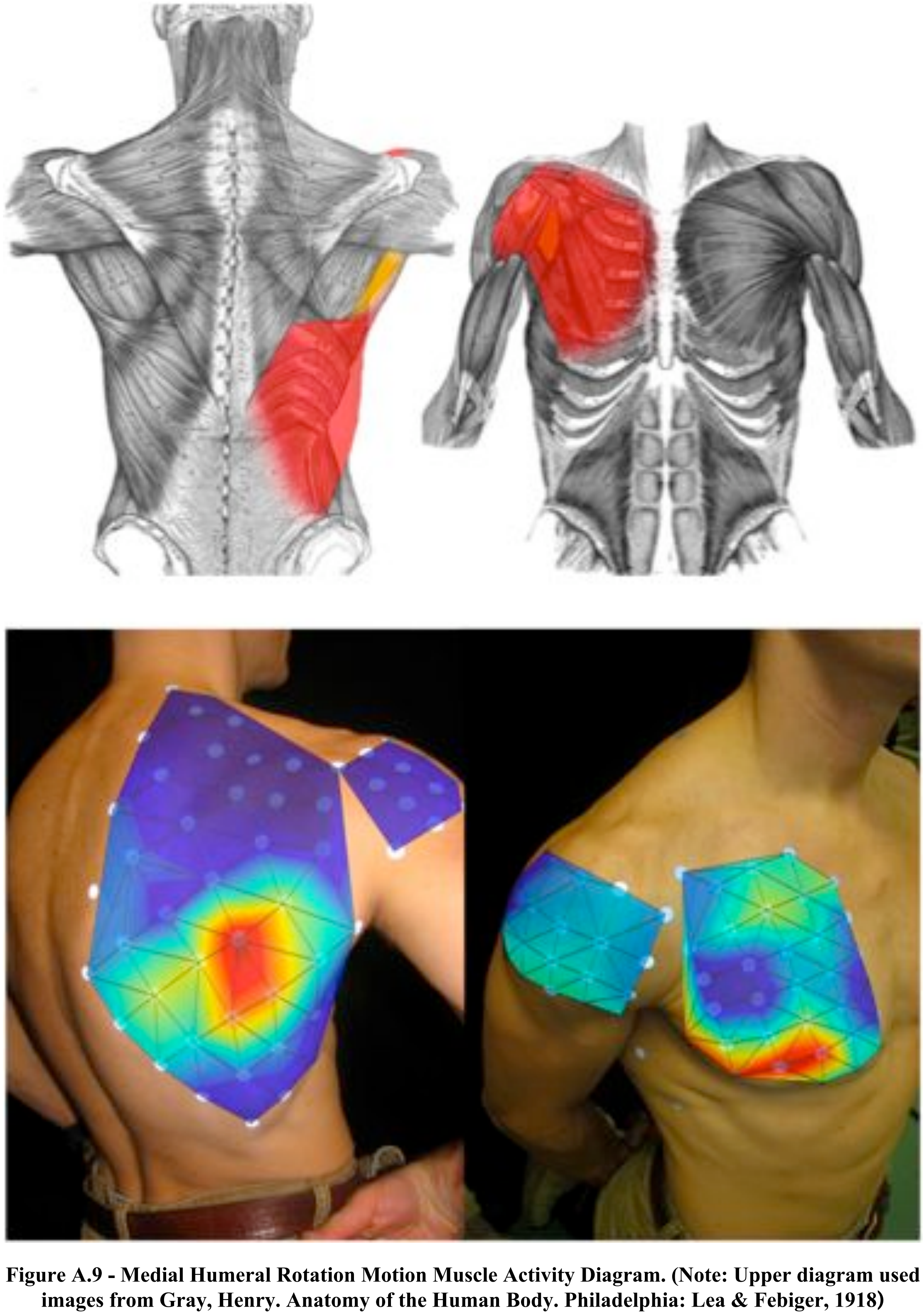

Figure A.9 - Medial Humeral Rotation Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

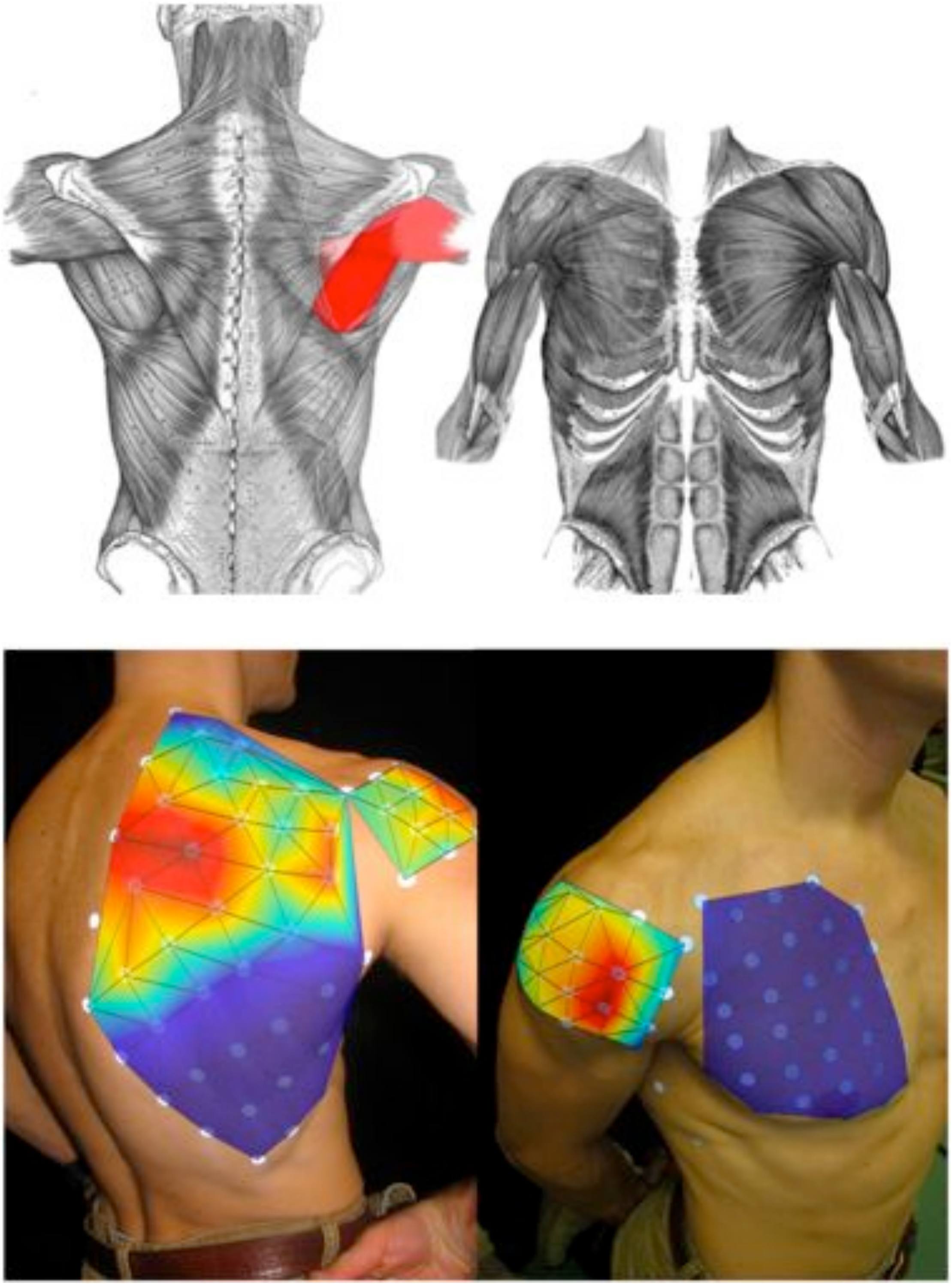

Figure A.10 - Lateral Humeral Rotation Motion Muscle Activity Diagram. (Note: Upper diagram used images from Gray, Henry. Anatomy of the Human Body. Philadelphia: Lea & Febiger, 1918)

Appendix B – Servo Manipulator Forward Kinematics

$$^{Global}T_{Endpoint} = {}^{Global}T_{JS\,1}\,{}^{JS\,1}T_{JS\,2}\,{}^{JS\,2}T_{JS\,3}\,{}^{JS\,3}T_{JS\,4}\,{}^{JS\,4}T_{Endpoint}$$

$$P = {}^{Global}T_{Endpoint}\left[0;0;0;1\right] \tag{6.2}$$

$$\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta_1 & -\sin\theta_1 & 0 & dx_1 \\ \sin\theta_1 & \cos\theta_1 & 0 & dy_1 \\ 0 & 0 & 1 & dz_1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & dx_2 \\ 0 & \cos\theta_2 & -\sin\theta_2 & dy_2 \\ 0 & \sin\theta_2 & \cos\theta_2 & dz_2 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\theta_3 & -\sin\theta_3 & 0 & dx_3 \\ \sin\theta_3 & \cos\theta_3 & 0 & dy_3 \\ 0 & 0 & 1 & dz_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & dx_4 \\ 0 & \cos\theta_4 & -\sin\theta_4 & dy_4 \\ 0 & \sin\theta_4 & \cos\theta_4 & dz_4 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & dx_{endpoint} \\ 0 & 1 & 0 & dy_{endpoint} \\ 0 & 0 & 1 & dz_{endpoint} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

where

$dx_1 =$ 0 mm	$dx_2 =$ 0 mm	$dx_3 =$ 0 mm	$dx_4 =$ 0 mm	$dx_5 =$ 0 mm
$dy_1 =$ 0 mm	$dy_2 =$ 0 mm	$dy_3 =$ 0 mm	$dy_4 =$ 0 mm	$dy_5 =$ 0 mm
$dz_1 =$ 560 mm	$dz_2 =$ -120 mm	$dz_3 =$ -200 mm	$dz_4 =$ -55 mm	$dz_5 =$ -290 mm

$$X = -290\left(\cos\theta_1 \sin\theta_3 + \sin\theta_1 \cos\theta_2 \cos\theta_3\right)\sin\theta_4 - 290\sin\theta_1 \sin\theta_2 \cos\theta_4 - 255\sin\theta_1 \sin\theta_2$$

$$Y = -290\left(\sin\theta_1 \sin\theta_3 - \cos\theta_1 \cos\theta_2 \cos\theta_3\right)\sin\theta_4 + 290\cos\theta_1 \sin\theta_2 \cos\theta_4 + 255\cos\theta_1 \sin\theta_2$$

$$Z = 440 + 290\sin\theta_2 \cos\theta_3 \sin\theta_4 - 290\cos\theta_2 \cos\theta_4 - 255\cos\theta_2$$

Appendix C – Informed Consent Form

UNIVERSITY OF NEW BRUNSWICK
INSTITUTE OF BIOMEDICAL ENGINEERING

INFORMED CONSENT

Residual Limb Motion Integration within EMG Classification Systems

Investigators: Yves Losier, Dr. B Hudgins & Dr. K. Englehart

Primary Investigator

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Dr. K. Englehart – Associate Director, Institute of Biomedical Engineering
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Purpose

This project seeks to investigate the potential benefits of incorporating shoulder motion position along with surface MES as inputs to new experimental input schemes developed at the Institute of Biomedical Engineering for the control of prosthetic limbs.

Procedure

The role of the research subjects in this research is to control a servo motor based robotic arm, using shoulder motion, in order to touch a series of pushbuttons. Either the MES produced by the muscles involved in these motions or the shoulder position itself will be measured and used as inputs to the specific control strategy. Up to sixteen channels of surface MES will be used from sixteen different control sites on upper arm, shoulder, pectoral, and back muscles. They will be chosen to reflect the muscles primarily responsible for the movement of the shoulder complex. A two-axis joystick will also be attached to the acromium skeletal landmark to allow the measurement of the joint's position. Each subject will attempt to control 3 different input control schemes. The subject will complete a training session then perform 5 pushbutton trials per input control scheme. The entire experiment will take between 1 1/2 – 2 1/2 hours.

Withdrawal

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

Feedback

Any questions, concerns or comments can be directed to any of the investigators at the Institute of Biomedical Engineering at the University of New Brunswick. Participants can also request any publications and information about the final results of conclusions from the study by contacting any of the investigators.

Telephone:	(506) 453-4966
FAX:	(506) 453-4827
Postal Address:	Institute of Biomedical Engineering University of New Brunswick PO BOX 4400 Fredericton NB E3B 5A3 CANADA

In the event that you might wish to discuss this project with someone who is not involved with it, you may contact Dr. Philip Parker, professor at the Institute of Biomedical Engineering at the University of New Brunswick, who may be reached at:

e-mail: pap@unb.ca Phone number: 453-4966

Risks

There are no known risks of injury or discomfort regarding this inverstigation. Surface electrode measurements are commonly made at the Institute of Biomedical Engineering and the risks associated with these measurements are minimal and include slight skin irritation associated with skin preparation. All measurement devices used in this experiment are isolated to ensure subject safety.

Potential Benefits

There are no direct benefits to participants in this study.

Confidentiality

The identity of the participant will be kept strictly confidential unless consent is obtained from the participant. Any scientific report, presentation, or publication of the data will refer to the participant using a subject number. Information on the participant's sex and age may be used.

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: ___________

Curriculum Vitae

Candidate's full name: Yves Gilles Losier

Universities attended:

University of New Brunswick; Fredericton, NB Canada
B.Sc.E (Mechanical), 2002
University of New Brunswick; Fredericton, NB Canada
M.Sc.E (Electrical), 2004

Conference Presentations:

Losier, Y., Englehart, K., Hudgins, B. "Residual Shoulder Motion Vector Projection", The 31st Canadian Medical and Biological Engineering Society Conference, Montreal, Canada, 2008

Losier, Y., Englehart, K., Hudgins, B. "High Density MES Mapping of the Shoulder Complex Musculature", The 17th Congress of the International Society of Electrophysiology and Kinesiology, Niagara Falls, Canada, 2008

Hargrove, L., Losier, Y., Englehart, K., Hudgins, B. "Feature Space Trajectories for use with Myoelectric Control of a Prosthetic Limb", The 17th Congress of the International Society of Electrophysiology and Kinesiology, Niagara Falls, Canada, 2008

Losier, Y., Englehart, K., Hudgins, B. "A Control System for a Powered Prosthesis Using Positional and Myoelectric Inputs from the Shoulder Complex", The 29th IEEE EMBS Annual International Conference, Lyon, France, 2007

Hargrove, L., Losier, Y., Englehart, K., Hudgins, B. "A Real-Time Pattern Recognition Based Myoelectric Control Usability Study Implemented in a Virtual Environment", The 29th IEEE EMBS Annual International Conference, Lyon, France, 2007

Losier, Y., Englehart, K., Hudgins, B. "Residual Shoulder Motion MES Classifier", The 30th Canadian Medical and Biological Engineering Society Conference, Toronto, Canada, 2007

Losier, Y., Englehart, K., Hudgins, B. "Prosthetic Control Using Multiple Degrees of Freedom of the Shoulder as Inputs and ANNs", The 28th Canadian Medical and Biological Engineering Society Conference, Quebec City, Canada, 2004