INVESTIGATION OF MUSCLE SYNERGIES AS A REAL-TIME CONTROL STRATEGY FOR MYOELECTRIC CONTROL OF UPPER LIMB PROSTHESES

by

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ABSTRACT

Electromyogram (EMG) pattern recognition has long been used for the control of powered upper limb prostheses by many researchers. However, several factors such as complexity of motions and variation of applied force challenge the robustness of pattern recognition control in practical use. Such challenging factors must be accommodated to yield truly robust performance of myoelectric control in real task oriented use. Motivated by the growing need to add functionality to current commercially available myoelectric prostheses, the current study is focused on helping with improvement of prosthetic device control toward being intuitive. The novel contribution of this research is the development and test of a platform and control algorithms based on a concept called muscle synergies which was initially introduced to explain the control strategy of the central nervous system (CNS) for coordinating muscles during motions. Based on the physiological attributes muscle synergies, the current research uses this concept toward control of prosthetic devices in a more natural feeling and physiologically expected manner.

One important factor in the proportional control of prostheses is to estimate the level of muscle activity produced by the user performing the tasks. Our first study was to investigate the ability of synergies in estimating the produced force with the goal of using this estimation toward proportional control. For this aim, a regression control was performed in which the output was explicitly a single or multi-DOF estimate of force. The extracted muscle synergies demonstrated high repeatability for different repetitions of the

same tasks and were quite robust across different force levels. The results indicated that muscle synergies are an effective representation of EMG in force estimation of multi-DoF tasks. Our observations strengthened the idea that predicting the forces produced in unknown levels can be possible by training the model with synergies. Also, it supported the idea that the synergies might be resilient to force changes to some extent. Evaluating their ability of force estimation in an offline test, synergies outperformed MAVs. However, a real-time control test reported no significant difference between the performance of synergies and MAVs.

In an attempt to understand the dynamics of synergies, they were used as features of a pattern recognition based task classification. Also the effect of several factors such as force variation, complexity of tasks, features that synergies are extracted from, and the number of EMG channels, on the performance of synergies were examined. In general, relatively low classification errors were yielded by synergies. However, other than the cases with relatively large number of channels and synergies, the study showed that synergies' performance was generally lagged behind that of TD features.

As the performance of the proposed classification model basically depends on the choice of features and synergies, methods of producing more reliable and robust synergies were also investigated. Moreover, alternative heuristic methods were explored in an attempt to improve the synergy results outside of straightforward pattern recognition methods. Accordingly, the final study addresses the training issues and explores the classifier architecture issues. To mitigate the training issues and to improve the consistency of extracted synergies, three strategies were tested: using a validation set to select synergies, increasing the training data size, and constraining the solution space for synergy extraction method. Although, all three methods improved the results achieved by synergies, in all cases TD features still showed better performance than synergies. To explore the classifier architecture issues, strategies such as pooling synergies with TD features and extracting task specific synergies were tested. Both strategies significantly improved the previously achieved results.

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ANN	*Artificial neural networks*
ANOVA	*Analysis of varince*
AR	*Auto-regressive*
ARMA	*Auto-regressive moving*
CFFs	*Converging force fields*
CNS	*Central nervous system*
CV	*Coefficient of Variance*
DOF	*Degree of Freedom*
EMG	*Electromyography*
FA	*Factor analysis*
FD	*Frequency domain*
FSR	*Force sensing resistors*
GMMs	*Gaussian mixture models*
HMM	*Hidden markov model*
IAV	*Integrated absolute value*

ICA	*Independent component analysis*
ID	*Index of difficulty*
iMES	*Implantable myoelectric sensor*
KF	*Kalman filter*
LDA	*Linear discriminant analysis*
MAV	*Mean absolute value*
MLP	*Multilayer perceptron*
MT	*Motion time*
MVC	*Maximum voluntary contraction*
NMF	*Non-negative matrix factorization*
PC	*Principle component*
PCA	*Principal component analysis*
RMSE	*Root mean square error*
SC	*Slope sign change*
sEMG	*Surface electromyography*
STFT	*Short-time Fourier transform*

SVD	*Singular value decomposition*
SVM	*Support vector machine*
TD	*Time domain*
TMR	*Targeted muscle reinnervation*
WL	*Waveform length*
WPT	*Wavelet packet transform*
WT	*Wavelet transform*
ZC	*Zero crossing*

CHAPTER 1 – INTRODUCTION

1.1. Motivation

Without the hand our idea of the world would be flat and lacking contrasts [1, 2]. The inability to grasp and manipulate objects, inability to sense and explore the surrounding world, and inability to use gestures to support speech and express emotions, only partially reflect the situation forced by limb deficiency. Congenital limb deficiencies and amputation surgeries leave an estimated 2.5 million amputees living in North America alone [3]. A current technological aid for upper limb amputation and deficiency is represented by the use of upper limb prostheses. These devices are of three types; (i) cosmetic, (ii) body powered and (iii) myoelectric. Cosmetic prostheses are passive and do not provide precise hand control or grasp. Body powered prostheses use a harness fastened around the user's shoulder or upper torso with a mechanical hand or hook at the other end, which is controlled by upper body movements. Myoelectric prostheses, which are the focus of our studies, enables the user to control the prosthesis by contracting the muscles in the residual limb, generating EMG signals that activate the motor in the elbow, wrist or hand.

Leading industrial developers of myoelectric prosthesis are Ottobock (Germany), LTI (USA), Motion Control (USA), RSL-Steeper (UK), and Touch Bionics (USA) [4]. Yet surveys [5] on the use of these devices reveal that 30-50% of amputees do not use their prosthetic limbs regularly, basically due to its low functionality, poor cosmetic and unnatural appearance, lack of sensory feedback, and low controllability [4]. A recent survey of amputees indicates that they still desire that their prostheses can function in a life-like manner and to be more intuitively controlled [6].

Understanding that loss of a limb results in a significant change in lifestyle, it has become important to study the needs of amputees and to focus on ways to improve the usability of prostheses. One aspect of the performance of upper limb prostheses is the responsiveness of the prostheses. This factor requires that the user does not feel that they have to wait for the prosthesis to react. For a life-like movement the prosthesis is required to perform at the appropriate speed. For example, a finger should cover its full range of flexion in around one second, similarly for the wrist and elbow [7]. Controlling the joints at this speed is a consideration for the design and use of the control format.

Another factor of usability of prostheses is their dexterity, which refers to the speed and the number of degrees-of-freedom (DoFs) under control. Reliability is another factor in prosthesis usability. It indicates that under the similar circumstances, the prosthesis works always the same without occurrence of any unexpected function or fault. Naturally most users wish to have a prosthesis that allows them to conduct their lives with the minimum of outside help. Thus, they will not choose a hand that they cannot rely on and an unreliable prosthesis will rapidly be rejected.

The design and control of an upper limb prosthesis with the mentioned different but interrelated usability factors is a very challenging task. Despite many breakthroughs over the last several years [8-11], there is still a considerable gap between human hands and artificial hands in the efficacy of imparting control [12, 13]. Current research into control paradigms for myoelectric prostheses has recently focused efforts on investigating pattern recognition algorithms, which map individual functions and DoFs to the composite EMG activity pattern observed from all myoelectric input sites. Because of consistent improvements in the practical performance of this technique, pattern recognition-based myoelectric control has found acceptance and has recently been commercially deployed for the first time [14]. However, several factors such as load effect and variation in hand position, amount of applied force, and electrode placement challenge pattern recognition control in practical use. Such challenging factors must be accommodated to yield truly robust performance of myoelectric control in real task oriented use. It is expected that by improving the control strategies in different aspects of controllability including accuracy, intuitiveness and response time [15], upper limb prostheses might experience a higher rate of acceptance.

Motivated by the growing need to add functionality to current commercially available myoelectric prostheses, the current study is focused on helping with improvement of prosthetic device control toward being intuitive. The novel contribution of this research is the development and test of a platform and control algorithms based on a concept called muscle synergies which was initially introduced to explain the control strategy of the central nervous system (CNS) for coordinating muscles during motions. This is discussed thoroughly in Section 2.4. Based on the physiological attributes muscle synergies, the current research uses this concept toward control of prosthetic devices in a more natural feeling and physiologically expected manner.

1.2. Main Objectives

Considering the issues mentioned in the previous section about the current methodologies used for prosthesis control, it is essential to investigate solutions with the potential to improve the current control methods. This manuscript describes the author's investigations of the use of muscle synergies as a potential paradigm for the control of multi-DoF myoelectric devices. Muscle synergies have been proposed as groups of muscles whose activity levels are neurally coupled and form the basis vectors of complex muscle coordination patterns. Specifically, this work aims to discover if muscle synergies can be useful in pattern recognition control across the variety of intensity levels and force patterns observed during the formation of a wide range of hand postures. Also, this work investigates the power of muscle synergies in task identification toward simultaneous and proportional control of prostheses.

1.2.1. Predictive Framework for Intensity Level

One method identified for improving the quality of myoelectric control is proportional velocity control using modulation of contraction intensity. This method is available in some conventional commercial prostheses such as BeBionic3 [16], the iLimb Ultra [17], and the SensorHand Speed [18]. Also, some groups have proposed proportional control methods for pattern recognition control schemes [19- 21]; however, the consequence of using such methods can compromise classification performance [22]. The concurrent use of signal amplitude from multiple channels for both proportional control and as a feature for classification creates challenges, which are exacerbated by the existence of crosstalk and amplitudes that scale differently between channels as contraction intensity varies. Moreover, little work has been published specifically examining the optimality of proportional control algorithms for multi-channel myoelectric control. In this regard, objectives below are investigated in the current work:

- The effect of modulating contraction intensity for proportional control is examined when using pattern recognition based control.
- A novel strategy for deriving multi-channel proportional control is proposed
- The advantages of a neuromuscular synergy based paradigm for real-time proportional control of multi-DOF myoelectric devices are investigated.

1.2.2. Synergies as Control Inputs for Multi-Dof Control

It is important for the proposed synergy-based platform to be able to distinguish the tasks performed in various force levels. Such a paradigm may be more successful and intuitive for controlling myoelectric devices than the currently implemented paradigm based on the widely used time domain (TD) features proposed by Hudgins [23] because it potentially takes advantage of knowledge of the pre-existing neurally coded muscle groupings.

Many investigations have shown muscle synergies to be a viable means of reducing the dimensionality of the muscle coordination problem in motor control [24-26]. This has been done by demonstrating that a small number of synergies can describe a large percentage of the EMG pattern variability exhibited both within a task and across several tasks. The success of muscle synergies in previous investigations is important, yet inconclusive in that it is not clear if the results reveal information about the control paradigm of the neuromotor system, or only describe characteristics of the observed data. A more powerful assessment of muscle synergies would be to investigate their task identification and decoding power with regard to prosthetic control.

Regarding the points mentioned above, this work aims to answer the following questions:

- Are synergies underlying multi-DoF hand and wrist tasks able to distinguish the tasks performed at various force levels?

- Can muscle synergies form a robust lower dimensional predictive framework for the EMG patterns of various hand and wrist movements? And how significant is the predictive power of the established framework.

1.2.3. Studying the Muscle Synergies, Their Properties, and Their Potentials in Myoelectric Control

There is a need to better understand the properties of muscle synergies with regard to motor coordination. Namely, if muscle synergies are in fact basic building blocks of more complex muscle patterns, then they should exhibit certain properties. Two of these properties are low lability, and scalability [27]. Low lability means that the basis set of muscle synergies is robust and generalizable to different environmental and task conditions. Scalability means that the individual muscle activation elements within a synergy should retain the same relative proportion levels with increased activation of the synergy i.e. the structure remains invariant. This work investigates these two properties of muscle synergies within the framework of myoelectric control.

More specifically, this work will answer the following questions.

- How many synergies are needed to complete this lower dimensional predictive framework, and how robust are these synergies?
- How consistent are the synergies across varying force levels?
- How much training data are needed to define a robust muscle synergy set of this framework?

- How powerful is this framework in identifying challenging tasks in comparison with currently used methods?

1.3. Thesis Structure

Chapter 1 contains an introduction to the problem and the objectives behind the work. Chapter 2 provides a history of the different methodologies of control proposed for myoelectric devices. This chapter also gives a general background on current literature in the area of motor control that gives philosophical and physiological evidence for the central motor system implementing a synergy-based control for muscle coordination. This chapter conceptually and mathematically describes the muscle synergy model. Chapter 3 studies muscle synergies during variation of force and explores their robustness and potential to be used for proportional control. Chapter 4 investigates the potential of using muscle synergies for task identification in 2-DoF tasks and variable force levels and followed by a real-time study of force estimation. Chapter 5 follows with a discussion of the studies presented in Chapters 3 and 4, their motivations, and their outcomes. Finally, Chapter 6 draws some conclusions about the work, summarizes the major contributions and proposes future work.

CHAPTER 2 - BACKGROUND

2.1. Prosthesis Control

Upper limb prosthetic devices are either passive or active [28]. Passive prostheses, with no moving parts, are generally used for cosmetic purposes. Active or functional prostheses for upper limb amputees currently fall into 1 of 3 categories: (1) body-powered, (2) Externally- powered, and (3) hybrid.

Body-powered prostheses are largely mechanical devices [29]. To control them, amputees use remaining shoulder movements to pull on a cable and sequentially operate prosthetic functions such as the elbow, wrist, and terminal device. To switch between functions, users must lock the joints they wish to remain stationary by pressing a switch or using body movements to pull a locking cable [30]. Where a mechanical input is to be used, an attractive option is a servo system in which hand position is proportional to differential body movement. But mechanical systems can be difficult to keep in adjustment, and straps and cables may be considered both unsightly and inconvenient by the amputee [31].

The advantages of body-powered prostheses include: simple operational mechanisms with intrinsic skeletal movement (which voluntarily opens/closes a terminal device), silent action, light weight, moderate cost, durability and reliability, and rough sensory feedback about the positioning of the terminal device [32]. In addition, the motion of body-powered prostheses enables the wearer to sense device actuation through cable tension and harness position. Thus, direct feedback and potential control of the position, velocity and prehensile force of the device can be maintained in a manner known as extended physiological proprioception [33].

Externally-powered prostheses can use electric, pneumatic or hybrid electrohydraulic power systems. However, a battery power source is more common due to some limitations of other two. Electrically -powered prostheses can be differentiated based upon their control inputs, usually sensors, switches or the myoelectric signal (MES).

The main focus of this thesis is the use of the myoelectric signal as a control source. Myoelectric control uses the electrical activity of a contracting muscle as a control signal. In a myoelectric prosthesis, muscle remnants in the residual limb are used to provide control signals for powered components. Myoelectric control requires minimal physical effort for operation. However, the main motivation of using myoelectric prostheses is the feasibility of creating a self-contained, self-suspended prosthesis in approximately the dimensions of the missing limb [31].

2.2.Myoelectric Control

Myoelectric technology uses electromyographic (EMG) activity, a form of electrical signal, from the voluntary movements of the stump muscles. EMG signals, which provide a control signal to the electric motors of the prosthesis, are captured through surface electrodes. The amplitude of the EMG signal is generally proportional to the contraction level of the residual muscle. After amplification and transmission, the myoelectric control system activates the electric motor to operate the terminal device [32]. The control system of intact limbs and myoelectric prostheses are illustrated in Figure 2.1. The shaded area is removed by amputation.

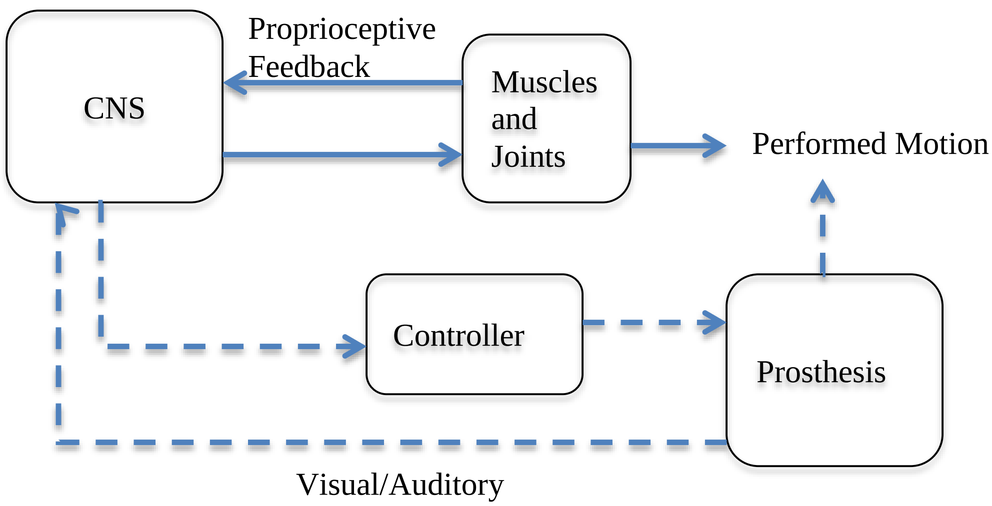

Figure 2.1–The essential elements of a myoelectric control system from the Central Nervous System (CNS) to Prosthesis.

The EMG signal is an important source of control because it contains useful information about the neuromuscular activity from which it originates [31].

Two major limitations of myoelectric control are the difficulty in recording suitable EMG signals and the shortage of information for the control of multiple functions. Many patients are unable to produce isolated EMG signals or have difficulty making repeatable contractions. The limited amount of control information forces patients to use switching techniques to operate more than one joint. In addition, shifting electrode locations and changing skin conditions (such as sweat) alter EMG signals and can cause control to be unreliable. Finally, the characteristics of the electrodes such as shape, dimension, materials, and location of electrodes on the skin also influence the EMG signal [31], [34, 35]. These limitations can result in less functional control, which in turn can lead to frustration and prosthesis abandonment [36, 37]. Three developing technologies—implantable EMG electrodes, EMG pattern recognition, and targeted reinnervation—may address some of the problems inherent in traditional myoelectric control [30]. In targeted muscle reinnervation (TMR), residual nerves in the arm are surgically connected to alternative residual muscles that are no longer active. Then, EMG from these muscles can be used to control the prostheses.

An invasive approach may offer advantages in comparison to the surface EMG (sEMG) for the control of prosthesis. One advantage is that the problems related to sEMG recording (displacement of electrodes) would be overcome and it provides more stable control sites [31]. However, intramuscular electrodes provide more local information and may be less representative of the global muscle activity. Moreover, needle and wire based intramuscular EMG can be painful for the subjects. An implantable solution such as implantable myoelectric sensor (iMES) is promising, but is still not yet validated for human use. It may be several years before it is available for clinical applications.

Generally, there are two approaches to myoelectric control: conventional control and pattern recognition based control.

Conventional myoelectric control schemes employ measures such as the root mean square or mean absolute value of the EMG to quantify the intensity of contraction in the underlying muscles. When these measures are above a predefined threshold, the controller triggers the desired prosthetic function mapped to this activity [35], [38]. Although such control schemes have been widely used commercially, they have limitations. They usually need two available independent antagonist muscle sites such as the biceps and triceps in trans-humeral amputees or the flexors and extensors in trans-radial amputees. Also, this form of control is often not physiologically appropriate as the natural motion elicited by the user is not consistent with the activated degree of freedom (DoF) of the prosthesis. In addition, conventional control is incapable of controlling more than one or two DoF. In cases where more than one DoF is to be controlled, mode switching techniques, in which a hardware switch or co-contraction of muscles is used to direct control to different DOFs, are often the only strategy available. These, however, can be slow and counterintuitive. Conventional myoelectric control systems are incapable of intuitively controlling multifunction prostheses which is inevitably a more challenging task [38].

To date, the two most distributed powered hand prostheses, those made by Otto Bock (Germany) and Touch Bionics (UK) [4], are based on conventional myoelectric control. The system electric hand by Otto Bock is a category of their myoelectric arms with three-finger grasping system. Proportional to the EMG intensity elicited by muscles, the hand controls the velocity of the movement. This classic control allows control of one DOF. The i-LIMB hand of Touch Bionics was the first prosthetic device with five individually powered digits. It uses two sEMG to open and close the fingers. To control the grip on an object and to control when to stop powering, it uses built-in torque sensors. The user can open each finger individually via a simple muscle flex. This limb offers six different grips which are controlled by means of mode switching. Both hands have been used successfully by amputees; however their major problem is that they are unable to control more than one function at the time.

2.3. Pattern Recognition Based Myoelectric Control

Pattern recognition-based myoelectric control is a signal processing technique that can be used to sequentially control multiple DOFs. This technique has shown great promise for improved dexterity of control in upper-limb prostheses. In this approach, some features are extracted from the EMG signal and provide a repeatable input pattern to a multidimensional classifier which determines the user’s intended movement. Each prosthetic function is stored as a predefined pattern and the classifier selects the most similar one to the input pattern as the output function. Pattern recognition systems rely on the assumption that a set of features describing the EMG signal are differentiable for different motions and that they are repeatable for the same motion. Myoelectric pattern recognition may be more intuitive than conventional control schemes, as it interprets synergistic patterns from multiple sites, and therefore often allows physiologically appropriate movements.

In order to implement a sEMG based algorithm, different actions of the prosthetic limb need to be coded. The control algorithm must recognize the user's intent embedded in sEMG from the residual muscles. Usually, EMG pattern recognition is composed of three main modules for: (1) signal acquisition, conditioning, pre-processing, and data segmentation; (2) decoding (feature extraction and pattern recognition); and (3) on-line control [4], [38]. Figure 2.2 depicts this general scheme for pattern recognition based myoelectric control systems.

As it is shown in Figure 2.2, in the pattern recognition based approach, first features are extracted from different time segments of sEMG and then they enter the classifiers for the recognition of muscle activation or for the prediction of different movements. Finally, an artificial device uses the result of classification to perform the task. Different parts of a pattern recognition based controlling system (feature extraction techniques, and classifiers) are shortly described in the following.

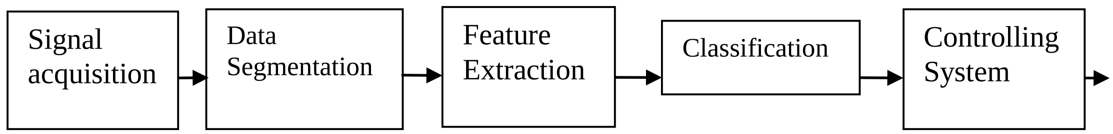

Figure 2.2 – Possible approach for sEMG pattern recognition based myoelectric control of artificial devices. From [39]

2.3.1. Signal Acquisition

There are two different methods for signal acquisition in order to capture as much information about the neuromuscular activity as possible through surface electromyography. One is through using a single channel with bipolar electrodes spaced widely apart [40]. A single EMG channel resulting from the summation of the activity of several muscles is captured using this approach. A lack of spatial discrimination in the activity of different muscles is the main disadvantage of this approach. In addition, destructive interference may occur due to differing information from different muscles. Also, a necessary condition for this method to work is the use of electrode with large surface area. If small electrodes are used, capturing EMG from many muscles would not be possible regardless of the distance.

The second option is to use multiple channels with closely spaced electrode pairs. Each closely spaced electrode is used to capture the activity of local muscle groups. This characteristic makes spatial discrimination possible and prevents destructive interference. Several studies have shown that control systems based on multiple channel approach outperform the systems based on single channel data acquisition. With advances in electrode array miniaturization and processing power of microprocessors, computational load and data bandwidth are not a concern anymore and implementation of the multichannel systems is more possible [41]. However, there are practical limits on the number of electrodes as consideration must be given to fit, location and comfort within a prosthetic socket [42].

2.3.2. Data Segmentation

Segmentation partitions the data into time slots or segments for acquiring sEMG data considered for feature extraction. For real time control, segments need to be short. However, as the segment length decreases, classifier performance degrades due to the rise of the variance of features. Thus, choosing the length of the segments involves a trade-off between the accuracy and responsiveness. The problem of data segmentation selection is deeply examined in [23], [43-45].

Surface EMG data are characterized by two states: (i) a transient state featuring the transition from rest to voluntary contraction of the muscle and (ii) a steady state where the muscle is constantly under contraction [4]. In a study by Englehart *et al.* [44] a direct comparison of the accuracy when using transient and steady-state data is shown. The results indicate that the steady-state data contains greater discriminating information than the transient data [44]. According to this study, another advantage of steady-state data over the transient state data is related to the effect of record length. The maximum record length is 256 ms due to the allowable response time of the classifier (300 ms is the longest acceptable delay in a prosthetic control system). The classifier performance degrades rapidly as the segment length of transient data is decreased from 256 to 128 to 64 to 32 samples. However, when using steady-state data, this degradation is less. Therefore, shorter segments of steady-state data can be used for a faster system response [44].

Segmentation of a continuous data may take the form of either disjoint segmentation or overlapping segmentation. Overlapping segmentation allows continuous classification of transient and steady-state sEMG data by utilizing the full capacity of the processor and reducing time interval between decisions made [43].

2.3.3. Feature Extraction

Feeding a myoelectric signal presented as a time sequence directly to a classifier is impractical due to the large number of inputs and randomness of the signal. Therefore, the sequence must be mapped into a smaller dimension set, which is called a feature vector. Features represent raw myoelectric signals for classification, so the success of any pattern recognition problem depends critically on the selection and extraction of features [39].

Different features of sEMG have been studied so far for classifying sEMG. Generally these features belong to time domain (TD), frequency domain (FD), or time-frequency domain (TFD) attributes of the sEMG signal.

TD features can be extracted easily from the signal since they are based on signal amplitude. This is one of the main reasons that they are the most frequently used features in myoelectric classification. These features are very suitable for real-time applications due to the low computational load of their extraction. Typical TD features are the mean absolute value (MAV) [23], [46], [47], integrated absolute value (IAV) [47], variance (VAR) [48], mean absolute value slope (MAVS), zero crossing (ZC) [23], slope sign changes (SSC) [49], waveform length (WL) [49], and EMG histogram [46]. For a mathematical definition of some typical features used for pattern recognition of sEMG signals see [4], [39].

FD features include power spectrum (PS) [45], mean and median of signal frequencies (FMN, FMD) [45], frequency ratio (FR) [50] whereas TFD features comprise a short-time Fourier transform (STFT), wavelet transform (WT) [44] and wavelet packet transform (WPT) [4].

It is crucial to find an effective feature or a feature set for robust and repeatable classification of EMG signals. That is why these features have been compared in their class separability, robustness, stability during changes in sEMG, and computational complexity [45].

Generally, there are two approaches to feature evaluation: structural and phenomenological approaches. In the structural approach, features are evaluated based on physical and physiological models, considered in a signal generating process. In this approach, selected features can be evaluated using synthetic signals generated by mathematical models. Some characteristics of features, such as bias, variance, and the level of sensitivity to noise, can be measured in this approach. The phenomenological approach roughly interprets stochastic signal notwithstanding its generating structure. In this approach, which is occasionally called the empirical approach, features are mainly evaluated based on a rate of classification performance, and their robustness [39].

The current study uses both structural and phenomenological approaches to evaluate and choose a set of features. Our selection of features that are subsequently used for synergy extraction is based on their performance in task classification. However, the selection of synergy components is based on the amount of variance of data that can be described by these components. Several studies have compared the relative performance of various single features and feature sets (multifeatures) of sEMG. Hudgins *et al.* [23] used a feature set including MAV, MAVS, ZC, SSC, and WL to classify the transient EMG signal from a single channel. Englehart *et al.* [44] extracted STFT, WT, and WPT features from the steady-state EMG to effectively represent the signal. Zardoshti *et al.* [46] evaluated and compared eight single TD and FD features based on their movement discrimination, robustness, and complexity and found Integrated Absolute Value (IAV) to be the most efficient feature, both with noisy and clean data. In [46], features based on TD showed a better performance than FD features for robust EMG pattern classification. Also, TD features have shown a better performance than TFD features in the classification of both transient and steady-state EMG signal using LDA in many studies [39], [51], [52]. Tkach *et al.* [52] investigated the robustness of various TD feature sets to the EMG changes caused by electrode shift, changing amounts of user effort during muscle contraction, and muscle fatigue. They showed that the use of at least four combined EMG features enhances the classifier performance, when affected by such challenges. In other work, Oskoei and Hu [45] compared several single features and feature sets and suggested the use of WL as the best single feature with regard to accuracy and stability. They also supported the TD feature set introduced by Englehart and Hudgins [43], including MAV, WL, ZC, and SSC, as a feature set which satisfies the three requirements of separability, robustness, and stability. This feature set has been widely used in the literature for myoelectric pattern recognition [43], [53], [54], as well as commercial pattern recognition systems [14] and will serve as the baseline for comparisons in this work.

2.3.4. Classification

After extracting the features, they need to be classified for recognition of the desired motion. Large variations might be seen in the value of a particular feature because of the nature of the MES. Moreover, there might be some changes in a single pattern over time due to external factors such as changes in electrode position, fatigue, and sweat. A desirable property of a classifier is that it should be able to accommodate these changes. Furthermore, classification should be fast enough for real-time applications and provide the possibility of on-line training.

Various classifiers such as artificial neural networks (ANNs) [23], [55], [56], linear discriminant analysis (LDA) [43], [44], [57], neuro-fuzzy [48], [58], [59], Gaussian mixture models (GMMs) [60], [61], hidden Markov models (HMMs) [62], and support vector machines (SVMs) [45], [63], [64] have been employed.

In 1993, Hudgins recognized 4 types of muscular contraction using a simple MLP NN and TD features [23]. They showed that conventional pattern recognition techniques could be successfully used for classifying single-site sEMG signals. He also showed that the application of ANN could reduce the training time required to achieve high recognition rates. Subsequently, Englehart compared some feature sets and two classifiers (LDA and MLP), increasing the number of classes (from 4 to 6), the number of electrodes (from 2 to 4), and comparing three different data sets: transient, steady-state, and continuous [43], [44], [65]. They demonstrated that exceptionally accurate performance is possible using the steady-state myoelectric signal. Exploiting these successes, they constructed a robust online classifier, which produces class decisions on a continuous stream of data. In recent years, more sophisticated classifiers have been developed (e.g., GMMs, HMMs). Experiments have been performed with a larger number of electrodes and the number of wrist movements and/or grasping tasks (e.g., opening, cylindrical and lateral grasping) to be decoded. Very high recognition rates (> 95%) have been obtained in studies frequently based on able-bodied subjects and amputees, with control of virtual and physical prosthetic devices [4].

In the last decade, soft computing, mainly composed of fuzzy logic, neural networks, and genetic algorithms, has achieved great success in many applications. Unlike traditional hard computing, soft computing exploits tolerance of imprecision, uncertainty, and partial truth to achieve tractable, robust, and low-cost solutions to decision problems [59]. Since the success of a myoelectric control scheme depends greatly on the classification accuracy, using a proper classification method plays a key role in myoelectric control of prostheses. Generally, Soft computing methods can be easily implemented in the digital form, which can be embedded microcontrollers commonly used in myoelectric control systems [66]. Despite their great advantages, soft computing methods are not commonly used in pattern recognition based myoelectric control. This is because of their iterative training methods, they are difficult to train, training generally takes a long time, and it is difficult or impossible to know if their solution is optimum. Hargrove *et al.* [67] showed that despite its relative ease of training and efficient real-time processing requirements, a simple LDA classifier performed as well as other more sophisticated classifiers. This classifier paired with four TD features introduced by Hudgins *et al.* [23] has often been cited as the standard in myoelectric control.

Consequently, this commonly used configuration is used as the baseline for performance comparison for all of the classification studies performed in this work.

2.3.5. Challenges to Clinical Application

Because of consistent improvements in the practical performance of pattern recognition technique, pattern recognition-based myoelectric control has found acceptance and has recently been commercially deployed for the first time by Chicago-based Coapt

LLC [14]. In laboratory settings, this approach has shown high accuracy in classification of user's intent, but to be considered a clinical option, these systems would require further improvements.

Robustness

The robustness of myoelectric pattern recognition methods strongly depends on two characteristics of extracted features: separability and repeatability. Separability refers to the ability to differentiate between the features of motion classes. This means that the extracted features must be different from class to class. Correspondingly, increasing separability has been the main goal in the literature when new feature sets and classifiers are selected and developed. Repeatability refers to the degree of coincidence between features extracted from different repetitions of the same class, relating to their reproducibility.

As discussed in previous section, high classification accuracies have been achieved so far in controlling upper limb prosthesis by pattern recognition methods. However, these studies are performed under ideal conditions in offline and laboratory testing on static contractions. Constrained protocols of these studies provides high repeatability of the classes, allows study of specific parameters and factors, and optimizes performance. However, those ideal conditions do not exist in real-world prosthetic use, which diminish repeatability, and therefore accuracy and metrics that attempt to capture usability will degrade. However, there is still much to be learned about what constitutes a clinically viable and robust pattern recognition based control scheme.

Factors that may challenge practical pattern recognition control can be grouped based on their effect on separability or on repeatability. Factors such as user ability [68], residual musculature, electrode site selection [69], feature selection, force and speed change of the motion, and simultaneous motions may affect the separability of the motion classes. These factors corrupt the separability of the extracted features in practical use, where the usage conditions of prosthesis are much less constrained and make proportional and simultaneous control of prostheses very challenging.

If the repeatability of features is highly degraded, the patterns within a motion become more variable and this can affect the separability between the classes and make the classification more difficult. Scheme proposed that the degradation of pattern recognition performance during practical use is largely caused by the factors that affect the repeatability of the EMG features [70]. He showed that changes in limb position cause significant degradation in classification accuracy and proposed the use of pooled or dynamic training data as a mitigating strategy. Scheme also showed that modulation of contraction intensities, caused by the concurrent use of proportional velocity control, produces similar deterioration. He introduced a novel class-normalized method of proportional myoelectric control and proposed training with various force levels to resolve this problem and improve the quality of proportional control.

Dexterity

A notable limitation of clinically available myoelectric control methods is that patients must control each degree of freedom (DOF) sequentially, i.e., one at a time. Neither conventional dual-site differential control [71] nor newly available pattern recognition control [72] allow simultaneous control of multiple DOFs. This prevents prosthesis users from experiencing the coordinated joint control possible in an intact limb. Although advanced arm systems [73], [74] including multi-DOF wrists, offer the mechanical means to restore such movements, there is still a significant need for systems that enable simultaneous control of such devices. A variety of approaches to providing simultaneous control have been investigated using surface EMG. Such approaches have included pattern recognition [75], [76], [76]-[78] the use of neural networks to predict joint kinematics [79], [80] or kinetics [81], [82] and analysis of underlying muscle synergies [80], [83]. These approaches are promising, but most studies have been limited to controlling the wrist without the hand, or have enforced equal velocities on all active DOFs, and thus do not provide independent proportional control of each DOF. Our focus in this thesis is on investigating the possibility of using muscle synergies toward reducing these constraints to create a myoelectric control system for myoelectric prostheses which is more robust in clinical application.

2.4. Motor Coordination Investigations

Motor control analyzes how the nervous system in human and animals controls movement [84]. In other words, it is a set of information processing related activities carried out by the central nervous system that organizes the musculoskeletal system to create coordinated movements and skilled actions. The motor system consists of peripheral parts such as muscles, both motor and sensory nerves, and the central part or Central Nerves System (CNS) containing cerebral cortex, basal ganglia, cerebellum, brain stem, and spinal cord [85]

When the body performs a motor task, the CNS excites muscles that subsequently develop forces that are transmitted by tendons and the skeleton to perform the task. Thus, muscles and tendons are the interface between the CNS and the articulated body segments. An understanding of the properties of this interface is important to engineers who design prosthetic and functional neuromuscular simulation systems to restore lost or impaired motor function. In motor control, online sensory information must be integrated with knowledge acquired through experience and learning. Thus, the associated neural machinery must be highly adaptive and versatile but at the same time be capable of performing highly complex sensory information processing, sensorimotor transformations and motor planning [86].

In order to explain how the CNS controls and coordinates the many degrees of freedom of the neuromuscular system, two major viewpoints have been developed. The first viewpoint is based on control of individual joints and muscles [87]. This viewpoint is largely based upon strict somatotopic[1] organization of motor control i.e., point-for-point correspondence of an area of the body to a specific point on the CNS. However, many researchers have argued against this viewpoint, stating that it does not account for the body of evidence from neuro-stimulation experiments [88]. The second viewpoint considers the redundancies of neuromuscular system and states that motor control is an “ill-posed” problem. According to this viewpoint, neuromuscular system uses fundamental primitives of movement to generate complex movements [89]-[91]. Using these fundamental control primitives, the neuromotor system is constrained and the problem of coordination is well-defined. Moreover, the efficiency of control can be increased. There is experimental evidence for movement primitives based on three areas: cortical stimulation, coordination of joint kinematics and kinetics, and coordination of muscle patterns.

2.4.1 Modularity of Motor Control: Cortical Stimulation

The somatotopic viewpoint toward motor control, the result of early cortical stimulating the primary motor cortex, or M1 area, indicate a strict point-to-point mapping of the hand. It was thought that specific non-overlapping areas of the brain are responsible

[1] Somatotopy is the point-for-point correspondence of an area of the body to a specific point on the central nervous system. Typically, the area of the body corresponds to a point on the primary somatosensory cortex.

for control of specific parts of the hand. Figure 2.3 shows the areas where movement of fingers, entire hand, and proximal arm were elicited through neuro-stimulation. As it is shown, these areas are not discrete. Instead, areas responsible for controlling different parts have overlaps. This suggests an alternative method to motor control, such as synergistic or pattern based, rather than individuated joint or muscle based control [92].

This viewpoint even suggests that the medio-lateral ribbon of M1 served to divide control of the thumb and index finger from the middle, ring, and pinky fingers [92]. However, a more in-depth analysis shows that control of some fingers can be elicited from both the medial and lateral sections of the cortex and there are some overlapping regions in motor cortex that control various limbs and muscles. These results are not consistent with the strict point-to-point map suggested by somatotopic viewpoint. In addition, some results showed that single stimulation point can generate movement in several fingers of the hand [92]. Due to the mentioned results, it seems that the hand is not somatotopically mapped to the primary motor cortex area.

Several constraints have been suggested on a strict somatotopic organization of the primary motor cortex [92]. First, for controlling a single muscle, there seems to be convergent outputs to its spinal motoneurons pool from large territories of the M1 cortex. Second, the outputs of single neurons in M1 cortex diverge to innervate motoneurons pools of multiple muscles. Third, there are horizontal connections between neurons that prevent motor cortex sites to act completely independently. Forth, an activation pattern related to even a single joint movement is distributed, and hence, the activation is not organized in anatomical order. Fifth, trauma induced partial inactivation of the M1 area generally results in weakness of the entire hand not only in individual parts. Sixth, the cortical area is observed to have plasticity during initial learning or rehabilitation learning. This shows that M1 regions are not hard coded to control specific joints or muscles.

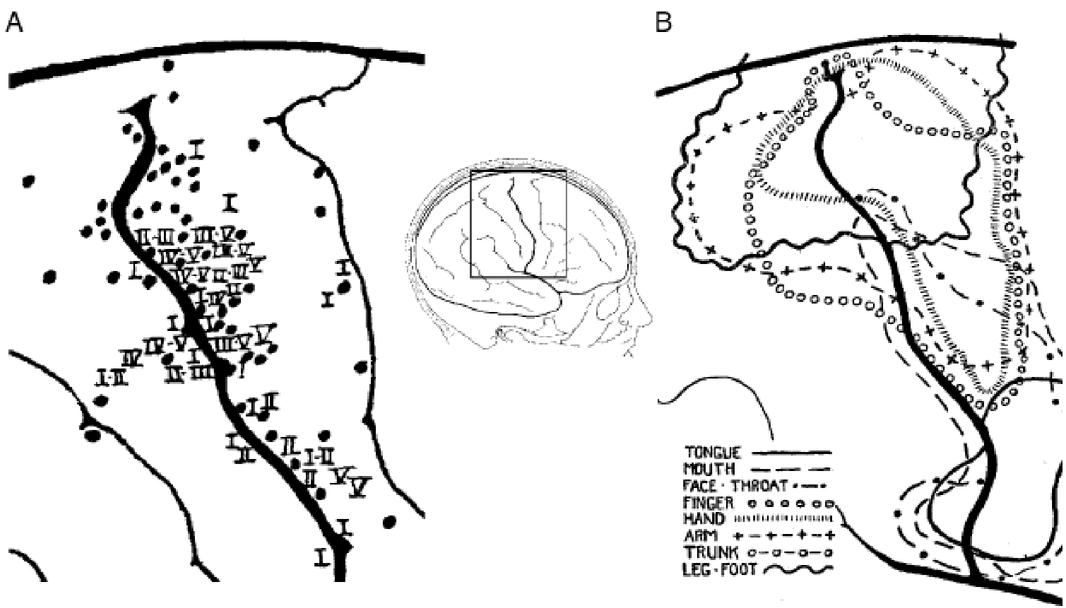

Figure 2.3 – Results from M1 area stimulation experiment of Penfield and Boldrey [93]. Dark dots show the stimulation points and fingers from thumb to little finger are shown by I to V. As it can be observed in the image, there are medial and lateral representations for almost all the fingers. In addition there are sites that control multiple fingers. The theory of a strict somatotopic (i.e. discrete organization) ordering of motor control is not consistent with these results [94].

Instead, these evidences show that organization of motor control is distributed instead of somatotopic. Some more in-depth studies have been done by [95] showing more accurate evidence for distributed organization of motor control. Some other studies about individuated flexion and extension of the fingers and wrists of monkeys reported that many neurons where related to multiple individuated movements. In addition, reconstruction of neuronal spatial distribution of the M1 hand area showed that active neurons for each individuated movement was over a large portion of the cortical area [96].

Also there is evidence indicating that control of individuated finger movements is more likely accomplished through the activation of a diverse population of neurons dispersed throughout the M1 area. Other researchers have performed similar studies of neuronal clustering and have found some evidence that the activity of neurons cluster into functional discrete groups, and that the activity of each group was correlated to the activity of a distinct group of muscles (i.e. muscle synergies), rather than individual muscles [93].

There are much more evidence found by several researchers, stating that the primary motor cortex is not characterized by a strict point-to-point somatotopic organization. Moreover, control of medial and lateral body parts are not necessarily regulated to medial and lateral parts of M1 area respectively, meaning that mapping is not spatially organized. This lack of organization means that the strategy of the motor cortex for controlling movements is not strictly controlling individual muscles and joints independently. Instead, its control strategy seems to be overlapping and distributed through the M1 area. Thus, there might be a pattern based means of coordination for the many degrees-of-freedom of the hand, potentially for the purpose of simplifying control [97].

2.4.2. Modularity of Motor Control: Joint Kinetics and Kinematics

There are two groups of evidences achieved in investigating motor coordination involving kinetics and kinematics that result from various muscle coordination patterns of movements. The first group is achieved from spinalized vertebrates experiments. The second group is the result of experiments in hand kinematics.

Evidence from Spinalized Vertebrates Experiments

Some investigators [98], [99] addressed the issue of motor coordination within a particular class of movements: the movements produced by spinal motor system. They suggest that spinal motor systems are organized into a number of distinct 'units' of motor output, which can be combined flexibly to produce a range of different behaviors. Possible involvement of such units in production of normal behaviors has been evaluated in several reviews [99-105] but perhaps the most systematic examination of the modularity of spinal motor systems has been performed in studies of the turtle spinal cord by Stein and collaborators [106]. They examined the hypothesis that vertebrate spinal motor systems produce movement through the flexible combination of a small number of units of motor output. In the turtle whose spinal cord had been disconnected from the brain stem, sustained cutaneous stimulation of different regions of the body surface evokes a rhythmic motor behavior, which acts to remove the stimulus [107]. Depending on the site of stimulation, one of three different forms of scratch reflexes[2] could be evoked. Their experiments showed that these three different forms of the scratch reflex are characterized by a temporal reconfiguration of three fundamental units of motor behavior: although all three have a basic alternation between hip flexion and extension, the timing of knee extension differs between the three different forms of scratches. Moreover, according to their results, these units can be reconfigured flexibly, showing a great deal of independence from one another [98], [99].

Bizzi *et al.* [103] and Giszter *et al.* [108] investigated the organization of the spinal circuitry in spinalized frogs. The frog's ankle was fixed in various positions while individual sections of the spinal cord were subjected to stimulation. At every position, isometric forces at the ankle were recorded to construct a force field (Figure 2.4.b).

[2] The scratch reflex is a response to activation of sensory neurons whose peripheral terminals are located on the surface of the body. Some sensory neurons can be activated by stimulation with an external object such as a parasite on the body surface. Alternatively, some sensory neurons can respond to a chemical stimulus that produces an itch sensation.

As it is shown in Figure 2.4, all of the forces converged to an equilibrium point where the recorded force would be zero. This equilibrium point would be the final ankle position if the leg was free to move. The researchers realized that there were only a few numbers of these converging force fields (CFFs) even with changing the parameters of stimulations. More interestingly, they showed that combining these CFFs can yield CFFs produced by simultaneous stimulation of multiple sites. Thus, these CFFs can be considered as fundamental primitives that CNS uses to generate complex movements.

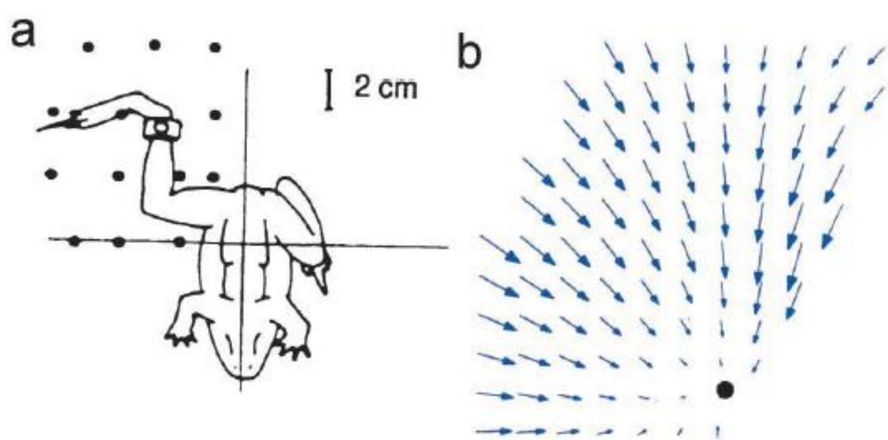

Figure 2.4 – Converging force fields (CFFs) in spinalized frogs [109]. Isometric forces were measured at the ankle while the spinal cord was micro-stimulated. The result is a force field, where all forces converge to an equilibrium point. This point is where there are no recorded forces at the ankle and would be the ankle position where the frog leg is free to move. It was reported that only a small number of these CFFs were observed despite varying various parameters of stimulation.

Mussa-Ivaldi *et al.* [110] showed that linear vector summation could be applied to these movement primitives to explain the CFFs observed during simultaneous micro-stimulation of two sites, with the predicted and actual results having a high coefficient of similarity. They expressed that the complex nonlinearities of neural and kinematic activity could be explained by applying a linear combination. This analysis was extended to supraspinal system and it is shown that supraspinal systems also generate motor outputs based on force field motor primitives, and that linear combination of CFFs can generate more complex motor behaviors [111]. In addition, the authors reduced the dimensionality of the resultant CFFs, using principle component analysis (PCA), to a small number of movement primitives to explain the variety of observed force field patterns. Hence, supraspinal systems may activate and linearly combine the same movement primitives that were observed during direct spinal stimulation. So, real limb behaviors and even on-line corrections could be explained by linear interactions between these force field movement primitives [112].

In summary, evidence suggests that both the circuitry of the spinal and supraspinal systems seem to construct complex motor behaviors through the use of movement primitives. These researchers have shown that these movement primitives could be represented as convergent force fields, which presumably are the force vectors resulting from the muscle synergy primitives interacting with the limb mechanics. Furthermore, these CFFs can be combined using vector summation to explain the observed force fields of more complex behaviors. These results are consistent with the notion that the biological system prefers to construct new and more complex skills on top of previously learned and simpler skills [113]. Much of this work is also reviewed in greater detail in [101], [109]

Evidence from Experiments in Hand Kinematics

Other researchers have hypothesized that there are parallel biomechanical constraints in addition to the neural circuitry constraints that are implicit in CFF models. The many biomechanical degrees-of-freedom make the hand able to perform highly complex movements. However, digit joint movement is not strictly individuated even when an attempt is made to move just one instructed digit. This observation has been quantified in rhesus monkeys through introducing the individuation and stationarity indices [114]. The individuation index is a normalized measure of the degree that other digits moved during the movement of a particular instructed digit, and the stationarity index is a normalized measure of the degree that a specific digit remained unmoved during the movement of a particular instructed digit [94]. Schieber studied the stationarity and individuation of hand fingers. He found high values of both individuation and stationarity for the thumb, index finger, and wrist suggesting that they were more individually controlled as compared to the middle, ring, and little fingers. However, no digit had perfect individuation or stationarity indices, indicating that control of no digit was completely isolated from all others.

Other investigators have confirmed these results in human subjects. This overall lack of digit independence has led many researchers to investigate the possibility that postural synergies in the form of joint co-variations, while naturally having some origin in the anatomical structure, may also have some origin in the neural circuitry.

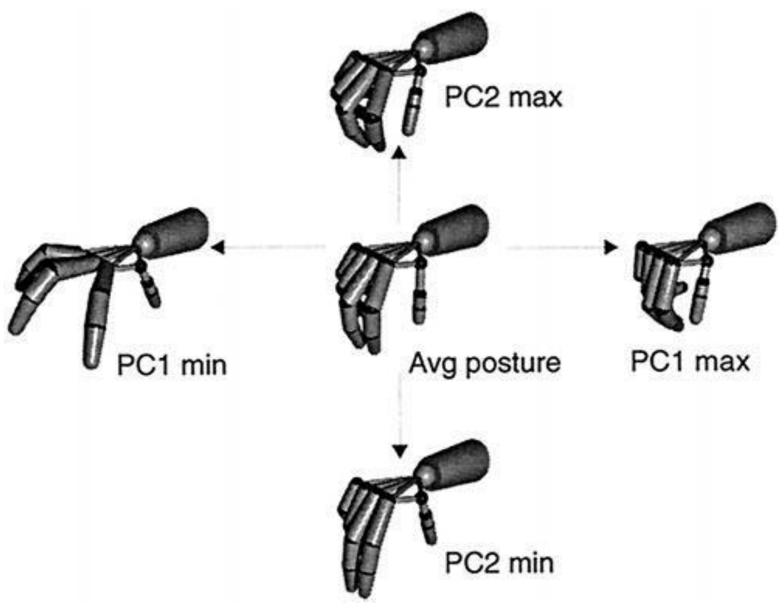

Figure 2.5 – PCs of Static Hand Postures [115]. A study of prehensile patterns used in grasping 57 everyday objects revealed that >80% of the variance observed between all grasp patterns could be explained by the first two principal components (PC1 and PC2). These PCs represent deviations from the average hand posture, and are characterized by flexion/extension or abduction/adduction of the metacarpophalangeal, proximal interphalangeal, and thumb joints.

Some investigations about the existence of postural synergies in static hand postures showed that not all joint angles were independent, but some seemed to linearly co-vary. This was verified using principal component analysis (PCA) which generally serves to reduce the dimensionality of the controlled space in the system [116]. The investigators found that the first three principal components (PCs) were enough to explain 90% of the data variance and the first two PCs were explaining 84%. They found that the fifteen DoF system could be approximated by control of only three DoFs, i.e. PCs. Each PC showing a postural synergy was a description of pattern of joint co-variation (Figure 2.5). Other researchers have done similar analysis for other types of movements such as grasping, and they found that only a few number of PCs are enough to explain the data variance.

To realize if dynamic hand postures can be explained by simpler movement primitives, the shape of the hand during movement (for grasping task) has been studied. The results showed that the shape of the hand during flight changes in accordance with the size and shape of the object to be grasped. During the flight, the hand gradually takes the form of the object's contour [115]. Researchers have examined whether or not this temporal gradual shaping could be explained by a set of kinematic movement primitives i.e. postural synergies [117].

The authors were able to reduce the kinematic data into a linear combination of orthogonal postural synergies via singular value decomposition (SVD) analysis [118] They named these postural synergies, eigen-postures which were constant with time-modulated weights. The investigators found that the first three PCs (eigen-postures) explained 99.5% of the variance, with the first PC accounting for 97.3%. This first eigen-posture was characterized by a generally open grasp with all the joints slightly flexed, and proved to be very similar for all subjects, regardless of the subject's hand size or the size of the grasped shape. The major shortcoming with this experiment was that the objects required the same power grasp hand pattern. Thus, it is no surprise that many of the eigen-postures were similar for different objects.

Santello *et al.* [119] addressed this issue by using objects that required hand shapes that visually differed in more than just size. Furthermore, they allowed their kinematic primitives to vary with time, as opposed to forcing them to be static and allowing the weighting coefficients to be time modulated. Santello found that despite varying the shape and size of the objects and varying the conditions of the reach-to-grasp (from memory versus sight), two time varying synergies could explain >75% of the observed data variance.

Finally, Todorov *et al.* [120], [121] used postural synergies to describe joint coordination pattern involved in dynamic object manipulations. Subjects were instructed to perform various object manipulation tasks such as turning the page of a book, crumpling a sheet of paper, manipulating Chinese balls, and fishing through a set of keys. Joint angles were recorded using a Cyberglove, and PCA was used to assess the covariance structure of the joint angles. According to this investigation, the joint covariances could also be explained by a set of dimensionally reduced synergies, although the dimension for hand manipulation was more than twice that reported for hand grasping by Santello *et al*. [120], [121]. These authors suggested that the extracted synergies showed a high level of task specificity, rather than being global enough for general hand posture construction.

They concluded that the overall body of work in this area provides evidence for several ideas. First, that the CNS does simplify the control of complex motions, and specifically hand control, through the use of simpler movement primitives – in this case, eigen-postures. Second, that the CNS does not control individual joints, but rather controls several joints, as evidenced by the fact that eigen-postures did not affect individual joints. Finally, they suggested that the dynamic acts of reach-to-grasp and object manipulation, and not just static hand grasp patterns, could be described by these postural movement primitives.

2.4.3. Modularity of Motor Control: Muscle Synergies Paradigm

This paradigm is based on the natural muscular activities selected by the CNS or on muscle synergies. The use of the natural modulation of muscles can represent an interesting solution for the control of hand prostheses. As mentioned in previous parts, many investigators have focused their research on the hypothesis that the spinal cord produces complex behaviors through the flexible combination of a small number of basic 'units of motor output'. Such units have been referred to using many different terms (e.g., half-center, unit burster, module, primitive, muscle synergy) with differences in their connotations and their implications about physiological implementation or functional interpretation [99]. Stein and Smith [98] clarified many of these terms and hypotheses nicely, characterizing their distinguishing features. However, their commonality is that they each propose that the spinally generated motor behaviors are produced by combining units of motor outputs. Regarding 'muscle synergies', this unit of motor output has been referred as consisting of the coupled activation of a group of muscles. The muscle synergies hypothesis suggests that intending to move is just activating the corresponding muscle synergy that turns on the muscles necessary to accomplish the movement. In other words, a functional muscle synergy is a pattern of co-activation of muscles recruited by a single neural command signal [122]. According to this definition, each muscle can be a part of multiple muscle synergies, and one synergy can activate multiple muscles.

Tresch *et al.* [123] applied a computational analysis to the muscle activation patterns evoked by cutaneous stimulation of different regions of the skin surface of the hindlimb. They investigated whether the patterns of muscle co-variations and the range of muscle activations could both result from the combination of a small number of muscle activation patterns or muscle synergies. According to this hypothesis, any given response should be describable as the linear combination of a small number of such muscle synergies. Further, both the elements of the synergies and their weighting within each response should be positive, because muscle activations are being considered. Tresch *et al.* [123] proposed that this specific hypothesis can be formalized in the following model:

$$m_j^{obs} = \sum_{i=1}^{N} c_{ij} w_i \qquad c_{ij}, w_i \geq 0 \tag{2.1}$$

Where m_j^{obs} is the *j*th observed pattern of muscle activations, $c_{ij}$is the positive weighting coefficient of the *i*th muscle synergy for the *j*th response, w_i is the *i*th muscle synergy and N is the number of muscle synergies. They tested how well this positive linear combination of muscle synergies model explained the patterns of muscle activations observed experimentally.

They extracted a set of four muscle synergies from the observed muscle activations for seven different animals using a computational analysis. This analysis aimed at finding the set of muscle synergies that could best predict the observed responses according to the model described above. Figure 2.6.c shows an example of extracted set of synergies and the weighting coefficients of each synergy used to reconstruct the responses evoked from cutaneous stimulation. The diagram of Figure 2.6.a shows the recorded EMG from different muscles of the frog and part b illustrates the observed patterns of co-variations. The table in Figure 2.6.c clearly shows how each response can be reconstructed using linear combination of extracted synergies with proposed coefficients. For instance, the first response was reconstructed as 0.65 of the first synergy, plus 2.47 of the second synergy, 0 of the third synergy, and 1.09 of the fourth synergy. The derived synergies were very robust to differences in initial conditions. Qualitatively, the observed (Figure 2.6.b) and predicted (Figure 2.6.d) responses were very similar to one another. Quantitatively, this similarity between observed and predicted responses was found to be very large for each animal.

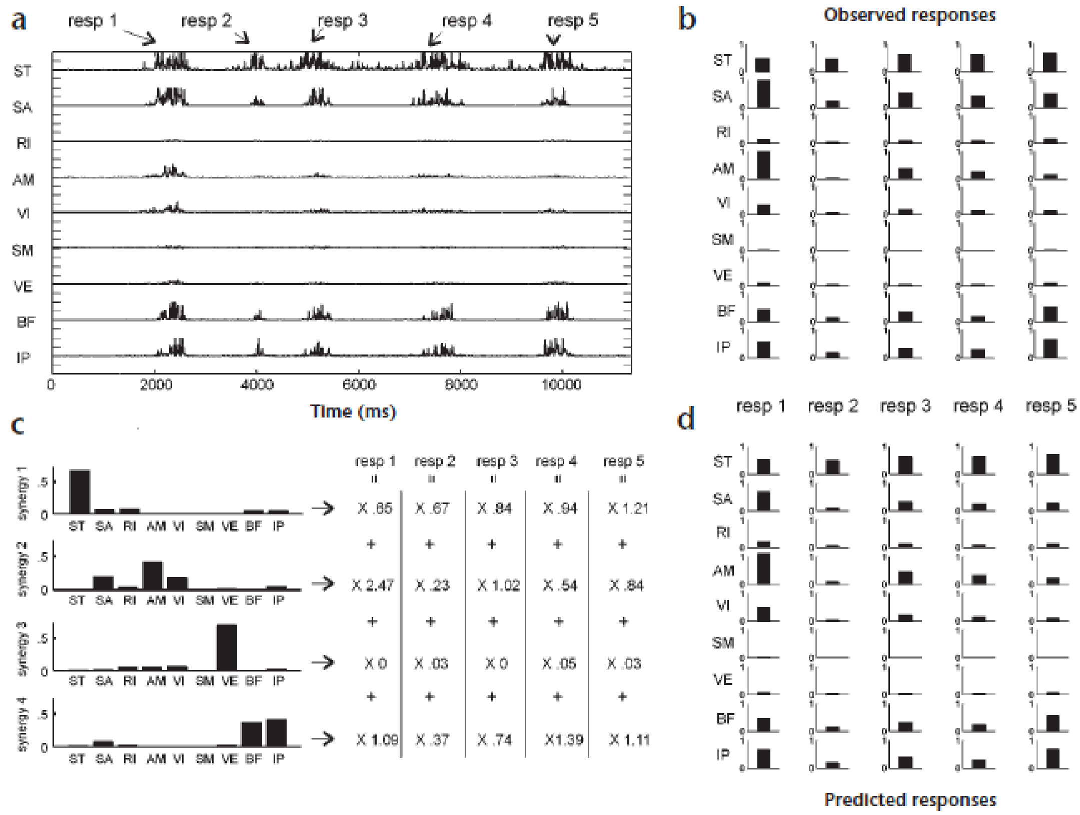

Figure 2.6 – Example of muscle covariation patterns within evoked responses [123]. (a) Raw EMGs for five responses evoked from stimulation of the same skin region. (b) Averaged, normalized activation for the muscles recorded in each of the responses shown in (a). Note that each muscle was normalized to the maximal value observed for that muscle across all responses evoked from any stimulation site in this animal. As a result, the muscle balances seen in (a) are slightly different than those shown in (b). (c) Responses can be explained as a linear combination of a set of muscle synergies. The synergies are shown to the left. The weightings of each of these synergies used to reconstruct the responses in (b) are shown to the right. (d) Responses resulting from the combination of muscle synergies shown in (c).

This study and several other studies in similar area reported that the muscle activation patterns involved in hindlimb withdrawal reflexes could be explained in terms of the combination of a small number of muscle synergies, consistent with the hypothesized modular organization of spinal motor systems.

D'Avella *et al.* [24] extended the definition of muscle synergies proposed by Tresch suggesting that activation of muscle synergies are not only amplitude modulated but also time modulated. Their examination of complex behaviors in intact animals showed that muscles within a putative synergy are activated asynchronously [124]. These temporal delays between muscle activations involve coordination of relative muscle activation timings as a basic unit of motor output. Thus, in time varying synergies there is both a spatial component, which is the balance of activations across the muscles, and a temporal component. Each muscle in a time varying synergy has a temporal profile that allows for delays between muscles within the same synergy [125]. d'Avella *et al.* in [24] propose that the fundamental building blocks are time-varying muscle synergies, i.e. "coordinated activations of groups of muscles with specific time-varying profiles", that are independently scaled in amplitude and shifted in time. They propose that in order to provide the flexibility necessary to capture the variability of the muscle patterns involved in a natural behavior, different synergies should be recruited independently. In this model each synergy is a sequence of vectors w(t) in muscle activity space. Here, the muscle activity patterns considered as a data set consisting of episodes of a certain behavior, like a set of kicks in different directions. Each episode j includes synergies w_i with different activation coefficients $c_{ij}$and time shifts t_{ij}. Thus, the sequence of muscle activities for a particular episode is defined as [124]:

$$m_j^{obs} = \sum_{i=1}^{N} c_{ij} w_i(t - t_{ij}) \tag{2.2}$$

Figure 2.7 shows an example of reconstruction of a muscle pattern by combination of (a) synchronous synergies and (b) time varying synergies.

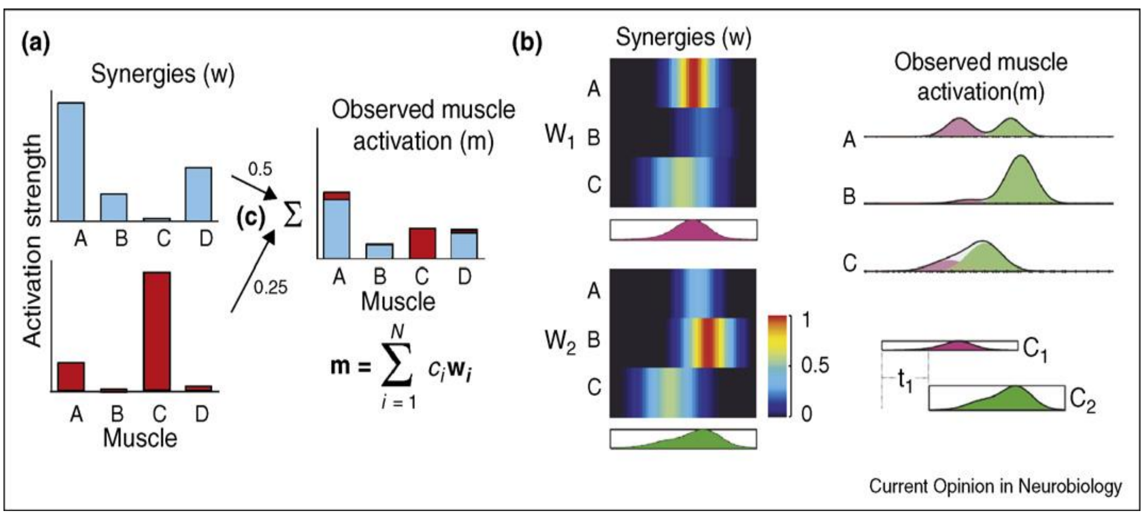

Figure 2.7 – Schematic representation describing muscle synergies hypothesis [125].

In Figure 2.7.a each synergy is related to four muscles and has a scalar coefficient which shows its activation amount in the task. The muscle activation for the task is simply yield by summing the weighted synergies together. Figure 2.7.b illustrates two time-varying synergies related to three muscles involved in the task. The activation pattern for each muscle in each synergy varies during the time unlike in synchronous synergies in which it is a scalar value. Moreover, the second synergy has shifted in time with respect to the first synergy. Summing up the weighted time shifted synergies, one can see the reconstructed activation of each muscle.

2.4.4. Properties of Muscle Synergies

To thoroughly test the hypothesis of muscle synergies a prescriptive framework must be established with testable properties. Lee [27] formalized several testable properties of a prescriptive framework of neuromotor synergies (i.e. muscle synergies). The first is that synergies should be robust and reliable regardless of changing input parameters and task requirements. Second, muscles within a synergy should maintain the same relative activation levels with scaling of the synergy. Third, synergies should be spatially coherent, meaning that they should be activated in an all-or-none fashion. Several investigations have been made about these properties among which some are presented in this section. During the studies performed in this thesis we investigated the mentioned properties under different situations such as variable force, combined motions, and multi-DoF tasks.

Descriptive Framework of Muscle Synergies

So far, several studies on muscle synergies have shown that they are able to present a proper framework that is able to describe the major part of the EMG data they are extracted from. In other words, only a few synergies are enough to describe a high percentage (usually above 80%) of the variance of the data. Tresch [123] evoked responses from stimulation of sites on frog's dorsal surface of the foot, the dorsal surface of the calf, the contralateral ankle, the ipsilateral and contralateral back and both forelimbs. The synergies obtained from stimulation of the hindlimb were able to explain over 80% of the variance in the responses evoked from sites on the dorsal surface of the foot and calf, the ipsilateral back and the contralateral ankle. Also, Weiss and Flanders [126] applied principal-components analysis to extract the muscle synergies responsible for the sets of joint angles that represented large numbers of complex hand shapes. Only two principal components (PCs) were needed to account for >80% of the variance in a set of hand shapes for 57 commonly grasped objects [115].

d'Avella *et al.* [24] reported that randomly generated time-varying synergies explained roughly nineteen percent of the data variance, thereby suggesting that significant information is contained in the muscle synergies they observed. So, synergies are able to create a descriptive framework that reduces the dimension of the motion control problem while saving the major part of the variance.

The study by Weis and Flanders [126] aimed to describe the hand postures associated with the ASL alphabet and with grasping of everyday objects with a low-dimensional set of muscle synergies, and to align these muscle synergies with postural synergies of the hand. While informative, this study failed to make a compelling case that the new framework established by their extracted synergies was useful within a physiological control paradigm. The efficacy of this framework in predicting new hand postures, which speaks to their robustness and generalizability, is a testable and necessary hypothesis given the accepted definition of muscle synergies [27]. However, this was not explored in their work. In short, the work of Weiss and Flanders only established that muscle synergies can form a descriptive framework for a wide variety of known hand postures.

Generality and Robustness of Muscle Synergies

With regard to the identified synergies in different subjects for a given task, muscle synergies have been shown to be nearly the same across different subjects. d'Avella *et al.* in [24] propose that the synergies extracted from each frog in kicking movements are very similar to the synergies extracted for other individual frogs. Also, Torres-Ovideo *et al.* in [122] show that most of the functional muscle synergies are similar across cats in terms of muscle synergy numbers, synergy activation patterns, and synergy coefficients. Robustness of synergy structure across perturbation types and subjects suggests that muscle synergies controlling task-variables are a general construct used by the CNS for movement and balance control.

Torres-Oviedo and Ting [127] show that four muscle synergies can reproduce multiple muscle activation patterns in cats during postural responses to support surface translations. They hypothesize that the synergy organization for postural control is robust such that a single set of functional muscle synergies underlies a variety of automatic postural responses under differing conditions [122]. Their results show that for all limb postures and perturbation types, the same set of muscle synergies and endpoint force vectors could reproduce the entire range of muscle and force responses observed during quiet stance and during multidirectional balance perturbations. They also hypothesize that the synergy organization is generalized across subjects. Their results show considerable similarity in both synergy composition and endpoint force across animals. Based on their findings of robustness and generality they suggest that muscle synergies controlling endpoint forces represent a general control structure used for maintaining balance, independent of the particular postural conditions.

Cheung *et al.* [128] recorded electromyograms (EMGs) from 12–16 upper arm and shoulder muscles from both the unaffected and the stroke-affected arms of stroke patients having moderate-to-severe unilateral ischemic lesions in the frontal motor cortical areas. Analyses of EMGs using a nonnegative matrix factorization algorithm revealed that in seven of eight patients the muscular compositions of the synergies for both the unaffected and the affected arms were strikingly similar to each other despite differences in motor performance between the arms, and differences in cerebral lesion sizes and locations between patients.

Scaling of muscle synergies is another necessary property of the neuromotor synergy hypothesis [27]. The muscles within a synergy should maintain the same relative activation levels, and the synergies involved within a task should remain consistent with an increase in the task's force requirements. Scalability of inputs in myoelectric control paradigms is important because it allows for implementation of proportional control, i.e. the speed of the motors of the controlled device is directionally proportional to the magnitude of the input signal. The activation levels of muscles embedded in synergies in addition to the activation levels (weights) of synergies can be considered a mechanism for proportional control. If it can be shown that their generality exists within a wide range of produced force, proportional control might be accomplished more accurately in a control space of a lower dimension via synergies. In spite of interesting attributes of muscle synergies, little research has been performed toward using these modules to control prosthetic hands. The only major studies that have examined the concept of muscle synergies as a dimensionality reduction paradigm for the production of a wide variety of human hand postures are done by Weis and Flanders [126] and [94]; both were briefly discussed in this chapter.

Are Muscle Synergies Task Specific?

While it is reasonable that the CNS organizes specific synergies to cope with the kinematics and biomechanical requirements of the movements involved in individual behaviors, some synergies might be shared across behaviors. To investigate this possibility, d'Avella and Bizzi [129] recorded electromyographic activity from 13 muscles of the hind limb of intact and freely moving frogs during jumping, swimming, and walking in naturalistic conditions. They compared the sets of five synergies extracted from their data by computing the similarities between their best matching pairs, i.e. counting the pairs with similarity above chance. They found that three pairs of synergies for jumping and swimming, four pairs for jumping and walking, and three pairs for swimming and walking had similarities that were significantly higher than the corresponding similarities of pairs of random synergies [129].

Also in [24] they again show that different behaviors in frogs such as kick, swim, jump, and walk contain some common synergies by comparing the synergies identified for each task with another. This comparison indicates that there are significant similarities among the synergies extracted from kicking and from different natural behaviors and suggests that there are synergies shared in control of different natural motor behaviors. This also suggests that the number of synergies needed to reconstruct a group of tasks can be limited to a few numbers. In other words, reconstruction of a wide range of natural behaviors by combining only a few muscle synergies may be possible. In fact, the decomposition of the muscle patterns for jumping, swimming, and walking as combinations of shared and specific synergies indicates that the muscle patterns for a large repertoire of movements can be constructed from a small set of building blocks and that some, but not all, of these building blocks are shared across behaviors.

Also, Chvatal *et al*. [130] hypothesize that a common pool of muscle synergies producing consistent task-level biomechanical functions is used to generate different postural behaviors. They identified muscle synergies using non-negative matrix factorization and functional muscle synergies that quantified correlations between muscle synergy recruitment levels and biomechanical outputs. Their results suggest that muscle synergies represent common neural mechanisms for Center of Mass movement control under different dynamic conditions: stepping and non-stepping postural responses.

Similar observations have recently come from the analysis of three types of behaviors of an invertebrate [131], suggesting that mixing behavior-independent and behavior specific modules might be a general strategy to flexibly yet efficiently construct complex behaviors.

The Relationship between Muscle Synergies and Movement Kinematics

Some investigators tried to connect each synergy to the kinematics of the given movement and they found some relationships between the recruitment of synergies and the movement kinematics [24], [122], [132]. For example, in investigating the functional role of synergies identified in frog's kicking, d'Avella *et al.* showed that both the direction and the magnitude of the displacement vectors depend on the level of activation of two extension synergies [24]. They have also studied the relationship between kick kinematics and temporal recruitment of the two extension synergies and observed a systematic shift of the difference in the synergy activation delay with changes in kick direction.

Also Ishida *et al*. [132] have identified three synergies from activity of six muscles during grasping movement and investigated the role of each synergy. They showed that changes in activity, e.g. horizontal grasping to vertical grasping, can be reconstructed by changing the activation coefficients of synergies and commands for different execution times can be realized by adjusting the onset of the synergies. In addition, simulations in human pedaling show that the same functional muscle groups can be used to perform variations within the task such as fast or slow, smooth or jerky, forward, backward, or one-legged pedaling [122], [133].

Studies of human hand kinetics have shown that most joint movements show some degree of coupling. Anatomical and neural factors combine to form coordinated joint movements, often referred to as kinematic synergies, i.e., simultaneous covariations in (relatively) independent mechanical DoFs. Tagliabue *et al*. [134] show that muscle synergy is in fact linked (correlated, and in phase advance) to the kinematic synergy during reach and during grasp-and-pull. Kinematic-and muscle synergies can simultaneously accommodate kinematic (grip type) and kinetic task constraints (load condition). They actually propose that the kinematic synergies may result from muscle synergies.

Tagliabue *et al*. [134] extracted muscle synergies (from EMG) using PCA (and not NMF) and compared them with the postural synergies (from joint angles). Jarrasse *et al*. [135] studied the postural synergies extracted from the joint angle variations in human hand; however they are different from muscle synergies. To the author's best knowledge, no other investigation extracted muscle synergies from EMG by NMF from human hand and wrist. Either their definition of synergy is different from ours or the method they used is different from our method.

CHAPTER 3- MUSCLE SYNERGIES TOWARD PROPORTIONAL CONTROL

3.1. Introduction

To generate a force in the hand or wrist in a given spatial direction and with a given magnitude the central nervous system (CNS) has to coordinate the recruitment of many muscles. Because of the redundancy in the musculoskeletal system, the CNS can choose one of many possible muscle activation patterns which generate the same force. What strategies and constraints underlie such selection is an open issue. The CNS might optimize a performance criterion, such as accuracy or effort. Moreover, the CNS might simplify the solution by constraining it to be a combination of a few muscle synergies, a coordinated recruitment of groups of muscles.

Shortly after Kobrinski's introduction of a functional myoelectric prosthesis in 1960 with basic digital (on/off) control [136], Bottomley introduced the concept of proportional control to this field [137]. One important factor in the proportional control of prostheses is to estimate the level of muscle activity produced by the user performing the tasks. With Bottomley's system the myoelectric signal intensity had a fairly linear relationship to velocity when the hand was moving and a similar relationship to grip force when the hand was closed. Although force estimation has been the subject of ongoing interest, a novel approach is required to accommodate intensity estimation when using multiple EMG channels. Although Bottomley's 'proportional control' definition originally involved both velocity and force relations to intensity, today it is usually defined as a means of estimating speed in combination with decision logic (either a conventional controller or classifier). In this work however, the focus is on performing a regression control, in which the output is explicitly a single or multi-DOF estimate of force.

Methods have been proposed to provide proportional control when using pattern recognition [20], [82], [138]; however, the consequence of using such methods can compromise classification performance [22], [139] as different force levels will occupy different locations in feature space. The ability to determine a force estimate of the intended motion is confounded by the existence of crosstalk and amplitudes that scale differently between channels as contraction intensity varies.

Most pattern recognition based approaches described in the literature do not inherently provide proportional control. Although recent work has proposed methods for its inclusion, e.g. [139], [140], it has the effect of compromising classification accuracy. Furthermore, pattern recognition based approaches do not typically accommodate combined motions, and thus the selection of DOFs is sequential. Recent preliminary work [141], [142] as investigated the use of pattern recognition for control of combined (simultaneous) DOFs. Despite these modifications however, a classification based approach combining both aspects of simultaneous and proportional control of multiple DOFs has yet to be developed. Using current pattern recognition based control methods, a user is required to perform movements sequentially in order to complete a given task, which imposes significant motor planning challenges, and prevents fluid life-like motions.

This has motivated the mapping of EMG to a continuous representation of user intent (such as force or position) so that the simultaneous activation of multiple DOF can be estimated. Most of this work involves either linear or nonlinear regression between the EMG (it's features) and either force or position.

There has been previous work in regression-based control of wrist motions [81], [138], [143] but not much has been done to provide multichannel proportional grasp force control. Jiang *et al.* [138]showed that the multi-channel mean square values (MSVs) can be modeled as a non-linear mixture of the forces produced at the multiple DoF of a muscular joint, which is termed the force functions. Thus, a supervised source separation approach, employing multilayer perceptron network (MLP), was proposed to estimate the force functions. The estimated forces were subsequently used for proportional and simultaneous myoelectric control. The results presented in [138] and a subsequent study [80] were very promising, particularly for the two DoFs of the wrist: wrist flexion/extension and ulnar/radial deviation. However, when the third DoF, i.e. supination/pronation, was activated, the estimation results were not satisfactory. Most importantly, the clinical applicability of the approach proposed in [138] is limited because the method requires the simultaneous recording of the ipsilateral force (force generated from the amputated limb) and EMG signals for training the estimation algorithm. This training approach is not feasible in amputees.

Nielson *et al*. [82] investigated possibilities of improving the estimation performance of the force functions for three DoFs (wrist flexion/extension, radial/ulnar deviation, and wrist pronation/supination), by using four sEMG features: MAV, ZC, SC and WL. They included both single and multiple DoF contractions in the training data that were provided to the MLP. When compared to the approach used by Jiang *et al.* [80], they reported an improvement of 5.7% and 14.4% in root mean squared error (RMSE), respectively for excluding and including the third DoF. However, only two DOFs of wrist were considered. This is while for a clinical application, it would be necessary to include some of the functions of the hand (grasping and pinching). This extension will require the inclusion of more types of contractions in the training set. Ameri *et al*. [81] applied support vector machines (SVMs) for proportional control of three DoFs of wrist using four TD features (MAV, ZC, WL, SC). In spite of the improvement in force estimation achieved via SVMs, this work did not investigate grasp force control.

The muscle synergy viewpoint hypothesizes predetermined patterns of co-activations of muscles, i.e. muscle synergies, during task performance as the primitive modules of muscle coordinatio. These muscle synergies imply a coupled activation of a group of muscles. On the other hand, redundancy in the neuromotor system potentially allows for multiple modalities of muscle coordination to produce sub-maximal forces for different tasks [144]. Hence, the relative proportions of muscle activations could potentially change with different conditions of force level during a movement. Accordingly, the activation levels of muscles embedded in synergies in addition to the activation levels (weights) of synergies can be considered a mechanism for proportional control. If it can be shown that their generality exists within a wide range of produced force, proportional control might be accomplished more accurately in a control space of a lower dimension via synergies. Ajiboye and Weir showed that the dominant synergies involved in cylindrical and lateral force-tracking tasks do linearly scale with grasp force; however, they did not describe a method of multi-DOF control.

The methods employed in this work differ from the mentioned investigations not only in testing a broader task set which includes both hand and wrist motions, but also in the nature of the inputs. The physiological attributes of synergies are the main motivation behind our investigations as discussed previously. This chapter reports our studies on using muscle synergies in estimating force.

3.2. Force Estimation in Multiple Degrees of Freedom from Intramuscular EMG via Muscle Synergies

This section discusses how muscle synergies may have the potential for providing effective proportional force control. This was investigated by examining the consistency of the muscle synergies involved in producing four different wrist movements (flexion, extension, abduction, and adduction) and their combinations and studied their power in estimating the produced force. This experiment involved acquiring intramuscular EMG along with the produced force while subjects performing these tasks. From these data, the muscle synergies and the neural inputs were extracted. These estimated neural inputs correspond to the estimated forces in each DOF.

3.2.1. Methodology

Intramuscular Data Collection

Recording the EMG intramuscularly, instead of from the skin surface, has several advantages over surface EMG for providing simultaneous control. EMG signals from deep muscles are significantly attenuated at the skin surface, whereas an intramuscular recording can acquire signals from the deepest muscles. Furthermore, intramuscular recordings have limited crosstalk [145]. Intramuscular recording thus allows EMG signals to be obtained from any muscle in the residuum with minimal noise from the surrounding musculature. In transradial amputees, intramuscular EMG may thus allow intuitive, simultaneous control of a multi-DOF wrist–hand prosthesis. In the past, control methods using intramuscular EMG were largely overshadowed by those using surface EMG because of a lack of clinically available implantable EMG recording devices. However, a variety of implants currently being developed [146]-[148] may make intramuscular EMG clinically feasible as a signal source. Furthermore, chronic intramuscular implants could address several of the issues that impair the performance of surface EMG-based systems. A chronic intramuscular implant may provide a more stable signal source that is less affected by electrode shift or changes in skin impedance caused, for example, by perspiration. The recent advances in implantable recording devices and their potential advantages suggest that intramuscular EMG-based myoelectric control systems could have considerable clinical impact [149], [150].

Data Collection Protocol

Our experimental protocol for data collection was approved by the University of New Brunswick's Research Ethics Board. Intramuscular EMG signals were collected from six superficial muscles, flexor carpi ulnaris (FCU), palmaris longus (PL), flexor carpi radialis (FCR), extensor carpi radialis (ECR), extensor digitorum communis (EDC), extensor carpi ulnaris (ECU), from eight normally limbed subjects (two female and six males within the age range 23 to 50). A pair of sterilized wire electrodes made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA, diameter 50 μm) was inserted into each muscle with a sterile 25-gauge hypodermic needle guided using an ultrasound scanner. The insulated wires were cut to expose only the cross section at the tip, providing high selectivity. The needle was inserted to a depth of a few millimeters below the muscle fascia and then removed to leave the wire electrodes inside the muscle. The location of the wires was further verified by asking the subject to perform the desired tasks and inspecting the generated EMG. Intramuscular EMG signals were amplified (AnEMG12, OT Bioelletronica, Torino, Italy) with a factor of 1000 and band-pass filtered (20 - 5000 Hz). A reference electrode was placed around the wrist. Intramuscular EMG and force signals were A/D converted using 16 bits (NI-DAQ USB-6259) and sampled at 10000 kHz.

After placing the electrodes, subjects were required to perform different movements associated with 2-DOF of the wrist including extension, flexion, abduction, adduction, and combinations of them. Subjects exerted force while seated in a chair with their right arm placed in an armrest and the hand and the wrist supported by a brace. A custom-made hand support incorporating a commercially available dynamometer (Gamma FT-130-10, ATI Industries) was used to provide feedback of the level of activation for each task.

MATLAB-based acquisition software was used to guide subjects through a data acquisition session. Each session consisted of two trials of multiple repetitions of each motion. Subjects were prompted to complete medium force isometric contractions followed by a 2-minute rest period between trials.

Extracting Muscle Synergies

Synergy extraction was performed using methods commonly described in the literature. Both the elements of the synergies and their weighting within each response should be positive, because muscle activations are being considered. The full model written in matrix form is:

$$V_{m \times o} = W_{m \times o} \times H_{n \times o} \tag{3.1}$$

where V is the m × o (m muscles, o observations) recorded EMG data matrix, W is the m × n (n synergies, m > n) column-wise matrix of synergies and H is the n × o matrix of time-varying neural inputs. V is given, and W and H are to be determined.

The method of identifying muscle synergies is to measure EMG signals from all muscles involved in a set of movements so that specific patterns of muscle activation can be identified for those actions. Because both the neural inputs and the muscle synergies of the model are not directly observable, estimation of these parameters has commonly been termed blind source separation (BSS) [151], [152].

Identification of muscle synergies can be done through different methods such as principal component analysis (PCA), maximum likelihood factor analysis (FA), nonnegative matrix factorization (NMF), and independent component analysis (ICA). Since NMF is the only one among these methods that imposes non-negativity to the neural inputs, it is the most common method used to identify muscle synergies and their activation coefficients underlying a set of muscle activation patterns [153]. This is because muscle activities measured in form of MAV or RMS is non-negative, and this advantageously constrains the solution.

Also, there are no explicit assumptions about the distributions of activation coefficients for NMF, other than they must be nonnegative. In several studies [153], the performance of NMF was reported relatively robust when the activation coefficients were drawn from different distributions. It is likely that the robust performance of NMF is to a large extent explained by the strong constraints imposed by its assumption of nonnegativity

[154]. Thus, NMF is chosen as the method for extracting the synergies and their coefficients in this study.

Determining the Number of Synergies

The procedure that is used for determining the number of synergies underlying a particular dataset consisting of nonnegative values is based on information content. Of all previously proposed criteria [155], this is the most commonly used method and has been shown effective in identifying the number of synergies enough to reconstruct the original data and reflect its major behaviour. In this method, the original data is reconstructed using increasing numbers of synergies. The coefficient of determination or R^2 computed between the reconstructed and original signal was employed to evaluate the extracted synergies based on the amount of variance of the original signal that they can describe. This term is defined as below:

$$R^2{}_j = 1 - \frac{\sum_{t=0}^{M} (\hat{f}_i(t) - f_j(t))^2}{\sum_{t=0}^{M} (f_i(t) - \bar{f}_j(t))^2} \tag{3.2}$$

where $f_j(t)$ is the cursor displacement associated to the *j*th DOF (e.g., for abduction-adduction, the vertical displacement), $\hat{f}_i(t)$ is the corresponding estimated output, $\bar{f}_j(t)$ is the temporal average of $f_j(t)$, M is the number of data samples, and $R^2{}_j$ is the coefficient of determination for the *j*th DOF.

R^2 of this reconstruction shows how much of the variance in the original data is described in the reconstruction result. Obviously, the more synergies involved in the reconstruction, the higher the R^2 value will be. The change in the slope of this increasing R^2 becomes smaller as the number of synergies becomes closer to the dimension of the original data. This method chooses the number by which more than 90% of the variance of the original data is described; and usually it is the point where the slope changes are minor.

Force Estimation

Data were segmented using 200 ms windows with a 50 ms increment. Multilayer perceptron (MLP) artificial neural networks (ANN) were used to learn the association between EMG features and the force from the wrist and hand. Extracted neural inputs (H in Equation (3.1)) are provided to an MLP with two hidden layers and 10 neurons. ANNs are commonly used for the same purpose and force estimation investigations in several studies [21], [82], [143]. The target of the ANN is the measured force in each DOF during training; with novel EMG data the output is an estimate of produced force. The ANN was trained for each subject separately. For 2-DoF tasks, the training data were extracted from the signal recorded while performing 2-DoF tasks. Since the recording trials included multiple repetitions of each movement, each trial was divided into three segments: the ANN was trained using the 50% of the repetitions from the trial and validated with 25% of the remaining repetitions and finally tested with the rest of the data that is not used in training and validation phase. The repetitions used in each of these three phases were chosen randomly. The network training stopped when either the validation error increased for six sequential epochs or the error went below a predefined threshold (0.001). In order to evaluate our estimation results, Mean Absolute Values (MAV) of the same data (of all the channels) were used to estimate the associated force.

Statistical Analysis

An analysis of variance (ANOVA) with factors Synergies and MAV was completed on the each performance metric (R^2 and RMSE) and p-values less than 0.05 were considered significant.

3.2.2. Results

Determining the Number of Synergies

We found the smallest number of components necessary to explain at least 90% of the variance in each subject using NMF. Figure 3.1 shows how this explained variance grows by increasing the number of synergies for a typical subject. For all the subjects and for all the trials only a few of synergies (two or three) were enough to describe 90% of the variance.

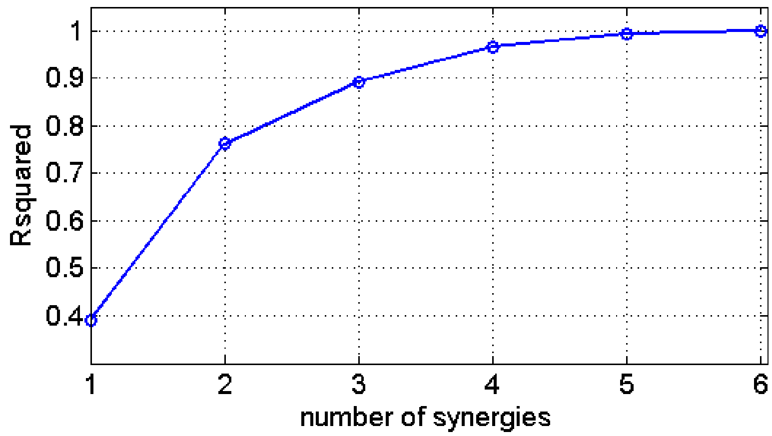

Figure 3. 1 – The change in the described variance by increasing the number of synergies

Estimating the Force

Extracted neural inputs were provided to an ANN (with two hidden layers and 10 neurons). The estimated neural inputs have considerable variance, and consequently were low pass filtered at 2Hz before being provided to the ANN.

Figure 3.2 shows three muscle synergies and their corresponding neural inputs extracted from a sample segment of intramuscular data including a number of wrist flexions and extensions (shown by *F* and *E* respectively). As Figure 3.2 shows, each synergy indicates a pattern of activities of six muscles and has a dominant active muscle making the synergies sparse. Also the relation between the synergies and the static force of each DOF can be observed in Figure 3.2. Activation of the flexors is mainly reflected by the second and the third synergy whose coefficients increase during the flexion part of the data.

On the other hand, the first synergy is mainly characterized by the extensors and a considerable increase is observed in the first coefficient during extension.

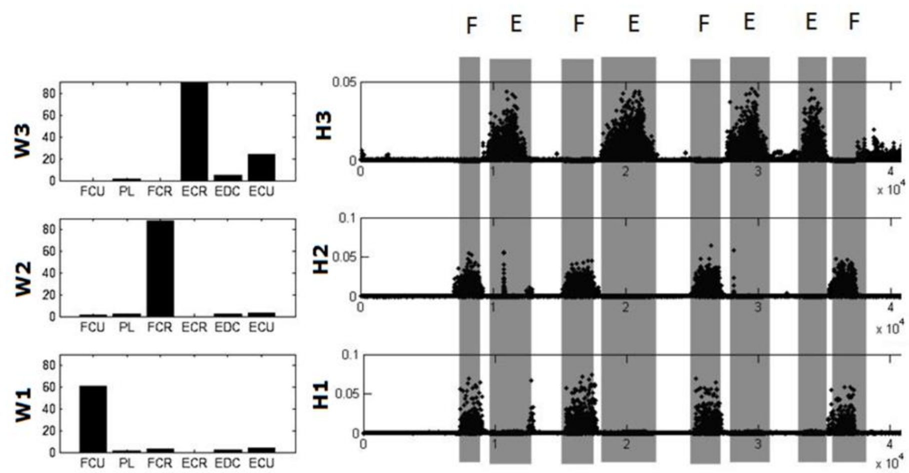

Figure 3. 2 – Example of extracted synergies and their coefficients. Dark shades on the neural inputs shows the associated movement (*E* for extension and *F* for flexion); the horizontal axis is time and the vertical axis is unit less.

Figure 3.3 shows the result of force estimation using three neural inputs for a sample segment of data including extension and flexion performed by a subject. For all four subjects, the R^2 values of the estimation and the correlation coefficients between the recorded force and the estimated values were computed and averaged to evaluate the accuracy of the estimation. The first three rows of Table 3.1 show the results for estimating the produced force in each DOF separately using the neural inputs.

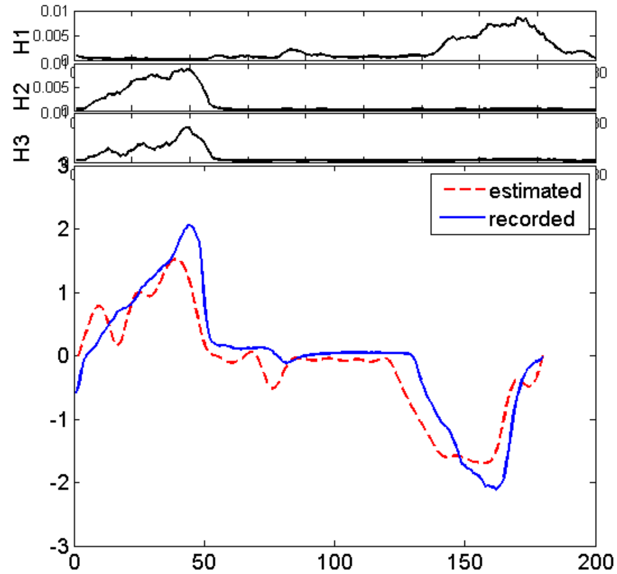

Figure 3. 3 – An example of three neural inputs (top plots) along with the recorded forces and the estimation result (bottom plot)

As Table 3.1 shows, the estimation results are highly correlated with the recorded force and R^2 values indicate high accuracy in the estimation considering the fact that only three features extracted from the 6-channel EMG signal are being used for estimating force. Most of the estimation error, as one can see in Figure 3.3 can be the result of scaling and/or delay in estimation with respect to the target. It is possible that further signal processing could reduce this error, but it is unlikely that a small but constant delay would affect real-time control. *This* will be assessed in the *real-time control* experiment in Section 3.5.

Table 3. 1– Force estimation results via neural inputs (NI) and mean absolute value (MAV)

Task	Input to the estimator	Correlation Coefficient (NI)	Correlation Coefficient (MAV)	R^2 (NI)	R^2 (MAV)
Flexion/ Extension	Neural inputs	0.91	0.93	0.81	0.84
Abduction/ Adduction	Neural inputs	0.87	0.90	0.77	0.80
Flexion/Extension + Abduction/Adduction	Neural inputs	0.93	0. 92	0.79	0.76

It is also relevant to further evaluate the achieved results by comparing them with results of estimation via another type of input. In order to facilitate this comparison, we used the MAV of the same data (for all the channels) to estimate the associated force. When using MAV as input, the accuracy of the estimation is slightly higher than using only two or three neural inputs. Statistical difference between synergies and MAV was observed when using five or less Neural Inputs. However, as Figure 3.4 shows, increasing the number of extracted neural inputs can improve the accuracy of the estimation and sometimes even outperforms of MAV estimation.

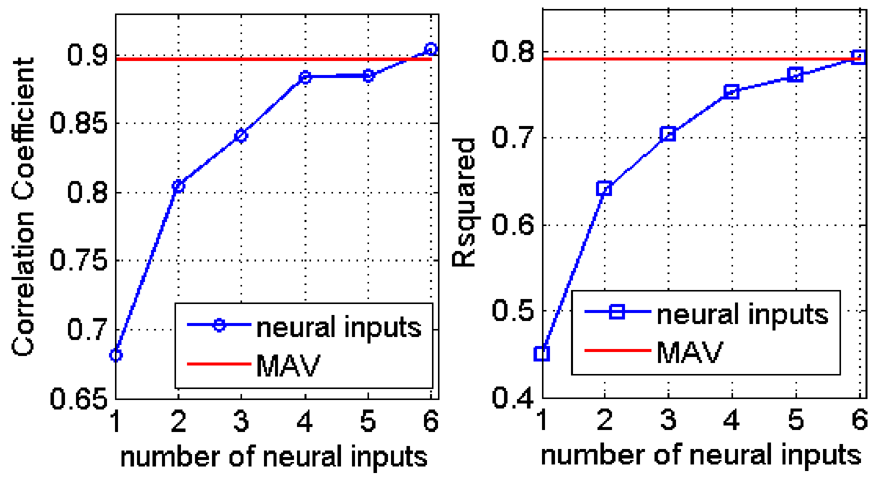

Figure 3. 4– Changes in Correlation coefficients and R^2 by increasing the numbers of neural inputs for a typical subject, also compared with result of using MAV as input. R^2 (unitless)

3.2.3. Discussion

We observed the changes in coefficients of the synergies while switching from one task to another. As the produced force increases, we observed an increase in the coefficients or the neural inputs.

Our observations also showed that the components (synergies) extracted by this method are quite consistent with the muscle activities during each task. For example activation of the flexors is mainly reflected by the synergies whose coefficients increase during flexion. The R^2 values of the estimation along with high correlation between the estimated and the target values show that the estimated values can reflect the major behaviors of the target force and thus the neural inputs are able to estimate the force values with a relatively high accuracy. We also showed that this result is usually not as accurate as what MAV yields particularly when the number of synergies is low. However, the ANOVA test showed that when the number of synergies is increased to six, their estimation result is comparable to those achieved by MAV in multi-DOF force estimation (*p-values* <0.05).

Furthermore, the numbers of neural inputs required for estimating the force is usually few, i.e. much less than the number of muscles involved in the movement. Thus, using neural inputs not also keeps the estimation in an acceptable accuracy but also reduces the dimension of the estimation model.

3.3. Toward Proportional Control of Myoelectric Prostheses with Muscle Synergies

In our previous investigation we observed that muscle synergies are able to estimate the force produced in 1 and 2-DoF wrist tasks. The next step is to expand the previous study not only by including more complex tasks such as grasps, but also examining the robustness of the synergies across variable force levels and compare their ability of estimating unknown force levels regardless of the task. So, the other major goal of this study is to quantify the robustness and repeatability of the muscle synergies that are involved in producing different wrist and hand movements across different exerted force levels. Also, it would be interesting to compare the ability of neural inputs in estimating force with MAVs in two different cases: in the first case the amount of force that the proposed model should estimate is already used for training. In the second case, the model is being tested with a new and untrained level of force. In this case robustness and scalability of the synergies are very important since if they do not exist, the model would be unable to estimate new force levels.

3.3.1. Materials and Methods

Data Collection Protocol

Our experimental protocol was approved by the University of New Brunswick's Research Ethics Board. Eight normally limbed subjects participated, one female and seven males within the age range 23 to 53, all right-handed (referenced as Sub1–Sub8). Subjects had no history of neuromuscular disorders.

Surface EMG data were collected in this work. The main reason for using surface data and not intramuscular data was that in this study our goal was to target a larger number of muscles and some of these muscles are very challenging to reach with intramuscular data collection. The difficulty of having a sufficient number of subjects given the invasive nature of intramuscular data collection, and the significantly longer duration of experiment motived the use of surface EMG.

Data were collected from seven superficial muscles (flexor carpi ulnaris (FCU), palmaris longus (PL), flexor carpi radialis (FCR), extensor carpi radialis (ECR), extensor digitorum communis (EDC), extensor carpi ulnaris (ECU), and biceps) and five intermediate and deep muscles at the site where they are accessible (flexor digitorum superficialis (FDS), flexor policis longus (FPL), pronator teres (PT), flexor digitorum profundus (FDP), and brachioradialis (BR)). Muscles were identified via anatomical and physical tests and the EMG electrodes (bipolar silver/silver chloride Duotrode, Myotronics, Inc.) were placed on the belly of each muscle. A reference electrode was placed on top of the lateral epicondyle. Surface EMG signals were amplified with a gain of 5000, bandpass filtered between 10 – 500 Hz and A/D sampled with 12 bits resolution.

Subjects were required to perform different constrained isotonic movements associated with two DoFs of the wrist including extension, flexion, pronation, and supination, as well as four hand motions including power, pinch, key, and spherical grasps. Combinations of the wrist and hand motions were performed as well. Figure 3.5 shows the set-up and the electrodes along with the grasp types used in this data collection.

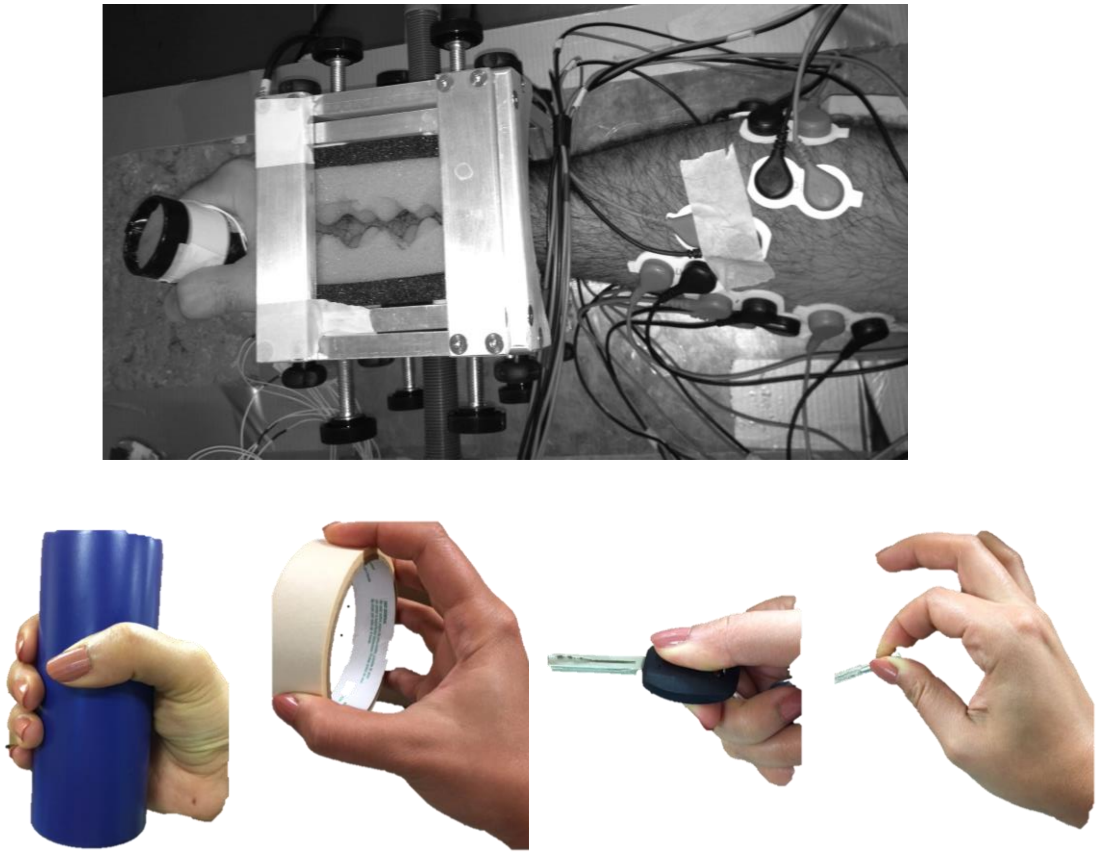

Figure 3. 5– Top figure shows the placement of surface electrodes on the subject's arm and the data collection setup. The subject hand is in the braces to limit the position variation of the hand. The dynamometers in the braces capture the force exerted by the wrist while they hold the object equipped with FSRs. FSRs capture the hand force on the finger tips. The bottom pictures show four grasp types that are used in the experiment: pinch, key, spherical, and power from right to left.

Setup for Recording Wrist Force

Subjects exerted force while seated in a chair with their right arm placed in an armrest. A custom-made hand support incorporating a commercially available dynamometer (Gamma FT-130-10, ATI Industries) was used to record and provide feedback to the subjects about the level of wrist activation for each task. In the setup, as shown in Figure 3.5, the subject passes his/her hand partially through the force-measuring device locating his/her wrist between the sensors. The distance between the sensors is adjustable and makes it possible to tighten the setup around the subject's wrist. Then the subject is instructed to perform four wrist tasks by pushing their hand against the restraint.

Setup for Recording Grasp Force

EMG muscle activity in the forearm is highly related to applied fingertip forces [156], [157]. Therefore, in this experiment, grasp force was estimated by measuring the fingertip forces as successfully employed by others [158].

To perform the grasping tasks, four different objects each associated with a grasp type were chosen for the subjects to hold. Figure 3.5 shows the grasps. There are measurement tools such as the dynamometers with different heads proper for measuring various grip forces. However, the reason we cannot use these devices is that we need the subject to perform isometric wrist tasks while grasping different objects and using the mentioned device is uncomfortable for the subjects. Thus, Piezoresistive force sensing resistors (FSR) were used as a measuring tool in this experiment. FSRs are very thin, flexible sensors that are also moderately priced and can be adjusted for different force ranges and thus were the most suited for the force sensor for measuring the grip force in our experiment. FSRs exhibit a decrease in resistance with an increase in the force applied to the active surface. Their force sensitivity is optimized for use in human touch control of electronic devices. FSRs are not a load cell or strain gauge, though they have similar properties. These sensors are relatively light and can be easily taped to the point at which force must be measured. Once a circuit was designed to use the sensors, each FSR would need to be calibrated, and the relationship between force and resistance determined on an individual basis. The force vs. resistance characteristics of the utilized FSRs are described in the Appendix.

Our initial idea to record the grasp force was to use a glove equipped with FSRs on the palm. This required a tight-fitting stretch glove, which was difficult for the subjects to don. It was much easier to locate the FSRs on the objects to be grasped (at the spots of finger contact), and this provided much greater FSR accuracy and reliability as well. Consequently, the objects were equipped with FSR sensors (Interlink Electronics, 1 cm by 1 cm) on their surface to measure the force applied by the fingertips. All signals were sampled at a rate 1000 samples per second. Figure 3.6 shows the circuitry used for reading FSRs data. Equations (3.3) and (3.4) show the formula to convert the voltage that is read by the circuit to force. The constants in Equation (3.4) are obtained by trial and error. Total Power was set to $2.2\Omega \times 5v$.

$$R_{FSR} = \frac{Total\ Power}{Voltage\ at\ FSR} - 2.2\Omega \tag{3.3}$$

$$Force_{FSR} = \frac{{}^{1}/_{R_{FSR}} + 0.0262}{0.1472} \times 0.6894 \tag{3.4}$$

Figure 3. 6 – The circuitry used for reading FSRs data

Recording Protocol

For each subject, after donning the EMG and force sensors and adjusting the set up parameters, the maximum voluntary contraction (MVC) was recorded twice for all motion classes. MVC was chosen as the maximum exerted force between two trials. This is used for future normalization of the data, and to ensure that the force levels required during the experiment were at a comfortable force level that could be reliably produced by the subject. Afterwards, a few training trials were performed to familiarize the subject with the Graphical User Interface and the correct way of performing each task. Finally, in the data recording phase the subject was asked to perform the upcoming tasks according to what was presented in the GUI each time. The subjects were asked to follow one of the two force profiles (25% or 50% MVC) each time. An example of a force profile and the UI is illustrated in Figure 3.7.

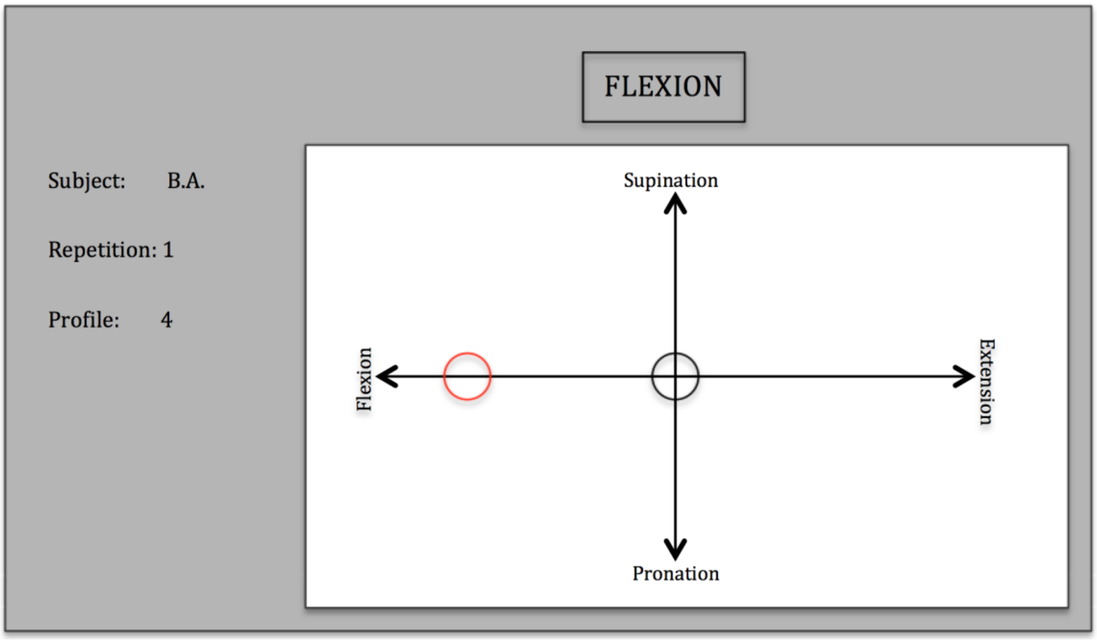

Figure 3. 7 – An illustration of a sample profile. This is provided to the subjects as a feedback so that they can follow the target with the amount of force they exert.

Subjects kept each posture for three seconds at the target and then returned to rest. Both transient data and the steady state data were recorded in separate files during the experiment. There are different trials of each task with different required force levels to reach the target, each called a *profile* in this study. Subjects performed two trials of each profile and each trial contained two repetitions of the same profile. The subjects could rest one to five minutes between the trials upon request to prevent muscle fatigue. The entire experiment included 121 profiles including the *no movement* profile performed by each subject[3]. The overall time needed for each experiment, including the set up time and performing the tasks, was about 1.5 hours. Each profile can include a 1-DOF single task or a multi-DOF combination of two tasks (one wrist motion and one type of grasp).

3.3.2. Data Analysis

Similar to the previous study, the appropriate number of synergies was determined as the smallest number of components necessary to explain at least 90% of the variance of the recorded sEMG for each subject using NMF.

Figure 3.8 shows how this explained variance grows by increasing the number of synergies for a typical subject. For all the subjects six or seven synergies were sufficient to describe 90% of the variance. In order to keep them within the bandwidth of the measured force, the estimated neural inputs were lowpass filtered at 2Hz before being provided to the force estimator model.

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[3] 24 1-DoF and 2-DoF tasks each repeated for two different force levels, with two repetitions at each level. The 24 training trials for the subject and one no-motion task, equals to 121 profiles in total.

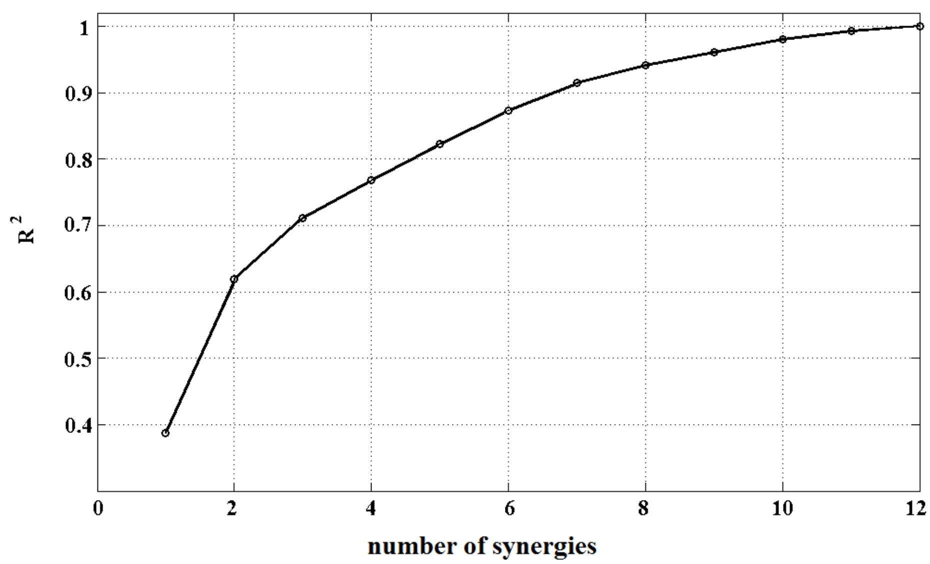


Figure 3. 8 – The change in the described variance by increasing the number of synergies (axes are unit less). Hand and wrist synergies are included.

Robustness and Repeatability of Muscle Synergies across Different Force Levels

The repeatability of synergy patterns is defined here to describe the consistency of results when running the synergy extraction algorithm on the same set of tasks multiple times. This clearly has a considerable effect on the reliability of the results achieved by synergies. The repeatability test is done across different repetitions of each task of the same force level.

The repeatability of the synergies was examined by extracting them from predefined sets of tasks. All tasks were included and each set contained two repetitions of all-low contraction or all-medium contraction tasks. Therefore, for each subject, four sets were created; two containing only 25% MVC tasks and two containing only 50% MVC tasks. The synergies were extracted from these four sets for each subject to determine how repeatable they are in different repetitions of tasks under the same conditions.

Generally a system is *robust* when it resists change without a need to adapt its initial configuration. Here we tested the robustness of synergy sets against the force change and examined their ability to cope with changes in force levels in force estimation. This means that changing the force level of the tasks should not affect the synergy patterns significantly.

Force Estimation

After extracting the synergies, the associated neural inputs were provided to an ANN. The target of the ANN was the measured force in each DoF during training; with novel EMG data the output is an estimate of produced force. The ANNs were trained using the backpropagation (Levenberg–Marquardt) algorithm. The 50% MVC data were used to develop training and validation sets in order to find the optimal structure for the ANN. The validation set was used to determine the optimum number of hidden layer neurons (eight), and to determine a stopping criterion for ANN training (when either the validation error increased for six sequential epochs or the error went below a predefined threshold of 0.001).

Data were segmented using 200ms windows with a 50ms increment. The ANN was trained 50 times and the ANN with lowest error on the validation data was used for testing in order to estimate the 25% MVC data.

The test analysis was performed on analysis windows of 200ms in duration. The processing delay upon this 200ms analysis window is minimal (less than 10ms). It is generally accepted that for a real-time application of the prostheses, the response time should not exceed 300ms. The low contraction profiles (25% MVC) were used for testing and the medium contraction (50% MVC) data were used for training and validating the force estimator model. Of the medium contraction data (training set), 85% (randomly chosen) were used during training and the remaining 15% were used for validation. The training set consisted either of solely 1-DoF or of both 1-DoF and 2-DoF contractions, depending on the estimation scenario as described below.

Two estimation scenarios were considered, both utilizing a predefined set of tasks from which the synergies were extracted. The extracted synergies were then used for calculating the neural inputs of test data. Since, for each subject, eight repetitions of each task were recorded, different training sets can be created for each subject. In the first scenario (2-DoF training), the estimator model was trained (at medium level) and tested (at low level) using both single and multi-DoF tasks. The training set of this scenario consisted of all repetitions of all 50% MVC 1-DoF and 2-DoF tasks. In the second scenario (1-DoF training), the 2-DoF tasks were eliminated from the training set; which makes it more practical in terms of the time and effort required of an amputee to train the system. This presents a more challenging estimation scenario, as the force estimator must generalize to 2-DoF tasks. However the test set still contained both 1-DoF and 2-DoF contractions.

The performance of force estimation analysis using synergies was investigated, and compared to the case of using the channel-based Mean Absolute Values (MAV) of the EMG as inputs to the ANN. The ability of the ANN to estimate force was quantified using the coefficient of variation (R^2) and root mean square error (RMSE). Here, RMSE is defined as the error between the actual and estimated force.

Statistical analysis

An analysis of variance (ANOVA) with factors Synergies and MAV, was completed on the each performance metric (R^2 and RMSE) and p-values less than 0.05 were considered significant. Results are provided as mean ± standard error across subjects.

3.3.3. Results

Repeatability and robustness of muscle synergies

The first two rows of Figure 3.9 (a) show the synergies extracted from two low contraction sets for two of the subjects. As it is shown the synergies are almost the same across low contraction data sets for each subject. This was typical for each subject, demonstrating high repeatability of the synergies. To quantify this we calculated the correlation between the synergies extracted from each base set and the average of the results on all subjects was 0.9934 ± 0.005.

Then, we extracted the synergies from multiple tasks of 25% MVC. Our examinations showed that these extracted synergies are able to describe more than 90% of the variance of the data collected in 50% MVC. The same examination was performed for all eight subjects. Comparing the rows of Figure 3.9 (a) with Figure 3.9 (b) shows that the synergies are scaled but their patterns are fairly consistent across different force levels (correlation > 0.9).

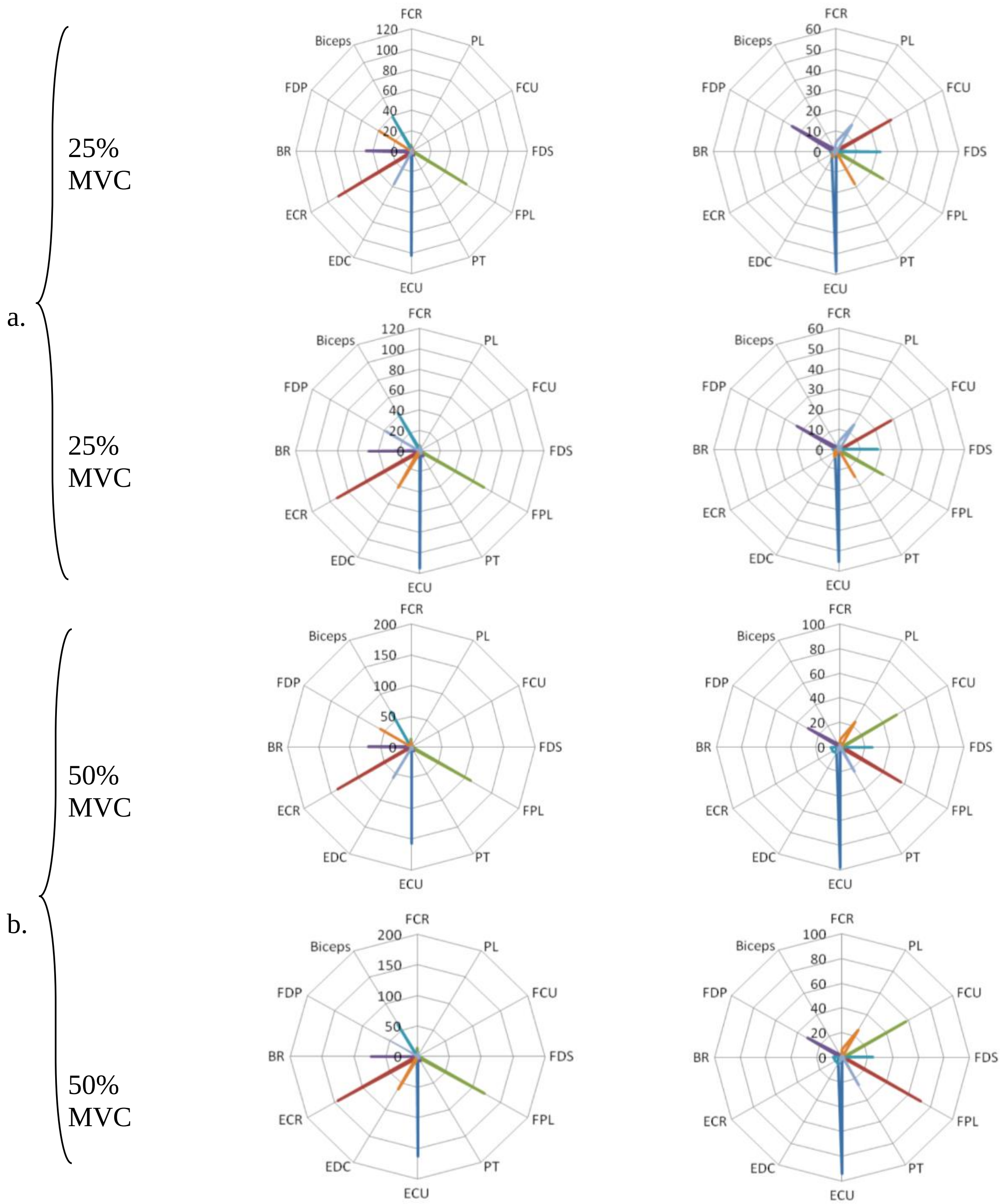


Figure 3. 9– Comparing the synergies extracted from a) two 25% MVC base sets and b) two 50% MVC base sets for two subjects. First column shows synergies of subject1 and second column shows those of subject2. The Y (radial) axis measures the synergies magnitudes and has arbitrary units. Magnitude of radial axis is normalized with respect to MVC.

Force Estimation

For the simple estimation problem (Scenario 1: 2-DoF training), the average (across subjects) of RMSE was 0.76 ± 0.42 and 0.88 ± 0.53 (p = 0.002) using synergies and MAV respectively. The average of R^2 was 0.84 ± 0.08 when using synergies and 0.84 ± 0.10 (p = 0.024) when using MAV. Figure 3.10 shows the result of force estimation using six neural inputs for a sample segment of data including wrist extension and power grip performed by one subject. Figure 3.11 shows the RMSE and R^2 averaged across all the subjects. As it can be seen in Figure 3.11, generally better results were achieved in wrist force estimation than in grasps.

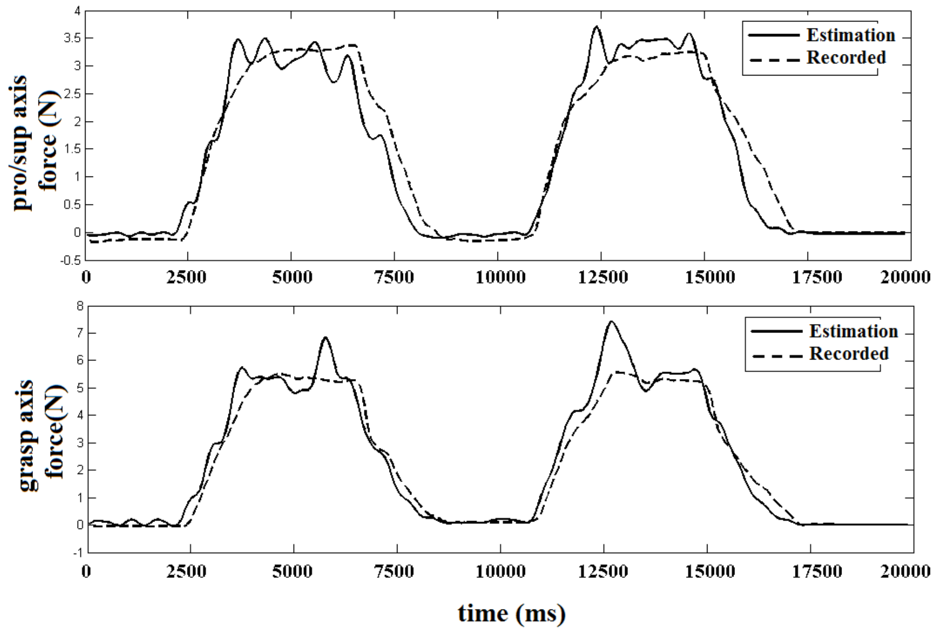
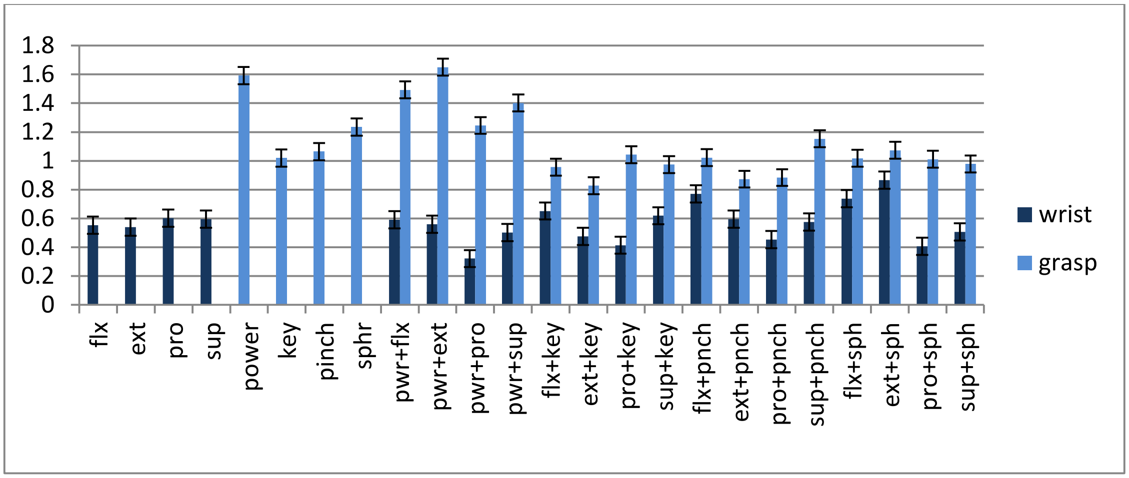
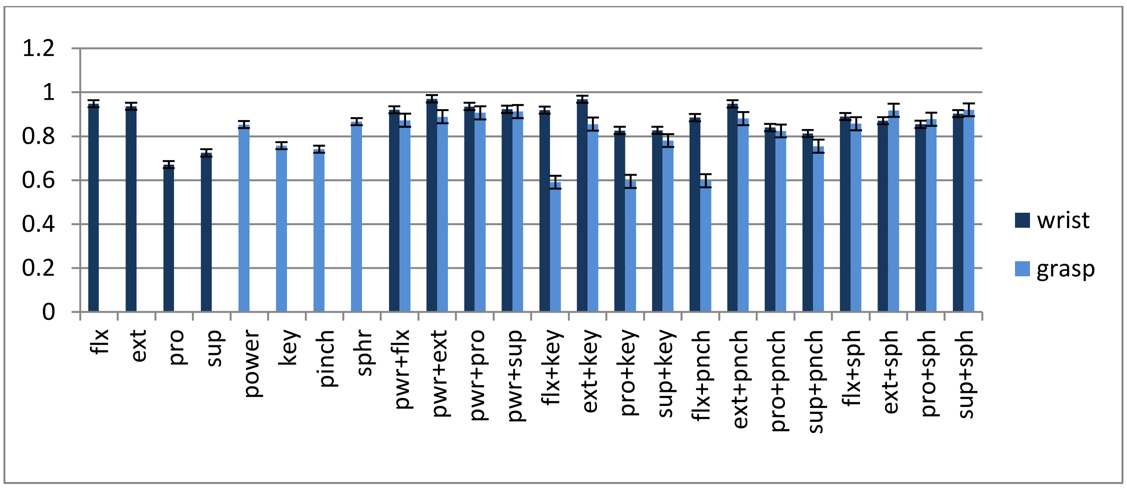


Figure 3. 10 – An example of force estimation using six neural inputs for a sample segment of data including wrist extension and power grip performed by one subject. The illustrated force values are already down sampled by window length of 200 and increment of 50 samples. The unit of RMSE is the same as the unit of force measurements (N).



RMSE



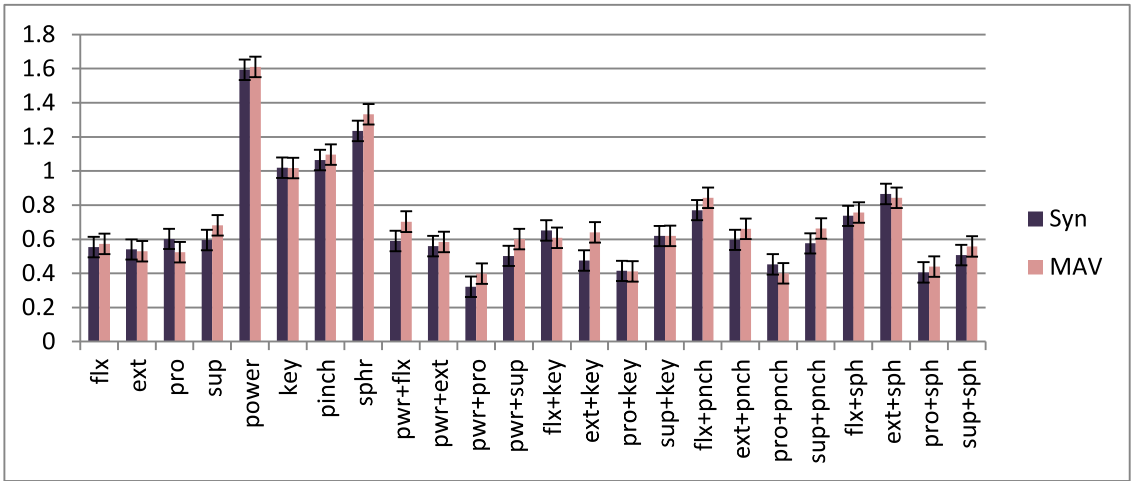
R^2

Figure 3. 11 –RMSE and R2 values of force estimation in the *2-DoF training problem* using synergies. The results are averaged across all eight subjects. The darker bars show the associated value to each plot for the wrist force axis and the lighter bars for the grasp force axis.

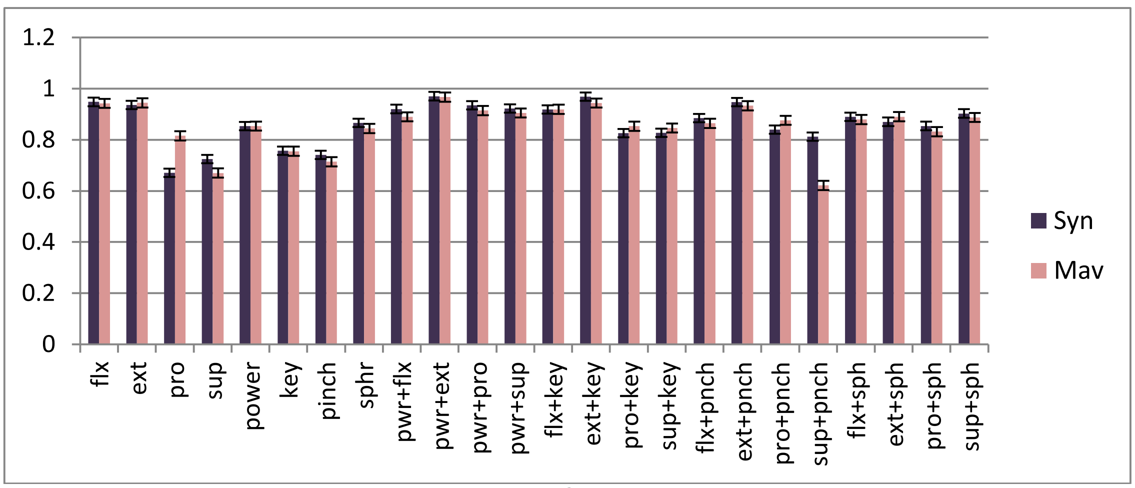
Figure 3.12 compares the results of using synergies with those of using MAVs. This comparison not only shows that synergies are able to estimate the force, but also in a majority of the tasks synergies outperformed the MAV in force estimation. Performing multivariate analyses of variance (ANOVA) on RMSE and R^2 showed that the methods were not significantly different (p-value > 0.05) when classifying 1-DoF tasks. Also for 2-DoF task classification the difference between the methods was not significant (p-value > 0.05). When classifying both single and multi-DoF tasks together, again the methods were not significantly different (p-value > 0.05).

In the more challenging estimation problem (Scenario 2: 1-DoF training), when classifying single and multi-DoF tasks all together, the average of R^2 across subjects was 0.76 ± 0.22 when using synergies and 0.52 ± 0.49 when using MAV. The obtained *p-value of* 0.002 showed that the methods were significantly different. Also RMSE was 0.90 ± 0.43 and 1.17 ± 0.64 using synergies and MAV respectively ($p = 0.002$).

When separating 1-DoF and 2-DoF tasks for ANOVA test, the results showed that in single-DoF tasks classification MAVs and synergies were not significantly different. However, in multi-task classification, synergies significantly outperformed MAVs (p-value <0.005). Figure 3.13 shows the results of using synergies and compares them to those of using MAVs. The first thing that can be seen in Figure 3.13 is that the force estimation was more accurate for 1-DoF tasks in comparison with the combined tasks. This was clearly expected since the combined tasks were unknown to the model and estimating the force produced during those tasks from the signals associated to them is more challenging for the model. However, relatively high R^2 achieved in many of the combined task profiles show that the model trained with the synergies of only 1-DoF tasks has the potential to be used for force estimation in more complex and untrained tasks.



RMSE



R^2

Figure 3. 12 – Comparing the results of using synergies with those of using MAV in *2-DoF training problem*. The results are averaged across all the subjects.

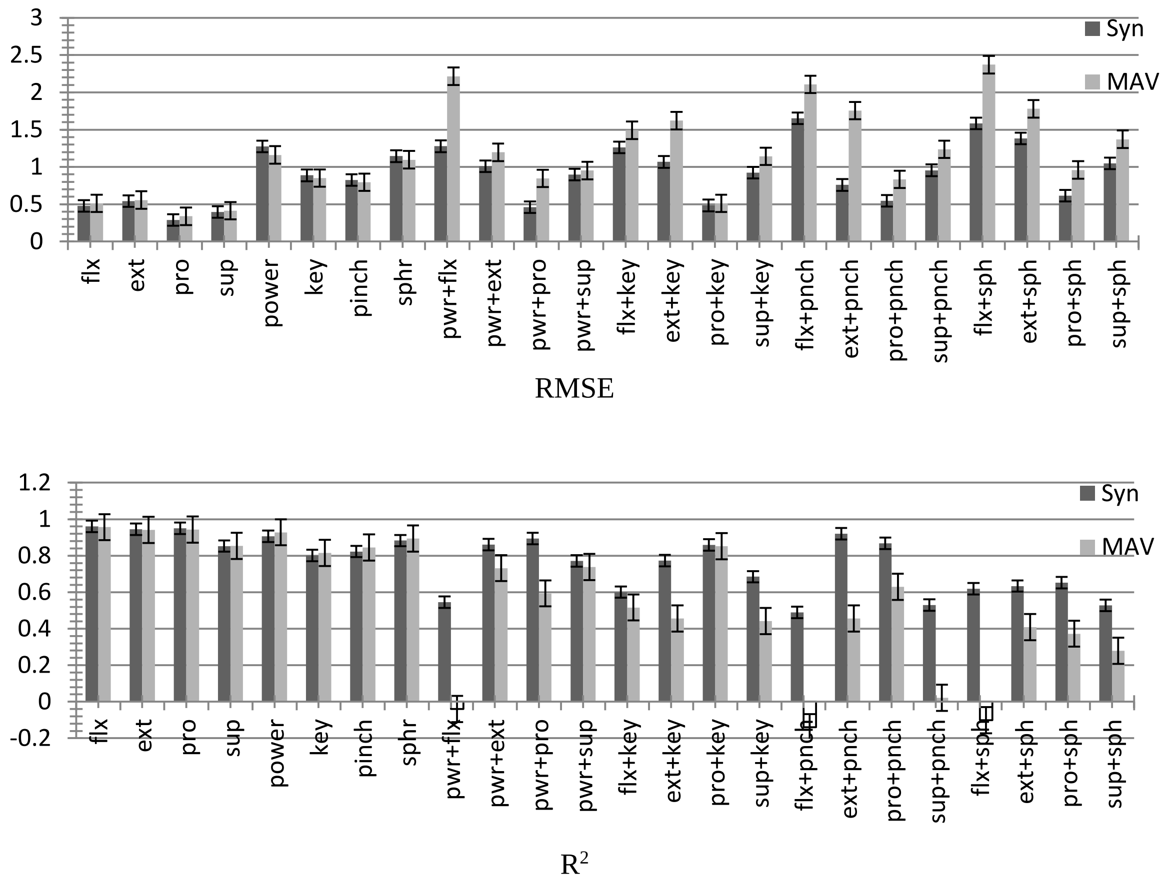


Figure 3. 13 – Comparing the results of synergies with those of MAV in 1 DoF training problem when model was trained with 1-DoF tasks only. The results are averaged across all the subjects.

Another interesting observation from Figure 3.13 is that while the results achieved by synergies and MAVs are nearly the same for 1-DoF training, synergies clearly outperform MAVs when it comes to the 2-DoF training.

3.4. Discussion: Offline Task Identification by Synergies

The muscle synergies extracted from a set of wrist and hand tasks demonstrated good repeatability for different repetitions of the same tasks and were quite robust across different force levels. The results indicate that muscle synergies are an effective representation of EMG in force estimation of multi-DoF tasks. Our observations strengthen the idea that predicting the forces produced in unknown levels can be possible by training the model with the synergies of only one force level. Also, it supports the idea that the synergies might be resilient to force changes to some extent. So they could be used for proportional control of prostheses when the produced force during the task performance is unknown. The correlation coefficients calculated between the synergy patterns of low and high contraction sets were very close to unity (the average was 0.9948 ± 0.004) which shows a strong linear relation between the two synergy sets and supports the robustness of synergies against force change. Since synergy analysis involves decomposing the EMG into the product of the synergy matrix and the neural inputs, this suggests that the estimated neural inputs may be effective in estimating force levels.

Generally better results were achieved in wrist force estimation than in grasps. The reason for this is likely that hand articulations distribute force across multiple fingertips, and a consistent estimate of grasp force is therefore difficult. Grasp force involves many more co-articulating muscles, and therefore, the relationship between EMG intensity and effort is more complex than wrist articulations. Another source of error may be the low accuracy of the force measurements using FSRs. These sensors are nonlinear and they drift during the measurements. Also, subjects' fingers could have slipped off one or a few sensors while performing the tasks. However, the relatively high R^2 values still show that the estimation results can be acceptable particularly in 1-DoF tasks considering the fact that only one feature extracted from the 12 EMG channels is being used for estimating force.

Comparing the results of MAV and synergies in the study (scenario 1) not only shows that synergies are able to estimate the force, but also in a majority of the tasks synergies outperformed the MAV in force estimation. Performing multivariate analyses of variance (ANOVA) on RMSE and R^2 showed that the methods are significantly different (p-value < 0.05) and the results achieved by synergies are better. These results can be explained by the fact that the muscle synergies and their associated neural inputs show how different muscles co-activate in performing different tasks and describe their relative involvement in each task independent from the force level produced. This is an important factor that makes the muscle synergies a powerful input for force estimation in proportional control.

When tested with an unknown force level, the neural inputs outperformed the MAV, particularly when trained with a practical protocol of 1-DOF contractions. The high R^2 achieved in this test demonstrates that synergies have a good potential to be used in estimating the force produced during multi-DoF force-varying tasks, which can be a valuable step toward improving proportional control of prostheses.

Also, a large amount of the estimation error can be the result of scaling and/or delay in estimation with respect to the target. It is possible that this mismatch could be accommodated using an estimator with a temporal component, such as a Time Delay Neural Network.

Another interesting observation is that while the results achieved by synergies and MAVs are nearly the same for 2-DoF training, synergies clearly outperform MAVs when it comes to the 1-DoF training. These results explain that the neural inputs extracted from 1-DoF tasks contain important information to estimate the force produced during simultaneous tasks. This advantage achieved by using synergies is supported by the fact that in the complex problem the R^2 of only four out of 16 complex tasks is below 0.6 and all of them are above 0.5. This High R^2 for majority of tasks shows that Synergies contain important amount of information about the tasks and the amount of produced force that can be used for force estimation.

Also, we have trained the model and tested it for various tasks and various subjects and the results were consistent across all these situations to prove that our achievements are not due to a random factor or limited to a particular data set or task. This suggests that the superposition property of muscles synergies allows the neural inputs to be effective for force estimation of more complex, multi-DoF tasks. Furthermore, the number of neural inputs for force estimation are fewer than the number of muscles involved in the movement, reducing the dimension of the estimation model, and thereby the computational requirements.

In general, predicting the grip force from the EMG signal is nothing new; the EMG-to-force relationship is well-known and has been modeled, among other methods, via linear regression [36]. Our model is novel in that it predicts the force to a similar degree of precision independently of the grasp type employed; although ipsilateral force measurements are still required. For future work, bilateral training for synergies can be examined. Nevertheless, it was shown that the proposed model could be used in parallel with the classifier, as it has indeed been done in [16].

3.5. Real-time Study

3.5.1 Introduction

A considerable amount of work has been done in myoelectric control of prostheses. Many of these methods have been able to predict the users' intent with a considerable accuracy in offline mode. However, how well offline results translate to real-time control is not clear. Lock *et al*. [159]reported minimal correlation between classification accuracy and usability. Simon *et al.* [160]found that even with a classification accuracy of higher than 90%, the users only were able to complete 69% of the targets in the target achievement test. This highlights the need for real-time tests in addition to offline tests to assess the performance. In addition to the estimation accuracy, the ability of the user to interact with the control system is an important aspect of real-time control.

In general, offline analysis and real-time control tests each have their own advantages and drawbacks. Offline assessment is popular because it is possible to test alternative signal processing approaches any time after the completion of the experiment. Offline analysis also removes any inter-trial variability by allowing direct comparisons been algorithms using the same data. Real-time assessments, however, can provide more information regarding the system usability. The user interaction is included in an online test so that the user receives visual feedback of the output and can correct some erroneous movements. The drawbacks of real-time tests are that any modification of the decoding method requires repeating a complete test, and no direct comparisons can be made using like datasets. The disadvantage of offline evaluation is that high offline results can be a result of constrained conditions and do not guarantee satisfactory control performance. Other factors such as system processing delay, which are not considered in offline assessment, can greatly affect the control performance. Offline results show the potential ability of the system, but it is not obvious if the user is able to use this potential to complete a task in a natural and intuitive manner. Since offline and real-time results may provide different information with regard to the system performance, it is useful to employ both measures to assess a control scheme. Qualitative assessment from the user's point of view should also be considered and may add extra information in addition to the quantitative performance analyses.

In computer based training tools, both velocity and position control have been employed in real-time analysis [161], [162]. In velocity control, the velocity of the prosthesis is controlled by the amount of exerted force. The greater the intensity of contraction, the faster the prosthesis moves. In position control, the position of the prosthesis is controlled by the contraction intensity. The stronger the contraction, the further the prosthesis moves. Zhai and Milgram [163] compared velocity and position control modalities in a target-reaching task. Two experiments with isometric and isotonic input devices were performed in which a cursor was directly controlled using either measured force (in isometric experiment) or position (in isotonic experiment), respectively. They showed that velocity control outperformed the position control in the isometric experiment, whereas position control outperformed the velocity control in the isotonic experiment.

In the current study a real-time control test was performed to assess the usability of synergy based model and to compare it with the usability of a similar system based on MAV features. Several studies [164]-[167] employed a Fitts' law [168]style target acquisition test. Fitts' law concerns fast, goal directed movements and relates the movement duration time to the distance and size of the target as in the Equation (3.5).

$$MT = a + b \ \log_2(1 + \frac{D}{W}) \tag{3.5}$$

where *MT* is the time taken to complete the movement, *b* is regression coefficient, *D* is the distance between the starting point and target, and *W* is the target width. When a linear regression model is built using experimental data, Fitts' law often appears with an a-intercept value. The index of movement difficulty (*ID*) is defined as:

$$ID = \log_2(1 + \frac{D}{W}) \quad (3.6)$$

It has been reported that the linear relationship between MT and ID is extremely robust in human motion, often with a correlation above 0.95, but the inclusion of a non-zero a-intercept cannot be explained theoretically; a task requiring no movement should conceptually take no time. Several interpretations of the non-zero intercepts have been reported, suggesting that it is due to modeling errors, user reaction time, or delay and/or feedback processing time in the psychomotor system. Regardless of the cause of the non-zero intercept, it indicates the presence of an additive factor unrelated to the index of difficulty.

Fitts' law is a human movement model that predicts the time to rapidly move to a target as a function of the target distance and target size, and is based on Shannon's original work in information theory [169]. This exhibits a speed-accuracy trade-off, so that the targets that are more distant and/or smaller are more difficult to achieve (Equation (3.6)). The results of repeated trials, using different target widths and distances are incorporated into a single parameter called throughput (TP), measured in bits per second and is defined as:

$$TP = \frac{1}{N}\sum_{i=1}^{N}\frac{ID_i}{MT_i} \quad (3.7)$$

where N is the total number of conditions, i is a particular movement condition, ID is the index of difficulty (Equation (3.6)) and MT is the time taken to complete the movement.

In the current study, in addition to the time of completion, other metrics such as *path efficiency*, *completion rate*, and *overshoot* have been used to provide more comprehensive information about control performance [165].

3.5.2. Experimental Design

As this would be the real-time version of the previous study, which was described in Section 3.3, the data collection protocol is similar to the offline study. The real-time test is employed where force estimation from EMG were used to control a curser. Six able-bodied subjects (ages: 26-39, all right handed) participated in the study of force estimation of wrist flexion-extension, wrist pronation-supination, hand power grip, and combination of grip with each of four mentioned wrist tasks. The protocol involved semi-constrained performing of each task meaning that the user's wrist was between the force sensors but their hand was able to perform some free movements to some degrees so that they can actually grasp a real object. Twelve bipolar wireless surface electrodes (Delsys Inc.) were attached to the subject's arm, targeting 12 surface and intermediate muscles of the forearm. The muscles were the same as those used in the offline version of this study and are described in Section 3.3. The EMG data were sampled at 1 kHz using a 16 bit A/D converter (NI PCIe-6363). The real-time raw EMG signals were visually inspected before the experiment for EMG quality insurance.

As mentioned earlier, it has been shown that position control outperforms velocity control in the isotonic experiment. Therefore, position control was chosen as the appropriate method for moving the curser in this real-time test because the tasks performed by users were isotonic. In order to control the cursor movement, the exerted force at each axis was estimated using the EMG intensity and then the cursor was moved proportional to the amount of estimated force at the time. Extension/flexion of wrist controlled the movement along the X axis and pronation/supination controlled it along the Y axis. The grip force estimated from EMG controlled the size of a curser to reach a certain target location and size. Table 3.2 shows the distance and target size measures that are used. Targets with combinations of two different widths and two different distances were used that generated four indices of difficulty as shown in Table 3.2. Values showed in the table are based on fractions of MVC.

Table 3. 2– Different target distances and widths and the resulting indices of difficulty.

Distance	Width	ID
0.25	0.35	0.77
0.5	0.35	1.28
0.25	0.15	1.41
0.5	0.15	2.11

Thirty-seven different profiles were used for training the synergy based and MAV based models separately. These training profiles included single-DoF tasks of wrist flexion/extension, wrist pronation/supination and power grip, each in four different difficulty profiles in addition to the rest position. During training, subjects were asked to hold the curser on the target for two seconds for each profile in order to provide sufficient training data.

After training the two neural networks for MAV and Synergy based models, the real-time test was performed. The EMG signals were used to control the curser and subjects were asked to reach a target and keep the curser within the displayed boundaries for 0.5 second. Figure 3.14 illustrates the visual feedback that was shown to the users during the data collection. The subjects were able to manipulate the size of the curser through power grip to keep it within the required boundary.

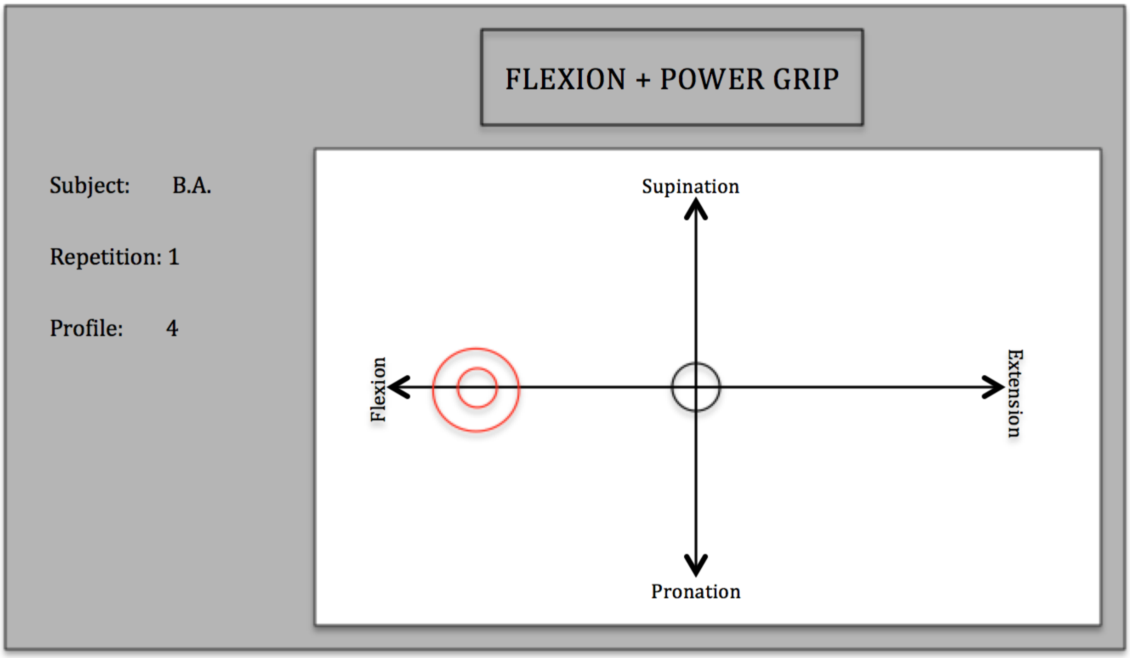


Figure 3. 14 – A screenshot of visual feedback to users during real-time test. The circle in the middle is the curser. User should move the curser and hold it between the red circles (target).

Subjects had ten seconds to accomplish each task and reach the target. After ten seconds, if the curser had not reached the target yet, the profile was tagged as unsuccessful. Upon completion, the success rate for each of Synergy-based and MAV-based models was calculated. Figure 3.15 illustrates the proposed model of training and real-time testing. The presentation of the MAV and synergy methods was randomized trial-by-trial for each subject.

For each real-time control performance metric, one way repeated measures ANOVA was used to compare the Synergy and MAV-based methods. The significance level was set to 0.05.

3.5.3. Results

The real-time test was performed for MAV and Synergy methods separately. Synergy and MAV feedbacks to the user were randomized profile by profile. Total time of accomplishing each task, number of overshoots, and the path length that the curser passed to reach the target were measured during each trial for each subject to further assess the control quality.

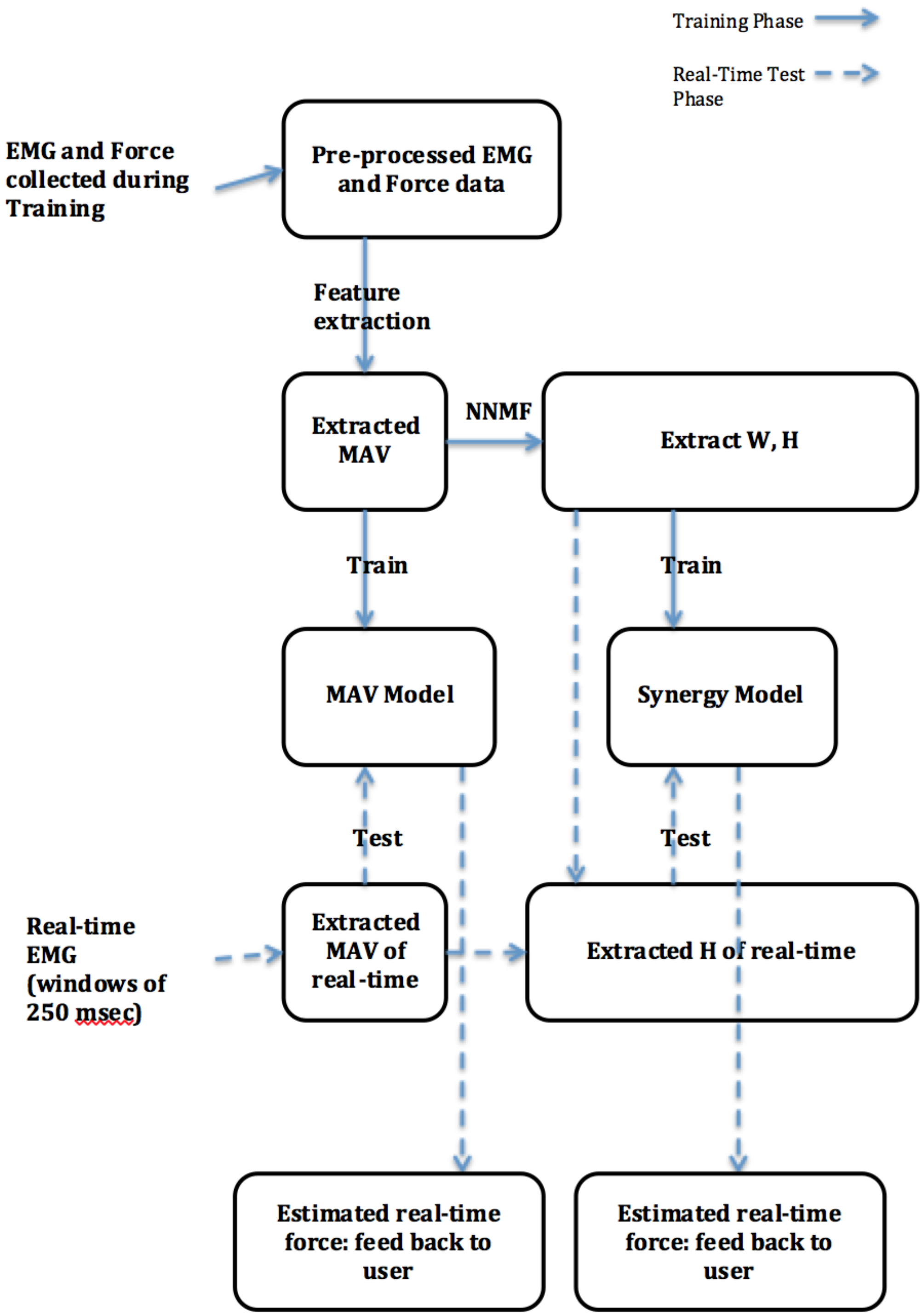


Figure 3. 15 – Training and Real-time testing model

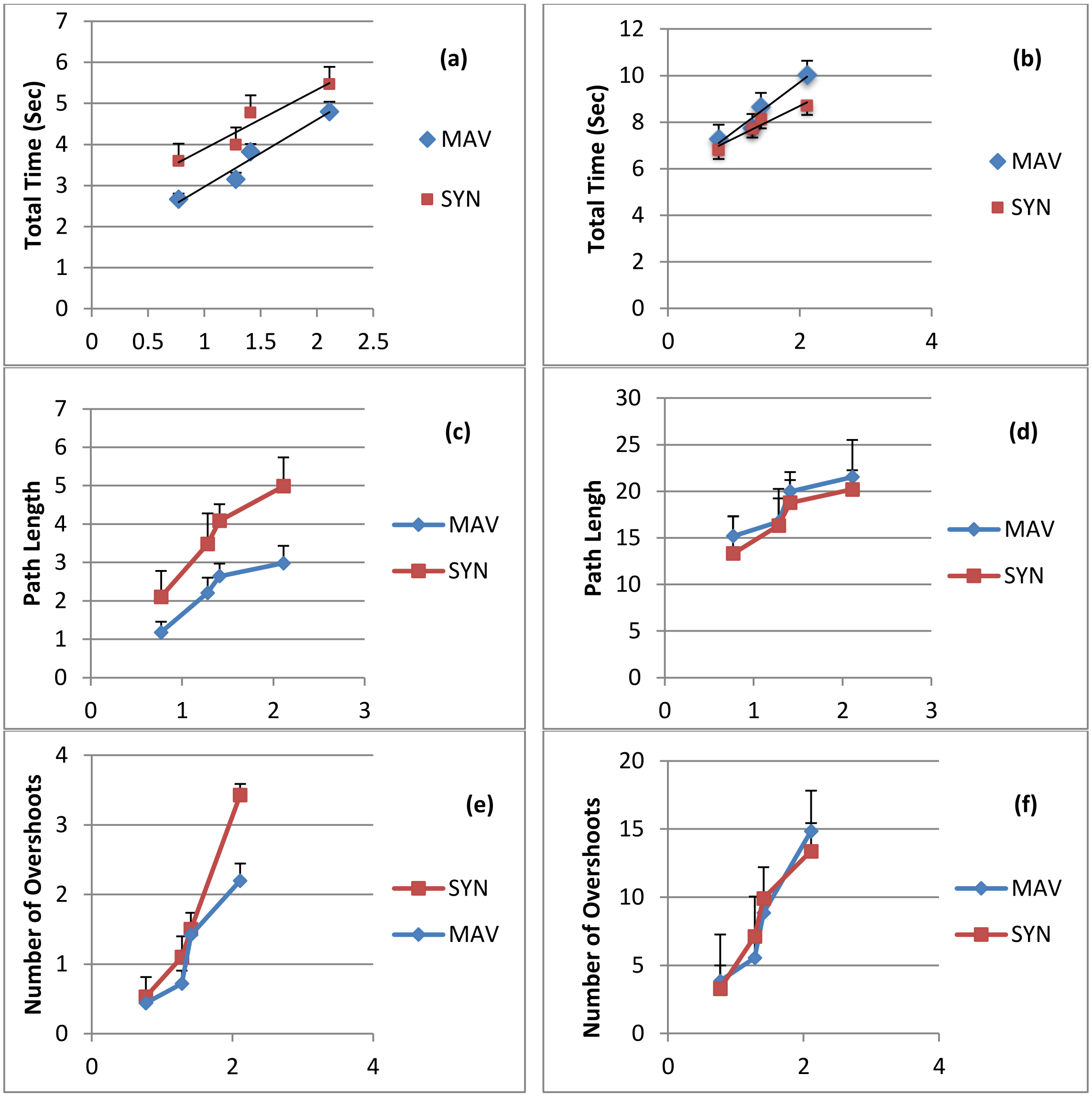


Figure 3. 16 – X axis shows the difficulty in all plots. a. The relationship found between movement time and index of difficulty was strongly linear (R^2>0.95) for 1-DoF tasks for both methods. Standard deviation bars are shown on one side only for clarity. b. The relationships found between movement time and index of difficulty were strongly linear (R^2>0.95) for 2-DoF tasks for both methods. c. Plot of path length and difficulty for 1-DoF. d. Plot of path length for 2-DoF. e. Plot of overshoot and difficulty for 1-DoF. f. Plot of overshoot and difficulty for 2-DoF.

Effect of Difficulty on Performing 1-Dof Tasks

The results are studied separately for 1-DoF and 2-DoF tasks to see how the real-time performance in each group is affected by MAV and Synergy methods. Figure 3.16.a, c, and e show how difficulty affects the performance for each method during 1-DoF tasks. The results are averaged over subjects.

The real-time results obeyed Fitts' law as linear relationships were found between the movement times and indices of difficulty in both control schemes ($R^2 = 0.96\%$ for both methods). Figure 3.16.a shows that as difficulty increases, it takes longer for the subjects to accomplish the tasks in both MAV and Synergy methods. Figure 3.16.a also shows that the average time of accomplishing the tasks for all tasks and all subjects is less when using MAV as compared to synergies, regardless of difficulty of the task. Also, subjects employed a lengthier path when using synergies all levels of difficulty, as shown in Figure 3.16.c.

Subjects have passed a shorter path using MAV method than Synergy method to reach the target during 1-DoF tasks. The effect of difficulty on the number of overshoots in both methods is also shown in Figure 3.16.e and indicates a more frequent occurrence of passing the target as the task becomes more difficult. Also, as the plots show the overall number of overshoots when using MAVs is less than when using synergies for all difficulty indices and the ANOVA test shows this difference is significant (p-value <0.05).

Figures 3.16.a, c, and e suggest that regardless of the index of difficulty, the MAV control outperformed synergy control in for 1-DoF tasks and ANOVA test shows this difference is significant (p-value <0.05) Also, users reported that a smoother control was possible by MAVs rather than synergies.

Effect of Difficulty on Performing 2-Dof Tasks

Figure 3.16.b, d, and f show how difficulty affects the performance for each method during 2-DoF tasks. The real-time results obeyed Fitts' law as strong linear relationships (R^2 =0.97 for both methods) were found between the movement times and indices of difficulty in both control schemes.

As Figure 3.16.b shows, it took longer for the subjects to reach more difficult targets in both methods. However, unlike 1-DoF tasks, here a shorter time of accomplishment was achieved by synergies than by MAVs. Also, as expected, comparing Figure 3.16.a with 3.16.b shows that accomplishing 2-DoF tasks took significantly (p-value <0.05) more time than accomplishing 1-DoF tasks regardless of difficulty index and method of controlling the curser.

Figure 3.16.d compares the path length for each method across different difficulty indices. Again, as the task becomes more difficult, the path length passed by the subjects to reach the target were longer which indicates a more challenging control over the curser. Here also synergy-based method led to a smoother control of the curser than MAV method

in most of the cases. However, ANOVA test did not show a significant difference between the methods here (p-value > 0.05).

Finally, Figure 3.16.f, shows the effect of difficulty on the number of overshoots. As expected, number of overshoots increased by increasing the difficulty in both methods. The relative performance of MAV vs. synergy is similar, although at the highest level of difficulty, synergies outperform MAV. Also, comparing this plot to Figure 3.16.e (overshoot for 1-DoF), number of overshoots are significantly larger (p-value <0.05) in 2-DoF tasks than those in 1-DoF tasks.

Comparing the Real-Time Performance for MAV and Synergy Methods

The Fitts' law test results are averaged across all subjects for all 1-DoF and 2-DoF tasks and are listed using mean ± standard error in Table 3.3. The corresponding statistical analysis results are shown in the last column of Table 3.3. As the size of our sample data is relatively small and they are not normally distributed, a non-parametric Friedman test of differences among repeated measures was conducted as an alternative to ANOVA test. This test rendered a Chi-squared value of <0.01 for throughput (significant difference), and a Chi-squared value of > 0.05 for completion rate, overshoot, and path efficiency which showed an insignificant difference.

Table 3. 3– Fitts' law test results averaged across all subjects for all tasks

	MAV	SYN	MAV vs. SYN (Chi square probability)
Throughput	0.43± 0.04	0.36± 0.04	<0.05
Completion rate %	97.2%	96.4%	>0.05
Overshoot	4.61	5.03	>0.05
Path efficiency	10.18	10.48	>0.05

The real-time performance metrics are plotted versus subject and control scheme for all 1 and 2-DoF tasks in Figure 3.17. As the plots show, throughput of MAV method was higher than Synergy regardless of subject. However, some subjects were able to achieve less overshoots and shorter path to reach the target using the Synergy method while it was not the case for some other subjects.

3.5.4. Discussion

The subjects were asked to comment about the control quality during the breaks and after the experiment. All subjects found that inadvertent cursor movements were significantly less with the MAV method than with the Synergy based method while performing 1-DoF tasks. The subjects found that the overall control quality was similar between the MAV and Synergy tests, and the influence of difficulty indices and 1-DoF and 2-DoF tasks on the quality of control were much more noticeable.

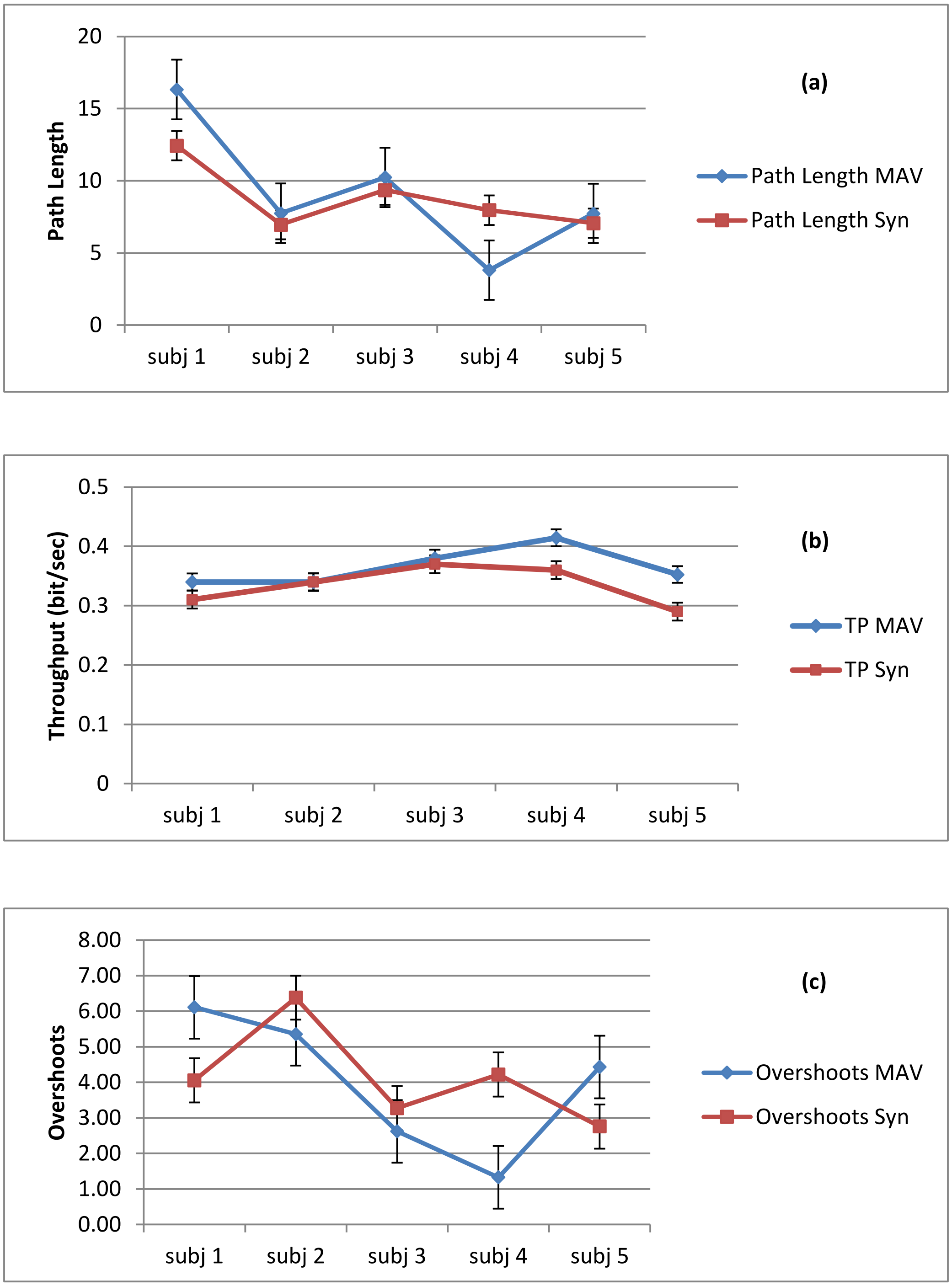


Figure 3. 17 – Real-time performance metrics versus subject and control scheme

The higher inadvertent cursor movements of the synergy-based test may be explained by lower performance of the synergies comparing to MAVs during 1-DoF tasks and tasks of lower force, which was observed during our offline study. This can significantly affect the control quality. For instance, when the users intended to perform pure wrist flexion during the real-time test, the other DOFs should have remained inactive. However, low estimation accuracy during inactive periods (for those DOFs) may have resulted in unwanted cursor movements in these DOFs. Consequently, instead of pure movement of the cursor in the flexion direction, unwanted cursor movement may have occurred. This deteriorates all real-time performance metrics.

In the offline study of section 3.3 where the models were trained with 1-DoF tasks only but tested with single and 2-DoF tasks, ANOVA test showed that the synergies significantly outperformed MAVs. When separating 1-DoF and 2-DoF tasks for ANOVA test, the results showed that in single-DoF force estimation MAVs and synergies were not significantly different. However, in multi-task case, synergies significantly outperformed MAVs (p-value <0.005).

In a similar but real-time study, we observed that MAVs performed better in controlling the curser during 1-DoF tasks (p-value <0.005) but no significant difference was observed between the two methods in 2-DoF task control (p-value >0.05). Also, in multi-task case, MAVs were not significantly better than synergies in controlling the curser for all single and multi-DoF tasks (p-value >0.05).

Overall, the observed results report no significant difference between the performance of Synergies and MAVs during real time control. Considering the fact that more computation is needed for the Synergy based method, MAV method seems to be the better option for real-time control in this study

CHAPTER 4- USING SYNERGIES FOR PATTERN RECOGNITION BASED CONTROL

4.1. Introduction

This chapter aims to better understand how knowledge of natural groupings of muscles, synergies, can be advantageous in a control paradigm for multifunction myoelectric prostheses, and specifically how well the muscle synergy model can serve as an EMG signal representation in classifying multiple wrist and hand grasp postures.

Based on the nature of the synergies and their physiological interpretation, they have the capacity to be linearly superimposed to reconstruct the original muscle activity patterns. According to the observations in the previous chapter, neural inputs demonstrated excellent performance in estimating the produced force and they were able to outperform MAV in force estimation, especially with unknown force levels of untrained 2-DoF tasks. Based on our definition of synergies, these components may also contain important information for identifying tasks, i.e., some attributes that vary from task to task and enable distinguishing each task from the others. In this chapter, based on fundamental properties of the synergies and their physiological aspect and also based on our observations of synergies' robustness and their reliability in force estimation, the potential of muscle synergies for task identification is investigated.

The idea of using muscle synergies as a myoelectric control paradigm has been moderately visited in the past, although in slightly different forms [170]. Basically, three different approaches can be taken when using muscle synergies for task identification:

The first approach is to develop task-specific synergy bases for each of *N* classes. These class-specific synergies may reflect the activation patterns of the muscles involved in each task. New data then would be projected to each of *N* bases. This approach is based on the main idea in [171] where components are extracted by PCA; synergies could replace PCA components here and the output classifier could instead be a nearest neighbor for each class. For this approach to be reliable, it is first required to see if synergies extracted from the same tasks are similar (repeatability analysis) and synergies extracted from different tasks are distinguishable (separability analysis).

Another approach is to use the synergy matrices, and not their coefficients, as a representation of different tasks. This approach treats the synergies like features extracted from EMG signal rather than a component that is defined earlier in this study. For this, one would need to compute the synergies on a per window basis as in a regular feature extraction method. A pilot study done on this method showed that due to the characteristics of the synergies and our method of extraction, this approach is not practical. The problem is that for classifying the task within 250ms we need to extract the synergies from a window of 250ms and the synergies extracted from this short window need to be consistent along the entire task. Performing a quick examination on the synergies, extracted synergies from a short window vary considerably during a task producing poor classification results.

Moreover, it is unlikely that synergies could be extracted in real-time (in 250ms increments), a requirement for myoelectric control.

The last approach considers the muscle synergies as the building blocks of a large set of motions which their coefficients (neural inputs), i.e. amount of contribution, for each task is the key element to distinguish the tasks. This approach is more consistent with the proper definition of muscle synergies: modules which reflect the patterns of co-activations of muscles and their combinations create different tasks. Based on the physiological evidence for modularity of motor controls, the muscle synergies extracted this way are the fundamental modules of the motions and they might be resilient to the force to some extent. Here one synergy matrix is extracted for all the tasks, and the coefficients of this synergy matrix are the parameters that change from task to task, and which are used for task identification.

This last approach is used in all of our studies in this work due to its consistency with the definition of muscle synergies, and the practicality of operating within a real-time classification scheme. However, the first approach was tested, i.e. task specific synergies, in one of the task identification studies and compared the results with the latter approach. As the second approach is not practical, it is not used in any of our studies here.

4.2. Identification of Single-Dof Tasks by Synergies

The initial study of task identification by synergies was conducted, to determine if synergies can classify some simple single-DoF tasks and compare their efficacy with that of TD features.

4.2.1. Methodology

The single-DoF tasks of 50% MVC from the data described in Section 3.3.1 were used for this study. The sEMG data were collected from 12 muscles of each subject. Eight subjects performed constrained isotonic movements associated with two DoFs of the wrist including extension, flexion, pronation, and supination, as well as four hand motions including power, pinch, key, and spherical grasps. The classification model used is linear discriminant analysis (LDA) which is described in detail in Appendix A.

The process of extracting the synergies and determining their numbers are the same as in the force estimation study: rectifying the signal and averaging on 250ms windows, and then extracting the synergies and neural inputs from the mean absolute values. The top diagram of Figure 4.1 shows the steps of this process. In the bottom diagram of Figure 4.1 training and testing procedures are illustrated. After obtaining the synergy matrix, mean absolute values of test signal are used to calculate the neural inputs of test data. These neural inputs are then provided to the trained classifier for the test phase.

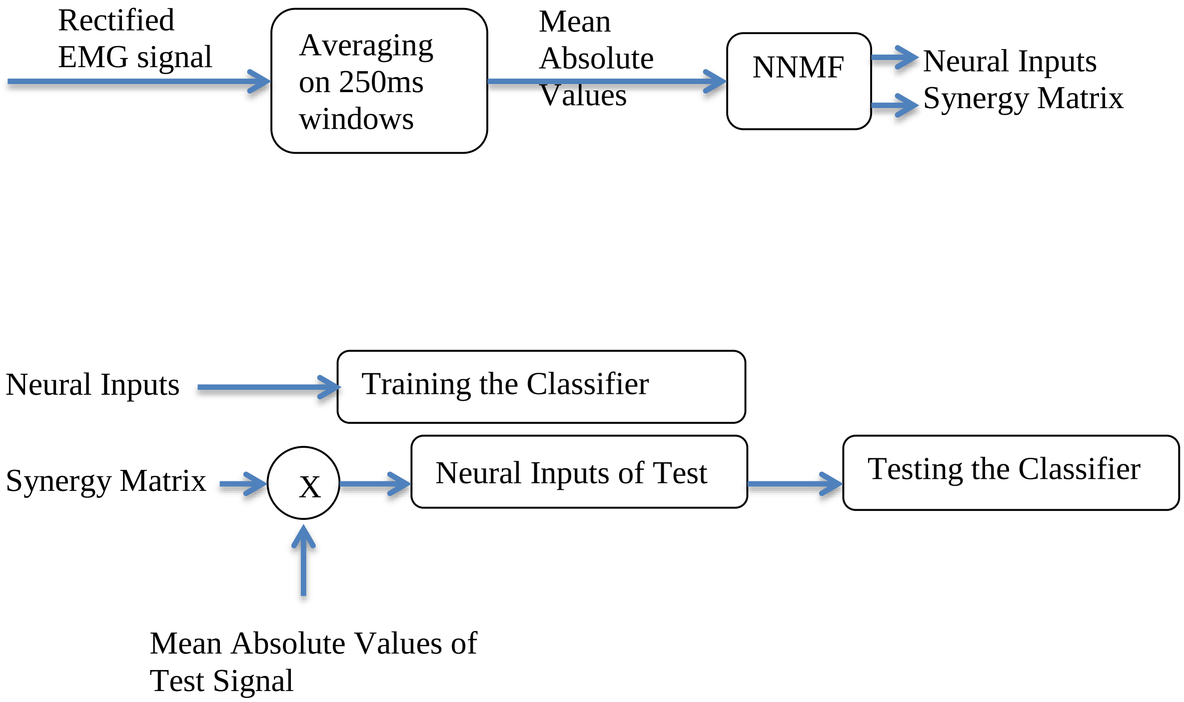


Figure 4. 1– Procedure of calculating synergies, training the classifier, and testing.

Six synergies were extracted for each subject. The number of required synergies was calculated by the same method that is used in Chapter 3. Using four-fold cross validation, three repetitions of each task (each lasting two seconds) were used for training the classifier and one was used for testing. An analysis of variance (ANOVA) with factors Synergies and MAV (or other TD features), was completed to evaluate the performance of synergies and p-values less than 0.05 were considered significant.

4.2.2. Single-DoF Results

Wrist Tasks

Here only the wrist postures (extension, flexion, pronation, and supination) were included in the task set. Figure 4.2 shows the classification errors when using synergies for eight subjects.

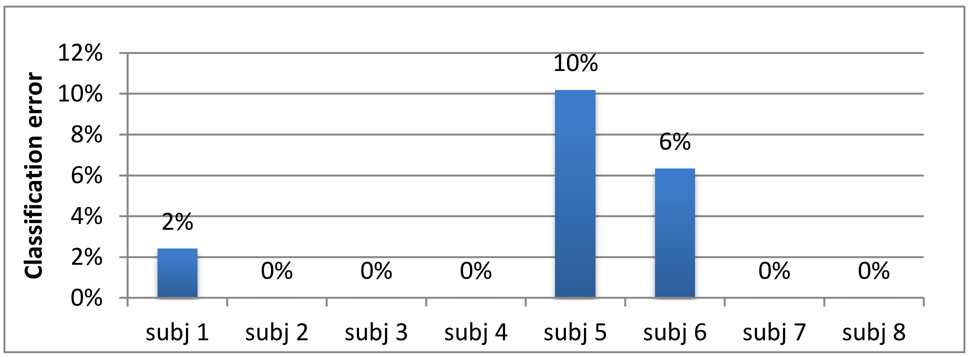


Figure 4. 2 – Classification results for wrist tasks when using synergies across task classification results for Synergies for eight subjects.

To assess these results, they were compared with the results of using four TD features for classification of the same data. Mean absolute value (MAV), waveform length (WL), zero crossings (ZC), and slope sign changes (SC) were extracted from windows of 250ms and provided to an LDA classifier to identify the tasks. The classification results were 100% accurate with no misclassification. This is while the average error for synergies was 2.36%. However, note that synergies are extracted from the MAV of the ensemble of 12 channels. This is a greatly reduced feature space compared to the MAVs. The synergy representation has a dimension of six, the neural inputs that result from a projection of the MAV from 12 EMG channels down to six synergies. By comparison, MAVs space dimension is 12 .

Extracting the Synergies from Different TD Features

So far, all the information needed to classify the tasks were obtained from MAV. MAV only contains a portion of the information of the raw EMG. If we already know that just the MAV feature underperforms the full TD feature set in pattern classification, using synergy extraction from only the MAV puts the method at a disadvantage. This means our approach ignores any other information that is embedded in other TD features. Even though the synergy components extracted from WL, SC, or ZC are not exactly the muscle synergies defined in the background chapter, they are still the product of co-activation of muscles. As TD features are very effective in task classification studies, synergy components extracted from them may contain important information about the tasks. Also, by extracting the synergies from all TD features a platform can be created to look at all TD features as possible sources from which information can be extracted.

Here the previous study of 1-DoF task classification was repeated and the results of new synergies were evaluated with those achieved by synergies of MAV and TD features. Note that in this case the dimensions of the input data have been still reduced considerably, by extracting six synergies from twelve EMG channels per feature and using them instead of a 36-dimensional TD space. Table 4.1 illustrates the results of this investigation. It is evident that extracting the synergies from MAV and WL results in 100% accurate classification similar to the result of using all four TD features. Synergies extracted from MAV, WL, ZC, and SC are shown by Hmav, Hwl, Hzc, and Hsc respectively.

Table 4. 1 – Percentage of misclassifications in synergy and TD features for four wrist tasks. H*mav* is the neural input extracted from MAV, H_{ZC} , H_{SC}, and H_{wl} are extracted from ZC, SC, and WL respectively.

Total Error for wrist	Input to classifier						
	Hmav	Hzc	Hsc	Hwl	All H	Hwl, Hmav	TD feats
subj 1	2.4%	0.0%	4.6%	0.0%	0.0%	0.0%	0.0%
subj 2	0.0%	0.1%	1.0%	0.0%	0.0%	0.0%	0.0%
subj 3	0.0%	0.7%	8.4%	0.0%	0.0%	0.0%	0.0%
subj 4	0.0%	2.7%	9.8%	0.0%	0.0%	0.0%	0.0%
subj 5	10.1%	3.9%	7.4%	0.0%	0.0%	0.0%	0.0%
subj 6	6.3%	0.0%	4.7%	5.9%	0.0%	0.0%	0.0%
subj 7	0.0%	7.1%	4.0%	0.0%	0.0%	0.0%	0.0%
subj 8	0.0%	0.2%	1.6%	0.0%	0.0%	0.0%	0.0%
Average error	2.3%	1.8%	5.2%	0.7%	0.0%	0.0%	0.0%

Hand Tasks

The above analysis was then repeated for the hand tasks. Table 4.2 compares the classification results for different inputs to the classifier. In both synergy cases (hand and wrist), using synergies extracted from MAV and WL together led to the best result among different methods. In the hand tasks case, adding the neural inputs extracted from ZC and SC actually degrades the classification results of synergies.

Table 4. 2– Percentage of misclassifications in synergy and TD features for four wrist tasks. H*i* is the neural input extracted from TD feature *i*.

Total error for hand	Input to classifier						
	Hmav	Hzc	Hsc	Hwl	All H	Hwl,Hmav	TD feats
subj 1	0.0%	2.6%	4.4%	0.0%	0.0%	0.0%	0.0%
subj 2	2.0%	13.9%	20.1%	1.0%	3.3%	1.8%	0.0%
subj 3	0.0%	31.6%	38.9%	0.0%	1.6%	0.0%	0.0%
subj 4	0.0%	26.8%	27.1%	0.0%	0.0%	0.0%	0.0%
subj 5	14.2%	4.7%	15.3%	22.3%	0.2%	1.8%	0.0%
subj 6	0.7%	17.2%	47.8%	0.0%	0.0%	0.0%	0.0%
subj 7	0.7%	17.2%	21.2%	1.9%	1.4%	0.0%	0.6%
subj 8	1.3%	2.6%	9.4%	0.0%	0.0%	0.0%	0.0%
Average error	2.3%	14.6%	23.0%	3.1%	0.8%	0.4%	0.0%

Although both synergies and TD features resulted in highly accurate classifications, ANOVA test showed that TD feats performed significantly better (p-value < 0.05) than the extracted synergies in the hand problem.

Overall, the synergies extracted from MAV and WL were the most effective in classification. The synergies from ZC and SC resulted in bigger errors in comparison to those extracted from MAV and WL. Also, combining the synergies extracted from different features improves the results. For example, combining the synergies extracted from MAV with those of WL led to better classification than using only synergies of MAV or WL alone.

4.2.3. Eight Hand/Wrist Task Identification Problem

In order to classify both hand and wrist motions, a synergy basis was developed from a task set which included all hand and wrist motions. Since, similar to the previous analysis, using Hmav along with Hwl led to the best results in the synergy case, these two features were chosen to be the inputs of the classifier in our classification investigations. Table 4.3 compares the synergy results with those of TD features.

Synergies showed highly accurate classification results and the average classification error for eight hand and wrist 1DoF motions was 0.83% across all eight subjects. Nevertheless, TD features outperformed synergies significantly (p-value < 0.05) by the average classification error of 0.05% for all the subjects.

Table 4. 3– classification of 8 hand and wrist tasks by synergies and TD features

Total error for 8 hand and wrist tasks	Input to classifier	
	Hwl,Hmav	TD feats
subj 1	0.0%	0.0%
subj 2	1.9%	0.1%
subj 3	0.0%	0.0%
subj 4	0.0%	0.0%
subj 5	1.8%	0.0%
subj 6	2.3%	0.0%
subj 7	0.5%	0.2%
subj 8	0.0%	0.0%
Average error	0.8%	0.0%

4.2.4. Discussion

Our observation in this study brings up this question: why adding ZC and SC to the feature set, when using TD features for classification, increases the performance but using the synergies that are extracted from them along with the synergies from MAV degrades the performance. One reason might be based on the nature of these features. WL and MAV represent an envelope of the signal, which adheres to the methodology of extracting synergies from the intensity of muscle contraction, and therefore are relatively smooth. But ZC and SC are both count-based features that estimate something more closely related to instantaneous frequency or fractal dimension, and they can change instantaneously. This gives them two disadvantageous properties: they can change relatively abruptly and they have a limited dynamic range. This makes it quite challenging for the synergy model to recognize the patterns in SC and ZC as they are poorly behaved. The other reason can also be that thresholding ZC and SC degrades their ability of class separability [172].

Other than ZC and SC, there are other features such as Entropy or Cardinality that could be explored when looking at a more global representation of the EMG from which synergies could be extracted. Although unstructured features like ZC do not work very well, other structured features that are different from MAV could be possible sources of information for a synergy-based model.

Although low classification error by synergies was observed, they could not generally outperform TD features. Extracting synergies from other TD features rather than only MAV allows for a more reasonable comparison between the results of synergies and TD feature sets. However, TD features were still more effective in discriminating eight hand and wrist tasks.

It should be noted that these classification errors are very low and consequently, it is difficult to say that synergies exhibit a clear performance deficit. Given that the classification task is quite easy, more difficult scenarios must be investigated (simultaneous classes) and real-time usability tests must be performed to determine if their performance is significantly different from TD features.

Based on the physiological aspect of muscle synergies and their potential in containing information about the co-activation patterns of muscles across different force levels, the actual power of synergies, in comparison to TD features, might be exhibited during variable force levels where TD features have been shown to be challenged in identifying the tasks [22]. In the next section the synergy power in identifying 1-DoF tasks was investigated when amount of exerted force is variable and unknown. The case of simultaneous classes and real-time tests will be addressed in later sections.

4.3. Task Classification with Different Force Levels (1-Dof Tasks)

For pattern recognition based systems to incorporate proportional control, the task recognition must co-exist and be robust with varying intensity levels. In our study of force estimation with muscle synergy, neural inputs excellent performance in estimating the produced force. They were able to outperform MAV in force estimation, especially in estimating unknown force levels of untrained complex tasks. As previous studies supported the idea that synergies contain useful information about the applied force during a task, they may also contain robust information for identifying tasks at varying force levels. The underlying hypothesis that synergies may be robust to varying force is based upon the observation that the synergies are reasonably invariant to force and, while the corresponding neural inputs increase with increasing force, they do so in a manner such that their relative magnitudes remain constant.

The present study primarily investigates the capability of muscle synergies to identify hand and wrist tasks that have been performed across unknown amount of force. This study also quantifies the robustness of the muscle synergies that are involved in producing various wrist/hand movements across various exerted intensity levels. Then the performance of the synergy approach was compared with TD features, mainly MAV [40]

4.3.1. Methodology

Data Collection and Experimental Protocol

Since different levels of force applied during the task performance were needed for this study, a new data set was used. The experimental protocol of this data set is described in [139], [173] in detail. EMG data were collected from 10 healthy normally limbed subjects (7 male, 3 female) ranging in age from 25 to 50 years performing seven hand and wrist tasks as shown in Figure 4.3. Subjects were fitted with a cuff made of thermoformable gel that was embedded with eight pairs of stainless steel dome electrodes. The cuff was placed around the right forearm (the dominant side for all participants), at approximately one-third of the length of the forearm, around the area of largest circumference. A reference electrode (RedDot by 3M) was placed over the back of the hand. The eight channels of EMG were differentially amplified using remote AC electrode amplifiers (BE328 by Liberating Technologies, Inc.), and low pass filtered at 450Hz with a 5th order Butterworth filter. Data were sampled with a sampling frequency of 1000Hz using a 16-bit analog-to-digital converter.

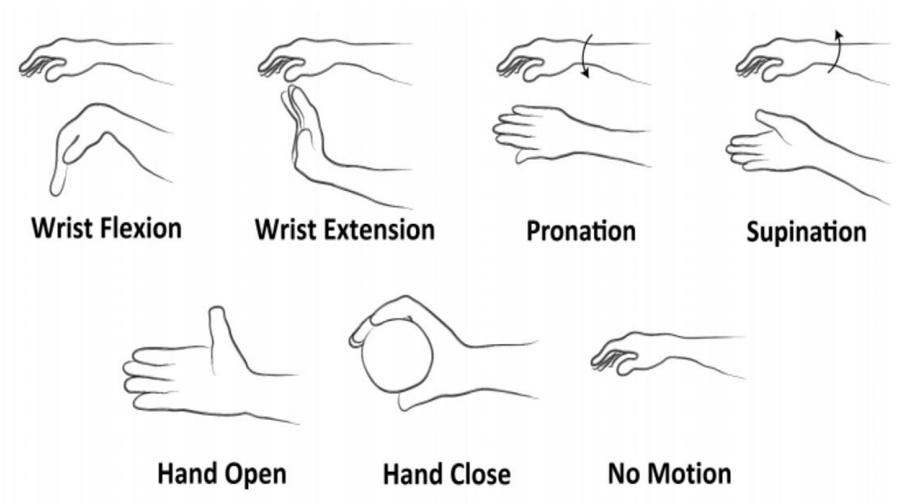


Figure 4. 3 – Seven classes of contractions used throughout this study.

Users were prompted to perform two repetitions of contractions at 100%, corresponding to a class-specific maximum voluntary contraction (MVC). Following the collection of the 100% repetitions, users were asked to track specific amplitude targets corresponding to percentage levels of effort (normalized by their 100% class-specific levels). The collection order was randomized but included 2 reps each of: 20, 30, 40, 50, 60, 70 and 80% of MVC. This entire process was then repeated (with the exception of the 100% reps) resulting in four reps of each level and a total of 46 reps of each motion class.

Synergies

Identification of muscle synergies is done through the same process used in our previous studies. For each subject the number of synergies adequately capturing the EMG data (*N*) was selected according to the fraction of data variation explained, defined as $R^2_{EMG} = 1-SSE_{EMG}/SST_{EMG}$, where SSE_{EMG} is the sum of the squared muscle activation residuals and SST_{EMG} is the sum of the squared residuals of the muscle activation from its mean vector. The criterion was a threshold of 0.9 on R^2_{EMG}. For all the subjects, either four or five synergies were sufficient to meet the criterion.

Classification

The 50% MVC data were used as training and validation sets to develop the optimal structure for the classifier. The classifier was then tested with other force profiles in order to determine the impact of force variations on the performance of the classifier. Four-fold cross validation was used for training and testing. During training, the entire training set is used to compose the synergy matrix. During classification of the test set, a 200-ms analysis window is projected onto a novel coefficient matrix using the synergy matrix.

After the synergies were extracted, the associated neural inputs were provided to an LDA classifier. The process of synergy extraction was repeated 50 times and the synergy matrix with the lowest error on the validation data was used for testing. In order to evaluate the performance of synergies they were compared to MAV features. Differences in performance measures were assessed by an *ANOVA* test. Also, due to the absence of a unique solution for NMF, the results of synergies are variable. Therefore, the synergies extracted this way are not unique. To deal with this problem and to increase the reliability of synergy results, besides having the validation phase, the same process of classification was repeated for 50 times and the results were averaged.

Before classifying the tasks, the change in patterns of neural inputs (which are used to identify the tasks) is explored across different force levels. If these patterns vary considerably across the force profiles, it indicates that the synergies do not remain consistent by force variation and the synergies extracted from a medium force level cannot be used for other levels accordingly. But if similarities are found between the patterns extracted from different force profiles, it means that the synergies remain consistent during force variations and thus they can perform consistently under such situation.

An analysis of variance (ANOVA) with factors Synergies and MAV, was completed to evaluate the performance of synergies and p-values less than 0.05 were considered significant.

4.3.2 Results

Consistency of Synergies during Force Variations

The synergy matrices extracted from a mid-level force profile (50% MVC) are used to calculate the neural inputs for other force levels. In order to measure the similarity between the neural inputs achieved by this method, the correlation between matched neural inputs is calculated and shown in Figure 4.4. All data profiles were used for the correlation study, and not just the training profiles.

Comparison between the correlations shows that the neural inputs are very similar for different force levels particularly for small amount of variations in force. When the force was changed from 20% MVC gradually to 80% some synergies disappeared and some new synergies appeared. However, the pattern of the dominant synergies stays the same while the force was changed between the medium force levels (40% MVC to 60% MVC). Figure 4.4 also shows that there is an unexpectedly higher correlation between the MAVs across force variation in comparison with the synergies. This phenomenon will be further explored by a classification study in the proceeding sections.

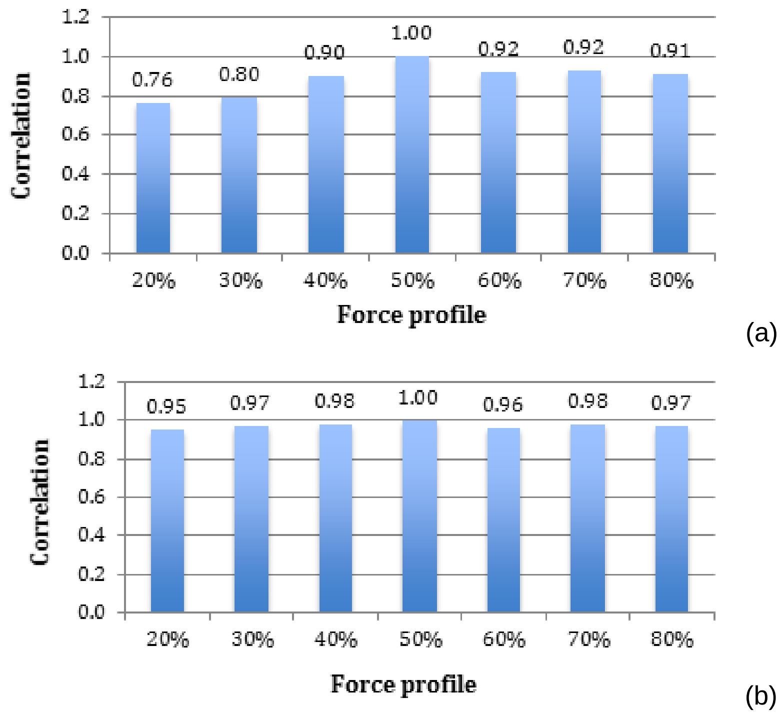


Figure 4. 4 – Correlation between the (a) neural inputs of dominant synergies and (b) MAVs of 50%MVC profile and those of other profiles (20%MVC, 30% MVC, etc.). The values are averaged across all components of the neural input matrix.

Identification of Wrist and Hand Tasks across Different Force Levels

In order to evaluate the performance of the extracted synergies, the classification results are compared with those when using MAV.

1) Testing Unknown Force Levels

Here, the extracted synergies from mid-level force profile are used to compute the neural inputs of other force profiles. Then, the model is tested with each profile separately. The same classification process is also repeated with MAVs. Figure 4.5 shows the comparison for each force profile. The results are averaged across all tasks and subjects. All of the neural inputs are normalized for training and the testing data is normalized according to the normalization factor of train phase. As the synergy results (darker bars) show, the average performance of classification by synergies improves when the force levels get closer to 50% MVC. Comparing the results of synergies and MAVs across all subjects showed that MAVs are significantly (p-value <0.05) better in classification of tested tasks.

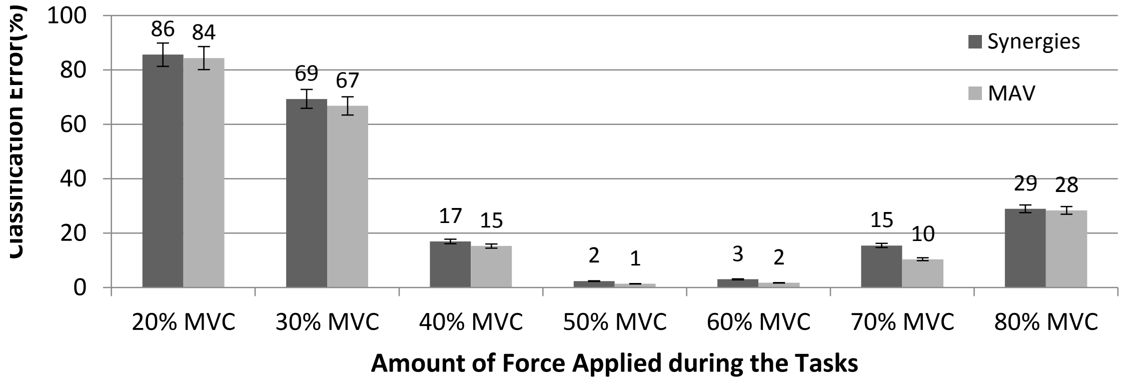


Figure 4. 5 – Classification results of synergies versus MAV when trained with 50% MVC and tested with 20% to 80% MVC.

2) Testing Known Force Levels

In Figure 4.6, the classification error is shown when the classifier is trained with the same force level as tested. Figure 4.6 shows the results for both synergy and MAV methods. Here, even though test and train force levels are the same, when the tasks are performed with only a little amount of force, e.g. in 20% MVC profile, their identification is harder for the classifier. This result is consistent with what was reported in [22]That partially explains the high rate of misclassifications in low-force profiles and relatively much lower misclassification rate in medium and high force levels in Figure 4.6. Nevertheless, MAVs performance was still better than synergies in general.

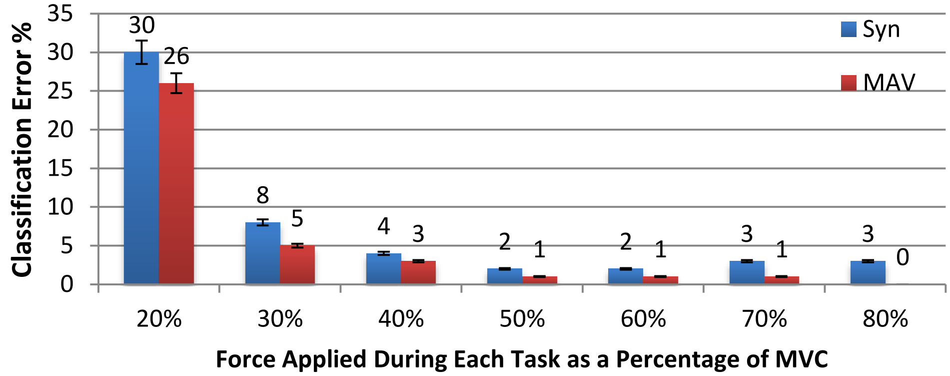


Figure 4. 6 – Classification results of Synergies versus MAV when test and train force levels are the same.

4.3.3 Discussion

One important factor in proportional control is that the controller inputs should be able to perform consistently during force variations. In this section the ability of muscle synergies in classification of tasks was studied when the amount of force applied during the tasks is different from the level used to train the classifier.

Observing more similarities between the extracted patterns when the force variations were smaller is physiologically understandable as we expect the brain will modify recruitment when high force levels are required. Some muscles may not have the necessary fast twitch fibers to keep up with high demand of power. However, by small changes in the force (e.g., from 50% to 60%) a big difference between the dominant synergies was not observed and most of the change is only scaling. This also supports our results of classification of tasks in different force levels. High correlation values (above 0.7) between the neural inputs of 50% force profile and other profiles showed that the synergy patterns involved in these profiles could be very similar. This motivated further explorations of classifying tasks of untrained profiles.

Our observations during classification of seven tasks and comparing the Synergy and MAV results are in accordance with the results of consistency studies since high correlations between the patterns were seen when the force variations were relatively small. This can be explained by the fact that the patterns of co-activations of muscles can vary with respect to the applied force level particularly when force variation is significant [41]. Thus it can be difficult for the classifier to distinguish the tasks when the amount of force exerted during that task is considerably different from what the classifier is trained with. Although significant similarities between the patterns of neural inputs related to different force levels was observed, great differences between these patterns could confuse the classifier and impact its performance.

Another point about the synergy results that is worth mentioning is their variability. Variations of the results of synergies are due to the absence of a unique solution for NMF. Therefore, the synergies extracted this way are not unique. To solve this problem and to increase the reliability of synergy results, besides having the validation phase, the same process of classification was repeated for 50 times and averaged the results. Although these averaged results show that synergies did not outperform MAV in general, there were a few cases when synergies were actually able to achieve better results than MAVs. This indicates that the synergies may contain some information that MAVs lack. However, since the optimum synergies cannot be achieved with the current optimization methods, we have to rely on the averaged synergy results that have been reported here.

In conclusion, our studies showed that muscle synergies contain important information for identifying tasks, i.e., some attributes vary from task to task and let us distinguish each task from the others. It is also worth mentioning that while synergies could not outperform MAVs in general, their results are still reasonably close to those of MAVs. Moreover, using synergies can have the advantage of reducing the dimensionality of the input space. Based on the muscle synergies hypothesis and as our investigations showed, only a small number of synergies is enough to describe high amount of variation in the data. So, in the case of having redundant data with high number of recording channels, using synergies instead of MAVs can reduce the dimension while keeping the performance close to what it can be using MAVs. The main advantage of this can be in high density EMG recordings when the dimension of the control space is very large due to the large numbers of the electrodes. In such cases, this large dimension can be reduced significantly by means of synergies.

4.4. Combined Task Classification

Pattern recognition based control schemes have been used to serially control multiple functions with accuracies >95% in laboratory settings. Although these control schemes have been improved and are close to clinical applicability, they can select only 1-DoF at a time, which imposes sequential, as opposed to simultaneous, control of DoFs. So far, the overall control of a prosthesis device with multiple controllable DOFs has not achieved a remarkable success in becoming similar to the intuitive and simultaneous control in human.

Several approaches to providing simultaneous multi-DOF commands have been previously investigated to provide classification of simultaneous movements. Many studies have focused primarily on either combined wrist movements [82], [138], [164], [174] or combined finger movements [94], [175] but few have investigated combined wrist/hand motions that are frequently used during activities of daily living [176]This part of our investigations is toward controlling combined movements and we aim to identify the wrist and hand tasks using synergies. As this problem is challenging for the TD features, we hope to see improvements by using muscle synergies based on Bizzi's studies on the converging force fields. As discussed in the background chapter, Bizzi realized that there were only a few converging force fields (CFFs) even when changing the parameters of stimulation. More interestingly, he showed that combining these CFFs could yield CFFs produced by simultaneous stimulation of multiple sites. Also, Gizster *et al*. [108] showed that linear vector summation could be applied to these movement primitives to explain the CFFs observed during simultaneous micro-stimulation of two sites. They showed supraspinal systems also generate motor outputs based on force field motor primitives, and that linear combination of CFFs can generate more complex motor behaviors. Thus, if we think of each CFF as a synergy set which produces a simple movement, it can be hypothesized that combining the synergies linearly can provide an estimate of the subjects' proportional control after selecting a movement and allows seamless transitions between classes. This approach focuses on extracting multiple parameters from a set of myoelectric input sites and characterizing the synergy patterns associated with each controlled function.

4.4.1 Materials and Methods

For this study two different data sets are used: one from single DOF tasks, and another including single and 2-DOF tasks. The single-DOF data set was analyzed which was already available from previous work, was used initially to compare synergy features with TD features on previously published work [19]. The results achieved by this data set motivate the extension of this study on a more complex set. Subsequently, a new data set that was acquired to demonstrate the performance when incorporating 2-DOF tasks. These are the same data acquired for the force estimation studies, described in Section 3.3.1.

4.4.2 Classification

Three previous approaches have been described in the literature for applying pattern recognition classification to combined motions. Davidge used a single linear discriminant analysis (LDA) classifier in which both discrete (1-DOF) movements and combined (2-

DOFs) movements were labeled as unique classes [177]. No information regarding how the motion classes may be related was used. Using this method, discrete and combined wrist flexion/extension and hand open/closed movements for three of four combinations were classified with a high accuracy. However, this is not a practical approach when the number of single and combined tasks grows as it makes the training phase long and exhausting. A second approach was proposed by Baker *et al*. [175], where a parallel classification scheme was used. Here, three separate LDA, classifiers were used to predict the motion of three digits simultaneously in a nonhuman primate. The LDA classifiers in this structure were trained only with discrete motions, using separate subsets of EMG channels for each classifier. A similar architecture of parallel classifiers using support vector machines was also suggested for providing classification of simultaneous movements of an elbow and a wrist/hand [178]

In this study, a relatively new method was used for classifying combined movements, recently proposed by Hargrove *et al*. [19]. This method employs a parallel set of LDA classifiers that use conditional probabilities to draw boundaries between similar motion classes. Two wrist DOFs, one functional hand-grasp pattern, and their combinations were used. They compared the performance of this new conditional parallel method to those of pattern recognition approaches previously described. As they showed, conditional parallel method resulted in a lower classification error for combined movements among the three mentioned methods., i.e, methods used by Davidge *et al.*, Baker *et al.*, and Boschmann *et al.* Due to the higher performance of conditional parallel strategy, this method was chosen for combined motion classification studies.

Conditional Parallel Classifiers

The conditional parallel strategy uses a parallel set of LDA classifiers, though here a classifier is designated for each discrete motion class. All 2-DOF movements need to be included in the training. Each classifier discriminates between its designated discrete movement and all combined motion classes that have this discrete movement as a component. Each classifier is therefore *conditioned* on an *a priori* assumption that this designated discrete motion class is active. For the example in Figure 4.7, the wrist flexion conditional classifier is trained with flexion and combination of hand open and hand closed with flexion. Then it chooses between wrist flexion with hand open, wrist flexion with hand closed or wrist flexion alone.

The no motion (NM) conditional classifier discriminates between all discrete movements and NM. Each conditional classifier discriminates between a unique set of motion classes, and each motion class is included in only two of the conditional classifiers. When classifying a movement, each of the conditional classifiers chooses a motion class from within its pool of possible classes. The final output of this architecture is the movement class that is selected by both of the conditional classifiers that contain this motion class. Figure 4.8 shows a flowchart detailing the exact operations of this classification strategy.

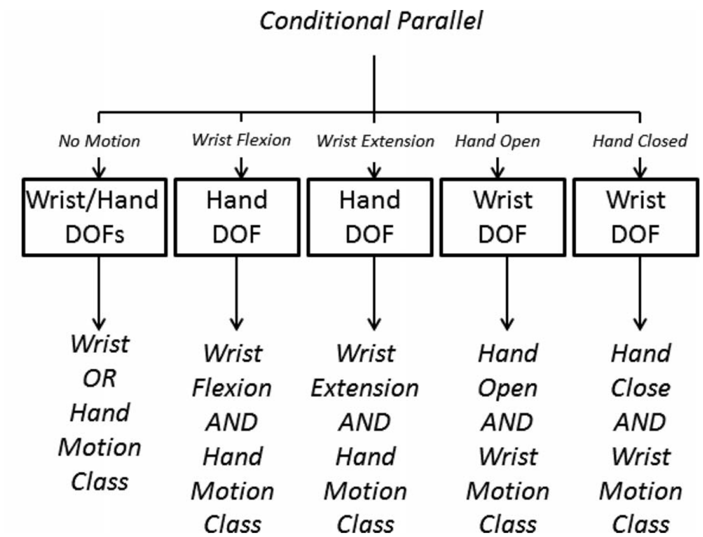


Figure 4. 7 – Block diagrams describing each classification strategy for two-DOF simultaneous wrist and hand movements. This diagram only shows classification strategies for two DOFs. Each box is an LDA classifier with motion classes from one or more DOFs as indicated by their label. The conditional parallel strategy has a separate classifier for each motion class, where each classifier has a class for a specific discrete movement and classes for each combined movement in which the discrete movement is one of the two movements. The two classifiers that choose the same combination of motions determine the output of the conditional parallel classifiers (adopted from [19]).

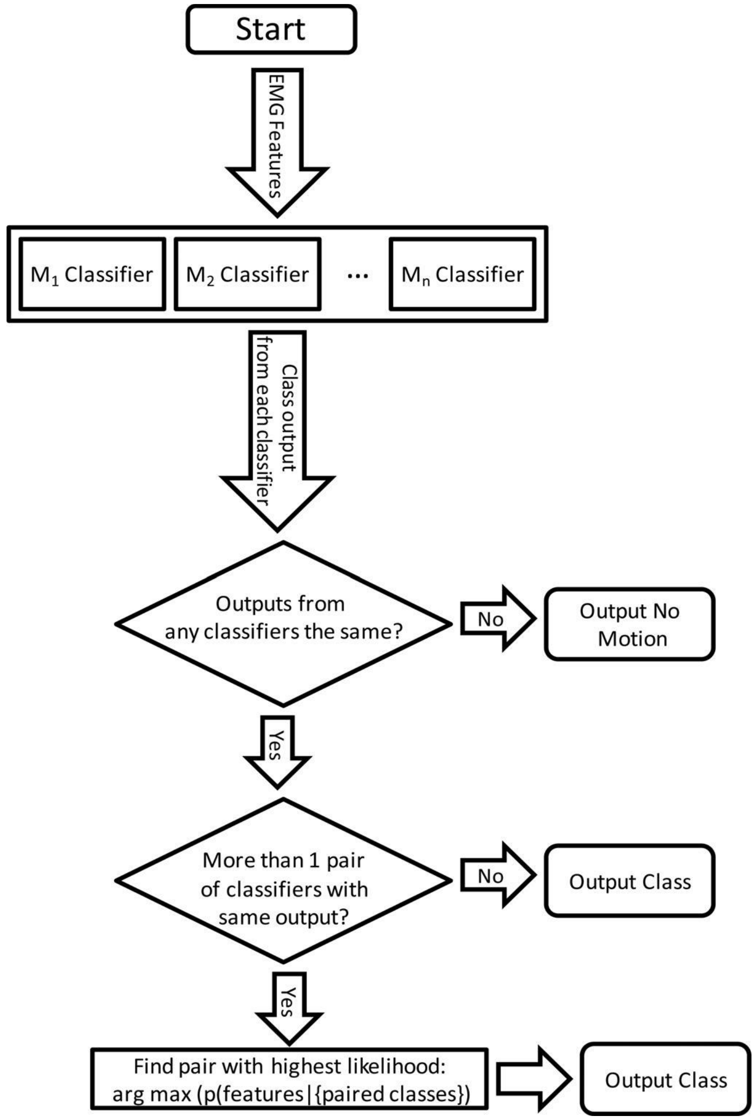


Figure 4. 8– Flowchart for a conditional parallel strategy. EMG features are sent to each conditional classifier and each classifier outputs two motion classes (note one or both outputs can be NM). The algorithm checks to see if any classifiers had the same output. If not, NM is selected. Otherwise, if only two classifiers had the same output, that output is selected. If more than two classifiers had the same output, then maximum likelihood of the pairs selected is performed to choose which pair to select. (adopted from [19]).

4.4.3. One-DoF Classification

In this study the data collected by [67] was used. This data set has 16 EMG surface channels. Task set includes four 1-DoF tasks: wrist flexion, wrist extension, hand open, and hand close as well as four combined motions which are combinations of a hand task and a wrist task. Four repetitions of each task were collected. Specification of the data used in this section is described in details in [67]. The classifiers and synergies were trained with three repetitions and tested with the other available rep. The window length for train and test phase was 250ms with 50ms overlap. For each subject six synergies were extracted and classification results averaged across all subjects.

Results

As shown in Figure 4.9, synergies extracted from both WL and MAV outperform the results of MAV. However, having both MAV and WL in the TD feature set for classification, leads to a more accurate classification than using the synergies.

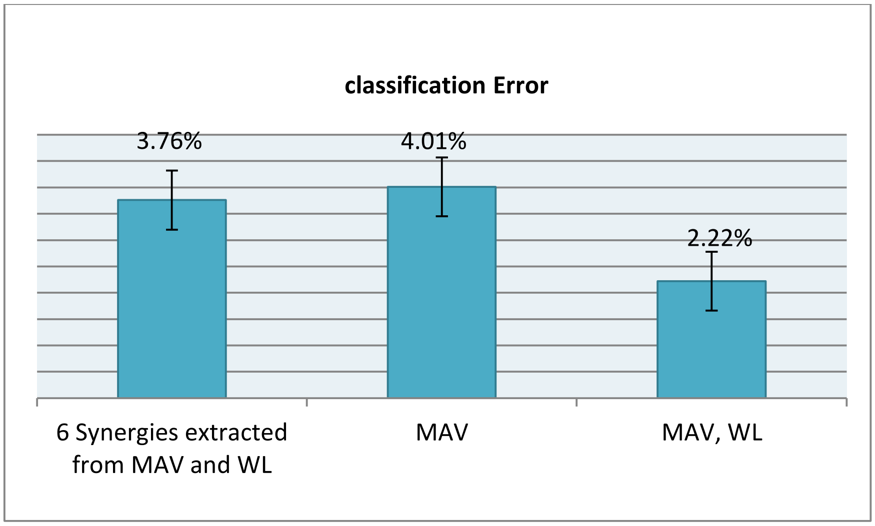


Figure 4. 9– Comparison of performance when using synergies, MAV alone, and MAV along with WL

Also the effect of number of synergies on the classification results was studied. Figure 4.10 below shows how the accuracy of classification changed with increasing the number of extracted synergies. As the values in the plot show, by increasing the number of synergies the classification became more accurate. Having at least ten synergies used for classification, the result of synergies outperformed MAV, WL results. So, it was concluded that increasing number of channels added to the accuracy of results up to a certain point (number of channels/2 + 1 or 2) and after that it plateaued and no significant change was observed. Therefore, the study was continued with this number of synergies from now on because after this number, the results of synergies did not change significantly.

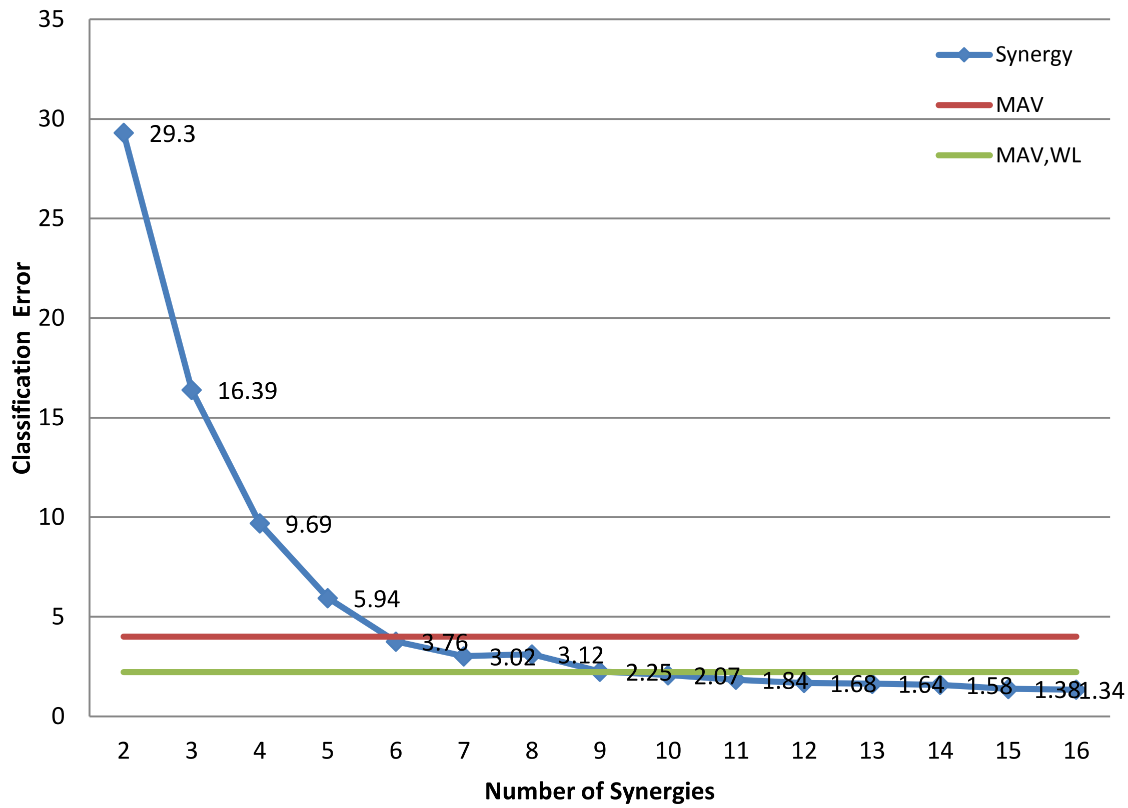


Figure 4. 10– Effect of number of synergies on the classification results. MAV error is 4.01% and MAV,WL error is 2.22%.

4.4.4. Effect of Number of Channels

Having 16 recording channels available in the data set, enough channels were available to perform a study on the effect of number of channels and redundancy of EMG data in the results achieved by synergies and TD features. The number of channels was reduced from 16 to eight, four, and two to see the effect of number of synergies on the classification results when having smaller number of EMG channels. To reduce the channels, different methods of channel selections were used: equally distanced channels, targeted, untargeted, and random selection. Then the results of these trials were averaged and compared across different numbers of channels. Figure 4.11 compares these accuracies with those of MAV and when using both MAV and WL. The illustrated results are averaged across all subjects. Here our focus was more on the impact of the number of channels on the classification results rather than the methods of selecting the channels. Thus, a thorough investigation of these methods is beyond the scope of this thesis.

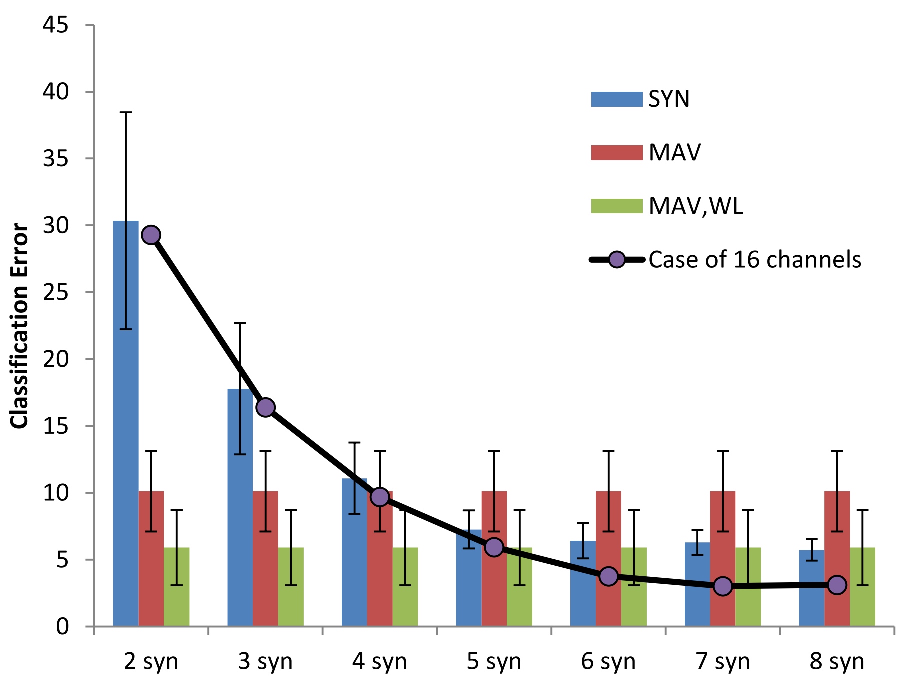
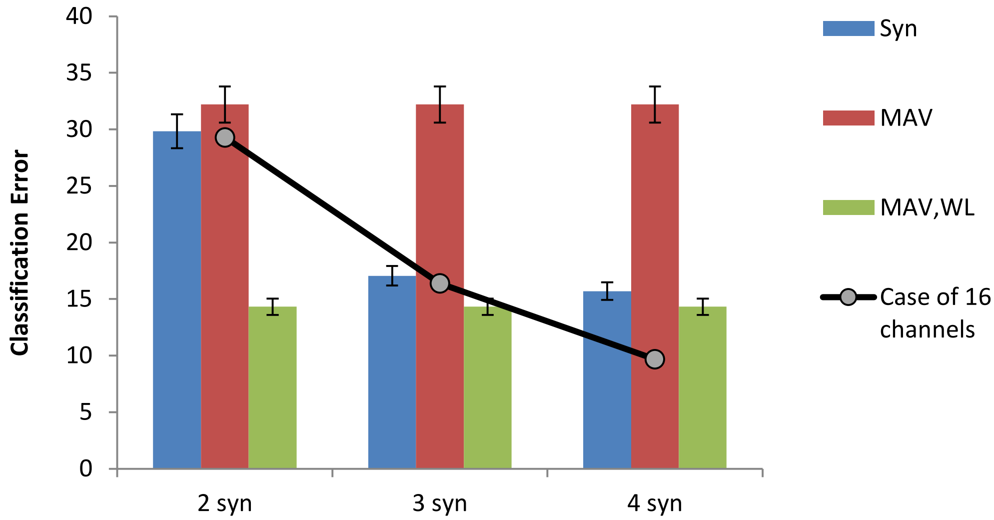
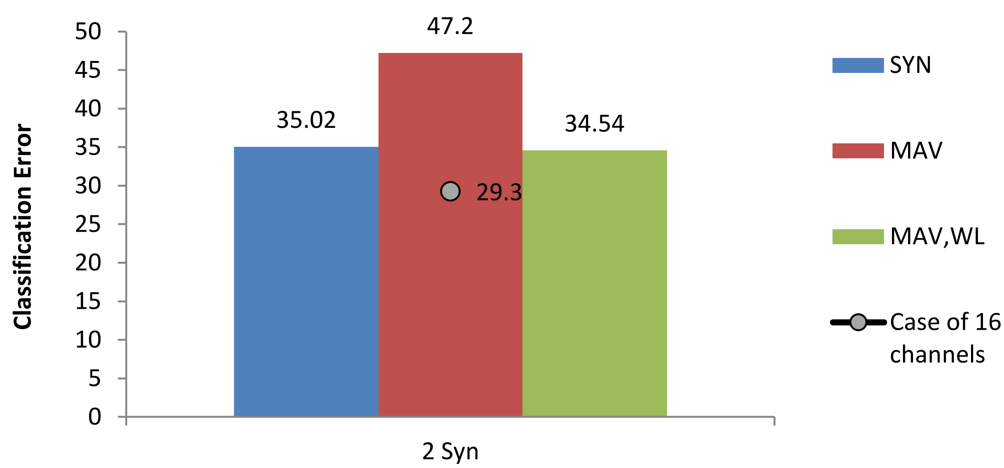


Figure 4. 11– Classification results when using eight EMG channels out of 16 available channels. The errors with 16 channels using synergies is also shown to simplify the comparison.



(a)



(b)

Figure 4. 12– a. Classification results when using four EMG channels out of 16 available channels. b. Classification results when using 2 EMG channels out of 16 available channels. The synergy result here is behind the MAV-WL due to their close values. However, Synergy error is slightly higher than the MAV-WL error.

Comparing Figures 4.10-12 shows that the more redundant the system became, the better the results of synergies were to the point that having16 channels, synergies could actually outperform the results of TD features. As the number of channels was reduced, the performance of all three methods degraded significantly. However, this reduction in the number of channels, affected the synergy model the most and they could not outperform TD features anymore when there were only eight or less EMG channels in the mode.

Another important observation was that regardless to the number of channels available, the synergy results became more consistent when the number of synergies was increased. A normalized measure of spread called normalized standard deviation was used to quantify this consistency. The normalized standard deviation (or *Coefficient of Variation*, CV) is in fact the standard deviation divided by the mean:

$$\delta_n = \frac{\delta}{\bar{x}} \tag{4.1}$$

The standard deviation is given as a fraction of its mean. Using this statistic allows the spread of the distribution of a variable with a large mean and correspondingly large standard deviation to be compared more appropriately with the spread of the distribution of another variable with smaller mean and correspondingly smaller standard deviation.

Figure 4.13 shows the CV of the synergy results for 50 runs for each number of synergies extracted from eight channels. Higher CV means greater dispersion in the results, which is not desired.

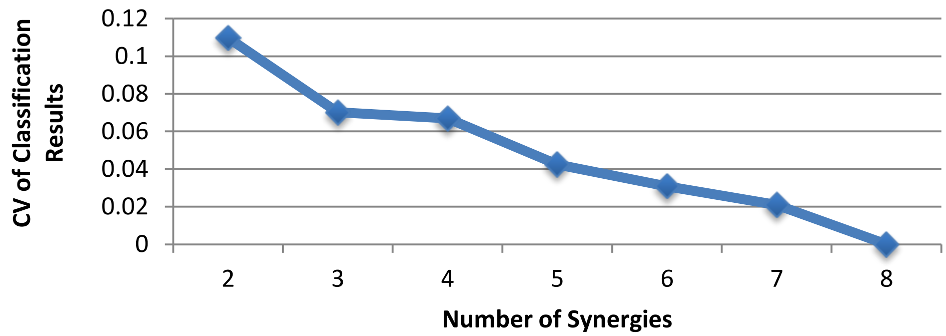


Figure 4. 13– The Coefficient of Variation of classification results with synergies and the effect of number of synergies on the consistency of the results with eight EMG recording channels.

4.4.5. Discussion

Based on our observations in this study, the redundancy of the system, i.e. number of recording channels, and the number of extracted synergies are two factors that affect the performance of the synergy model. It was shown that if one provides a sufficient number of channels (here at least eight) and extract enough number of synergies, this method could outperform the classification results of the MAV,WL features. The effect of the number of synergies used for classification is indeed a function of the model redundancy. If the system is not redundant enough, using even all the available synergies cannot result in a better classification than TD features. In a redundant system a large number of muscles that are involved in the motion are being captured, so synergies extracted from this redundant set of muscles are more informative about the motion performed. If we instrument each muscle independently, i.e., an electrode on a given muscle, and have the precise activation for each muscle, one particular viewpoint on the muscle co-activation patterns can be captured. But instrumenting a number of muscles, allows for observing more subtle contributions. So, having multiple electrodes that each capture the activation of muscles from different locations is a different viewpoint. This is also important in more redundant data collection systems like high-density collection method, as the role of reducing the dimension of system can be crucial. In such models extracting muscle synergies and using them for task classification or force estimation can lead to significant improvement.

4.5. One and Two-DoF Classification

The previous study was extended to classify 24 hand and wrist tasks using muscle synergies using the data described in Section 3.1.1. This data included 1-DoF wrist contractions (extension, flexion, pronation, and supination) as well as four grips (power grip, pinch grip, key grip, and spherical grip) and also 2-DoF contractions, which were combinations of each of the wrist tasks with each of the grips. The conditional parallel classifier architecture was used, as described in Section 4.4.2. The number of required synergies is computed based on minimizing the reconstruction error and classification error (a validation set was used). Using more than five synergies did not significantly change the results for any of the subjects. Thus, five synergies were used for classifying the tasks. Since four repetitions of each task were collected, four-fold cross validation was used and the error of classification was averaged across all folds and all tasks. Table 4.4 shows the classification results for two different force levels using synergies and TD features. Synergies were extracted from MAV and WL since it was showed this was the best set for extracting synergies. Our set of TD features for evaluating the synergy results consisted of MAV and WL.

Table 4. 4– Classification error across different force levels using conditional parallel strategy. Train and test force levels were the same.

	25% MVC	50% MVC
Synergies	19.38%	19.60%
TD features	14.30%	15.70%

Note that these data include 24 hand and wrist single and combined motion classification and the classifier is only trained with single-DoF motions. A large amount of the classification error in both methods is due to the complexity of the problem.

4.5.1. Consistency of Synergy Results

Although TD features outperformed synergies on average, the observations showed that synergy results were not consistent enough to allow for a consistent comparison. Figure 4.14 shows the results of classification by TD features and synergies separately for each subject. As the Figure 4.14 illustrates, for some subjects, synergies are performing better than TD features.

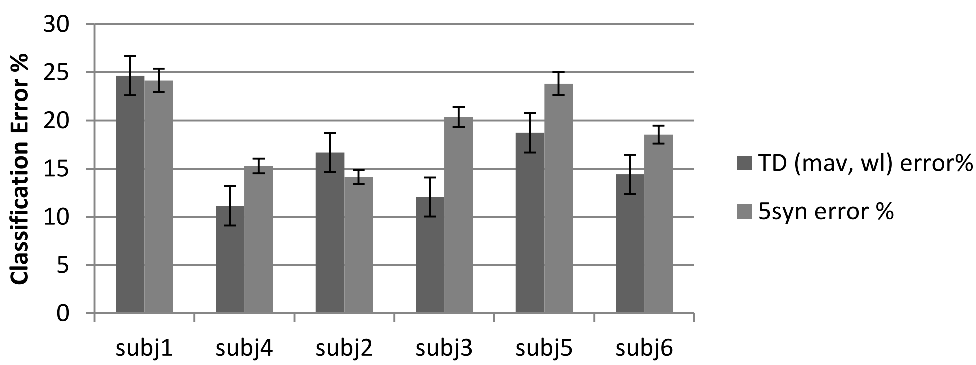


Figure 4. 14– Results of classification by TD features and synergies across subjects.

Multiple runs of this study showed that every time the calculation was run, the extracted synergies were slightly different. Although they all resulted in very close reconstruction errors, their classification results were significantly different. As an example, running the same analysis 50 times for synergies, gave us 50 different classification errors with a variance of 2.14 for average error of 18.89%.

Again most of these comparisons did not show any improvement by synergies, but the best results of these 50 runs during validation, considerably outperformed TD feature results, as shown in Figure 4.15.

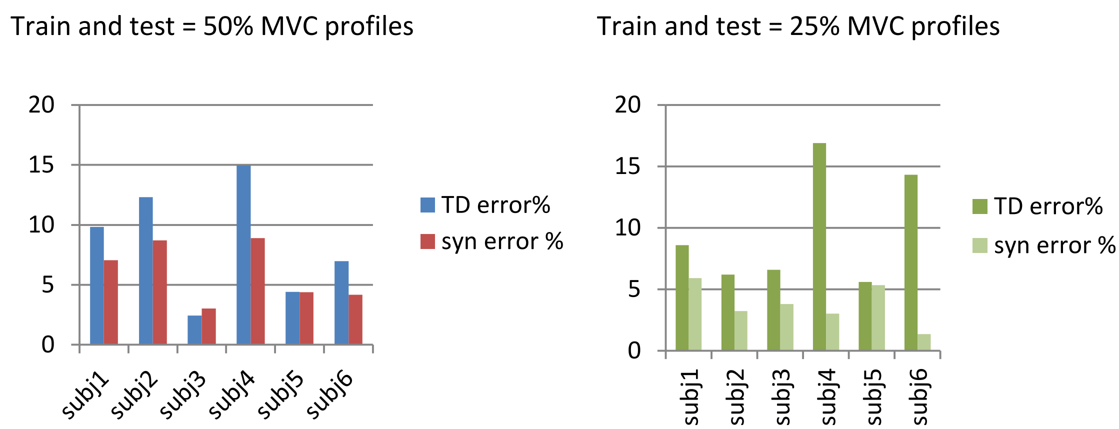


Figure 4. 15– Best results achieved by synergies over 50 runs and comparison with TD results.

Choosing the best synergies based on the test results is of course not practical, but this results show that some synergies might be potentially capable of offering some important information about the classes which can lead to better classification results than the TD features.

If the classification results by synergies can be made more consistent, a more favourable conclusion can be driven when comparing them with those of TD features. The synergies extracted from the signal are not unique and this is inevitable due to the iterative method of extracting synergies using NNMF. Potential solutions to determine an "optimum" synergy decomposition are explored in the next chapter along with some other heuristic methods to improve the synergy results.

4.6. Chapter Summary and Discussion: Task Classification by Synergies

This chapter was an attempt to understand the dynamics of synergies used as pattern recognition features. In this chapter the effect of several factors on the performance of synergies were examined. The features that synergies are extracted from play a fundamental role in their performance. As expected, using WL along with MAV increased the performance of synergies. However, as described earlier, this improvement was not observed as ZC and SC were added to our resource of extracting synergies.

As our initial results of TD features and synergies show, having adequate number of channels and consequently enough numbers of synergies, our proposed synergy model outperformed a MAV, WL feature model. However, when the same study was performed on the dataset of 24 hand and wrist tasks, no improvement over TD features by synergies was observed. This could partially be due to the fewer number of channels that were in the 24 task data (12 channels) in comparison with 16 channels that recorded the previous data set. However, other than the case with relatively large number of channels and synergies, the study showed that synergies' performance is generally lagged behind that of TD features. The most likely explanation is that the NNMF synergy decomposition algorithm produces variable results, and it is difficult to ascertain the "optimum" projection in terms of the minimum test set error. This appears to be exacerbated by more complex data sets, inherent in the 24 task set.

One of the challenges in producing reliable results by muscle synergies was the consistency of the synergies that were extracted by NNMF algorithm. This challenge was brought by the fact that NNMF does not provide a unique solution to the factorization problem, and this affected the consistency of the results that were achieved by synergies. In fact, there is no certain set of synergies that is optimum for the problem. This is while the performance of the classification model basically depends on the choice of synergies. For example, in an idealized situation where the best synergies were chosen, the classification accuracy significantly improved and outperformed TD features results. Unfortunately, finding the best synergies based on the test results and making sure that they will work for the tasks being performed in the future is not practical. The next chapter describes proposed solutions to address the consistency issue with the synergies. Also, since an improvement in classification by synergies was not observed, alternative heuristic methods were explored in an attempt to improve the synergy results outside of straightforward pattern recognition methods.

CHAPTER 5 –HEURISTICS TO IMPROVE MUSCLE SYNERGIES PERFORMANCE

This chapter explores alternative methods to improve the performance of muscle synergies in task classification. The first section addresses the training issues and the subsequent sections explore the classifier architecture issues.

5.1. Training Issues in Synergy Based Model: Consistency of Extracted Synergies

As mentioned in the previous chapter, the fact that NNMF algorithm does not offer a unique solution for the synergy extraction problem can significantly affect the consistency of the synergy results across multiple runs of decomposition. To overcome the consistency issue with muscle synergies, we attempted to narrow down the numerous solutions of NNMF by imposing restrictions to the solutions. Adding a validation phase, increasing the sparseness of NNMF solutions, and increasing the size of training data are the approaches that are explored here.

5.1.1 The Use of a Validation Set to Select Synergies

Methods

This strategy explored the use of a validation data set to select a synergy decomposition that provided the lowest classification error on data not included in the training set. This would put another resctiction to extracting the synergies and would lead to more similar answers for the classification problem. Also by this restriction, the answeres would be limited to the synergy sets who produce smaller classification error which would be beneficial for the classification problem. By putting such restriction on validation error, if the validation error is higher than a predetermined threshold error, the algorithm repeats the synergy extraction and trains the model with the new synergy set until achieving a lower validation error. If could not achieve an error smaller than the threshold after a limited number of iterations, the algorithm returns the synergy set with the smallest error as the answer. Then this new set of synergies will be used in the test part to compute the coefficients of test data.

Results

From four available reps of each task one rep was chosen for test, one for validation and two other reps for training. Figure 5.1 compares the two cases: choosing the synergies with and without the validation phase. Variability of results in both cases were quantified by coefficient of variance. In no-validation case the calculated CV value was 0.26 and in the case with validation CV value was 0.08. As expected, adding the validation phase reduced the variations of synergy results. However, the classification errors achived in the case of having the validation phase were higher than the other case. The errors are averaged across all folds and users and are showed in Figure 5.1.

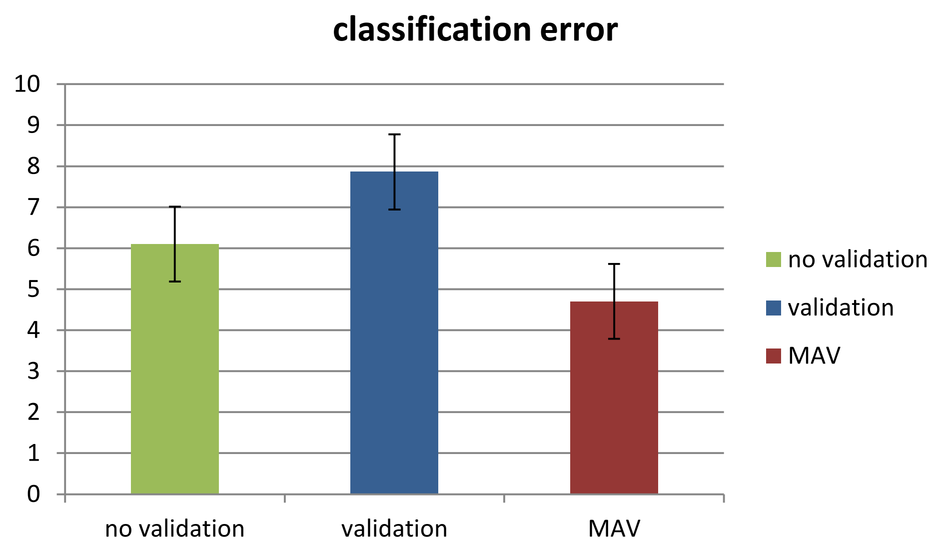


Figure 5. 1– Classification error compared for two cases: choosing the synergies with and without the validation phase.

Observing larger error in validation in comparison with the no-validation case, suggests insufficient training of the model or a validation set that does not properly represent the test set. Both issues introduce the need for a larger data set to be used for validation or training. Therefore, another data set was recorded with 24 repetitions of each task to find the sufficient training size, so that increasing the size of data used in training and validation could resolve this issue.

5.1.2 The Effect of Training Set Size

Methods

For this part the data collection was repeated with a similar protocol as in the previous chapter, Section 3.3.1. These data contain four 1-DoF wrist contractions and four grips as well as the combinations of each of the wrist contractions with each of the grips. This time 24 repetitions of each task were collected, as compared to four reps in the original data set, to ensure that enough samples are available for the classifier. The twelve EMG electrodes used in this collection were Trigno™ Wireless EMG System (Delsys Inc.). During an experimental session, the subject sat in a chair with their right forearms secured to an armrest. Then the subjects were instructed to exert wrist motions of a moderate but consistent intensity without changing the position of their elbow. Five normally limbed subjects participated: two female and three males within the age range 26 to 61, all right-handed. Subjects had no history of neuromuscular disorders. A few training trials were performed to familiarize the subject with the user interface and the correct way of performing each task. In the data-recording phase, the subjects were asked to perform the tasks according to what they were asked each time on the screen. They followed a moving curser up to a target. Then they kept the curser at the target for two seconds and then as the target moved back to the rest position, they followed it back. Steady state data (of EMG) were recorded during the experiment when the curser reached the target and the subject was holding it there for two seconds. Each subject performed 24 repetitions of each task profile. The subjects could rest one to five minutes between the trials upon request. Each profile could include a 1-DOF task or a multi-DOF combination of two tasks (one wrist motion and one grasp).

This data were then used to investigate the effect of training set size on the classification results to find the number of reps adequate for training the system.

Results

The new dataset (24 reps of each of single and combined task), allowed us to train the system with different numbers of reps and to study the effect of training set size on classification error for both synergy based and TD features based models. In order to choose the reps for training the model, up to 50 possible selection of the reps were chosen where applicable, and the test results were averaged for each certain number of training reps. Figure 5.2 shows the classification errors for the synergy based model. Starting with training the model with two reps of each task, as Figure 5.2 shows, the classification error was very high, i.e., about 24%. However, as the number of reps in training increased, a dramatic drop in the classification error was observed as the curve converged to 14% classification error at about 14 training reps.

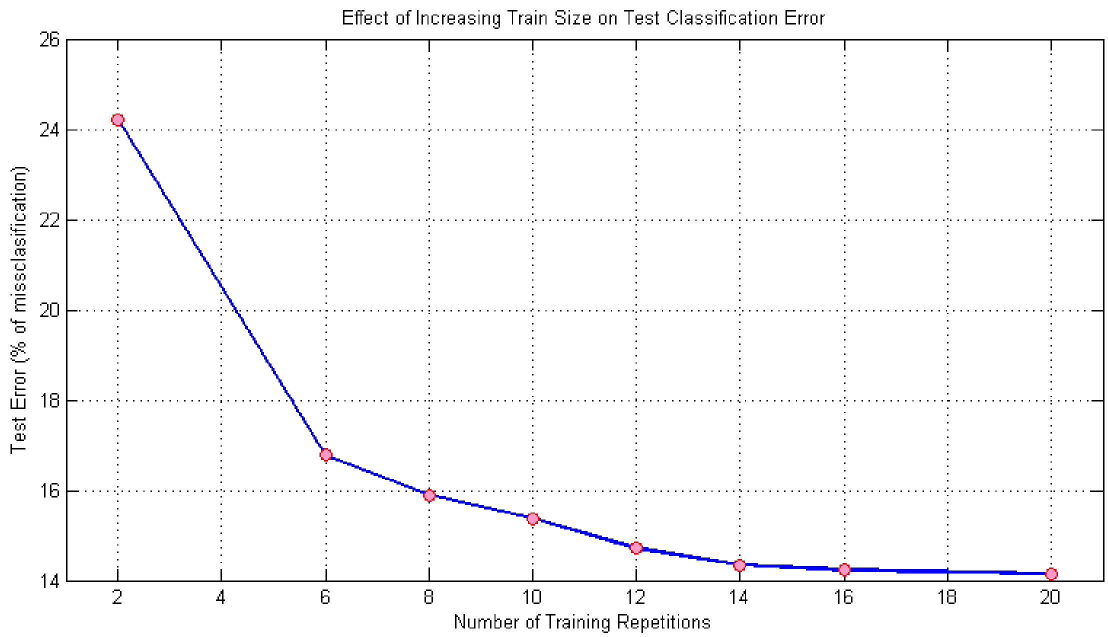


Figure 5. 2– Effect of increasing the train data size on the classification error in synergy based model.

Repeating the same study for TD features, a corresponding decrease in the classification error was observed. Figure 5.3 compares the results for the two approaches.

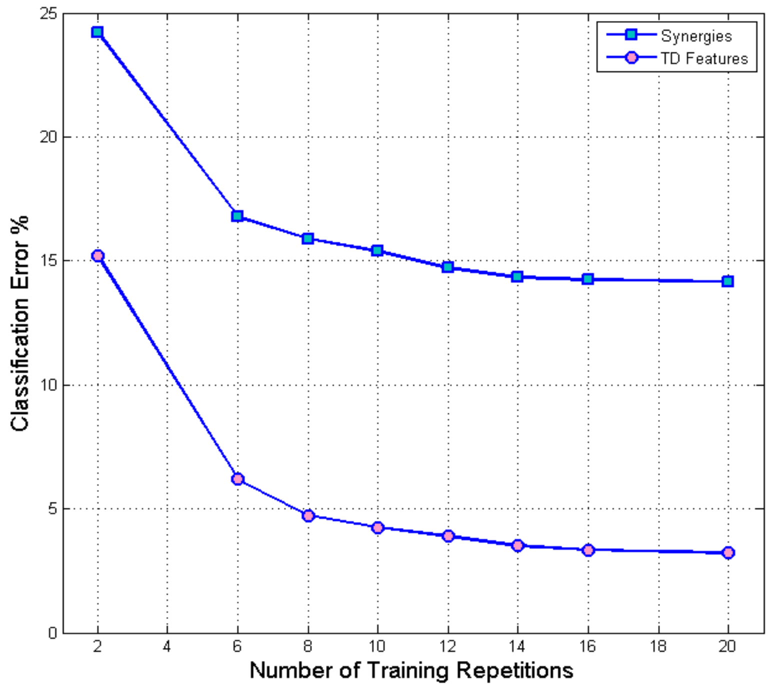


Figure 5. 3– Effect of increasing the train data size on the classification error in synergy-based model compared with the TD-based model

As illustrated in the Figure 5.3, the error curve for both methods reaches a lower limit at about 14 reps. This is an important observation as it shows the effect of the training size exists in methods. Comparing the errors of two models shows that TD features significantly outperformed synergies in this classification problem.

Also the 2-Dof tasks and 1-Dof tasks were separated and the effect of train size on each group was explored to see how the training size affects the classification error in each group. Figure 5.4 illustrated this effect on each task set and each input.

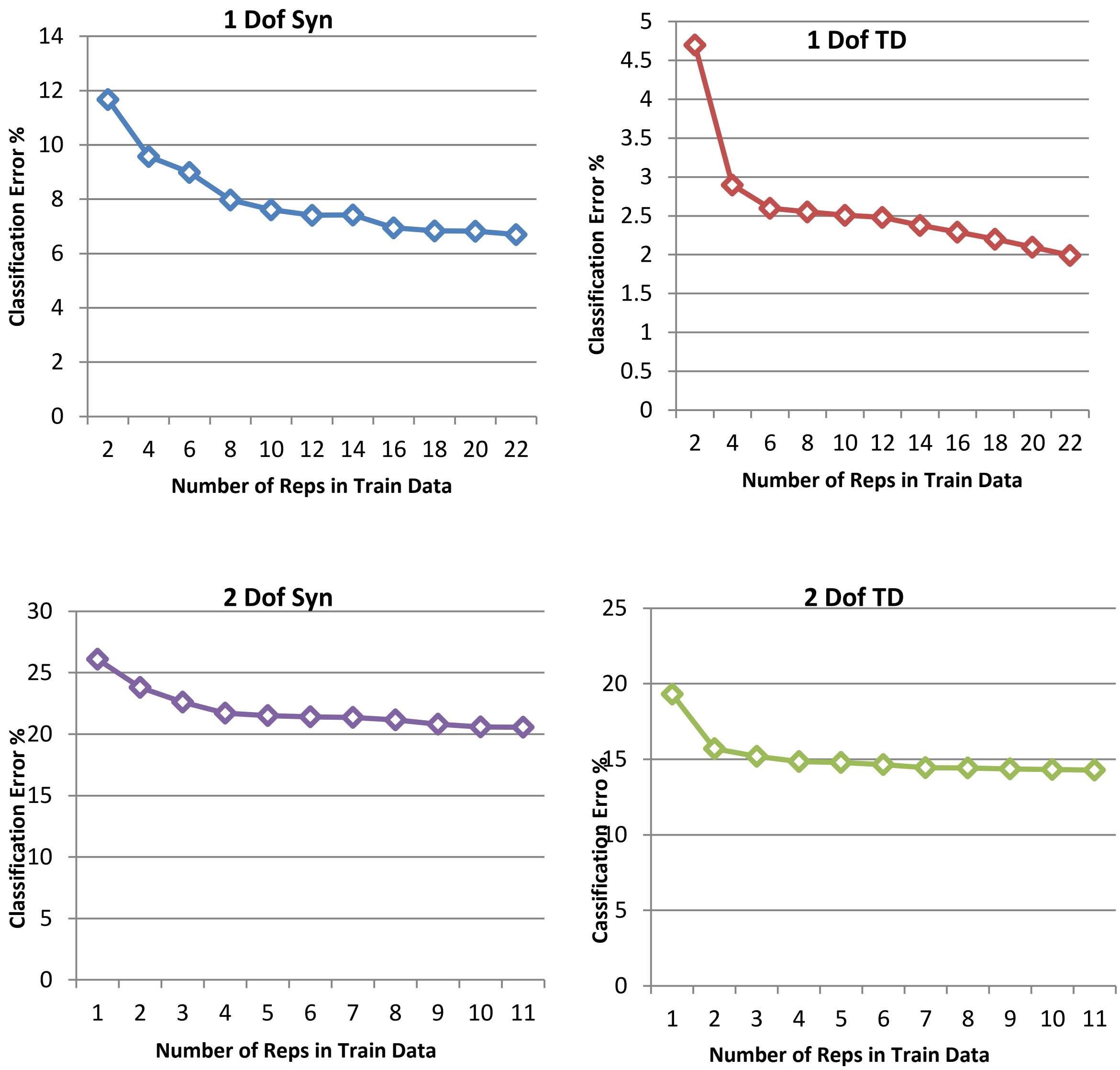


Figure 5. 4– Effect of train size on 1 and 2-DoF classification for Synergy and TD feat based Models

In both models increasing the training size had a more significant impact on reducing the error of 1-DoF tasks classification, 42% reduction for synergies and 58%

reduction for TD features measured between 2-rep training and 22-rep training. However, a closer look at the TD curve, one can see that the drop in the error is very minimal after four repetitions. Figure 5.5 shows the effect of train size on classification error for five subjects separately in the 1-DoF synergy-based model. The overall trend is similar for all subjects, i.e. performance improves by increasing the train size and then plateaus. However, this improvement is not the same for all subjects. As it is shown, for some subjects classification error reduces very fast by adding a few reps to the training data. This might be due to lack of repeatability in performing the tasks by these subjects which may caused by distraction or poor performance.

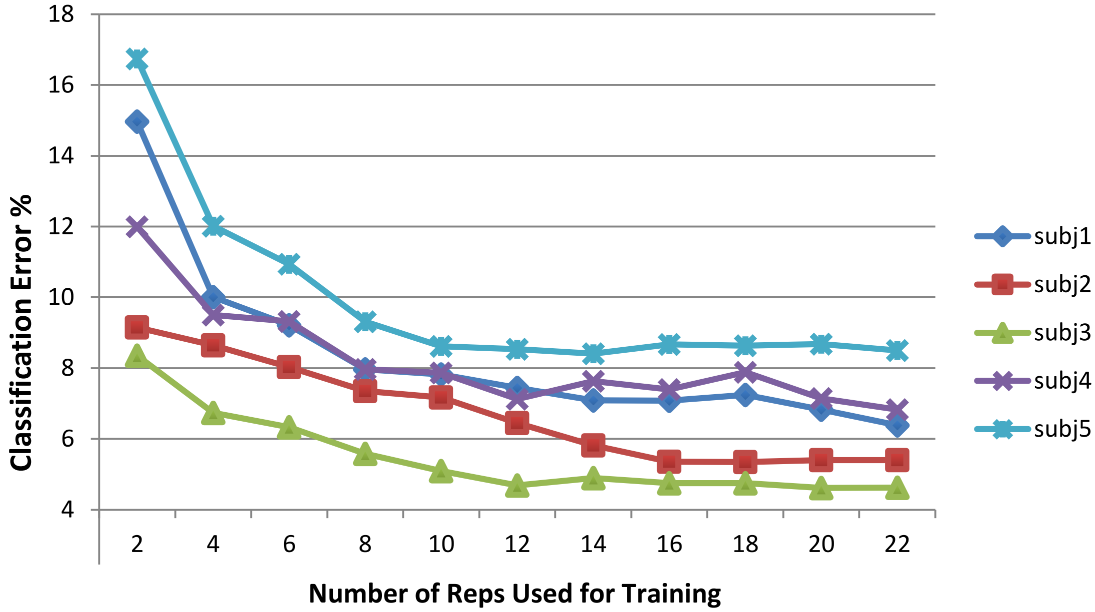


Figure 5. 5– Effect of train size on classification error for five subjects separately in the 1-DoF synergy-based model

Having adequate training samples the classification was repeated for synergies with and without validation phase. Also the same classification was repeated with an LDA classifier instead of the parallel classifiers in order directly compare the LDA to the conditional classifier architecture. Figure 5.6 compares the results of the tested models with TD features where MAV and WL were the extracted features. Fourteen reps from each task were used to train each classifier.

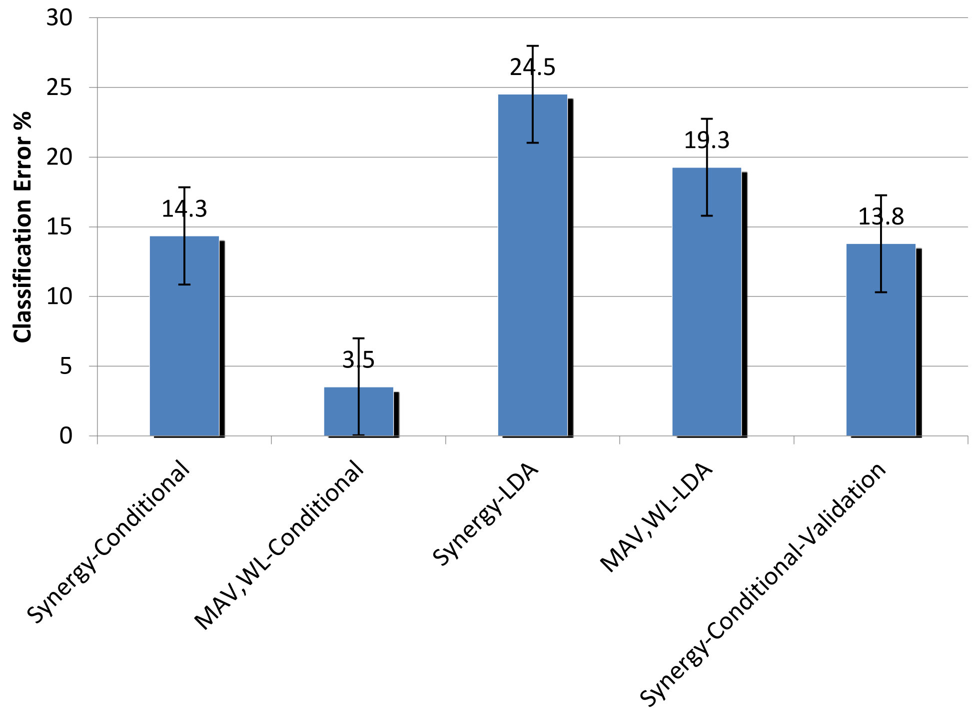


Figure 5. 6– Classification error with 14 training reps.

As Figure 5.6 illustrates, adding the validation phase improved the synergy results. However, synergies still could not outperform TD features in classifying 24 hand and wrist tasks. Also, comparing the errors of conditional method with those of LDA shows how effective is this method in classification of multi-DoF tasks regardless to the inputs used for classification.

It was observed that the training set size can also affect the robustness of extracted synergies. To quantifying this effect, Coefficient of Variance was used as described previously in this chapter.

The coefficient of variance of the results across different sizes of training data was calculated and shown in Figure 5.7. The change in the variance was very small and it did not saturate after a certain number of repetitions and continued to drop. This indicates that there is still benefit in increasing the number of reps even after 20. The accuracy became more consistent as training set size is increased. This demonstrates that the synergies extracted from a larger data set are more robust and lead to more repeatable classification.

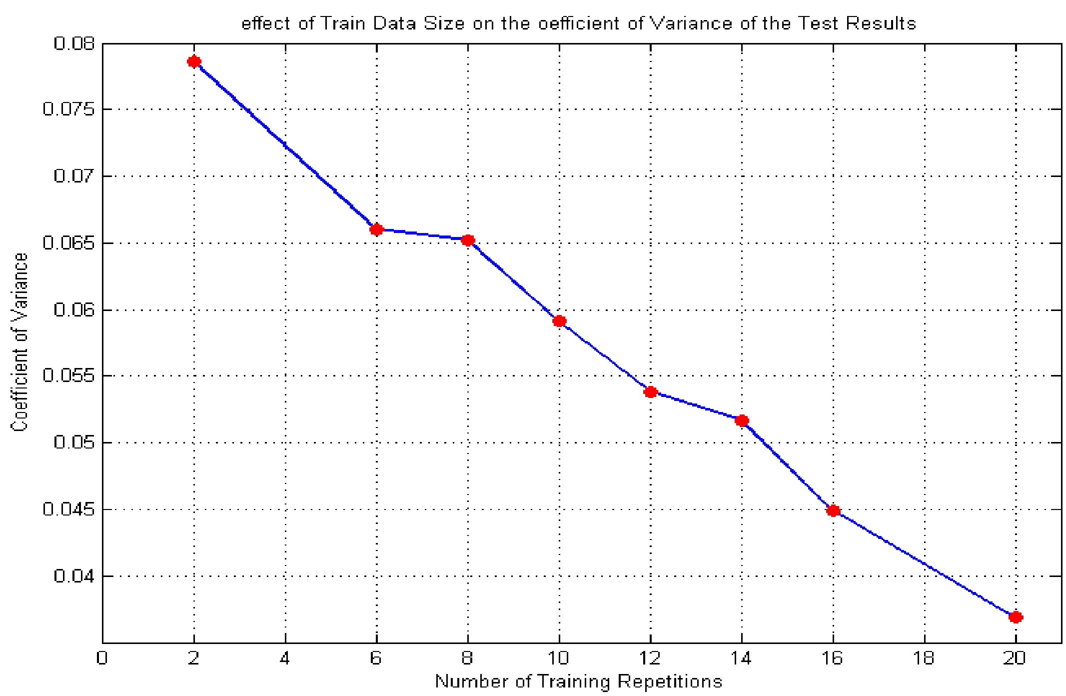


Figure 5. 7– Effect of train size on Coefficient of Variance for classification results

5.1.3 Uniqueness of NMF Solution

Using a method proposed in [179]NMF was extended to include the option to control sparseness explicitly. This allows us to achieve parts-based representations that are qualitatively better than those given by basic NMF. Such representation encodes much of the data using few active components, which makes the encoding easy to interpret. Also, because a new constraint is being added to the synergy decomposition method, it potentially creates more similar solutions. Therefore, the sparser the components are, the more robust they might become and these more robust synergies may lead to more repeatable synergy results.

The sparseness measure used in this study is based on the relationship between the L^1-norm and L^2-norm:

$$Sparsness(x) = \frac{\sqrt{n} - \left(\sum |x_i|\right) / \sqrt{\sum x_i^2}}{\sqrt{n} - 1} \tag{5.1}$$

where n is the dimensionality of x. This function evaluates to unity if and only if x contains only a single non-zero component, and takes a value of zero if and only if all components are equal (upto signs), interpolating smoothly between the two extremes. So, in order to impose a certain degree of sparseness to synergies in $V \approx WH$, the non-negative matrices of W and H are found such that minimum reconstruction error is achieved under the sparseness constraint. The algorithm for this method is described in [179]. The Matlab implementation of this method is available in [180]and used for our sparseness studies.

Clearly, a trade-of between the sparseness of the synergies and the error of the reconstruction that this may cause is required. Different values of sparseness constraint were tested for the synergies and compared the consistency of the results across variations of this value. Then selecting the appropriate value with regards to the reconstruction error and consistency of results, the consistencies of classification results and the case with no sparseness constraint were compared.

Results

As Table 5.1 shows, no significant difference between the two cases was observed. Imposing sparseness constraints to the extraction model did not affect the consistency of their classification results.

Table 5. 1– comparison of CV when having a sparseness constraint and when not having the constraint.

	Without sparseness constraint	With sparseness constraint
Coefficient of Variance	0.061	0.057

Although this is a method to restrict the possible solutions for synergy decomposition, the solutions are still different enough to cause variations in the classification results. Therefore, this is not a very significant factor for our goal of reaching more consistent classification results with synergies.

Discussion

To overcome the consistency issue with muscle synergies, it was attempted to narrow down the numerous solutions of NNMF by imposing restrictions to the solutions. Adding a validation phase, increasing the sparseness of NNMF solutions, and increasing the size of training data where the solutions that were tested. Among these three solutions, size of the training data had the most significant effect on the consistency of the extracted synergies and consequently on the classification results. However, for this particular study it was concluded that 12 to 14 reps are needed to get a fairly repeatable classification result by synergies, which is not much practical due to the long data recording sessions that this requires.

It was shown that the training set can grow quite large and the performance still continues to improve. This is the case with TD features too. It was shown that the size of the training set has a great influence on the performance of classification both 1-DoF and 2-DoF tasks with TD feats or synergies. It can be concluded that the more reps included in the training phase, the better classification can be achieved until the error curve finally saturates. This can be important in designing the data collection protocols for similar studies as most of the studies on pattern recognition methods use only a few numbers of repetitions of each task to train their models. However, having this many repetitions means a long data collection session, which might not be reasonable and practical for some studies.

5.2. Classifier Architecture Issues

5.2.1.Pooling Synergies and TD Features

Since it is apparent that synergy features, by themselves, are not as effective as TD features in pattern recognition, the idea that they may augment TD features was explored. With the idea that synergies offer some advantage over MAV with regard to representing force and that they may contain some important information about combination of tasks, then concatenating them with TD features may offer improved classification accuracy.

The data with 24 reps were used in this set of studies. As concluded earlier, 12 repetitions of the data were adequate to have robust synergies. Therefore, this size of training data is also used in the current study.

Starting with eight single-DoF tasks, 12 reps were randomly chosen for training the model, one was chosen for test and 11 were chosen for validation phase. Cross-fold validation was performed and the results were averaged for each subject. The extracted synergies and the TD features were normalized between 0 and 1. The normalization factors, i.e. factors by which inputs of classifiers were normalized between 0 and 1, were determined from the training set, and used for both training and test phases. Six synergies were extracted from each of the TD features (MAV and WL) and the associated neural inputs were provided to the classifier. Then another classifier was trained with TD features (MAV and WL). Finally the neural inputs and the TD features were pooled together to form an input of a higher dimension for a third classifier. The results are shown in Figure 5.8 for each subject. Figure 5.9 compares the results of these three classifiers averaged across different trials of random selections of train and validation reps for each subject.

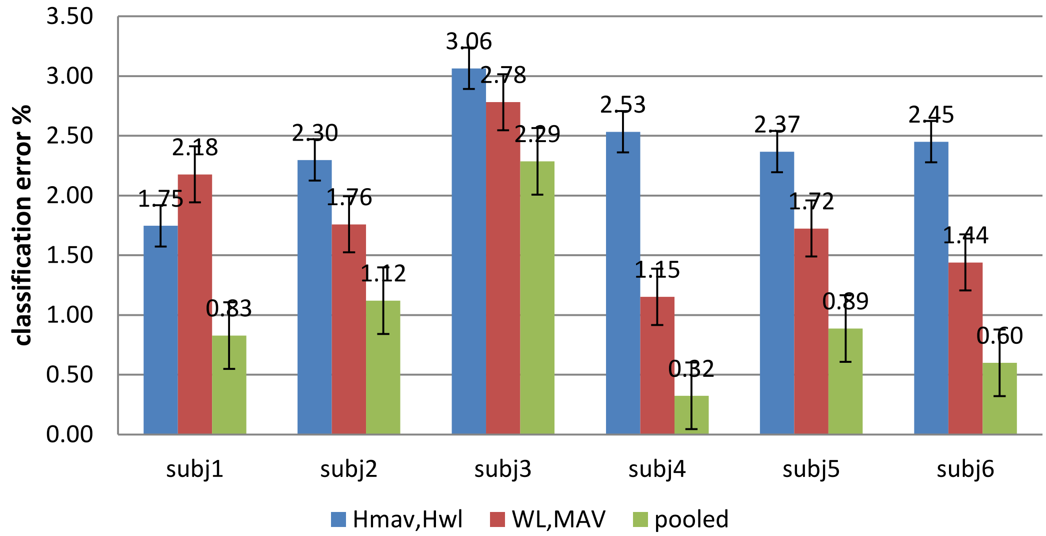


Figure 5. 8– Comparison of classification error for 1-DoF tasks averaged across different trials of random selections of train and validation reps.

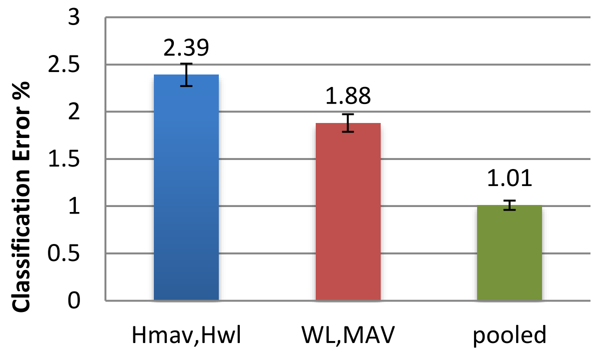


Figure 5. 9– Results of three classifiers averaged across subjects

5.2.2. Discussion

Comparing the results of three methods shows that pooling features with synergies can improve single-DoF task classification results. ANOVA statistical analysis showed that this improvement is significant (p-value <0.05). This shows that in single-DoF case some information in the synergies were observed that may not be contained in TD features. Therefore, the study was preceded with checking the same method for multi-DoF task classification problem.

5.2.3. Pooled Synergies and TD Features for Multi-DoF Tasks

The synergies and TD features were pooled for multi-DoF task classification. The data with 24 reps of 24 tasks were used. After pooling the features 12.51 % error of classification was observed, which was a relatively large error in comparison with the

Synergy error (9.12 %) and TD features error (5.16 %). This could be due to the high dimension of the input after pooling. Since the model trains very well (training error smaller than 1%) but the test error is high, the model has been saturated by high dimensional input, a.k.a. *curse of dimensionality*. To solve this problem the dimensionality of input was reduced by applying PCA and selecting 12 most important components. This number was achieved by running the analysis with all possible values of PCA components to determine the optimum number.

There was a reduction in classification error by pooling, but not as much as with 1-DoF tasks. This could due to the need to use PCA for dimensionality reduction; some information is lost by reducing the dimensionality of the pooled features. Figure 5.10 compares the results for 2-DoF tasks for three methods averaged across all the subjects. As it is illustrated, pooled results after PCA were just slightly better than TD alone and the difference between the results of two methods were not significant when ANOVA test was performed across the subjects (p-value>0.01).

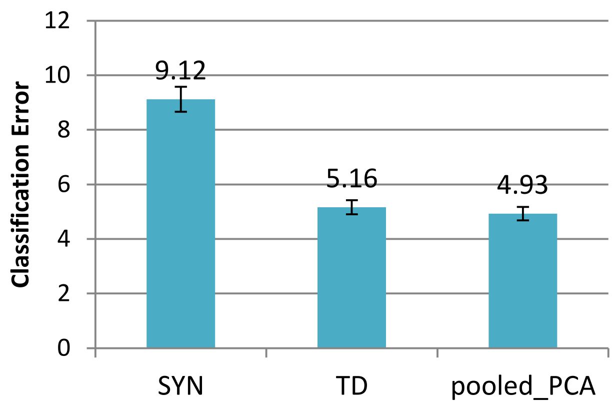


Figure 5. 10– Comparison of classification errors for 2-DoF tasks for three methods averaged across all the subjects, tasks, and test reps.

Figure 5.11 shows the results of each method for all single and multi-Dof tasks averaged across all subjects.

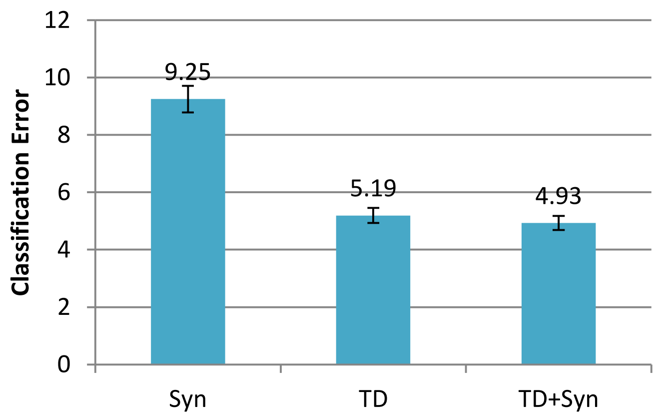


Figure 5. 11– Comparison of classification errors for 1 and 2-DoF tasks for three methods averaged across all the subjects, tasks, and test reps.

Discussion

Here, pooling TD features and Synergies created a very high dimensional input space that due to the curse of dimensionality resulted in a poor classification. To solve this, it was required to reduce this dimension and PCA was used to do so. Reducing the dimensionality of the original space means that some components need to be eliminated and the inputs should be limited to the most important ones. This could have an impact on the performance of the classification since some information is being excluded from the input data. That might explain why the results of pooling TD features with synergies are not as good as TD features alone in a few cases. However, averaging the results across all the subjects, tasks, and test data, the observations showed that results of pooled features are slightly better than TD. Statistical analysis on these results (p-value>0.05) indicates that synergies are not adding significant information to TD features as pooling them with TD features does not significantly improve the classification.

Dimension reduction was also done for TD features and synergies separately and then the reduced components were pooled and provided to the classifier to examine if the small reduction of error in pooling case was due to loss of information during dimension reduction or it was because of lack of additional information in the synergies. As Table 5.2 shows, the results were not significantly different from the case in which the reduction was done after pooling the TD features with the synergies. However, in the case where data reduction was done for both TD features and Synergies separately, pooling the components will significantly reduce the classification error if compared to TD results. Therefore, the small drop in error that was observed in the previous 2-DoF case must have been due to the dimension reduction not the irrelevance of information included in synergies. This shows that Synergies contain some useful information but it is not enough to outperform TDs if used alone. However, it can improve the accuracy of TD features if used together.

Table 5. 2– Comparison of classification errors for synergy-based and TD-based methods. Also the results compared with reduced dimension cases of each method and reduced pooled method.

Input	Dimension	Classification Error %
SYN	12	5.5
TD	24	2.6
reduced TD	6	4.4
reduced SYN	6	8.3
reduced (TD+SYN)	12	2.53
reduced TD +reduced SYN	12	2.56

5.2.2. Task Specific Synergies

Another approach can be taken in which synergies are extracted from each task separately. This approach looks at the synergies more as features of EMG signal, which can discriminate different tasks. The patterns extracted in this method are not compatible with the definition of muscle synergies that were used in the rest of our studies. However, it can be considered as a new approach to muscle synergies. So, here we have class specific synergies each reflecting the activation patterns of the muscles involved in a certain task. Then the coefficients of these synergies are used for task identification.

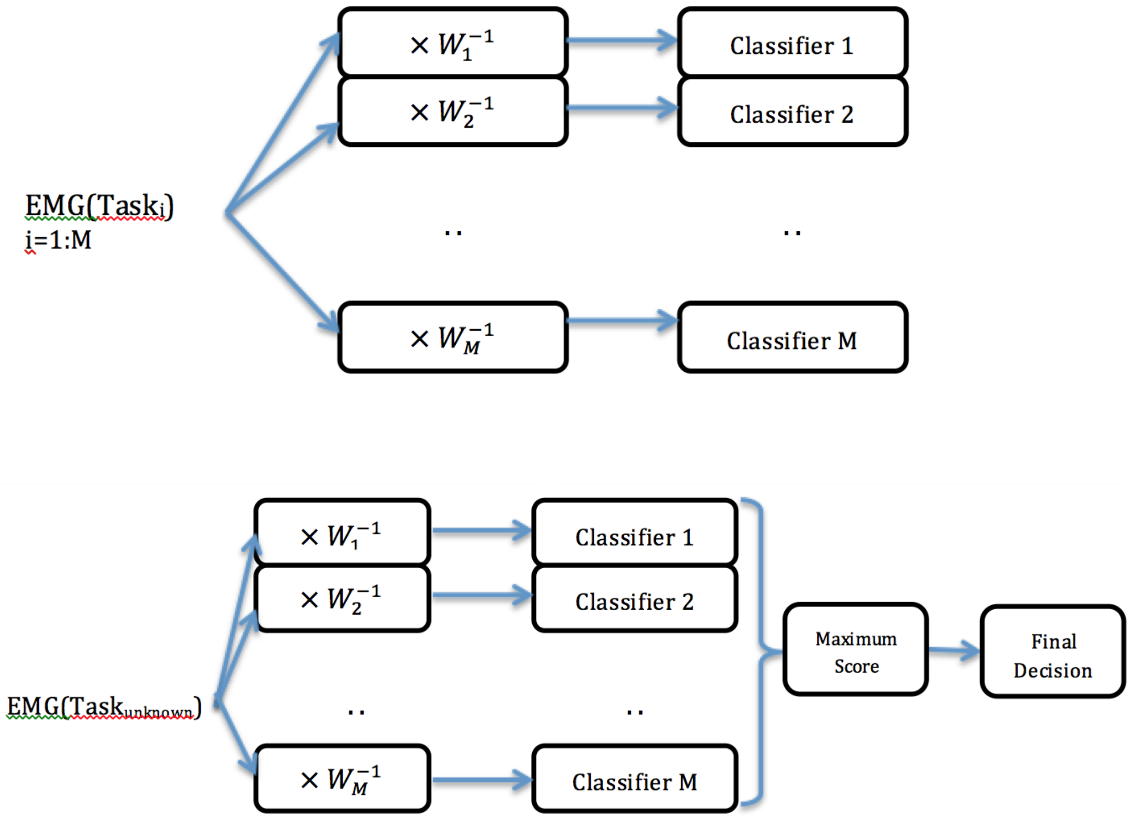


Figure 5. 12– Training and testing model for the proposed method of classification by task specific synergy

Method

For this goal, separate tasks are used to extract synergies that are specific to those tasks: EMG (Task$_i$)= W_i *H_i. Also, the product of multiplying the synergy of *i*th task (W_i) and the EMG of other tasks were calculated: W_i^{-1}*Task$_j$. This product does not really reflect any information about $Task_j$, but training the model with this product can be helpful to distinguish the task during testing the model when only synergies of different tasks are available. Diagrams of Figure 5.12 illustrate the training and testing models.

Results

First the 1-DoF tasks were analyzed and the results of task specific synergies, regular synergies, and TD features are compared in Table 5.3. Then the multi-DoF task classification was analyzed and again the results of task specific synergies, regular synergies, and TD features are compared in the Table 5.3.

Table 5. 3– Classification results of task specific synergies, regular synergies, and TD features are compared.

Input	1-DoF Classification error %	2_DoF Classification error %
MAV, WL	1.24	4.1
Regular Synergies	2.40	7.6
Task Specific Synergies	1.47	6.15

Statistical analysis showed that extracting synergies from separate tasks could significantly (*p-value* <0.005) improve the classification results comparing to the original method of synergy extraction. Moreover, these results are significantly different from TD feature results and TD features still offer the best inputs for task classification among the three methods.

Consistency

To check if the results are consistent in the task specific case and to see how much they depend on the extracted synergies, a repeatability test was done on the synergy results. Task specific synergies were more repeatable than the regular ones. With the regular synergies: Min error = 1.49 %, max error = 5.59 %, coefficient of variance = 0.08. Of course, this factor decreased by increasing the size of train data. However, even after increasing the training data from 12 reps to 20 reps, the results were still very sensitive to the extracted synergies (coefficient of variance = 0.04). For the task specific synergies in the same condition this sensitivity was much lower. Using 12 reps of data for training: Min error = 1.31 %, max error = 1.36 % and, coefficient of variance = 0.02, which shows more repeatability of the results in this case.

Task specific synergies are very similar to the features they are extracted from. In fact, they are the result of reducing the dimensionality of the TD features without introducing any new information. This may be why they are more repeatable than the regular synergies and also the reason that their classification results are better than regular synergies. Unlike the synergies that were originally used in our studies, task specific synergies do not add any information to what was achieved from TD features and also they have all the weaknesses of TD features as well. For example, in force or position variations or for simultaneous task classifications, no improvement by task specific synergies was expected.

5.3. Chapter Summary and Discussion

This chapter explores alternative methods to improve the performance of muscle synergies in task classification. The first section addresses the training issues and the subsequent sections explore the classifier architecture issues.

To overcome the consistency issue with muscle synergies, we attempted to narrow down the numerous solutions of NNMF by imposing restrictions to the solutions. Adding a validation phase, increasing the sparseness of NNMF solutions, and increasing the size of training data are the approaches that are explored here. Among these three solutions, size of the training data had the most significant effect on the consistency of the extracted synergies and consequently on the classification results. However, for this particular study it was concluded that 12 to 14 reps are needed to get a fairly repeatable classification result by synergies, which is not much practical due to the long data recording sessions that this requires.

Additionally, it was shown that the training set can grow quite large and the performance still continues to improve. This was the case with TD features too. It was shown that the size of the training set has a great influence on the performance of classification both 1-DoF and 2-DoF tasks with TD feats or synergies. It can be concluded that the more reps included in the training phase, the better classification can be achieved until the error curve finally saturates. This can be important in designing the data collection protocols for similar studies.

During the studies of this chapter, it became apparent that synergy features, by themselves, are not as effective as TD features in pattern recognition. Therefore, the idea that they may augment TD features was explored in the rest of this chapter.

Examining the results of pooled synergies and TD features showed that pooling can improve single-DoF task classification results. ANOVA statistical analysis showed that this improvement is significant (p-value <0.05). This shows that in single-DoF case some information in the synergies were observed that may not be contained in TD features. For multi-DoF task classification problem, pooling TD features and Synergies created a large input space that due to the curse of dimensionality resulted in a poor classification. To solve this, this space were reduced by PCA and some components were eliminated and the inputs were limited to the most important ones. Averaging the results across all the subjects, tasks, and test data, it was observed that results of pooled features were only slightly better than TD. Statistical analysis on these results (p-value>0.05) indicated that synergies were not adding significant information to TD features as pooling them with TD features does not significantly improve the classification. Although synergies contain some useful information, it was not enough to outperform TDs if used alone.

In the next study of this chapter, a different approach was taken in which synergies were extracted from each task separately. This approach looks at the synergies more as features of EMG signal, which can discriminate different tasks. The patterns extracted in this method are not compatible with the definition of muscle synergies that that were used in the rest of our studies. However, it can be considered as a new approach to muscle synergies. So, here we had class specific synergies each reflecting the activation patterns of the muscles involved in a certain task. Then the coefficients of these synergies were used for task identification. To check if the results were consistent in the task specific case and to see how much they depend on the extracted synergies, a repeatability test was done on the synergy results. Task specific synergies were more repeatable than the regular ones. The reason could be that task specific synergies are very similar to the features they are extracted from. In fact, they are the result of reducing the dimensionality of the TD features without introducing any new information. This could also be the reason why their classification results are better than regular synergies.

CHAPTER 6- CONCLUSIONS

Several factors challenge pattern recognition control in practical use, which should be accommodated to yield truly robust performance of myoelectric control in real task oriented use. It is expected that by improving the control strategies in different aspects of controllability including accuracy, intuitiveness and response time, upper limb prostheses might experience a higher rate of acceptance.

The current study was focused on helping with improvement of prosthetic hand control toward being intuitive. For this aim, a platform and control algorithms based on a concept called muscle synergies, was developed and tested. Based on the physiological attributes of muscle synergies, the objectives of this work is to control of prosthetic hands in a more natural feeling and physiologically expected manner.

6.1. Summary and Discussion

6.1.1 Using Muscle Synergies for Proportional Control

The exploration of muscle synergies started by using muscle synergies for estimating force. First, the changes in coefficients of the synergies were observed while switching from one force level to another. As the produced force increases, an increase in the coefficients or the neural inputs was observed.

Observations also showed that the synergy components were quite consistent with the muscle activities during each task. For example activation of the flexors was mainly reflected by the synergies whose coefficients increase during flexion. The R^2 values of the estimation along with high correlation between the estimated and the target values showed that the estimated values could reflect the major behaviours of the target force and thus the neural inputs were able to estimate the force values with a high accuracy. This result was also shown not to be as accurate as what MAV yielded particularly when the number of synergies was low. However, ANOVA test reported that increasing the number of synergies, their estimation result was better from those achieved by MAV in multi-DOF force estimation (*p-values* <0.05).

Furthermore, the numbers of neural inputs enough for estimating the force was usually few, i.e. much less than the number of muscles involved in the movement. Thus, using neural inputs not also keeps the accuracy of estimation high but also reduces the dimension of the estimation model.

The muscle synergies extracted from a set of wrist and hand tasks were quite robust across different force levels. The results indicated that muscle synergies were an effective representation of EMG in force estimation of multi-DoF tasks. These observations strengthen the idea that predicting the force produced in unknown levels could be possible by training the model with the synergies of only one force level. This also supports the idea that the synergies might be resilient to force changes to some extent. So they could be used for proportional control of prostheses when the produced force during the task performance is unknown. The correlation coefficients calculated between the synergy patterns of low and high contraction sets were very close to unity (the average was 0.9948 ± 0.004) which showed a strong linear relation between the two synergy sets and supports the robustness of synergies against force change. Since synergy analysis involves decomposing the EMG into the product of the synergy matrix and the neural inputs, this suggests that the estimated neural inputs may be effective in estimating force levels.

Hand articulations distribute force across multiple fingertips, and a consistent estimate of grasp force is therefore difficult. Thus, better estimation was achieved for wrist tasks than grasps. Grasp force involves many more co-articulating muscles, and therefore, the relationship between EMG intensity and effort is more complex than wrist articulations. However, the relatively high R^2 values still show that the estimation results can be high particularly in 1-DoF tasks considering the fact that only one feature extracted from 12 EMG channels is being used for estimating force.

In a case where the model was trained with all available force levels, comparing the results of MAV and synergies showed that for the majority of tasks synergies outperformed the MAV in force estimation. Performing multivariate analyses of variance (ANOVA) on RMSE and R^2 showed that the methods were significantly different (p-value < 0.05) and the performance achieved by synergies was higher. These results can be explained by the fact that the muscle synergies and their associated neural inputs show how different muscles co-activate in performing different tasks and describe their relative involvement in each task independent from the force level produced. This is an important factor that makes the muscle synergies a powerful input for force estimation in proportional control.

When tested with an unknown force level, the neural inputs outperformed MAVs, particularly when trained with a practical protocol of 1-DOF contractions. The high R^2 achieved in this test demonstrates that synergies have a good potential to be used in estimating the force produced during multi-DoF force-varying tasks, which can be a valuable step toward improving proportional control of prostheses.

Another interesting observation was achieved in a case where the model was trained with 1-DoF tasks only and then tested to estimate the force of combined motions: synergies clearly outperformed MAVs. These results confirm that the neural inputs extracted from 1-DoF tasks contain important information to estimate the force produced during simultaneous tasks. This advantage achieved by using synergies is supported by the high R^2 of estimation for the majority of combined tasks that were tested. Also, the results were consistent across all tasks and subjects to prove that our achievements are not due to a random factor or limited to a particular data set or task. This suggests that the superposition property of muscle synergies allows the neural inputs to be effective for force estimation of more complex, multi-DoF tasks. Furthermore, the number of neural inputs for force estimation is fewer than the number of muscles involved in the movement. This leads to reducing the dimension of the estimation model, and thereby the computational requirements.

In general, predicting the grip force from the EMG signal is nothing new; the EMG-to-force relationship is well known and has been modeled, among other methods, via linear regression [36]. Our model is novel in that it predicts the force to a similar degree of precision independently of the grasp type employed. So it can be used in parallel with the classifier.

Performance of the proposed Synergy model was also compared with a MAV-based model in a real-time force estimation study. All subjects found that inadvertent cursor movements were significantly less with the MAV method than with the Synergy based method while performing 1-DoF tasks. The subjects found that the overall control quality was similar between the MAV and Synergy tests, and the influence of difficulty indices and complexity of tasks on the quality of control were much more noticeable. This was also observed by the outcome of our real-time analysis. MAVs performed better in controlling the curser during 1-DoF tasks (p-value <0.005) but no significant difference was observed between the two methods in 2-DoF task control (p-value >0.05). Also, in 2-DoF case, MAVs were not significantly better than synergies in controlling the curser for all single and multi-DoF tasks (p-value >0.05).

6.1.2. Task Identification by Muscle Synergies

Chapter 4 continued the investigation by classifying tasks using muscle synergies and compared their performance with TD features. One interesting observation in this chapter was an increased classification error when adding more features to our synergy components. Having less accuracy when extracting the synergies from all four TD features than extracting them only from MAV and WL, was not expected. To explain the degradation observed, two important factors that could be considered are: the separability between the classes, and the coincidence between the training and test datasets, before and after addition of other features. Using synergies extracted from MAV and WL, the difference between training and test data clusters is slight and therefore, the trained classification boundaries still largely apply to the test data. So, the test error is very small. However, adding two other features change the training and test datasets. Therefore, even though the classes are more separable using all four features compared to using two of them only, the trained classification boundaries are highly different from the optimum boundaries, because of the low repeatability. This confuses the classifier and degrades the classification performance. Although not thoroughly tested in this thesis, investigating the effect of adding these features to the feature set on the results could be an interesting subject of future investigations.

Our observation also brings up the question that why adding these features when using TD features for classification, increases the performance but using the synergies that are extracted from them along with the synergies from MAV degrades the performance. One reason might be based on the nature of these features. WL and MAV represent an envelope of the signal. But ZC and SC are both count-based features and they can change instantaneously. This gives them two disadvantageous properties: they can change relatively abruptly and they have a limited dynamic range. This makes it quite challenging for the synergy model to recognize the patterns in SC and ZC as they are poorly behaved. Although unstructured features like ZC do not work very well, other structured features such as Entropy or Cardinality, could be possible sources of information for a synergy-based model.

Although low classification errors by synergies were observed, they could not generally outperform TD features. Extracting synergies from other TD features rather than only MAV allows for a more reasonable comparison between the results of synergies and TD feature sets. However, TD features were still appeared more effective in discriminating the tested hand and wrist tasks.

Effect of force variation on the proposed model

Based on the physiological aspect of muscle synergies and their potential in containing information about the co-activation patterns of muscles across different force levels, the actual power of synergies, in comparison to TD features, seemed to be in more complex classification problem; specially in variable force levels where TD features are not very powerful in identifying the tasks. Therefore, the synergy power in identifying 1-DoF tasks was investigated when amount of exerted force is variable and unknown.

One important factor in proportional control is that the controller inputs should be able to perform consistently during force variations. So, the ability of muscle synergies in classification of tasks was studied when the amount of force applied during the tasks was different from what the classifier was trained with.

Our studies started with exploring the consistency of synergies across force variations, and as expected, the smaller the variations were, more similarities observed between the extracted patterns. This is physiologically understandable the brain modifies recruitment when high force levels are required. Some muscle may not have the necessary fast twitch fibers to keep up with high demand of power. However, by small changes in the force no big difference between the dominant synergies was observed and most of the change was only scaling. This also supports our results of classification of tasks in different force levels. As shown, when training with a medium force level, the accuracy of the classification degrades as the force performed during the test data gets distant from the medium levels for example goes up to 80% MVC or down to 20% MVC.

The similarities of synergy patterns across force levels were quantified by measuring the correlation between the patterns. High correlation values (above 0.7) between the neural inputs of 50% force profile and other profiles showed that the synergy patterns involved in these profiles could be very similar. This motivated further explorations of classifying tasks of untrained profiles.

In the next step, synergies were used to identify seven different hand and wrist tasks. The classification results were compared with MAV results for evaluation of proposed method. Results achieved by MAVs were generally better than synergies. Applying ANOVA to the results achieved from nine subjects showed that MAVs significantly (p-value <0.05) performed better. These observations are in accordance with the results of consistency studies since high correlations between the patterns were seen when the force variations were relatively small. This can be explained by the fact that the patterns of co-activations of muscles can vary with respect to the applied force level particularly when force variation is significant. Thus it can be difficult for the classifier to distinguish the tasks when the amount of force exerted during that task is considerably different from what the classifier is trained with. Although significant similarities between the patterns of neural inputs related to different force levels were observed, great differences between these patterns could confuse the classifier and impact its performance.

In conclusion, our studies showed that muscle synergies contain important information for identifying tasks, i.e., some attributes that vary from task to task and let us distinguish each task from the others. It is also worth mentioning that while synergies could not outperform MAVs in general, their results are still close to those of MAVs. Moreover, using synergies can have the advantage of reducing dimensionality of input space. Based on the muscle synergies hypothesis and as our investigations showed, only a small number of synergies is enough to describe high amount of variations in the data. So, in the case of having redundant data with high number of recording channels, using synergies instead of MAVs can reduce the dimension while keeping the performance close to what it can be using MAVs.

6.1.3. Advantages and Challenges of Using Muscle Synergies as a Control Input

Based on our observations, redundancy of the system, i.e. number of recording channels, and the number of extracted synergies are two main factors that affect the performance of a synergy-based model. It was shown that by providing enough number of channels and extracting enough number of synergies, this method could outperform the classification results achieved by TD features. The effect of number of synergies used for classification is indeed a function of the model redundancy. If the system is not redundant enough, using even all the available synergies cannot result in a better classification than TD features. This is an important observation, as it proves when a redundant system is available, synergies can actually outperform the TD features. In a redundant system a big number of muscles that are involved in the motion are being captured, so synergies extracted from this bigger set of muscles are more informative about the motion performed.

Another point about the synergy results that is worth mentioning is their variability. Variations of the results of synergies are due to the absence of a unique solution for NMF. Therefore, the synergies extracted this way are not unique. To solve this problem and to increase the reliability of synergy results, besides having the validation phase, the same process of classification was repeated for 50 times and the results were averaged. Although this averaged result showed that synergies did not outperform MAV in general, there were few cases when synergies were actually able to achieve better results than MAVs. This indicates that the synergies may contain some information that MAVs lack. However, since the optimum synergies cannot be achieved with the current optimization methods, we have to rely on the averaged synergy result.

A part of our studies was an attempt to understand the dynamics of synergies used as pattern recognition features. As mentioned earlier, one of the challenges faced in producing reliable results by muscle synergies was the consistency of the synergies that were extracted by NNMF algorithm. This challenge was brought by the fact that NNMF does not provide a unique solution to the factorization problem, and this affected the consistency of the results that were achieved by synergies. In fact, there is no certain set of synergies that is optimum for the problem. This is while the performance of the classification model basically depends on the choice of synergies. For example, in an idealized situation where the best synergies were selected, the classification accuracy significantly improved and outperformed TD features results. Unfortunately, finding the best synergies based on the test results and making sure that they will work for the tasks being performed in the future is not practical.

A number of solutions to address the consistency issue with the synergies were proposed. Also, since no improvement in classification by synergies was observed, in the rest of this thesis, alternative heuristic methods where employed to improve the synergy results outside of the straightforward pattern recognition case.

One of the tested approaches to overcome the consistency issue with muscle synergies, was to narrow down the numerous solutions of NNMF by imposing restrictions to the solutions. Adding a validation phase, increasing the sparseness of NNMF solutions, and increasing the size of training data where the solutions that were tested. Among these three solutions, size of the training data had the most significant effect on the consistency of the extracted synergies and consequently on the classification results. However, for this particular study it was concluded that 12 to 14 reps are needed to get a fairly repeatable classification result by synergies, which is not much practical due to the long data recording sessions that this requires.

It was also showed that the training set can grow quite large and the performance of a synergy-based model still continues to improve. Also, this was found to be the case with TD features too. It was also showed that the size of the training set has a great influence on the performance of classification of both 1-DoF and 2-DoF tasks by TD features or synergies. It can be concluded that the more reps included in the training phase, the better classification can be achieved until the error curve finally saturates. This can be a challenge in designing the data collection protocols for similar studies as most of the studies on pattern recognition methods use only a few numbers of repetitions of each task to train their models. However, having this many repetitions means a long data collection session and a computationally heavy and long training phase which is not reasonable and practical. So, the studies were continued with only four repetitions of data knowing that our developed model has the potential to improve by increasing the training size.

Continuing our investigations on muscle synergies, some heuristic methods were explored to improve the performance of muscle synergies in task classification. It was observed that pooling features with synergies could improve single and multi-DoF task classification results. Statistical analysis showed that this improvement is significant (p-value <0.05). This demonstrates the existence of some information in the synergies that may not be contained in TD features but it is not enough to outperform TDs if used alone. However, it can improve the accuracy of TD features if used together.

Finally, in this work we showed that in many situations, TD features are better tools for task classification. Although using synergies does not impose a significant computational burden to the model, the improvement that could be achieved by using them is minor in many conditions. However, it was shown that there are some challenging situations like force variations and multi-DoF tasks where classification is challenging for TD features. And these are the cases where some improvement was observed via a synergy-based model.

6.2. Contributions

The research conducted throughout this work has resulted in a significant contribution to the field of pattern recognition based prosthetic control. The novel contribution of this research is the development and test of a platform and control algorithms based on a concept called muscle synergies. The general outcomes of this work can be described as follows:

1. A predictive synergy-based model for intensity level was designed. The effect of modulating contraction intensity for proportional control was examined when using

pattern recognition based control. A novel strategy for deriving multi-channel proportional control is proposed and the advantages of a neuromuscular synergy based paradigm for real-time proportional control of multi-DOF myoelectric devices were investigated.

2. As a novel study, the ability of synergies underlying multi-DoF hand and wrist tasks to distinguish the tasks performed at various force levels were explored. Also, a robust lower dimensional predictive framework was formed by synergies for the EMG patterns of various hand and wrist movements and the predictive power of the established framework was evaluated.

3. Based on the existing need to better understand the properties of muscle synergies with regard to motor coordination, this study investigated the muscle synergies, their properties, and their potentials in myoelectric control. These investigations answered the following questions:

    - How many synergies are needed to complete this lower dimensional predictive framework, and how robust are these synergies?
    - How consistent are the synergies across varying force levels?
    - How much training data are needed to define a robust muscle synergy set of this framework?

- How powerful is this framework in identifying challenging tasks in comparison with currently used methods?

6.3. Future Work

Although the performance of the proposed synergy-based model was evaluated in this study, the effect of synergies on the separability and repeatability of the patterns can be investigated in more details and is suggested as a future work.

The issue of consistency of synergy results and uniqueness of solution for NMF algorithm was studied and some attempt were made to overcome this issue. However, this can be expanded to exploring more methods toward finding a unique optimum solution for synergy extraction problem by adding more constraints to the problem.

As already mentioned, the real power of synergies in comparison with TD features is in redundant systems where many recording channels are available. Accordingly, testing the proposed framework with high-density recording data for force estimation and tasks identification problem is suggested as an extension to the current study.

Exploring how the synergistic patterns of muscle activations are similar or different in both arms and hands during the performance of same task would be another interesting study that can be examined through a bilateral training for synergies. Moreover, as all the subjects attended in this study were able bodied, exploring the muscle synergies of amputees and evaluating the proposed model for amputee subjects is suggested as a future work.

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Curriculum Vitae

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EDUCATION

PhD in Biomedical Engineering- Electrical Engineering, Institute of Biomedical Engineering, University of New Brunswick (UNB), Fredericton, 2016 (Expected).

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MSc in Artificial Intelligence, Department of Computer Engineering, Shahid Beheshti University, Tehran, Iran, 2010.

Thesis: *Predicting the Onset of Epileptic Seizure via multi-channel prediction of EEG signal.*

BSc in Computer Software Engineering, Shahid Beheshti University, Tehran, Iran, 2007

SELECTED PUBLICATIONS

- B. Atoufi, E. Kamavuako, B. Hudgins, K. Englehart, *Classification of Hand and Wrist Tasks in Variable Intensity Using Muscle Synergies*, in press in Proceedings of 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2015.
- B. Atoufi, E. Kamavuako, B. Hudgins, K. Englehart, *Toward Proportional Control of Myoelectric Prostheses with Muscle Synergies*, Journal of Medical and Biological Engineering, vol. 34, pp. 475-481, 2014.
- B. Atoufi, E. Kamavuako, B. Hudgins, K. Englehart, *Force Estimation in Multiple Degrees of Freedom from Intramuscular EMG via Muscle Synergies*, Proceedings of 36th Canadian Medical and Biological Engineering Society Conference, 2013, Ottawa.
- B. Atoufi, H. Shah-hosseini, *Bio-Inspired Algorithms for Fuzzy Rule-Based Systems*, Chapter in TMRF ebook: Advanced Knowledge Based Systems: Models, Applications & Research, Editors: Priti Srinivas Sajja, Rajendra Akerkar, vol. 1, pp.126-160, 2010.
- B. Atoufi, A. Zakerolhosseini, C. Lucas, *Improving EEG signal prediction via SSA and channel selection*, Proceedings of 14th IEEE Conference on Computer Science 2009, Tehran.

- B. Atoufi, A. Zakerolhosseini, C. Lucas, *A Survey of Multi-Channel Prediction of EEG Signal in Different EEG States: Normal, Pre-Seizure, and Seizure,* Proceedings of 5th Conference on Computer Science and Information Technologies Conference, 2009, Yerevan.

PROFESSIONAL WORK EXPERIENCE

DIRECTOR OF BUSINESS DEVELOPMENT *June. 2015 to Present*

Mitacs Fredericton, NB, Canada

- Work closely with members of Mitacs Business Development, Research, and Programs teams to deliver high-quality programming
- Create and maintain a network of partners/clients in industry and academia Introduce companies to various Mitacs events and programs
- Introduce companies to various university researchers
- Providing support to the Business Development Team as needed
- Providing business development support to all Mitacs programs as needed

CO-FOUNDER *Dec. 2013 to Present*

Lorikeet Entertainment Fredericton, NB, Canada

- Brainstorming and critical thinking while collaborating with other co-founders on developing short- and long-term strategies and tactics for growth.
- Presenting the idea, networking to build contacts, and discovering opportunities for raising capital.
- Analyzing the competition and developing the company's go-to-market message.

RESEARCH ASSISTANT *Sep. 2010 to Present*

University of New Brunswick– Institute of Biomedical Engineering Fredericton, NB, Canada

- Supporting and assisting in evaluation, development and execution of multiple NSERC and DARPA funded research projects.
- Peer reviewer for scientific journals.
- Coordinating and leading short-term research projects for graduate summer students.
- Assisting in designing scientific experiments and protocols for research projects.
- Preparing detailed reports and presentations.
- Presented novel research works at several conferences.

SOFTWARE DESIGNER/DEVELOPER *Jul. 2007 to Aug. 2009*

Negasht Software Development Company Tehran, Iran

- Communicated frequently with the marketing team and the clients to effectively transfer user requirements to the development team.
- Involved in all aspects of producing new software from feasibility research to marketing.
- Presenting the products in several demo sessions for potential costumers.

EXTRACURRICULAR ACTIVITIES AND VOLUNTEERING

- Member of judging team for Canada-Wide Science Fair, 2015
- President of the UNB Electrical Engineering Graduate Student Association, 2012-2013
- Organizing committee member of the *MEC Symposium*, Fredericton, NB, Canada, 2011 and 2014
- Technical committee member of the *IranOpen International Robotic Competitions*, Qazvin, Iran, 2006-2010
- Member of robotic team of Shahid Beheshti University, Tehran, Iran, 2003-2010

ACHIEVEMENTS AND HONORS

- Presidential Tuition Award (2010 to 2013), UNB
- National Sciences and Research Council of Canada Scholarship Recipient

- 4th Place award in International RoboCup competitions 2006, Rescue Simulation League, Germany
- Ranked 53st from 12,000 in the National Entrance Exam for MSc Studies, Iran, 2007