Sensing and Adaption for Long-Term Hand Rehabilitation

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Declaration

Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award. 36335 words.

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Abstract

Following the loss of a limb, the success of the rehabilitative process for prosthesis control is dictated by the robustness of the prosthesis control scheme, the capabilities of the prosthesis, and the ease of the rehabilitative process. Unfortunately, limitations within current prosthesis sensing for hand rehabilitation are lacking and subsequently prosthesis rejection is still considerably high. Typical modalities in bio signal sensing focus on the usage of surface electromyography (sEMG) due to its nature of being non-invasive, intuitive, and effective. While the performance in laboratory settings have shown great promise, these methods typically are focused for intra-session or intra-day based efforts but are seldom applied to inter-day applications, leading to a reduction in the quality of life of amputees. To address lack of long term rehabilitation outcomes through bio signal sensing it is important to gain a deeper understanding into the nature of the transience within sEMG data and to expand into whether bio-signal led hand rehabilitation can be improved through fused sensing and adaption modalities. The contributions from this work therefore focus on how understanding and exploitation of intra-day sEMG signals can be exploited for long term use, the use of a-mode ultrasound sensor fusion for long term rehabilitation, and finally enacting closed loop haptic based hand control in a Virtual Environment based rehabilitation system.

Firstly, sEMG sensing strategies are proposed to support long term use with minimal patient input. Through the exploitation of transient changes within sEMG data during intra-day periods, a generalized system of long term hand motion recognition can be achieved. This thesis provides a deeper insight into the transient change of sEMG during frequent intra-day sensing by demonstrating the decay of hand motion recognition during a

period of daily use. These transient changes are then exploited in training strategies that provide increase hand motion recognition accuracy for long term use.

Secondly, this thesis investigates the effect of sensor fusion led modalities towards long term hand motion recognition by means of a-mode ultrasound and sEMG. Unlike sEMG, a-mode ultrasound is capable of providing insight to deep muscle activity within the forearm while also being robust to crosstalk from neighboring muscle activation. The application of traditional sEMG features to a-mode ultrasound is evaluated when concerning sensor shift. Then a novel a-mode ultrasound led hand rehabilitation strategy is proposed through combination with sEMG sensing during large arm movement centred exercises demonstrating superior performance to sEMG alone.

Thirdly, in order to improve the feedback provided during rehabilitation and to enable closed loop hand control a virtual environment enhanced haptic rehabilitation system is proposed. In the proposed system, participants were provided feedback to their grasping effort through either visual force bars or electrotactile feedback while controlling a virtual hand. The performance of this rehabilitation strategy demonstrated a significantly reduced training period and highly repeatable finite hand control in various scenarios.

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Chapter 1

Introduction

1.1 Background and Motivation

In our daily life such actions as buttoning a shirt or drinking from a glass are frequently taken for granted. Such dexterous gesture interaction and object manipulation produced by the human hand can be defined as a closed loop system of many actuators and sensors working in almost perfect unison to perform a desired task. through upper limb impairment or amputation the capability of a hand to perform such seemingly pedestrian tasks can be heavily limited if not outright removed, subsequently causing a massive negative impact to a persons quality of life. Such changes to quality of life may manifest across a persons entire life from their sense of autonomy, ability to partake within social interactions, in work environments, and independent daily living.

Within the UK alone, the rate of hand amputations per year can be expected to be 10,000 of 250,000 per year whereas 55000-60000 amputees seek specialist support and rehabilitation services.

As society develops, as does the drive to further focus on providing a form of upper limb motor prosthesis that can primarily serve the purpose a patients original limb provided and to furthermore do so in a way that is as natural and life like as the original limb. There has been great focus and research towards answering the question as to how to provide a upper limb prosthesis that can behave in such a similar way to a natural hand. When considering the form of how such an ideal prosthesis should manifest, Cordella et al. [3] specified that of accurately and reliably achieving activities of daily living, providing the user with sensory feedback, stable control with less visual attention, the capability of stable grasps and better handling of small or delicate objects. It is from these objectives of achieving an ideal prosthesis that a form of divide manifests within the focus of upper limb prosthesis between the hardware development branch and the Human Machine Interaction (HMI) branch.

Within both branches of development for upper limb prosthesis, continuous development to provide a more capable and usable prosthesis solution has occurred continuously for decades. Although the simple cosmetic effect of prosthesis is highly desirable as a base requirement for many amputees, a clinically viable and usable dexterous prosthesis is vital for not just enabling some degrees of environmental interaction for amputees but furthermore to assist in establishing their sense of autonomy.

The concept of a functional as well as cosmetic upper limb prosthesis is nothing new, yet early devices were simplistic with control coming from simple cable pulls and often provided functionality but in a non fluid or natural manner with limited scope of grasping ability. Moving forward from limited functionality prosthesis to fully dexterous hands with multiple degrees of freedom has been a large popular focus, where modern prosthesis may enable various traits such as multiple degrees of freedom, dynamic movements, proportional control, and various sensors and actuators to provide responses or assisted control during use. Such work into the hardware design exists further than just in the scope of ideas such as prosthesis to include human controlled exoskeletons to assist restoration of motor function. Although the extents of development have seen a great degree of variation in control of upper limb prosthesis motions, the range of gestures and grasps to perform still remain somewhat limited regardless of improved dexterity. Furthermore, although modern prosthesis have a highly impressive range of actuator functionality and sensing controls, the actual control schemes and implementations of commercial prosthesis are largely similar to that of prosthesis developed in the mid 20th century.

The reasoning behind this seeming lack of development in actual control for prosthesis when the hardware implementations of today enable so much more control is potentially due to the human machine interfaces used to translate bio-signals into prosthesis movement have largely focused on the early direct control schemes and mappings to perform a subset of clear actions based largely on simple threshold functions or impulse patterns instead of exploiting the larger range of control that modern prosthesis permit.

It could largely be concluded that the focus on simple direct control methods largely route from the challenge of how to accurately infer motion intention from produced bio signals in a device that requires minimal cognitive and physical burden for the user. The typical commercially available powered upper limb prosthesis uses a noninvasive form of surface electromyography (sEMG) as the main form of interpreting motion intention from the user.

A typical sEMG based sensing modality for upper limb prosthesis follows the pattern of sEMG signal collection from electrodes placed on the user which are then amplified and preprocessed by the sensing device or linked device. The preprocessing stage attempts to remove certain noise that may exist from external sources such as powerline noise and any signals outside of the target frequency range for the device. Certain traits or features of the signal would then be collected from the raw sEMG signal and a decision stream will be produced that would manifest as a response from the prosthesis.

Within academia there has been great focus across the spectrum of sEMG sensing from hardware devices to improve the quality of collected signals, improved filters and preprocessing methods to provide clean signal free from external noise, methodologies to reduce the variable input stream of raw sEMG signal into features that can easily be computed, and to algorithms to better decode the sEMG signal stream with further additions to post processing to either improve a trained model for classification.

As stated before, although there exists an extensive quantity of research into sEMG sensing modalities and processing methods to interpret motion intent the methods produced in academia are seldom moved into clinical environments. The growing divide between sensing and actuating has led to a situation where actuating devices can provide a remarkably advanced degree of motion in comparison to prior years while the sensing and motion interpretation methods used in commercial systems are very reminiscent of early myoelectric upper limb prosthesis.

Potential reasons behind the lack of acceptance of many approaches to sEMG sensing in academia may largely be attached to ensuring viable long term usability of control strategies found within academia. As the mechanisms that produce sEMG signals are highly susceptible to changes in both the biological systems producing the signal, such as experienced from fatigue, and the sensing medium, such as electrode displacement, long term accuracy of predictive methods for motion recognition may not be assured.

Further aspects to present implementations of powered upper limb prosthesis exist from the capability of proportional control yet enabling such control schemes to dynamic scenarios encountered during daily use is challenging. This challenge exists in both current commercial prosthesis control schemes and pattern recognition based approaches as the existence of an open loop in prosthesis control limits the mechanism of ensuring accurate grasping to only visual feedback, which may inform of grasp yet not the exact degree of force in use.

When considering the gap between sensing and actuating devices, it is evident that HMI approaches must be improved with a focus to enabling long term use that is robust to transient signal changes and in enabling proportional control.

Therefore this thesis intends to investigate and develop a series of methodologies and strategies in hand motion recognition to resolve the problems and challenges described in section 1.2

1.2 Problems and Challenges

Regardless of modality used, a prosthesis user would most value a powered upper limb prosthesis to provide intuitive control that performs as expected with a high degree of accurate and fast response to their motion intention whilst also requiring the minimal degree of training and cognitive burden during active use.

Within these goals are the focus that whichever subset of gestures the prosthesis can perform are capable of accurately being performed inline with the users motion intention. Although there is an inherent mechanical delay within the prosthesis the delay between muscle activation by the user and the activation of the prosthesis should be imperceptible. A prosthesis that may only be used following years of training for the user or requires heavy burden to perform simple actions is simply not viable for daily use. For a prosthesis to provide the desired quality of life improvement in a user the prior aspects must be addressed and be consistent over long term use.

Although there exists many control schemes that may be implemented for such a prosthesis, the usage of sEMG sensing has proven to be extremely popular both in academia, clinical, and commercial implementations. As sEMG based sensing typically involves attempting to distinguish motion intent from the same muscle groupings that had previously been used to control the users original limb it is very fitting in both concept and implementation to extract the patterns of signals produced during contractions as the primary control of a prosthesis.

Ideally, the patterns produced form the residual muscle groupings would be able to provide an accurate representation of the users motion intent. Within the focus of pattern recognition based control there has been great progress in accurately sensing motion intent through improved feature extraction approaches and classification methods. It is through these pattern recognition approaches that great promise has been displayed within clinical environments to perform tasks that would typically be involved in activities of daily living.

However, the usage of sEMG based sensing with pattern recognition has appeared to approach a form of bottleneck in providing a robust interface to the transient aspects of sEMG based control during long term use. Aspects of the randomness and susceptibility of sEMG based sensing has been stated and approached by numerous researchers however a complete solution has so far been illusive with some of the mechanisms involved still not being fully understood [4]. Therefore to better provide a sensing solution for prosthesis control during long term use, the following challenges must be addressed:

1.2.1 Lack of Robustness in Pattern Recognition Approaches for Long Term Use

Many researchers, have found that the quality of sEMG based hand motion recognition accuracy degrades as a function of time throughout a day and across multiple days. There are numerous factors that may cause this decay in recognition accuracy that must be accounted for to create a robust interface, specifically factors such as fatigue, electrode shift, and skin impedance. As a consequence, many pattern recognition based approaches must be retrained or calibrated both during daily use. For research prototypes to be used clinically there must be a low burden of re-training and re-calibration for the user and for such processes to be as infrequent as possible. In order to achieve ambitions such as limited or no retraining based control schemes it is vital to exploit the invariable aspects of the sEMG signal.

If it can be assumed that outside of aggregating transient changes within an sEMG signal there exists invariable traits that may persist over multiple days then these traits of the sEMG signal can be focused on to improve the hand motion recognition accuracy.

Methods of extracting quality features of sEMG signal through TDAR approaches have long been examined and developed to be robust for purpose. Moreover mature methods of classification approaches such as Linear Discriminant Analysis (LDA) have been widely used and applied for sEMG hand motion recognition. However, combined approaches still experience difficulties in accurately providing robustness to changes in the sEMG signal during long term use. Were it possible to exploit the invariant traits of the sEMG signal during long term use then it may be possible to further improve the robustness of matured mechanisms of sEMG hand motion recognition.

1.2.2 Apparent Limitations from sEMG Based Sensing

The degree of variable traits in sEMG signal from transient changes in signal and crosstalk from neighboring muscles provides many issues when considering the applicability of such sensing methods for long term use. As the non invasive nature of sEMG based sensing limits any detected activity to any electrical manifestation detected at skin surface level there exists constraints on the extent of accurate information that sEMG based sensing may provide. Moreover changes in signal quality from sweat or fatigue hinders long term reliability during expected daily use. The limitations imposed by variability of the sEMG signal and more importantly that sEMG based sensing is unable to accurately recognize deep muscle activity it could be argued that hand motion recognition through sEMG has reached a bottleneck when looking towards clinical viability. The unimodal approach of sEMG sensing today may be sufficient for limited usage scenarios yet for clinical viability may require a further modality that are proficient in the areas which are limiting to sEMG.

1.2.3 Difficulty in Enabling Proportional Control due to Open Loop Prosthesis Control Schemes

Although current actuators in powered upper limb prosthesis provide a vast array of dynamic control actual exploitation of these capabilities is seldom seen in implementation. While there does exist many hand motion recognition approaches that can provide proportional control the capability of natural interaction within an environment is very challenging as the only form of feedback reliably provided to the user is that of visually seeing the prosthesis grasping an object. It is through this absence of direct feedback beyond infrequently useful visual ques that such grasping can be considered as open loop feedback, or rather absent of feedback to guide user outside of a task either being completed or failed. Numerous methodologies have been proposed to close the loop in proportional prosthesis control however few have seen much clinical acceptance. Existing challenges are that of provision of feedback that can be implemented within a prosthesis environment without being cumbersome or distracting to the user. Furthermore, in the provision of feedback there must exist clear difference between feedback levels and for feedback to provide timely responses that may be able to guide the user in such a way to provide reliable guidance during proportional control of an upper limb prosthesis.

1.3 Overview of Approaches and Contributions

Considering the above challenges, this thesis proposes sensing and adaption approaches to promote long term hand rehabilitation with a particular focus on the human factor of prosthesis control. Through training strategies for long term sEMG based hand rehabilitation, multimodal sensing using a combination of A-mode ultrasound and sEMG sensing, and a closed loop electrotactile feedback enhanced virtual environment for precise prosthesis control.

1.3.1 Long-term EMG Usage Inter-day

Firstly, this thesis contributes to the domain of sEMG based hand motion recognition for long term use through training strategies that attempt to exploit temporal characteristics of the sEMG signal. The setting for this contribution was collection of 16 data collection sessions across a typical day with a period of 30 minutes between sessions for a total length of 5 days. Firstly, typical classification strategies are explored with training data consisting of a single session and the testing data being made of the 15 unseen sessions of the same day. From the results of exploring the change in accuracy across a typical day, through exhaustive comparison of same day samples, it is demonstrated that there exists a period of 2 hours for a given data collection session to be considered still adequate for sEMG hand motion recognition before the trained models motion recognition accuracy is no longer considered reliable. Therefore it is through recognition of this repeatable decay in sEMG accuracy across a day that the concept of sEMG signal data freshness is introduced when considering hand motion recognition. Secondly, as this concept of sEMG signal data freshness can be considered the period of time such that the negative impact of variable traits within sEMG signals can most easily be observed and inversely is such a period where invariant traits of the sEMG signal may become more pronounced. The proposed strategy therefore attempts to exploit the concept of sEMG signal data freshness through constructing a training data set that splits each set of 16 sessions into 3 or 4 windows and chooses a session from within each window in such a way that the variable aspect of each class is maximized while the invariable aspects of the signal remains constant. This spaced data selection strategy is then expanded to inter-day applications utilizing either the data from 1 or 2 days as training against the remaining sessions from a second day and all unseen days as testing. In the second day a window of the first 2 hour period, or the first ”fresh” window is used as a calibration data set.

The proposed data selection strategy is compared against several alternative data selection strategies and is shown to either outperform alternative strategies or perform to a similar quality with dramatically reduced burden of data collection. Therefore the proposed data collection strategy is shown to exploit the invariant traits of the sEMG signal in a manner that contributes to providing robust long-term use.

1.3.2 A Mode Ultrasound Lead Long-term Hand Rehabilitation

Secondly this thesis contributes to attempting to resolve challenges in sEMG based sensing through an ultrasound led multimodal approach to hand motion recognition.

The applicability of sEMG based feature extraction methods on A-mode ultrasound signal is found to be feasible. As A-mode ultrasound based hand motion recognition had previously been highlighted as potentially being vulnerable to probe shift this research also contributes to exploring the nature of A-mode ultrasound probe shift. Multiple feature selection strategies and combinations are explored and the feasibility of different sEMG feature extraction methods are demonstrated in conditions of varying probe shift. Finally, a multimodal fusion based hand motion recognition approach is investigated using synchronised ultrasound and sEMG data capture. The proposed model attempts to exploit the deep muscle activity that can be detected through ultrasound based sensing to provide deeper information regarding hand activity while sEMG signal collection enables robustness to larger changes in muscle activity through distributed electrodes.

The proposed multimodal fusion based pattern recognition approaches are proposed through firstly conducting feature extraction on both the sEMG and A-mode ultrasound signal and subsequent concatenated feature vectors comprised of sEMG TDAR features and the modified sEMG features for use on A-mode ultrasound signal, thereby providing improved recognition accuracy through the fused sensing modalities.

1.3.3 Virtual Environment Based Haptic Control for Hand Rehabilitation

Thirdly, this thesis contributes towards improving the quality of hand rehabilitation for precise control with a virtual environment enhanced rehabilitation system that attempts to close the loop of prosthesis control through electrotactile feedback. The proposed virtual environment primarily interprets the degree of muscle activation performed during a grasping exercise directly to that of a virtual prosthesis with a corresponding deformation model to simulate pressure placed upon an object. To explore feasibility for the environment for hand rehabilitation through grasping exercises three objects are assigned to be grasped with a finite quantity of grasping force to simulate attempting to not only grasp an object but lift it without breaking it. An open loop or otherwise no feedback condition is compared against visual feedback through the provision of force input bars and electrotactile feedback through spaced and mixed coding. The performance metrics of the length of the rehabilitative exercises and success of the rehabilitative exercises are shown to experience improvement through the provision of reliable feedback to a user and contributes to hand motion rehabilitation.

1.4 Outline of Thesis

The remaining chapters of the thesis are as follows.

Chapter 2 reviews the state-of-the-art work on muscular sensing based hand motion recognition across various sensing modalities with a focus on sEMG based sensing. A comprehensive understanding of hand motion recognition algorithms is provided to the readers on classical and prominent methodologies. An extensive insight into the field of hand rehabilitation for haptic sensing and achieving desirable rehabilitative outcomes. finally the chapter concludes by summarising the current progress within the state of the art and the limitations or challenges currently experienced, finishing with future directions that may be taken.

Chapter 3 firstly considers the challenge of sEMG sensing during long term use and the currently challenging function of time on sEMG hand motion recognition accuracy. The seeming robustness of LDA during long term use in comparison to other classification strategies is then used to better evaluate the changing nature of sEMG hand motion recognition accuracy over time. A period of 5 non sequential days each with 16 sessions spaced by 30 minutes is collected throughout and for each day is analyzed through simple 1-1 training testing within each day. the shifting classification from time of collection to time when hand motion recognition accuracy is no longer deemed viable is subsequently referred to as the period of sEMG signal freshness. It can be considered that this period of sEMG signal freshness is the function of time caused by various physiological changes within the sEMG signal. As the challenge of detecting invariant elements of the sEMG signal may be too cumbersome it is assumed that through combination of sEMG signal datasets that are relatively not considered "fresh" to one another would provide a median aspect of the signal closest to representing the invariable traits. To achieve this, each day is segmented into several windows where from each window an individual dataset is taken for use in a combined training dataset. The spaced dataset strategy is then tested against the 4 remaining days both with and without a dataset from the first 2 hour period of the testing day. In comparison, a morning only selection strategy, minimal data strategy, and full prior day strategy are evaluated in comparison as to verify performance results stemming from the proposed concept of exploiting data freshness as opposed to the concept of simply expanding a dataset.

Chapter 4 incorporates an A-mode ultrasound sensing modality into current unimodal sEMG sensing approaches for muscle activity sensing and hand motion recognition. Firstly this chapter investigates the application of sEMG based feature extraction methods on A-mode ultrasound data. Secondly, this chapter then evaluates the performance of A-mode ultrasound under probe shift conditions. Finally, multimodal sensing fusion through combining sEMG and A-mode ultrasound sensing specifically utilizing ultrasound as the leading sensing modality when generating decision streams. This fusion approach is then verified my major arm movements with healthy volunteers.

Chapter 5 targets the importance of closing the loop within prosthesis control through proposing a Virtual hand rehabilitation system that utilizes virtual and haptic feedback. Within this work, typical non feedback prosthesis control, otherwise referred to as open loop feedback, is evaluated against feedback providing, closed loop feedback, approaches. These approaches are specifically a Virtual guidance platform and electrotactile feedback system. The feasibility of the proposed virtual system is verified in terms of rehabilitative efficiency through comparison of typical open loop feedback to the closed loop virtual feedback and electrotactile feedback conditions. The improved performance from closed loop feedback and assisted rehabilitation through the virtual environment is evaluated and discussed.

Chapter 6 finally, summarises the contributions detailed within this thesis to the current body of knowledge and discusses building points from this research and potential future directions to undertake.

Chapter 2

Literature Review

2.1 Introduction

The human hand can be considered to be an extraordinary complex system of collaborative sensors and actuators to enable many various forms of control with instantaneous feedback to the nervous system. The developments afforded to humankind through the structure of the hand can be considered a large factor towards the development of humans in relation to other species of animal. In a single hand there exists 27 bones with numerous areas of connective tissue, muscle, ligaments, cartilage, etc. All of which serving to enable the hand to perform numerous dynamic actions, absorb various degrees of shock, and to interact with the surrounding environment. An innate sense of goal attainment enables humans to be able to utilize this complex system to articulate and interact with vast variety of objects with ease. Through amputation, injury, or sickness, the capability of a human to utilize a hand to the manner that they are used to may be compromised or outright lost. For amputees, there is the promise of powered upper limb prosthesis, however, these devices are typically heavily simplified in their control scheme as to enable the patient to perform simple tasks with minimal burden, most frequently with simple on / off control of grasping. Furthermore, although many modern commercial powered upper limb prosthesis have a vast array of potential for dexterity this may be seldom utilized in daily use. Although the powered upper limb prosthesis may also provide faster and more powerful grasping than a typical human hand the lack of sensing and natural adaption to the surrounding environment during dynamic contraction causes these beneficial aspects to provide little real world benefit.

When considering the prosthesis itself, there is the further aspect in how to interpret the human intention and perform a matching action correspondent to the users desire. There exists challenges into how such human intention may be collected and subsequently what methodology can be best used to interpret it into a physical action by the prosthesis.

Presently, the prime modality to control commercial prosthesis is sEMG based approaches with direct control approaches. It is easy to understand that the direct relationship between the sEMG based signal to the imparted effort on a muscle to perform an action. However present sEMG based approaches lack the same sense of intuitive control that an original limb provided. One solution would be to focus on pattern recognition based approaches for prosthesis control with sEMG. Alternatively, there may exist a sensing modality or combination of sensing modalities which provide a better sense of control during daily use. This following section will attempt to explore present sensing modalities alongside potential combinations of sensing modalities to enable a better sense of prosthesis control.

2.2 Sensing Modalities for Hand Rehabilitation

The control of any movement can be described as the result of the brain weighing the reward of a movement to the cost of effort imparted [5, 6, 7]. In healthy individuals this leads to optimising movements based on the bodies own closed loop feedback system from the actions performed nerve and muscle reactions combined with the sensory feedback provided by sight, touch, force, etc. However, in situations where the hand or arm muscle are otherwise impaired, whether through reduced muscle activity, feedback, or amputation, such optimisations of muscle activity are harder to achieve. Subsequently, it is needed to assist in this decision making process by producing sensing modalities that can provide an accurate representation of the muscle activity and subsequently the patients motion intention.

In this next section, several of these sensing modalities will be explored and evaluated with regards to their mechanism of sensing, the processing of the data these modalities acquire, and subsequently their implementation within the realm of hand rehabilitation.

2.2.1 Surface Electromyography (sEMG)

Within the realm of hand rehabilitation, sEMG has long been a popular sensing modality to represent muscle activity. The applications of this sensing modality range from simple muscle analysis, to active control in most commercial upper limb prosthesis and exoskeletons for motor limb restoration.

At its core, myoelectric sensing is based around detecting the electrical manifestation of active motor units (MUs) that occur during muscle contraction. These MU's each consist of the cell body, neuron, and muscle fibers, which act as one unit. Within this system, the neural control can excite the muscle fibres. Within these units, there exists an ionic difference between the inner and out spaces of the muscle, described as a resting potential. Through a process dictated by an internal ion pump, such that excitation along a motor nerve sends a brief influx of Na+ ions. Following this influx of Na+ ions, a state of depolarisation occurs, which is immediately restored through a backward exchange of ions, referred to as repolarization [8]. Provided a certain threshold of Na+ influx is achieved then the depolarization of the membrane causes an Action Potential (AP). The action potential in that moment creates a mono polar electrical burst before being immediately restored through repolarization. After Hyperpolarization where the cell membranes potential falls below that of the resting potential. The formed action potential then spreads through the muscle fibre in both directions to its origin. As a result of this excitation, linked chemical processes provide shortening to the contracting elements of the muscle, which can be observed as the muscle activation [8].

Therefore, this relation between action potential and muscle contraction can be exploited in an EMG system. Typically, many sEMG devices attempt to use paired electrode schemes where the depolarization wave along the muscle fibre can be inferred as the potential difference between electrodes can create a bipolar signal within a differential amplification process. As each motor unit consists of many muscle fibres, the placed electrodes are capable of seeing many of the innervated fibres within this motor unit. The collective impulse of the excited muscle fibres within a motor unit can be considered as the Motor unit action potential (MUAP). When looking towards sEMG with regards to detecting these MUAPs is the recruitment of MUAPs across a muscle and their subsequent firing rate [9, 10, 11] where a raw sEMG signal can be considered as the observed recruitment and firing rate within a targeted muscle.

2.2.1.1 Hardware & Systems

When processing sEMG signal, there are several considerations into the hardware to be utilized, specifically towards the factors of electrode type, signal amplification, A/D resolution, A/D Sampling Rate, Signal filtering, and form factor elements such as hardware power supply and size. When considering the sampling rate of the sEMG signal from Analog to digital, the Nyqist sampling theorem should be considered such that the sampling rate is at least twice the sampling rate of the input signal. In literature the maximum frequency of sEMG signal is observed to be 500Hz [12] therefore many authors set a sampling frequency of 1000KHz [13, 14, 15] although some authors have observed under and over sampling to find that oversampling largely provides little benefit while under-sampling may lose some signal or require anti aliasing [16, 17].

sEMG sensing may utilize several forms of electrode design, these are typically divided into wet and dry electrodes. Wet electrodes operate by having a conductive gel layer on the electrode itself and a surrounding adhesive region. Wet electrodes are frequently used within clinical environments as each electrode can be located on a target area under its own attachment and can be replaced or disposed with ease after use. In hospital environments this would be preferable as disposing electrodes minimizes time spent decontaminating equipment alongside reducing time spent ensuring a proper fitting. Dry electrodes, however, are typically the direct metal portion of the electrode, usually without any form of adhesive material, or rather embedded into an armband. A large benefit of dry electrodes is that they can be reused or moved as frequently as desired, unlike wet electrodes that are typically disposed after use. As dry electrodes do not utilize any conductive gel, other issues in sensing do appear. Common issues in dry electrodes may manifest from humans sweating and therefore impacting the skin impedance. As dry electrodes are frequently incorporated into armbands of elasticated bands, there is an increased risk of electrode shift during regular use although it is also recognized that recovery from electrode shift is possible with dry electrodes whereas wet electrodes would need to be reapplied.

Following the extraction phase, the raw sEMG is typically pre-processed as to reduce undesirable signals within the sEMG. Typically the more common set of undesirable traits is that of power line noise, which regularly manifests at 50hz or 60 hz, this often is through passing the raw signal through a Butterworth filter and notch filter. The aforementioned process also works towards preserving preserving all sEMG signal between desirable frequencies. Following this, the preprocessing may begin as to improve the quality of the inputted signal.

2.2.1.2 Features

Much akin to other pattern recognition problems, the quality of sEMG based hand motion recognition can often be only considered as good as the data and features provided. Traditionally these features are hand crafted and can be divided into several categories of Time Domain(TD), Frequency Domain(FD), and Time-Frequency Domain(FD). The features used in any given situation may vary based on certain traits of the application, such as whether the features used are required at a perceivable real time. Traditional sEMG features are listed as follows.

- Mean Absolute Value (MAV): MAV is defined as the average of the total absolute value for any sEMG signal during a defined period of time. It could be considered that mav is one of the most popular features in sEMG signal analysis having been used by many researchers throughout the years [18, 19]

$$\text{MAV} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{2.1}$$

- Root Mean Square (RMS) Root Mean Square is the square root of the mean values for a set of squared raw sEMG values over a period of time. This method is frequently used as a relatively stable measure in domain both hand motion classification and analysis of stroke patients [20, 21, 22].

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i-1}^{N}x_i^2} \tag{2.2}$$

- Waveform Length (WL) Waveform Length is the measure of complexity of the sEMG signal over a specific time segment [23].

$$\text{WL} = \sum_{i=1}^{n-1} |x_{i+1} - x_i| \tag{2.3}$$

- Zero Crossing (ZC) Zero Crossing is summation over a period of time that the input signal crosses the zero amplitude level. In order to avoid complications from small fluctuations in the signal it is not uncommon for this method to have a threshold implemented [24].

$$\begin{aligned} &\text{ZC} = \sum_{i=1}^{N-1} \left[\operatorname{sgn}(x_i \times x_i + 1) \cap |x_{i-xi+1}| \geq \text{threshold}\right]; \\ &\operatorname{sgn}(x) = \begin{cases} 1, & \text{if } \geq \text{ threshold} \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{2.4}$$

2.2.2 Ultrasound (US)

Ultrasound based imaging is a non-invasive sensing modality that has long been used as a diagnostic device to observe musculoskeletal disorders such as arthritis [25, 26]. The technique itself is non-invasive, utilizing an array of piezoelectric transducers to project a focused wave of ultrasound into the body between a range of 2-20MHz. As the beam of ultrasound interacts with the body tissues echoes are produced that can then be converted into a signal. Because different tissue components produce varying qualities of echo, it is possible to infer aspects of muscle state during contraction [27, 28]. It is through this capability to analyze muscle activity that the concept of utilizing ultrasound in hand motion recognition. Hodges demonstrated that it is possible to observe low level of muscle contractions where the physical muscle architecture changes the most, however, it was also described that moderate and higher levels of muscle contraction could not be differentiated due to reduced change in muscle architecture [29]. A benefit of ultrasound based sensing being sensitive to changes in muscle thickness is that ultrasound can provide insight into fatigue within an individual muscle while sEMG signals experience crosstalk from nearby muscle recruitment [30]. Moving further to detecting hand motions, ultrasound sensing had been demonstrated by to be capable of accurately detecting wrist extensions in complement to sEMG although it was highlighted that mounting both an sEMG electrode and ultrasound diode on the same targeted muscle is a challenge due to the space required for both sensors [31]. A further challenge to ultrasound based sensing for real time control is that processing of the b-mode ultrasound images can be computationally expensive, although some algorithms have been developed to resolve these issues and to enable real time control with a 1 DOF hand [32].

In following years, interest in ultrasound expanded further towards individual finger flexion, where ultrasound has been demonstrated as a very effective method in accurate finger position detection [33, 34, 35]. Castellini et al. observed that there exists a simple linear relation between ultrasound image features and exact finger position subsequently meaning that fine finger control of a prosthesis could be achieved with a wrist mounted b-mode ultrasound probe [36, 37]. This work was further expanded in 2013 to detect the amount of force impart by a finger while also limiting their data collection to minimum and maximum forces instead of a graded set of force patterns [38]. The capability of ultrasound to provide knowledge of focused muscle activation therefore is highly promising for enabling precision control over a prosthesis, as opposed to on/off motion activation. The performance of ultrasound and sEMG was further evaluated by Huang et al. [39], who found that ultrasound based sensing could provide a higher degree of accuracy in multiple finger based hand motions, whereas prior research focused on individual finger movements. It was inferred that the relatively superior performance of ultrasound is from sEMG based approaches experiencing a higher degree of crosstalk from neighboring muscle activity, while an ultrasound based method is robust against crosstalk. While ultrasound sensing has shown itself to be highly effective at recognition of individual finger movement in comparison to sEMG, there does exist the issue of making the device wearable. Although B-Mode probes are excellent for providing high resolution information [40, 41], they are generally cumbersome and require both larger hardware to process their signal and also a dedicated power source. To resolve the issue of creating a wearable device, researchers have investigated single transducer based A-mode designs [35, 42]. A further investigation into the application of unimodal A-mode ultrasound is explored in chapter 4.

There are, however, some trade offs from the A-mode exclusive designs, specifically relating to the nature of the signals being received and their transmission through the body. As sEMG signals can travel across neighboring MU's there will be an experience of crosstalk. However, ultrasound can ignore crosstalk due to the limited beam of Ultrasound signals and their echoes. This state of the limited beam of ultrasound somewhat eliminating crosstalk becomes a double edged sword as any probe shift may remove important signal information from muscle activity while sEMG approaches will still be capable of detecting the reduced muscle activity under shift. While the majority of crosstalk is eliminated, it is hard to be certain if crosstalk from the action of adversarial muscles may provide axis shift to the ultrasound probe, which may not be anticipated in a trained model. Considering that A-mode uses a single beam, the concept of probe shift may pose issues in daily use. Presently there has been little investigation into this aspect of A-mode ultrasound as to cover the robustness of A-mode ultrasound and subsequently the optimal spatial placement of ultrasound probes as to achieve high quality signal and robustness to shift.

Another aspect to consider is that ultrasound requires a couplant to function effectively. While modalities such as sEMG may be able to use pre-gelled or ”wet” sensors, the construction of ultrasound probes makes it uneconomical to create disposable pre-gelled transducers. Therefore in ultrasound based approaches, a gel based couplant needs to be applied prior to sensing as to ensure clean signal.

2.2.3 Force Sensor Resistor FSR

Force Sensor resisters attempt to provide an interesting modality for bio signal sensing through observing the force imparted during muscle contractions. The exact locations of force sensing can range from forearm mounted sensors that take expanding force of a users muscles against a fixed sensor rig whereas other applications may utilize the force imparted on the back of a hand through a glove.

2.2.4 Near Infrared Spectroscopy NIRS

Near Infrared Spectroscopy attempts to utilize light based laser diodes to project a beam of light into the targeted tissue area. Under the assumption of tissue and bones consuming the light beam in varying quantities it would therefore be possible to extract a degree of inner muscle activity from the reflected beam of light. As numerous detectors work in partner with the pulsing beams it would therefore be capable of capturing dynamic contractions alongside information surrounding the metabolic state of the target muscle.

2.2.5 Fused Sensing Modalities

Frequently in literature, research for prosthesis control focuses on unimodal sensing methods. In prosthesis control this modality is typically sEMG, while other methods are seldom seen outside of laboratory or research environments although they may be used in other environments for diagnostic reasons such as with ultrasound. While a single core reason behind methods other than sEMG not achieving clinical acceptance is unknown [1], it could considered that the reason may be that few other methods have outperformed sEMG in various conditions. While Mechanomyography has the benefit of not requiring skin preparation nor is it affected by skin moisture [43] the sensors used are highly sensitive and have to be calibrated prior to usage [44], which makes the sensors less fit for convenient long term use. The relative performance of Ultrasound to sEMG found by Huang et al. [39] is promising, however, the lack of acceptance for ultrasound based hand motion recognition may lie behind lack of sufficient testing for daily use factors such as shift, donning and doffing, alongside continuous intra and interday use.

While these methods are yet to achieve acceptance over sEMG, there exists clear evidence that several of the described unimodal sensing methods can outperform sEMG in certain scenarios. Further to the lack of alternative unimodal sensing gaining clinical acceptance, pattern recognition based sEMG hand motion recognition has also yet to gain clinical acceptance over direct control sEMG control schemes which has led to some researchers considering that there exists a bottleneck in sEMG sensing due to the limitations in sEMG compositions [45]. Considering the state of the art in alternative unimodal sensing applications it can be recognized that alternative approaches to sEMG sensing provide superior performance in areas where sEMG sensing currently is limited. Therefore, to overcome the existing sEMG bottle neck and to translate better in terms of clinical use would require mixed modality sensing.

The first aspect to consider when approaching multi modal sensor fusion is that of the implementation of the multi modal control scheme, this can be divided as follows:

- **Single Fusion Algorithms:** Features for each modality are extracted and fed together as a combined feature into a single algorithm.
- **Unimodal Switching:** A primary modality detects transitions between operating modes and switches the classifier accordingly. In this scheme a secondary modality is the only input to the classifier.
- **Multimodal Switching:** As with unimodal switching, a single primary modality is used to detect transitions between the operating modes and switches to the best fitting classifier. The difference in this approach is that both the primary and secondary modalities are fed into the classifier.
- **Mixing:** Multiple classifiers run in parallel and each classifier may be fed by one or more modalities. The output of all classifiers are added together (mixed) with the independent weighting of each classifier decided by another modality.

The above definitions of approaches to multimodal sensing can be seen represented in fig. 2.1. A further continuation to multimodal strategies is the selection of unimodal sensing methods to apply. Typically, sensing modalities for hand motion recognition can be divided into contact based such as sEMG and Data Gloves or Non-contact based sensing modalities like depth cameras.

Presently there exists several popular methods for implementing single fusion algorithms. Concatenation of features is a popular and simple method in multimodal sensor fusion with sEMG and alternative modalities such as finger joint angles [46], force and trajectory [47] , load cells [48], MMG [49], and with EEG [50, 51]. In a comparison of simple fusion, a Naive Bayesian fusion approach by Leeb et al. [52] found that Bayseian sensor fusion can be robust to fatigue in EEG and sEMG interfaces. Linear decoders such as linear Wiener filters were found to be viable in mapping EEG data to limb kinematics [53]. However, non-linear relationships between neutral activities and limb movements suggest complications in realtime applications of linear decoders [54]. An alternative to linear decoders for joint angle recognition with EEG is that of Unscented Kalman Filters [55, 56, 57]. Kalman filters have also demonstrated promise in recreating handwriting from a fusion of pen state and sEMG data [58]. However Kalman filters typically see usage towards fusion for trajectory planning, as opposed to hand gesture recognition.

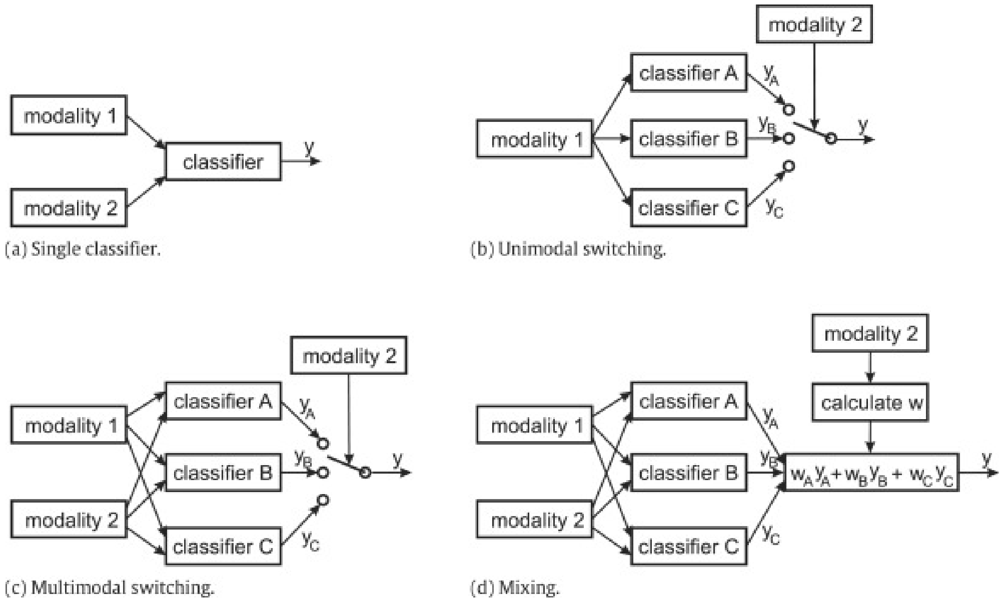

Figure 2.1: Four approaches towards fusing two modalities in a wearable robotic control scheme, indicated by a single classifier approach (a), unimodal switching (b) multimodal Switching (c), mixing (d) [1]

2.2.5.1 Accelerometers and sEMG

Fougner et al. [59] described the impact of adding an accelerometer to motion hand motion classification such that the addition of a single accelerometer could provide a significant increase of classification accuracy of large arm movements than the addition of two sEMG electrodes. However, the benefit of accelerometers in the motions used varies heavily on location as the forearm accelerometer provided a large benefit while an upper arm accelerometer provided little benefit. Potentially the largest impact of accelerometers towards multimodal classification with sEMG is in removing the issues caused by large movements. Typically, sEMG classification in lab environments seeks to focus on hand based gestures that introduce fewer variables from large movement artifacts a consequence is that less scrutiny is paid to maintaining classification when larger movements are performed. While Foughner et al. demonstrated that larger electrode setups with prior training to expected arm movement locations the results were still below that of multimodal sensing. [60] et al. revealed that larger motions typically may get misclassified as the hand at rest position yet with an accelerometer these misclassifications were resolved to their correct motion class.

The performance of multimodal systems using sEMG and accelerometers has been shown to further improve through the implementation of unimodal switching from the accelerometer to provide further context towards the sEMG motion as opposed to using single fusion algorithms [61].

2.2.5.2 Dataglove Based Fusion

Datagloves offer a powerful advantage in hand motion sensing, often featuring multimodal sensing in the form of pressure and bend sensing. The capability of datagloves enables precision measurement of hand motions and hand freedom therefore making datagloves useful in the concept of hand motion evaluation [62, 47]. The scope of datagloves and the information they can provide through typically joint bend based information make them very suitable for hand motion recognition and human robot collaboration [63, 64].

As datagloves are typically limited to bend sensing and force sensing it is difficult to determine the differences between motions that are similar in hand but rely upon information from the arm to infer motion intent. Xue et al. [65] combined a dataglove with sEMG sensor to evaluate both the unimodal and multimodal performance when performing numerous complex tasks. While sEMG performed worst as a unimodal system it was observed that the multimodal approach outperformed each unimodal approach. Xue et al. further made the observation that, while performance may be superior in the multimodal approach, the varied keyframes in certain multi modal approaches may delay recognition and activation time potentially causing user frustration in daily use.

2.2.5.3 Force and sEMG

As stroke patients may display changing sEMG patterns due to fatigue and abnormal coactictivation [66] there exists a strong case for utilizing multimodal approaches. A specific fusion of multimodal sensing for stroke patients was demonstrated by Park et al. [67] through the addition of bend and pressure sensors during grasping exercises. A noticeable trait of the work by Park et al. was to utilize different control systems without formal identification where control could be sEMG driven, bend sensor driven, pressure driven, or a combination of each set of sensors.

Jaquier et al. [68] concluded that the combination of sEMG and Tactile-Myography (TMG) could prove beneficial in real time performances in relation to unimodal sEMG.

2.2.5.4 NIRS with sEMG

Hermrmann et al. recognized that the small size of NIRS sensors could enable the development of a combined NIRS and sEMG sensor [69].

Paleari et al. [70] explored the fusion of sEMG and NIRS in hand motion recognition citing that NIRS could be used individually or in synergy. One caveat of the combination of sEMG and NIRS that Paleari highlighted, however, is that the bandwidth of sEMG is 500Hz whereas NIRS sits at 5Hz alongside experiencing a slower response time yet it was highlighted that these factors could be improved through future research. This stance was mirrored by Guo et al [71]. that NIRS and sEMG could be successfully combined within a single sensor yet experienced limitations related to temporal resolution yet it was highlighted that the resolution delay still rests within 300ms which is typically the period of time that is considered the cutoff point for noticeable delay therefore making NIRS still fit in real time prosthesis control. A further aspect of NIRS with sEMG that Guo highlighted was that the improved spatial resolution of NIRS could prove complementary to the high temporal resolution of sEMG in further research such as in detailing muscle fatigue information. A challenge, however, is that nirs signals are associated with limb movements and therefore depend on the residual limb condition [72].

2.2.5.5 Ultrasound with sEMG

As highlighted prior in section. 2.2.2 , ultrasound has demonstrated the capability to reveal a wealth of information about deep muscle activity within the human body. However the combination of Ultrasound and sEMG in a multimodal environment is somewhat scarce as opposed to other modalities.

Botter et al. aimed to achieve both the deep muscle activity of ultrasound with the wide reaching activity detection of ultrasound as a diagnostic tool through the development of electrodes that would be transparent to Ultrasound [73]. A general challenge of combining ultrasound and sEMG also lies within enabling clear ultrasound signal and sEMG signal within the same region. Botter et al. [74] proposed a solution to this issue may be possible through a single patch that uses hydrogel as both the medium to ensure conductivity for the electrodes and a medium to transmit ultrasound signals, with a spacer in between as to prevent short circuiting from the hydrogel. In this situation the probe used was still a B-mode probe therefore potentially limiting the applications of this probe type to strictly laboratory environments until such a time that B-mode probes and sensing hardware can be made portable.

Xia et al. [75] proposed an alternative solution to establishing a combined sEMG and ultrasound probe through opting to utilize A-mode ultrasound and dry electrodes. An immediate change between the design proposed by Botter and that of Xia is that Botters device can be directly affixed to the human body with a reasonable degree of grip and subsequently the patch design may serve to prevent electrode or ultrasound diode shift. Xia's diode typically involves a form of elasticated wrist band which requires application of ultrasound transmission gel to ensure a stable connection and due to this design there may exist a risk of electrode or diode shift during use. In terms of long term use, there is potential that Botter's electrode may provide longer intra-session use yet as with any wet electrode will need to be replaced following use whereas Xia's design is reusable therefore making it more viable for interday use and robust to erroneous doffing. Although Xia's design may lack the wide area spatial information that Botter's achieves, the increased portability of the design appears promising for potential future implementation in a prosthesis.

When considering a multimodal sensing approach, important factors would be on the ease of implementation of a modality, the robustness of each modality, and importantly what limitations are overcome by the additional modality. The common shortfall of sEMG based sensing is that of collected signal being shallow muscle activity which may be vulnerable to crosstalk. Surface level sensors such as force may provide detailed information regarding touch yet will present pitfalls outside of grasping gestures and may present challenges with proportional control. Both NIRS and Ultrasound show distinct promise in providing deeper muscle activity on top of the surface level activity gathered by sEMG. However, a challenge with NIRS sensing is the delay in sensing, which may impact the intuitive nature of a prosthesis. Ultrasound demonstrates viability for usage in a prosthesis in terms of complementing the data gathered by sEMG while providing a low latency and a high unimodal motion recognition accuracy. A further examination of the viability of ultrasound based sensing with sEMG is provided in chapter 4.

Outside of sensing modalities, a further challenge to consider in providing an intuitive control scheme is that of the specific classifier used. The next section will provide an overview of the current state of the art in upper limb sEMG based sensing.

2.3 Algorithms in Upper Limb sEMG Based Sensing and Adaption

When considering pattern recognition based approaches towards hand motion recognition there exists two major branches of sensing algorithms based on those that use feature based information and those that use more modern deep learning based approaches. A particular focus here shall be placed on sEMG based sensing.

2.3.1 Hand Crafted Feature Based

For feature based sensing there is a long history of different classification strategies and implementations which have been widely studied towards bio signal based sensing in offline and online environments. Typically many researchers will opt for Linear Discriminant Analysis (LDA) or Support Vector Machines (SVM) based classifiers likely due to their reliability, ease of implementation, and likely due to their prominence in research [76, 77, 78, 79]. Although LDA and SVM are popular methods they may not promise the best quality results. Within the state of the art other frequently used classifiers include Quadratic discriminant Analysis (QDA)[80], K-Nearest Neighbors (KNN)[81], Multi-layer Perceptron Networks (MLP)[82, 83], Hidden Markov Models (HMM)[84], Artificial Neural Networks (ANN)[85], Fuzzy Logic (FL), Gaussian Mixture Models (GMM) [86].

All of the above algorithms have demonstrated excellent performance in laboratory conditions for sEMG based hand motion recognition for various forms of hand motions and object manipulation, often seeing accuracy scores of over 90%. The real challenge with these sensing approaches exist when moving towards clinical environments and longer term use. As described previously, there exists many variable traits of sEMG signals from changing physiological aspects of the user and environmental factors during sensing. Towards clinical applications, researchers have observed the performance of varying algorithms when considering fatigue [87, 88]. Whereas other researchers have explored the capabilities of various algorithms towards inter day use and others for the feasibility of inter subject use.

A common challenge seen in these tests is that of how to best approach the seeming randomness of bio signals. One solution that has been experimented with is that of constructing datasets which have larger training datasets that may contain these variable changes. An alternative approach is that of utilizing adaptive algorithms to update a trained model to whichever changes are seen. A promising route is that of semi adaptive algorithms which require user input to update a model with new exemplars however a limitation of these models is that intervention is required which may cause frustration during use. Unsupervised adaptive methods have also been proposed to change during active use. A further investigation into the challenges of long term sEMG based sensing algorithms is performed in chapter 3.

2.3.2 Deep learning

While hand crafted feature based approaches have long been the dominant method for sEMG based pattern recognition, recent years have seen a growing interest in deep learning. Typically, deep learning approaches had been connected to computer vision, particularly that of object detection. The process of deep learning based approaches to progressively extract low level input and convert it into high level features is particularly valued in computer vision. It is this feature learning trait of deep learning trait of deep learning that holds particular promise over traditional hand crafted features for sEMG based hand motion recognition. Although deep learning methods are capable of extracting high level features from a dataset, the nature of deep learning networks demands a large dataset otherwise they risk overfitting and lack of generalisation. The risk of overfitting is a particular challenge when converting deep learning approaches from computer vision to sEMG based pattern recognition due to the relatively small datasets traditionally used in sEMG sensing. While it is possible to construct a large enough sEMG dataset for deep learning, large datasets such as the Ninapro dataset [89] provide both large volumes of sEMG data and a wide array of gestures for benchmarking methods.

Deep learning approaches are often divided into three categories of unsupervised pre-trained networks (UPNs) such as Deep Belief Networks, convolutional neural networks (CNN), and recurrent neural networks (RNN). Shim et al. [90] utilized a Deep Belief Network (DBF) on locally collected two channel data with 7 grasps, demonstrating superior performance of a DBF against LDA and SVM. Of the forms of deep learning network, convolutional neural networks appear to attract the most interest in sEMG based sensing and other fields. It was in 2016 when CNN's begun to be applied to sEMG based sensing, where a CNN was demonstrated to achieve higher inter-subject motion recognition than SVM [91]. Geng et al. [92] further applied CNN's on single sEMG images from a frame of data to enable instant recognition, which was further improved across a 40 frame window with majority vote. Inter-day evaluations of CNN's further show promise as demonstrated by Du et al. [93] on two day interday data compared against feature based classifiers. The long term viability for interday classification with CNN's was demonstrated by Rehman et al. [94] across a period of 15 days. Rehman et all posed that CNN approaches may overcome the feature calibration challenges of hand crafted feature based approaches.

While Deep learning based approaches demonstrate promise over traditional methods, the resource intensive nature of deep learning may pose challenges in clinical environments, such as during user training.

With any combination of sensing modalities and algorithms to infer user intent, a particularly vital aspect in sensing and adaption is that of user training and rehabilitation. It is important to verify that a training approach can ensure repeatability and applicability to a users daily life. Furthermore, an ideal prosthesis would provide intuitive control alongside feedback that can best guide its user. The next section will firstly focus on present metrics to gauge rehabilitative performance and to train users. Secondly, the next section will include an overview and evaluation of prosthesis haptic feedback methods.

2.4 Hand Rehabilitation and Application

Throughout each sensing modality there remains the important factor of user training and the approach to rehabilitation. An important factor within hand rehabilitation and subsequently in prosthesis control is for the patient to be able to produce both repeatable and consistent signals during operation. This process can vary in complexity and approach dependent upon the situation of the patient.

2.4.1 Rehabilitative Performance Metrics

As the range of hand functionality that is to be assessed during hand rehabilitation can range from simply demonstrating motion to completing real world complex tasks, the metrics that we use to evaluate functionality will vary dramatically. In early rehabilitation, such as assessing muscle functionality, it may be necessary to only monitor the intensity of any sEMG signals to focus on being able to produce consistently detectable signals before moving onto more complex tasks.

When hand motion or simple control of a prosthesis becomes possible for a patient, the rehabilitative focus can be assessed through to provide a benchmark on their recovery. It is often seen that methodologies to evaluate performance come from needing a method to benchmark different sensing modalities and algorithms.

Evaluation of sEMG data, particularly that of offline recognition accuracy is both one of the more trivial and covered metrics within academic research. Typically the most popular public datasets is that of NinaPro [95]. The Nianapro dataset consists of ten datasets from various sensing modalities and numerous subjects that are both able bodied and amputees. The range of this dataset renders it to be very useful for researchers focused on verifying algorithm performance on multiple subjects with larger datasets. Unfortunately, the scope of interday data is limited to a dataset consisting of only upto two datasets per participant across 5 days which may not be fit for evaluating the conditions highlighted by Kaufman over long term use [96]. For multimodal data, the Ninapro dataset extends to kinematic, inertial, eye tracking, visual, clinical, and neurocognitive data. While Ninapro proposes some of the modalities highlighted in section 2.2.5, modalities such as ultrasound, NIRs, and force are not used. Alternative datasets to Ninapro have also been proposed, typically using subsets of the Ninapro gesture set and high density sEMG acquisition modules. The CapgMyo dataset

Table 2.1: Inter Session recognition accuracies (%) of different evaluation protocols on CSL-HDEMG (27 gestures) and CapgMyo (8 gestures for DB-b).

	CSL-HDEMG	CapgMyo DB-b
Inter Session - no adaption	62.7	47.9
Inter Session - with adaption	82.3	63.3

[97] utilized a 128 dimensional sEMG signals within an 8x16 electrode array. The CapgMyo dataset consists of three sub-datasets, DB-a, DB-b, DB-c. DB-a consisted of 8 gestures from 10 of the 23 subjects. DB-b and DB-c both consisted of only 10 subjects although DB-b used the same gestures as DB-a, DB-c consisted of 12 gestures relating to finger flexion. A larger focus of the CapgMyo dataset is that of inter and intra subject detection. Although DB-b provided some capability for longer term validation through consisting of two recording sessions that were over a week apart. A third popular dataset is the CSL-GDEMG dataset proposed by Amma et al. [98] consisting of Inertial Measurement Units and 192 dense electrodes on the forearm muscles. The total dataset consists of 5 subjects across 5 days, performing 27 gestures. During evaluations for inter-session recognition accuracy performed by [97] and shown in table 2.1, it can be assessed that expected interday recognition accuracy would fall between 47.9-62.7% without adaption and 63.3-82.7% with adaption performed by deep domain adaptation.

In the case of rehabilitation there maintains the aspect of laboratory success to clinical success. A control system or algorithm may demonstrate effective results with in a laboratory but may not be robust enough to provide usability [99]. A factor that has led to this dichotomy between laboratory and clinical environments could be considered due to the different evaluation criteria, where laboratory and offline evaluation typically focuses on classification accuracy. Therefore researchers who focus on online recognition systems have been gradually proposing, adopting, and adapting different tasks for patients to perform. Certain tasks may focus on manipulating the hand itself while other tasks integrate object manipulation tests.

The motion Test was originally devised by Kuiken et al. [100] as a method of observing the performance of patients who had received TMR. The system enabled the control of a multifunctional prosthesis within a virtual environment. From the participants perspective, an on screen window would display the reference image of the intended motion alongside the virtual character that would provide feedback to the participant. This method of evaluation incorporated the traditional motion recognition accuracy yet also considered matters such as motion selection time, motion completion time, and motion completion rate. Through these additions it became possible to not only evaluate the performance of an algorithm but also of a patient's recovery during rehabilitation.

Although the Motion Test is very much capable of demonstrating the relative recognition accuracy of an algorithm or the speed of a participant to perform a task, there still maintains a degree of rigidity to the test itself. Within the Motion Test, it is assumed that all actions performed would be identical provided that they achieved a particular class. The issue is then in the scope of proportional control of a prosthesis. Simon et al. [2] addressed this aspect through their proposed Target Achievement Control (TAC) test. As with the motion Test, the TAC test utilizes control of a multi-function prosthesis within a virtual environment. The defining difference between the TAC test and the Motion Test is that the TAC test targets the capability to accurately position a prosthesis within a virtual environment. In order to achieve this goal, the participant is instructed to perform a motion such as wrist flexion until the on virtual users prosthesis matches the virtual target position. Once the participant had achieved the desired positioning then they were instructed to maintain that position for two seconds, any loss of position would restart the process until the test period had concluded. The TAC test demonstrates several benefits to the motion Test through enabling the participant to control the relative speed of the virtual prosthesis under their control through changing the intensity of their muscle contraction, whereas the Motion Test was binary in assessing if a motion was being performed or not.

Recognizing Motion Test is targeted to verify the performance of gestures and the TAC test can be used to asses proportional control, both approaches are limited to demonstration of activity as opposed to task solving. As detailed in fig. 2.2, the tac test is capable of simulating prosthesis movement across multiple degrees of freedom. Fittz law traditionally was a predictive model that attempts to model the time to move a cursor towards target area rapidly. A 1-dimensional form of Fittz Law was examined by Park et al. [101] through mapping two squares directly to the sEMG signal intensity from a participants triceps and biceps. Through this work, it suggested that both sEMG

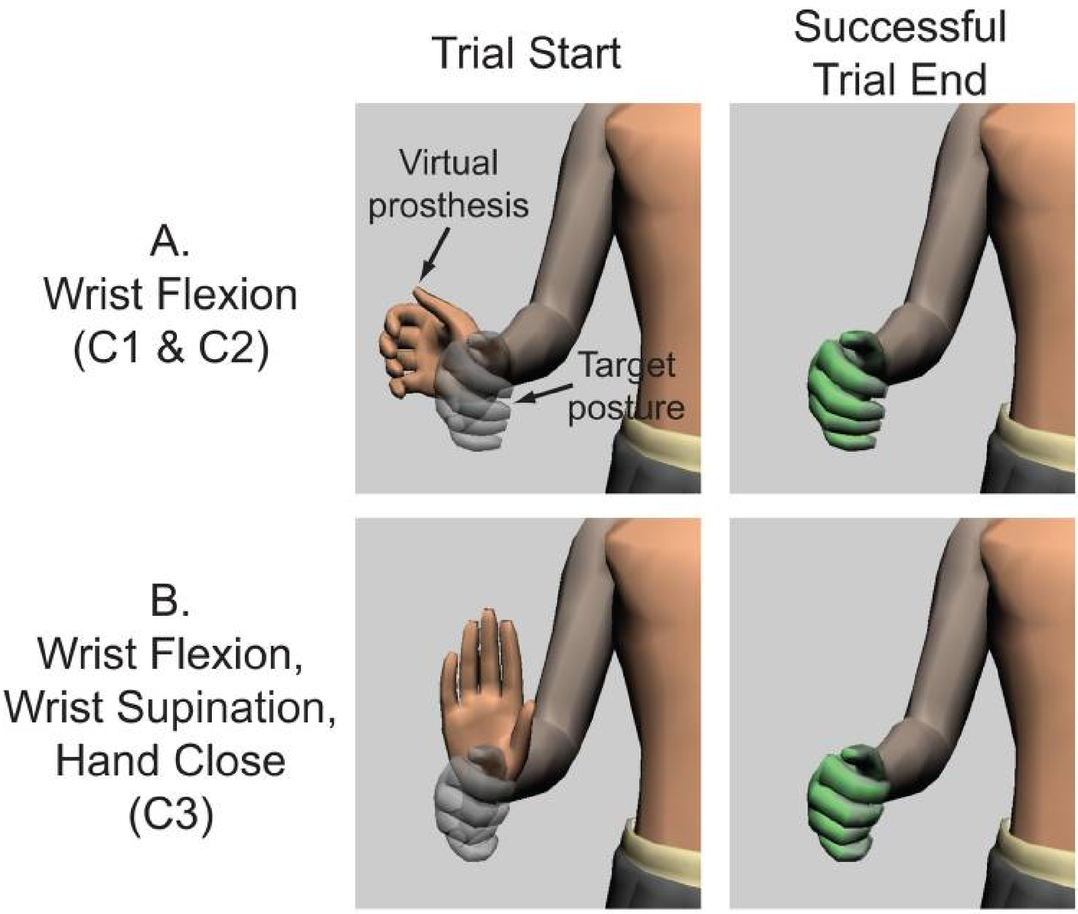

Figure 2.2: The above figure demonstrates the Tac Test virtual environment and an example task. The participant is shown the location of a virtual prosthesis and the target location for that virtual prosthesis to achieve. The total gesture pool was wrist flexion, wrist extension, wrist supination, wrist pronation, hand open, one hand grasp, and no movement. Dependent upon the scenario, the participant could be provided one to three degrees of freedom of motion. In the above example, the start and finish positions are shown for C1 and C2 where one to three degrees of freedom may be provided but only movement on one degree of freedom is required. The lower image shows the C3 condition, where three different movements are required to complete the task [2]

and force signals as control signals did follow Fittz Law. The implementations of Fittz law within EMG would later focus on mapping individual hand motions classes to the directional control of the cursor [102] would allow a good summary of motion performance. Direct hand motions from the TAC test had also been considered intuitive for the Fittz law test and therefore could be used in addition to hand open and close gestures to enable a sense of 3-dimensional control [103].

When considering an ideal metric for performance during rehabilitation, virtual environments appear to provide viable alternatives to traditional prosthesis based training due to their ability to mimic ADL's, ease of implementation, and ability to engage patients. An environment should be modeled to provide the gestures or actions intended for the final prosthesis such as those in the Fittz law test while being viable for early prosthesis users like seen in the motion test and the TAC test. Chapter 5 attempts to utilize the beneficial aspects of these environments while extending their implementation to precise control of individual gestures.

2.4.1.1 Control Schemes

Following traditional amputation, bio-signal controlled prosthesis typically can be controlled by sequential signal inputs or through controls not located in the residual limb. These sequential input controllers in collaboration with modern prosthesis are able to mimic a large degree of movements performed with their original limb. There does exist some limitations to this approach as there would be a limit on the numbers of degrees of freedom, the sequential control requirement causes actions performed through these systems to not be in a natural, and the control strategy would be unintuitive for the user. As a consequence, commercial prosthesis may require an increased training period as to accommodate the unintuitive control strategy or may see reduced capability as to reduce the cognitive burden experienced during the rehabilitative process and subsequent usage. This causes some issue in attempting to provide a relatively natural form of control which utilizes an intuitive control strategy as to avoid the issue of prosthesis rejection that manifests from unintuitive prosthesis control strategies [104, 105, 106].

In the case when enough of the residual limb remains, whether before or after amputation, then it has been shown possible to perform reinnervation surgery to transfer a nerve to another muscle through a method referred to as Targeted muscle reinnervation (TMR). Typical muscle locations in this surgery focus on the medical biceps and shoulder region. The subsequent benefit of this approach is that it allows these new regions to produce highly separable signals due to the separation from the crosstalk that is typical in the lower arm muscle groupings. Prosthesis control through TMR had previously been shown as a promising method by researchers such as Miller et al. and Kuiken et al. [107, 108], although the tests conducted to evaluate TMR to non-TMR testing were noted to be less capable of demonstrating an advantage of TMR due to the relative performance ceiling of evaluation methods where both approaches performed equally well.

As a benefit of the new spatial locations of the reinnervated nerves, it can become possible for practitioners to better separate similar muscle groupings in an attempt to shift further away from the sequential control schemes of commercial prosthesis. In the case of proportional control and simultaneous control, it can therefore be possible to exploit this mapping process to utilize it in a control strategy that enables concurrent control of multiple DoFs. This concurrent control scheme achieved through TMR was demonstrated to provide highly functional and natural control when completing Southampton Hand Assessment Protocol (SHAP) and the Clothes Pin Relocation Test (CPRT) by Aszmann [109].

Although there does exist benefits to the TMR process, there still demands a period of training as to first be capable of producing motor activity from the new sites. As with any rehabilitation, a major challenge is that of patient willingness that may stem from demotivation after losing a limb. Delay in undertaking physiotherapy and occupational therapy after receiving TMR may reduce patient outcomes as it has been demonstrated that early therapy and feedback is crucial in fast and successful reinnervation and signal generation [110, 111]. Maintaining patient motivation is further emphasized by the process of voluntary activation at the TMR sites often being seen after a period of 3 months of therapy [112].

The issue of demotivating delaying the process of voluntary control and subsequent need for early therapy was support by Schweisfurth [113] when early patient demotivation could be linked to visible voluntary EMG signal production. It was further realized by Schwisfurth that HD-EMG could be used with TMR patients to enable control of 12 separate motions to a superior degree than with standard EMG. However, the long term applicability of HD-EMG with TMR is still to be investigated and may remain problematic to achieve due to the migratory nature of hotspots produced by TMR surgery.

2.4.1.2 Feedback

Although simple on/off control of prosthesis can provide satisfactory functional results in real life user, they still are not a fully satisfactory replacement. The typical human hand can be considered to be a multi articulate structure of actuated muscles that have contain a densely packed series of sensors which provide real time feedback to the brain therefore enabling a sense of self within an environment.Without this sense of connection to a surrounding environment then a large degree of proportional and interactive control that a typical human hand is expected to perform daily would not be possible. Moreover, factors such as lack of adequate sensory feedback within prosthesis are often cited as a cause of prosthesis rejection among amputees [106, 114].

In consideration of feedback measures, there exists numerous modalities as to provide feedback as to either directly simulate missing sensations or provide a form of stimulation as to indicate the activity imparted by either the subjects muscle activation or sensation imparted on the prosthesis.

Vibrotactile feedback is a particularly popular form of feedback. Vibrotactile methods attempt to use vibration motors mounted on the subjects arm to simulate varying forms of touch. As vibration motors are well established, researchers have investigated a wide array of various sensors that may provide larger or smaller spatial feedback or upper range frequencies depending on the design of the device. Vibrotactile is perhaps one of the more common approaches as shown in table.2.2. When considering the viability of vibrotactile, [115] found that when attempting to recognize the area of stimulation, subjects were able to recognize the location of vibration in 93.9% of cases during bicep tests and 92.1% with forearm tests. When considering force related to grasping exercises with a virtual hand subjects were able to recognize the correct gesture in 85% of cases during bicep stimulation and 82.1% of attempts with forearm stimulation. The researchers believe that the decrease in accuracy from spatial recognition to grasping pattern recognition is due to the grasping exercise utilizing multiple motors which while phase shifted also may appear as a similar profile to a different grasp profile. The gap between individual and multiple motor recognition appears to support this. During robotic teleoperation exercises in [116], subjects demonstrated a 110% increase in manipulating an object through a cluttered environment when vibrotactile feedback is afforded as opposed to a non-feedback scenario. Towards considering the forms of activation and intended usage [117] found that LRA based activation provided good responses when binary activation and low power consumption are desirable whereas ERMs proved more suitable to scenarios where the intended application requires more information and for encoding complex signals. Further investigation into spatial encoding with various levels of feedback was explored by [118] where the five subjects were capable of interpreting the sensory information provided by the ERM vibrators relating to three levels of force per actuator on each finger. When moving towards potential implementation in a prosthesis [119] were able to demonstrate through a modified rubber hand illusion experiment that a sense of embodiment could be achieved through the provision of vibrotactile feedback, supporting the findings of prior researchers. Furthermore, with promise towards viable usage in a prosthesis, [120] found that a vibrotactile system was capable of increasing a prosthetic hands ability to manipulate and recognize various objects across even when visual contact could not be confirmed.

In an attempt to provide a more immersive form of feedback than vibrotactile methods, researchers have since shifted to methods that attempt to directly manipulate the patients skin to evoke sensation. Pressure feedback is one such method that typically attempts to provide tactile feedback through placing pressure or vertical deformation of the skin. The hardware design for this method typically involves a servomotor driven lever that applies pressure through a small button, frequently measuring 12mm in literature, however some systems also utilize air pressure from direct air pressure or balloon actuators. Several systems used in pressure feedback are described in table.2.3. Antfolk et al. [121] explored the provision of feedback from an artificial hand to a subjects forearm, it was recognized that the proposed system could provide some improvement to a prosthesis device. This work was later expanded upon in 2013 [122] where it was found that both the 5 amputee and 5 healthy participants were able to accurately discern the location, level of pressure, and combination of grips simulated through an on screen virtual hand from the pressure feedback. The effect of pres-

Table 2.2: Summary of research with Vibrotactile feedback

Author	**Subjects**	**Stimulator**
Fontana et al. [115]	30	Three 10mm circular Vibration motors on the subjects forearm and bicep
Bimbo et al. [116]	12	Four 9mm Vibration motors
Huang et al. [117]	15	Nine linear resonant actuators (LRAs) and nine Eccentric Rotating Masses (ERM) in two silicone plates
Nabeel et al. [120]	6	10mm Vibration motors
D'Alonzo et al. [119]	9	Two distinct miniature vibrators (310-101 series, Precision Microdrives)
Li et al. [118]	5	Five ERM Vibrators in a glove with one motor on each finger

sure feedback was investigated by [123] where the implemented device demonstrated improved grip strength during a two finger grip lifting task.

In order to provide a sense of haptic sensation through touch, the concept of skin stretch feedback has been proposed. This method attempts to utilise a gripping device that may rock, move linearly, or rotate according to the anticipated feedback condition. Due to the stretching behaviors experienced in the skin, it is very possible for this method to produce fairly distinctive patterns of feedback that are less susceptible to reduced sensation. One caveat of this feedback method, however, is that usage of this feedback approach is recommended to only be performed for a period of a couple of hours in some cases being limited at two hours of usage. A summary of present skin stretch approaches is formed in table.2.4. Bark et al [124, 125] demonstrated that skin stretch feedback can assist in the recovery of sensation when implemented into a prosthesis, however, the researchers highlighted that several hours of training with the device were necessary to achieve good results. A device posed by [126] was able to assist in performing blind movements to a higher degree than with no feedback. Subsequently the device was found to have promise towards assisting in proprioceptive

Table 2.3: Summary of research with Pressure feedback

Author	Subjects	Stimulator
Antfolk et al. [121]	2	Five digital servomotors controlling 15mm plastic levers that had 12mm diameter buttons against the skin on the subjects forearm
Antfolk et al. [122]	10	Single digital servomotor controlling a 15mm plastic lever with 12mm diameter plastic button
Kim et al. [123]	2	Wearable haptic device that imparts 9N of maximum pressing force to the subjects fingertip

feedback, however, the researchers warned that the device should not be used for more than 2 hours due to negative slipping of the device. The potential for skin stretch feedback in teleoperation was explored by Chinello et al. [127]. The haptic feedback approach posed by Chinello et al. was a viable solution for navigation feedback in both a human guidance and robotic telemanipulation exercise. However, it was recognized that the performance was less natural to follow than visual stimuli. The researchers suggested that a combination of utilizing this feedback system to augment visual que stimuli.

Through provision of squeeze feedback, an elasticated band is moved laterally along the feedback site providing the sensation of a squeeze or caress. While the implemented hardware used in literature may deemed this modality as unwieldy in a prosthesis, there it has been demonstrated that squeeze feedback can provide the sense of grasping objects of differing weight. An auxiliary element of this feedback method is that of research into emotional states that may be relayed through the squeezing sensation, potentially making this viable as a further form of feedback to compliment other direct control related feedback approaches. The state of the art squeeze feedback devices are described in table 2.5. Cassini et al. [128] proposed a feedback design of a workable and wearable haptic device that could provide both pressure and skin

Table 2.4: Summary of Skin Stretch Feedback research

Author	Subjects	Stimulator
Bark et al. [124, 125]	10	Two 14mm circular end effectors driven by ultrasound piezoelectric
Wheeler et al. [126]	15	Two 14mm circular end effectors driven by ultrasound piezoelectric
Chinello et al. [127]	10	Four independent servomotor driven cylindrical end effectors

stretch. Grasping information from a robotic hand was shown to be easily understood and healthy participants and one amputee participant. Through exploring more sensitive touch parameters by [129], a wearable squeeze haptic device could elicit the sensation of a caress like haptic stimuli in both detection of the stimuli alongside force and velocity of the stimuli. Damian et al. [130] explored the comparison in squeeze feedback between regular force feedback against slip feedback. The proposed device was capable of displaying both normal forces from grasping alongside slip forces in a fast and silent manner. The participants observed that the normal force feedback provided a higher quality result than the slip speed feedback.

A fairly novel form of feedback in prosthesis is that of thermal feedback. Typical hardware designs for this methodology is with peltier elements that may range from 15c to 40c in most literature. Unlike other methods of haptic feedback in this review, the implementation of thermal feedback is seldom used to provide primary senses of feedback, instead thermal feedback is typically used to provide auxiliary feedback to interactions with the surrounding environment. The reason for this may likely come from feedback methods requiring a seemingly instantaneous response time, however, peltier elements requires a longer period of time to reliably heat or cool to fit the desired setting. While there exists implementations that attempt to alleviate this issue, the usage of thermal feedback does not presently appear reliable enough as a unimodal feedback method yet is included for completeness in table.2.6. Ueda et al. [131], explored subjects controlling a prosthetic hand through EMG, which upon touching

Table 2.5: Summary of Squeeze Feedback research

Author	Subjects	Stimulator
Cassini et al. [128]	7	Clenching upper limb force Feedback (CUFF)
Bianchi et al. [129]	6	A single piece of rectangular fabric (60mmx160mm) driven by two rollers along the forearm, each roller powered by a HITEC DC Motor.
Damian et al. [130]	10	Single actuator haptic device around the forearm using a slip belt and force belt respectively to indicate grasping

an object would trigger thermal feedback from the peltier element. Subjects could interpret the five sets of applied temperatures with a success rate of 88%, demonstrating good feedback from interaction however the control scheme used open loop feedback to provide sensation as opposed to assisting control.

Gallo et al [132] proposed an interestingly novel multimodal implementation of thermal and pressure feedback. During recognition tests for simulated materials against physical materials, subjects were able to recognize simulated glass, wood, plastic, and metal at a similar rate as the physical object. A particularly notable aspect is the shift from preheated peltier elements to dynamically changing elements. The pressure feedback could be considered an important factor towards ensuring that heat gradients would be more noticeable by the subjects. Nakatani [133] further expanded on multimodal thermal feedback through the fusion of vibrotactile and thermal feedback, subjects claimed to experience a realistic tactile experience of water being poured onto their finger. An alternative multimodal thermo feedback method was proposed by [134] through the combined platform of thermal feedback and a haptic thimble demonstrated good promise for accurate and consistent interaction with virtual surfaces on the human fingertip.

Often utilizing similar electrodes to that in sEMG based sensing, electrotactile feedback is a promising modality of providing haptic feedback through the usage of

Table 2.6: Summary of Research with Thermal Feedback

Author	Subjects	Stimulator
Ueda et al. [131]	10	Peltier Element
Nakatani et al. [133]	5 able bodied	Four Peltier Elements with integrated vibrotactile unit
Gallo et al [132]	5 able bodied	Novel thermotactile display
Gabardi et al [134].	3	Two Peltier Cells and integrated haptic thimble

low-level electrical current impulses on a subjects skin to impart sensations. Unlike other listed approaches, electrotactile feedback has a major benefit of no mechanical component warm-up therefore enabling a faster degree of feedback in active use therefore being better suited to situations where instantaneous feedback is important, such as during dynamic grasping commands. Electrotactile feedback has shown promise in simulating textured surfaces alongside providing a sense of weight and shape to objects. There does exist caveats to the electrotactile feedback modality such as complication in present electrotactile implementations is that the system may cause excessive noise if used with sEMG systems. Moreover the varying skin impedance's between subjects requiring better calibration before use and more importantly that incorrectly or excessively enabled electrotactile feedback may provide discomfort. However, with correct calibration the benefits of instantaneous feedback conditions enable a degree of real time adaptive control that may not be as effective in other feedback conditions. A series of electrotactile implementations in the state of the art are described in table.2.7. In a study conducted by Strbac et al. [135], spatial coding of electrotactile feedback was was investigated on amputee subjects. All amputee subjects were capable of accurately recognizing the active electrode pad during stimulation through each stimulation approach. Franceschi et al. [136] further expanded on spatial coding, where all subjects of the study were capable of recognizing different patterns drawn through through electrotactile stimulation, particularly with simple patterns and movement direction. Further studies conducted by Strbac et al. [137] found that amputee subjects were capable of exploiting electrotactile feedback to adjust their muscle contraction levels to fit a desired level. Feedback assisted learning although became less important as subjects gradually developed a stable model of prosthesis function. This could imply that the feedback itself may prove a useful guide for improving training as a temporary aid. During force grasping tasks, [138] found that subjects were capable of actively exploiting electrotile feedback. However, performances displayed increased uncertainty when compared to visual feedback due to a limited feedback resolution. When considering the concept of phantom limbs, [139] found electrotactile feedback able to evoke phantom finger perception within the subjects of the study suggesting that targeted electrotactile stimulation can provide sensations of individual finger touch as feedback from a prosthesis. Through controlling multiple stimulation parameters such as intensity, frequency, and pulse width, [140] demonstrate it was possible to evoke distinguishable sensations across the palms of the subjects hands in a relatively real time manner. The above aspects of electrotactile stimulation to provide a real time feedback response through both spatial and mixed coding are particularly promising towards the application of haptic feedback to a prosthesis user.

Cipriani et al. [141] experimented with a vibrotactile feedback scheme that utilized a single vibrating motor which modulated at different frequencies. Although the effect of the vibrotractile motor utilized by Cipriani did not appear to provide a noticeable impact on grasp success rate, user responses to the feedback suggested that the sensation provided was important. Moreover, the form of feedback provided was recognized to potentially hold a negative impact on subjects if the implemented control scheme is either too interactive or complex as too much effort would be required for normal usage of the prosthesis therefore suggesting that a control scheme should be distinct yet simple to reduce cognitive burden.

When considering forming a sense of self, it has been recognized that users of a tool or prosthesis may often overestimate the length of their limb or residual limb [142]. Within this, Casper et al. [143] demonstrated that congruent actions with a robotic hand could promote a sense of self while incongruent actions decreased the sense of self although also that a form of feedback, even if not anticipated, still provided a sense of self.

Further to that the sense of self from this closed loop feedback is an important factor when performing tasks and maintaining a sense of agency [144, 145, 146]. A

Table 2.7: Summary of Electrotactile Feedback research

Author	Subjects	Simulator
Strbac et al. [135]	10	MaxSense with 16 channels using spatial coding laterally around the forearm
Franceschi et al. [136]	8	MaxSense stimulator using E-skin electrodes forming a 32 channel system with spatial coding along forearm in a 4 x 8 matrix
Strbac et al. [137]	9	MaxSense with 16 channels using spatial coding laterally around the forearm
Dosen et al. [138]	10	MaxSense with 16 channels using spatial coding laterally around the forearm, only 15 channels used due to the circumference of some subjects arms being too short.
Chai et al. [139]	2	Transcutaneous Electrical Nerve Stimulation (TENS) using single stimulating electrode and reference electrode on forearm
Germany et al. [140]	5	Single channel electrotactile stimulation

large matter concerning this closed loop feedback is that of congruent sense of action and feedback where the visual stimuli must be in some form visibly linked in short proximity to the direct feedback. In literature, the manifestation of sense of self can be described as the sense of agency. Typically sense of agency alone refers to a persons sense of control over their body and its actions within the world. This concept of sense of agency is further separated into that of body agency and external agency. Body agency typically defining a persons cognitive recognition of initiating and being in control of their bodies voluntary movements. External agency, typically refers to that of how the world outside of that persons body interacts with their body. This relationship between a persons own sense of agency against that of its impact externally could be considered a foundation of control [147].

Wen [148] described the behavior of body agency as opposed to external agency as two separate states of our cognitive sense of agency towards action and sensation. Within the sense of body agency it could be considered as the function of feeling a natural sense of connectivity to the action and the feedback on themselves whereas external agency may be considered as the function of performing an activity and experiencing an external event forming a reaction to that activity. The relationship between action and reaction in temporal terms saw a highly detrimental relationship during long-delayed sensory feedback in body agency whereas external agency was seen to be far more flexible to delayed feedback.

Interestingly, Huynh et al. [149] demonstrated that a sense of self and control over a prosthesis could be experienced in a situation where there was a significant delay between effort being exerted and any action or feedback provided that both the mechanical actions of the prosthesis and the tactile sensory feedback were synchronised. Although, the results demonstrated may be incongruent with dynamic prosthesis control due to the anticipated motor action delay in larger motions decreasing a sense of agency and self. Placing the findings of Huynh in context of that of Wen then there does support a notion towards the relationship formed from control and feedback stimuli. Wen considered that the susceptibility to temporal delay on body agency may be directly linked to a dominant comparison mechanism that expects seemingly immediate results whereas external agency may be open to the body to interpret the delay and adapt accordingly. Keetles et al. [150] similarly saw the adaption to external agency during a finger tapping agency with video delay potentially indicating that such delay may be adaptable. However, as discussed in relation to shortly delayed feedback, albeit visually, there does exist a situation where the bridge between body agency and external agency which may form an uncanny valley of agency that only serves to decrease sense of agency and subsequently sense of self [151, 152]. The approach in providing feedback to prosthesis should consider the aspect of whether the feedback is to affect body agency where it must be below the typical 300ms window or towards targeting external agency where there must be a distinct relationship between human activity and feedback.

When considering feedback in terms of usability, the present literature would suggest that an ideal feedback scheme would have to be easily discernible, a simplistic implementation, and feedback that has either minimal delay or a reliably delayed response. While the methods listed for vibrotactile feedback in table 2.2 can provide a simple implementation and may hold minimal delay, there exists issues as to how easily a user may distinguish the signals in both single site and spatial encoding schemes. Thermal feedback methods described in table 2.6 were shown to be effective at imparting detailed information to a user. Unfortunately, thermal feedback implementations tend to experience bulky implementations that make wearable devices difficult and have difficulty in providing dynamic feedback without non-uniform delays in feedback provision. Pressure based feedback approaches descried in table 2.3 were promising with regards to ease of implementation, minimal delay, and can assist in providing discernible feedback. Although pressure based feedback approaches typically provided good feedback for multiple gestures, the feedback patterns were typically only used to impart a sense of light or strong force reliably. While pressure based approaches may hold promise in a direct control prosthesis, there may exist issues in providing reliable feedback in a proportional control based prosthesis. An alternative to pressure feedback was that of skin stretch, which appealed to providing a good sense of proportional control while in a similar form factor and with a reasonable response time. It is to be considered, however, that skin stretch methods may not be currently viable for clinical or long term use as much of the research discussed in table 2.4 warned against continuous usage for more than two hours. A promising methodology for provision of low latency feedback in a discernible fashion is that of squeeze feedback, covered in table 2.5. Squeeze feedback promises variable feedback to a user in a single location, although the effectiveness with spatial coding is something that appears less observed in literature. A further aspect of squeeze feedback is that present implementations share a similar challenge to other mechanical feedback approaches where the system used may prove to be unwieldy during daily use outside of laboratory environments. A method that does demonstrate a reasonable compromise in terms of implementation, usability, and latency is that of electrotactile feedback as described in table 2.7. The main aspects of consideration with electrotactile feedback is that of the methods viability with mixed and spatial encoding during dynamic contractions. The profile of electrotactile devices also indicate that they may be easily used without proving cumbersome or uncomfortable during daily or long term use.

Therefore an ideal prosthesis, in theory, should be expected to provide full closed-loop sensory feedback to the user which targets a clear boundary of body agency with instantaneous feedback for natural sensation or delayed focus external agency where sensory feeling may be slowly adjusted relating to the feedback provided.

It was highlighted that while classification results with different sensing modalities may be promising, the metrics used may be limiting. To improve on this, the status of online performance should intend to focus on task based performances that mirror real life use. This may be performed through manipulation of objects, such as in the SHAP. Virtual environments enable observation of tasks and recording task performances. Through a virtual environment it is possible to relay clear instructions, alongside demonstrate extra information to the patient. The motion Test enables the ability to simulate prosthesis control prior to any fitting although only provides simple feedback. The TAC test provides a good representation of precision actions that can be performed by a patient with regards to proportional control of hand motions or finger movements. Larger movement or general hand motions can be represented well in a virtual environment through modified forms of the Fittz Law Test, where direct feedback based on a multidimensional form of object or pointer can represent a direct relationship to either force or predicted hand motion activity.

Although virtual environments can present visible feedback to users in a variety of novel manners, both virtual environments and physical environments are still unable to provide direct closed-loop feedback to patients as many commercial prosthesis only sense. The subsequent issue with open-loop control schemes is that patient reassurance to their actions under proportional control or hand gesture performance is only provided by visual stimuli which may only form under undesirable conditions. As it is further highlighted that prosthesis rejection can be affiliated to a lack of feedback from prosthesis, it should be investigated as to how closing this loop through physical feedback may improve the rehabilitative process. While vibrotactile feedback is a popular method, other methods such as electrotactile feedback are growing in popularity. The issue of feedback separability and subsequently the range of potential feedback can be expanded effectively through implementing spatial and mixed coding schemes for closed loop control.

2.5 Challenges & Directions

A recurring trend among numerous publications is that there exists an increasing gap between academic research and clinical use. This gap at present only continues to widen while prosthesis rejection remains a pressing issue. Frequently prosthesis users may choose an aesthetically pleasing prosthesis over functionality or in the cases when functionality is desirable then simple direct control systems may be chosen. Ideally a prosthesis should enable intuitive and natural control, which is robust to long term and dynamic use, providing real time performance for low computational complexity and low user burden during use. Other traits that would be desirable would be a reduced complexity of implemented hardware design while still detecting a good degree of muscle activity, easier user training, and closed loop feedback that could better facilitate the rehabilitative training process and to better inform the user when interacting with their environment.

Although numerous efforts have been undertaken as to implement these ideal properties in recent years, there still remains numerous challenges and limitations along the road to developing an ideal prosthesis implementation.

2.5.1 Inherent Sensing Challenges Posed During Long Term Use

Although many researchers have demonstrated the capability of sEMG based sensing to produce high quality results during offline performances and within short laboratory sessions, these performances still experience challenges when extending to longer period use and inter day use. Typical pattern recognition approaches tend to focus on the assumption that the produced sEMG signals will remain either consistent during use. However, clinical and daily implementations of prosthesis typically differ greatly in the range of physiological variables experienced and environmental variables which produce inconsistent signals which are difficult to predict within a laboratory environment. As a consequence of this inherent instability and variation across daily use of a prosthesis many pattern recognition based approaches would require retraining or re-calibration that imposes heavy burden upon the user. Although it may be possible to prepare for individual variables, such as electrode shift, typically inter day use of a powered prosthesis would encounter a combination of impeding factors that frequently will be worsened by aspects that introduce muscle produced crosstalk which poses increased randomness in a given system.

2.5.2 Limitations of Single Modality Sensing

The current state of the art shows sEMG based sensing to be very promising in terms of accuracy within laboratory environments and adequate for simple prosthesis control. However, within clinical environments there exists challenges towards interpreting muscle activity over long periods of time due to factors such as fatigue producing crosstalk from neighboring muscle groups. As sEMG based sensing attempts to sense the manifestation of electrical energy as it transmits across the upper layers of fibres within the human body there exists the inherent bias of sEMG based sensing towards surface level muscle activity. While it is very possible to accurately infer motion intent from surface level EMG signals there exists numerous dexterous finger movements that are closer related to deep muscle activity. As a result of this bias towards surface level muscle activity the ability to recognize dexterous hand motions may become limited, especially during long term use where physiological changes within the signal may contribute to unstable sEMG based detection whereas physical muscle activity may appear more constant for other methodologies.

2.5.3 Haptics - Closing the Loop

As discussed, an ideal prosthesis can enable not just intuitive control and interaction within an environment but to further enable an accurate sense of self with the prosthesis and during interaction. Through poor control schemes and lack of adequate feedback during use the issue of prosthesis rejection becomes more prominent. Unfortunately, although there exists multiple viable methodologies for provision of haptic feedback these methodologies are seldom implemented within active prosthesis control schemes. While novel haptic feedback approaches such as thermal or stretch based feedback can inspire realistic sensations of touch they still maintain caveats such as limited safe usage during long term use and more importantly present implementations of these feedback methods are bulky and cumbersome therefore limiting their viability within a upper limb prosthesis. Furthermore, it has been recognized that a feedback approach must be capable of seemingly providing instantaneous feedback whether based on prosthesis activation of whether from sensed interaction via force sensors. Vibrotactile feedback proposes promising compact solutions for implementation within a prosthesis yet the ramp up time of this methodology may cause false positives or confusing feedback during dynamic use. Electrotactile feedback appears as a promising route of feedback due to instantaneous response with no ramp up time and present implementations can be made in a non bulky, wearable, manner. To date, while many promising haptic feedback solutions to enable better prosthesis control have been proposed there still exists limited research into clinical use.

2.5.4 Burden of Rehabilitation and User Training

The concept of adequate rehabilitative results are distinctly varied based on the intended outcomes. However, there exists the complication of defining a general approach to an ideal outcome. While exhaustive rehabilitation and training may provide desirable results the degree of repetitive and cumbersome processes involved make such exhaustive practices undesirable to users especially given the potential burden imparted on them. It is within this challenge of recognizing that user training can promote the formation of consistent sEMG patterns in users while also balancing the extent and implementation of user training. Many laboratory environment implementations of sEMG based sensing focus on training the user for consistent single strength sEMG patterns whereas this challenge is further complicated when considering that daily needs of a user may require dynamic contraction strengths.

2.6 Summary

This chapter systematically reviewed aspects of sensing modalities towards prosthesis control in terms of variations in muscle activity and hand motion recognition. Furthermore this chapter attempts to provide an in depth review of the state of the art and existing challenges in hand rehabilitation with regards to provision of user training, enabling sense of self, and haptic feedback.

Firstly, the current state of the art in non invasive modalities for muscle activity sensing are introduced alongside relative aspects of their implementation in terms of hardware and processing. It is highlighted that sEMG based sensing exists as the commercially and clinically accepted form of active control in prosthesis and muscle activity detection in rehabilitative environments. Although the implementation of sEMG based sensing is widely popular and frequently accepted in academia, several caveats of sEMG based control towards long term use in current implementations are highlighted. A typical challenge within sEMG that is recognized is the limitation of detecting deep muscle activity reliably especially during long term use. Alternative methodologies towards sensing such as ultrasound, NIRS, and FSR are explored and evaluated for their unimodal qualities. Considering the unimodal qualities of each sensing modality a further review is made into fused sensing modalities.

Secondly, The integration of alternative modalities to sEMG in sensing is shown to provide great promise in exploiting the widely recognized success of sEMG sensing in sensing surface activity while further enhancing the quality of hand motion recognition through implementing modalities such as those described for their unimodal implementations and further modalities such as accelerometers, force sensors, and datagloves. Fused sensing modalities are found to provide many novel expansions on typical unimodal approaches, particularly in cases where each implemented modality is particularly adept at observing aspects of muscle activity which are noted as being lacking in the paired sensing modality.

Thirdly, a thorough review of haptic feedback to enable closed loop feedback and a sense of touch are explored. the importance of enabling haptic feedback to a user is highly stressed in aspects of quality of life and the value of enabling a sense of self from a prosthesis is discussed. Current trends of haptic feedback systems are explored in depth for their relative merits. It is shown that there exists novel forms of tactile feedback such as stretch, thermal, and pressure feedback that can provide seemingly realistic sense of touch for their individual application yet are limited from aspects of speed of response within thermal feedback, the complications of potential injury, discomfort, and skin damage from stretch based feedback, and hardware limitations that exist with regards to implementation within an upper limb powered prosthesis. Both vibrotactile and electrotactile feedback approaches are found to provide great promise enabling seemingly accurate senses of touch and in proportional control schemes. It is further explored as to how each feedback form may be adequately utilized in such a way as to provide a relative sense of agency to a user.

Finally, The current methodologies utilized in rehabilitation are highlighted and their respective qualities towards achieving desirable rehabilitative outcomes and the burden of training involved are compared. The process involved with each rehabilitative structure can be seen as complementary or within stages of each other such that certain rehabilitative methodologies such as the SHAP test are better suited to later rehabilitation sessions. The issue of physical rehabilitative exercises is explored and the feasibility of virtual systems to assist the rehabilitative process is examined.

Based on the reviewed progress and limitations, potential future research directions in sensing modalities and their place within rehabilitation are as follows. Current approaches towards sEMG based sensing provide highly promising results within laboratory environments yet are limited when placed within clinical environments and during long term use. It can be assumed that sEMG based hand motion recognition accuracy degrades as a function of time due to numerous physiological changes within the signal which could appear random due to their causes being potentially due to arm position, physiological changes, and environmental changes. Therefore it is important to gain a deeper understanding into the changing state of the sEMG signal in an attempt to better define whether there is a predictable element of these changes and furthermore if there exists a method to better exploit any expected form of change in the signal. Furthermore, it is important to question if the current limitations of sEMG sensing may have reached a form of bottleneck due to the limitations of current sEMG sensing experiencing bias towards surface level muscle groups and whether the addition of non invasive methods that can better view deep muscle activity could assist in overcoming this challenge. Finally, it is recognized that current prosthesis control schemes are limited due to a lack of feedback and while there exists numerous potential feedback approaches the extent of implementation is frequently limited to laboratory environment experiments to verify sense of touch. Furthermore, the rehabilitative process is found to be one that must be simplified and further enhanced as to ease the process of learning and reduce burden on the patient. Therefore it should be investigated as to the quality of providing haptic feedback within fine control prosthesis challenges and furthermore if the addition of haptic feedback can improve the quality of existing rehabilitative approaches.

It can can therefore be considered that existing pattern recognition methods, while successful within a laboratory environment, are lacking in providing robust long term use for prosthesis users. A first aspect is that typical experiments for long term sEMG based sensing only incorporate one to two sets from each day [96, 4]. A deeper investigation into the influence of sEMG data from collection time in a day would be required to verify any influence on interday classification accuracy.

Next, the bottleneck challenge of sEMG based sensing on prosthesis control and subsequent research into fused modality approaches would suggest that a mixed modality approach may be most viable for long term use. Ultrasound based approaches currently enjoy high degrees of classification accuracy against both sEMG and other approaches for simple hand gestures and proportional control, making ultrasound a viable additional modality. A challenge with ultrasound, however, is that of seldom research into feature extraction of A-mode ultrasound signal. Therefore a pilot investigation would be required to determine which features would be most robust for A-mode ultrasound and subsequently an investigation to A-mode ultrasound with sEMG sensing for larger arm gestures than previously used in literature.

Thirdly, the lack of feedback in prosthesis control is considered an issue during active daily living for a prosthesis user. Furthermore, the present lack of feedback and rehabilitative processes can be considered an aspect towards lost patient motivation and subsequently prosthesis rejection. Electrotactile feedback, as shown in the above review, promises to be adaptive and viable for daily use. Secondly, virtual environments have shown themselves to be adaptive and engaging during the rehabilitative process. Through combination of a virtual environment and electrotactile feedback, it may be possible to establish an environment that could give a user precise control over voluntary contractions with lower error and in a shorter training period than without virtual or haptic feedback.

In this thesis, inherent sensing challenges posed during long term use of sEMG based sensing is explored and training strategies to exploit the temporal changes within sEMG signals are explored respectively in chapter 3. Due to a perceived bottleneck within the current state of clinical implementation of sEMG sensing, and to overcome the limitations of single modality sensing, a multimodal sensor fusion approach is explored in Chapter 4. Firstly the viability of ultrasound based sensing for hand motion recognition with regards to utilizing sEMG styled feature extraction and subsequently the robustness of ultrasound sensing to probe shift is examined. Subsequently, a ultrasound and sEMG sensor fusion approach is proposed for hand motion recognition during large movements. Finally, the challenge of closing the loop in feedback and overcoming the burden of rehabilitation and user training recognizing is posed in chapter 5. Through identifying that rehabilitative approaches and prosthesis control experience challenges due to cognitive burden on the user and lack of adequate feedback, Chapter 5 introduces a Virtual reality rehabilitative system that utilizes both virtual and electrotactile feedback within a clinical styled environment that uses fine control grasping exercises of a virtual object. The proposed system is explored for potential to both better guide the user and decrease the burden of the rehabilitative process.

Chapter 3

Training Strategies for Long-term sEMG Based Hand Motion Recognition

Although feature selection is considered pivotal in providing desirable accuracy with even naive classifiers, transient changes in the signal itself can often render a pattern recognition system unusable. One of the more interesting transient changes in sEMG signal is that of the effect of time passing. While it is possible to directly observe the immediate effects of transient changes such as electrode shift, fatigue, changes in skin impedance, etc. The impact these changes across time on a persons sEMG signals is one that is harder to observe and subsequently one that is still not fully understood [4]. In some manners, the impact of time could be considered as the summation of transient changes across any given period.

Therefore, this chapter explores the changing nature of sEMG signals during intra-day use and attempt to isolate elements of any potential changes in the sEMG signal to promote training strategies to improve long term inter day use. Firstly this chapter shall cover a brief background on the challenge of sEMG sensing during long term use followed by the experimental setup and design. The methods of data representation to infer an understanding of changing sEMG signals during intraday use will be described. The results of the intraday sEMG inspection will then be devised into training strategies that may be applied during interday sEMG hand motion recognition. The results of interday hand motion recognition will be described. Finally, the conclusions of the findings of this chapter will be presented alongside the contributions to sEMG sensing for long term use.

3.1 Introduction

Surface Electromyography (sEMG) is the method of analysing the electrical impulses from various muscles within the human body. Through pattern recognition, a machine may be trained to both understand and predict motions from muscle activations. Although, in a laboratory setting, results are promising, clinical success of pattern recognition based prosthesis is still limited. In academia, there exists increasingly promising methods for recognition of motion intent, with motion recognition accuracy rates commonly reaching above 90%. However, much of the academic research focuses on training with offline datasets, whilst online classification results are not as satisfactory. There are several potential causes for poor accuracy during online classification such as: skin-electrode impedance [153], electrode displacement and shift [154], and fatigue [87]. Although each of the potential causes can be tackled individually, this chapter will attempt to explore a training strategies to mitigate the cumulative impact of these during daily use and subsequently through activities of daily living.

3.2 Background of sEMG in Long Term Hand Rehabilitation

Across a given period of time, classification error can be expected to increase. Unfortunately, as stated by Amsuss [4], there still needs to be a better understanding of how this change manifests and the long-term dependence on classification accuracy. This challenge has pushed researchers to attempt to quantify the shift in sEMG data and classification error across time [155]. Kaufmann [96] compared how classification accuracy deteriorated when training a classifier with early data sets, recent datasets, and gradually updated datasets. It was suggested that there exist some variable components within sEMG signals, based on the deteriorating accuracy. If it can be assumed that there exists variable components of the sEMG signal, there exists potential to construct a dataset that can reasonably predict this change, whilst remaining computationally efficient. Research into long term use typically focuses on sequential day degradation [96] or sessions with a period of time between [97]. it can be considered from this that the current academic focus for long term use may exist within that of a two weeks to a month.

All of these traits are natural during daily use of a prosthesis, and therefore likely to cause classification failures during long periods of usage. Through recalibration, the effective usage of a prosthesis can be extended. The main methods for recalibration is through supervised means and unsupervised means. Supervised recalibration requires the prosthesis user to manually decide if the prosthesis is not performing optimally, and to collect a new training dataset for the device. The new set of training data will either be appended to the existing data or shall replace the previous training data. This retraining has often been done through screen guided training [156] through the usage of on screen text / image prompts or through virtual prosthesis controlled by either the system or the subject. A prosthesis guided training method was proposed by Chicone et al [157], upon recalibration, the prosthesis would perform a series of gestures for the user to mimic. It was found that the prosthesis guided approach can both provide better training samples and reduced the need for any additional devices to the prosthesis. Unsupervised methods, however, require no conscious input on the prosthesis users behalf. Adaptive algorithms are used to regularly update the existing training data based on different adaptive strategies. There is much research on the adaptive techniques such as [158, 159, 160]. For example, Sensinger et al [161], noted that unsupervised methods that rely on high confidence of classification could provide usable rates of recognition accuracy, yet could suffer over-training over long periods of time. It was further found that adaptive methods based on low confidence of classification could decrease over training but were not reliable when unsupervised.

Although Adaptive methods are can improve the overall time between conscious calibration, and may subsequently provide higher degrees of long term motion recognition accuracy, the data selection schemes are not fully applicable for clinical use. There are two general problems must be addressed with selecting a training scheme. Firstly, in schemes that directly modify the training set for retraining, the overall size of the training dataset should be minimal as to avoid over-training and to reduce the computation time during training. Secondly, that concept drift within sEMG signals is not fully understand and therefore difficult to adequately model the change over time, or to capture a training data set that is representative of the range of gestures. Generally the selection of original data could be more important for initial use, largely due to the variable nature of sEMG signals throughout a day.

The major factors and manifestations of changing sEMG signal over time can be considered under the following categories.

3.2.1 Fatigue

During non fatigued contractions a targeted muscle should be capable of providing necessary activation to perform a grasp based on the localized MU's. As the muscle experiences increasing degrees of fatigue, the capability of local MU's will gradually decrease and it will need to be supplemented by neighboring MU's. The shift to neighboring MU's and muscles to assist in facilitating muscle activation will therefore create MUAP chains that causes minor temporal delay following transmission through the muscle fibres alongside decreased amplitude and potentially different signal patterns to those originally anticipated.

In pattern recognition based systems, small changes to the sensed signals can lead to complete loss of detection particularly in models that are trained with a large volume of relatively similar motions and moreover as the spatial changes in muscle activity may reduce the visibility of the detected signal in the target sensor location alongside noise in non target sensor locations for that particular gesture.

3.2.2 Electrode Shift

Electrode shift is a prominent issue when considering long term use, and may even manifest during short term use when aspects such as large arm movements or clothing interferes with the sensor location[162]. Typically, electrode shift manifests with dry electrodes whereas wet electrodes typically lose sensing. Some adaptive systems may be capable of recognising gradual shift, as with fatigue, the noise or loss of targeted muscle detection may cause a trained recognition model to no longer be usable. Although electrode shift may be problematic, it is largely to be expected during long term dry electrode use. Hardware aspects of sensor arrangement may assist in decreasing the risk of electrode shift such as how the sensors within a prosthesis are fitted or if an armband based electrode setup is used then elasticated bands that provide a degree of corrective flex may improve long term robustness to shift [163].

3.2.3 Concept Drift

While fatigue and electrode shift manifest as physical sensing problems caused by physiological and hardware based changes in the signal and sensing equipment, there also exists the psychological aspects of concept drift such as mental fatigue [164]. Concept drift can be defined as the gradual mental shift from how a particular motion was originally performed in terms of which specific muscle groupings were activated and the degree of effort exerted during a particular motion. While it has been identified that the exact recruitment potential of a person may not decrease, their imparted effort and attempts to perform an action would be modified [165, 166]. Ideally the rehabilitative approach would train a user to be able to produce consistent sEMG patterns throughout daily use yet it is anticipated that a degree of change will manifest whether through distraction or through mental fatigue instead of physical fatigue. As the factors related to this form of concept drift are harder to predict than physical fatigue or electrode shift then producing algorithms to anticipate this form of random shift of sEMG signal becomes more complex [167].

Therefore, considering the above described traits of sEMG signals that may manifest during daily use, it is important to consider that there exists multiple sources of randomness in sEMG signals during daily use. When considering the change in sEMG signal there may not exist a single approach to adapt to each form of transient changes. However, there may be potential to exploit the invariant traits of the produced sEMG signals, which manifest alongside the variable aspects.

In this study, an investigation into methods of data selection to improve the long term inter-day stability of a trained dataset shall be conducted. The following sections shall cover data collection in section 3.3.2 , data selection in section 3.4.6, and processing in section 3.4.1 , before a discussion on the findings of this research, ending in a conclusion and suggestions towards future work.

3.3 System and Experiments

3.3.1 System for Long Term Data Capture

To collect sEMG data, an 16 channel Elonxi sEMG acquisition device (Elonxi Ltd, UK) was used with 12 bits ADC resolution and 1Khz sampling frequency. The range for collected sEMG data was 10Hz to 500 Hz through a band pass filter in the hardware, 50Hz powerline noise was removed with a notch filter in the hardware and a comb filter in the software. The sEMG data was transferred from the device via USB, and processed on a Windows based PC. More details may be found in the previous works[168, 169] .

The devices structure is that of a sleeve with 18 embedded electrodes, consisting of 16 channels and two reference electrodes. The exact configuration of electrodes within the sleeve are arranged as to improve the signal repeatability [170]. A second elasticated sleeve was worn over the main electrode sleeve to ensure a tight fit on all electrodes. The sleeve was worn on the subjects dominant arm, or preferred arm in cases of Cross-dominance. To ensure each day saw the same fitting, a marker was used to denote the location of both bias electrodes on the subjects arm, in-line with the top and bottom of the sleeve, as shown in Fig.3.1. The degree of shift experienced on the sleeve was updated by new markings before each instance of data collection. The benefit of the dual sleeve arrangement in this device is that it maintains both pressure and contact upon a larger section of the arm. Through the increased surface contact, the device is subsequently less likely to shift through and dramatic degree during wearing. During the course of this study it was found that once the sleeve had begun to imprint upon the skin, that any shift would gradually re-align with the original rotation on the arm. The flexible design of the elasticated fabric further meant that relative positions of the electrodes to the arm are very stable.

Issues such as sweating may be a factor in warm climates, or if the wearer is performing much physical activity, however, neither of these issues were encountered during the data collection. In a situation where the device was exposed to cold climates the wearer would allow the device to return to the ambient room temperature before data collection. The potential reasoning for this is that colder climates lead to a drier skin surface and subsequently high skin-electrode impedance.

For this research, a single male participant was used. While additional participants were considered, the high frequency nature of data collection across the study period made it less feasible to expand the subject pool. Furthermore, it was considered that the lower quantity of participants would be offset due by the quantity of data collected offsetting the potential for outlier datasets. Experiments were conducted in accordance with local ethics guidelines, ethics reference number: TECH2019-PB-03.

3.3.2 Dataset Representation

Data collection began at 10:00 for each day and ended at 18:00, for a period of 5 days over 3 weeks. A 30 minute window was granted between data collection providing a total of 16 sessions per day. the 30 minute window is designed to keep constant records of sEMG data without placing unnatural fatigue on the subject. sEMG capture was performed by the subject sitting in front of a computer monitor, with elbows in a fixed position. Thirteen separate hand gestures, as shown in Fig.3.2, were shown to the subject with 5 seconds to transfer between gestures and 5 seconds of holding a gesture. The series of gestures were presented to the subject in a pseudo-random order, as to prevent the subject learning the order of gestures and transferring to a new gesture too early. For this research, the 13 gestures selected were chosen due to the majority being common hand gestures within research and daily life. The addition of complex gestures was done in order to extend the focus of this research on gestures that are to be anticipated during daily life.

3.4 Methodology

3.4.1 Signal Pre-processing

Signal collection was performed through custom software, and processed in Matlab. As stated in the data collection section, the custom software would strip any remaining powerline noise and output the sEMG signal with minimal interference. Once the raw signal had been stripped of any interference and prepared for processing, the output sEMG signal data was stripped of the transient signal between gestures. This is to say,

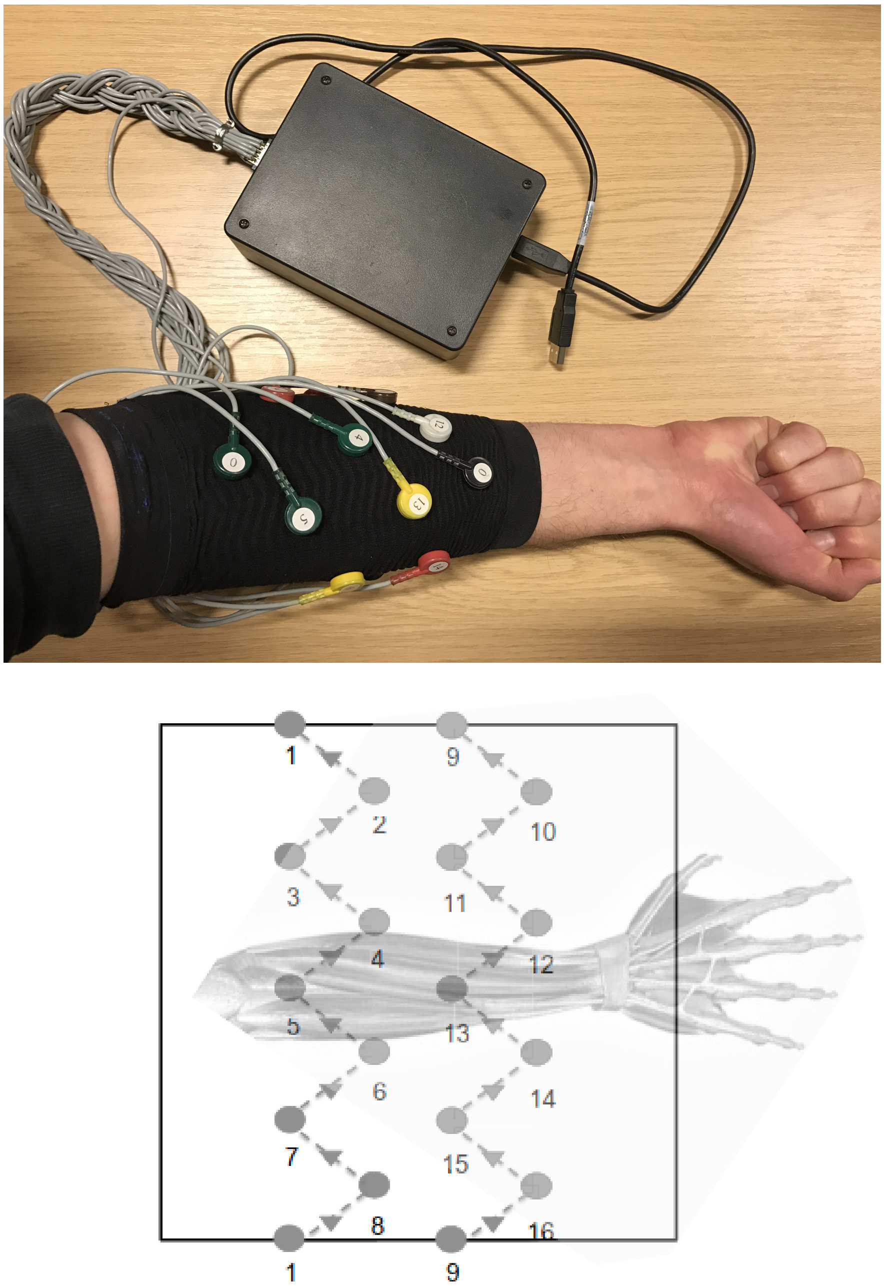

Figure 3.1: Elonxi sEMG acquisition device (Elonxi Ltd, UK) with muscle mapping depicted in 2d space

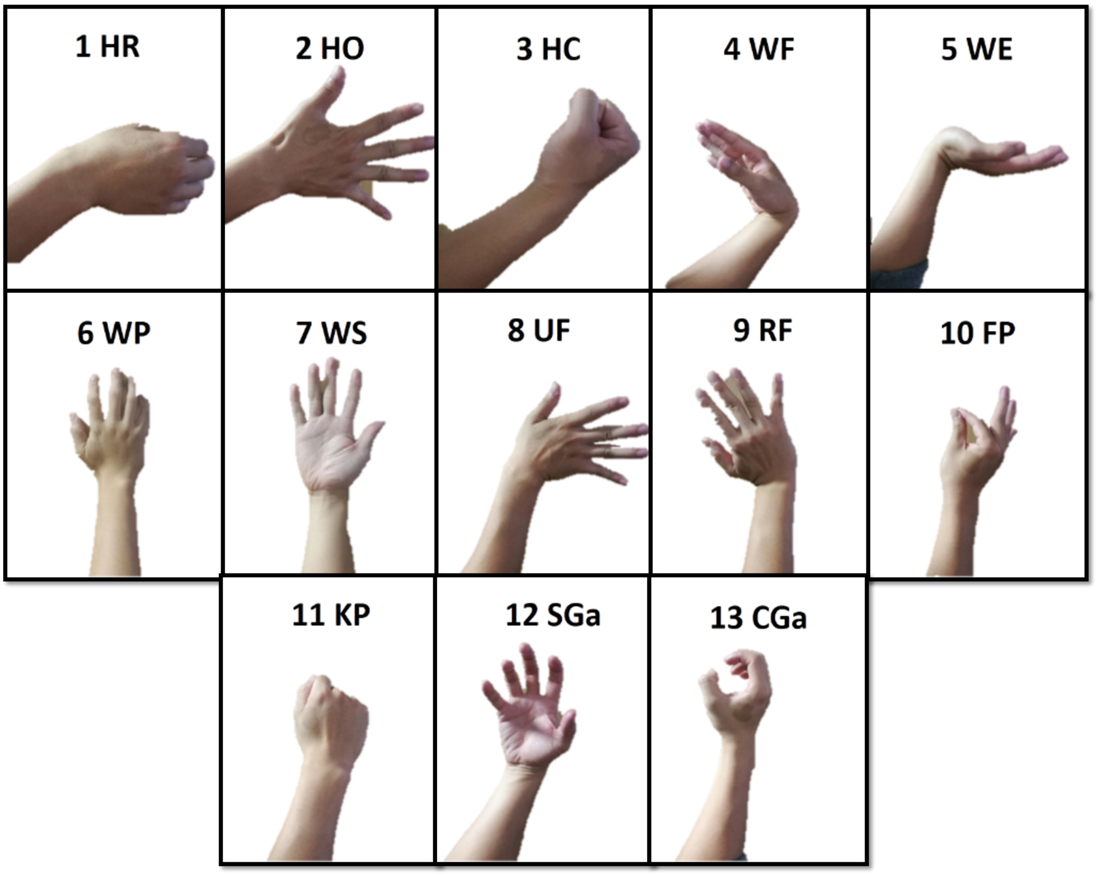

Figure 3.2: Training Gestures

the 5 second window of transition between each gesture was removed as to ensure each set of data is fully representative of the class.

3.4.2 Selected Features

The feature extraction was performed in a 250ms window, with a 50ms sliding window. The window size was chosen at 250ms in order to be under the 300ms delay needed to provide seemingly instantaneous feedback during use. The chosen features for this study were a combination of Auto-Regressive (AR) to the fourth order and root Mean Square (RMS), as the combination of these features had previously been shown to be both strong features and robust for long term classification [171, 172]. The relations of sEMG features to that of classifiers was explored by Adewuyi et al [173], where it was considered that the features themselves are equally influential under any given classifier, with the muscle grouping for the chosen features holding stronger influence.

3.4.3 Algorithms Used

For classification, Linear Discriminant Analysis (LDA) was used with a bayes-optimal classifier. Although Support Vector Machines (SVM) and Multi-Layer Perceptrons (MLP) are good algorithms for classification, LDA has previously been shown to be more robust during long term classification, although having lower intra session recognition accuracy. Both MLP and SVM performed well during intra session recognition yet decayed rapidly during inter session motion recognition [96]. It is due to this robustness that LDA was considered a viable method to evaluate the proposed training strategies in this study to verify the training strategies.

3.4.4 Defining sEMG Signal Freshness

The concept of data freshness is that of finding the minimum amount of time for a single given dataset to no longer be considered reliable for adequate operation of a pattern recognition based control scheme and subsequently the rate of decay.

As stated in the previous sections, the choice of features and classifiers to be used to define data freshness are not focused in to classification accuracy, but in the largest set of time points such that the classification accuracy can be considered usable. This model may provide varying performance with different features or classifier approaches yet will indicate a generalised period of time to provide guidance in how far to space out data collection, whether for similar data or time decayed data.

3.4.5 Anticipated Life of a Trained Model

In this research, the defined lifespan of a given trained model is when the hand motion recognition provided against a test dataset falls below 70%.

Through repeated training of a classifier with single datasets during a day and testing against individual datasets from the rest of the day we are able to map the shift in motion classification accuracy across a given period and subsequently acquire a form of median accuracy loss during daily use.

3.4.6 Training Strategies

To compare the relative performance of each method of selecting data, several data selection strategies were evaluated using a single day as training data and alternative days as testing days. These strategies were firstly applied without any testing day data and secondly with one of the first recorded sessions from the testing day. To compare the efficiency of the selection strategies, two control tests shall be used. It was found by Jain et al [174] that the performance of a single trained classifier can degrade to a recognition accuracy of 78.4% with a standard deviation of 2.33%, therefore the first control case shall be the performance a classifier trained from one of the first 3 sessions of the testing day. The second control case shall be a classifier trained with one of the first sessions of a non-test day, to monitor the decay of using minimal prior data.

The selection strategies used are as follows:

1. The first session of a non-test day
2. The first 2 sessions of a non-test day
3. The first 3 sessions of a non-test day
4. The first 4 sessions of a non-test day

5. All 16 sessions of a non-test day

6. 3 sessions, randomly selected from 3 points of a non-test day

7. 4 sessions, randomly selected from 4 space points of a non-test day

8. A single session of a test day

The first 3 selection strategies are to observe the impact of adding sequential sessions into the training dataset. The second and third case also provide a direct comparison of sequential data selection, as opposed to representative data selection. The usage of an entire day (16 sessions) is to observe the effect of using a larger dataset to represent an entire day of sEMG signals.

The final non control cases are both within the proposed method of representative data selection. In this method, a given day is separated into descriptive periods such as: morning, middle day, and evening. The intention of this method is to provide a good representation of the shifts in the sEMG signal during any given day whilst using a minimal quantity of recording points in aforementioned day. An example of selection of random data points for training data is demonstrated in Fig.3.3.

3.4.6.1 Evaluation

As this study focuses on the general performance of the data selection strategies, the temporal change that causes a reduction in classification accuracy along consecutive days has not been recorded. Therefore, each day in the dataset is considered as a unique training day against all other days which are considered as testing days, without considering for their appearance in sequence. Leave-p-out validation was then applied where p is the remaining datasets in each test day, dependant on whether an initial testing day data was also used in training set. This process was then reapplied to each non training days data exhaustively. The decision for this exhaustive testing scheme over alternative cross-validation approaches was taken to best mirror previous research into long term stability of sEMG control schemes [4, 96].

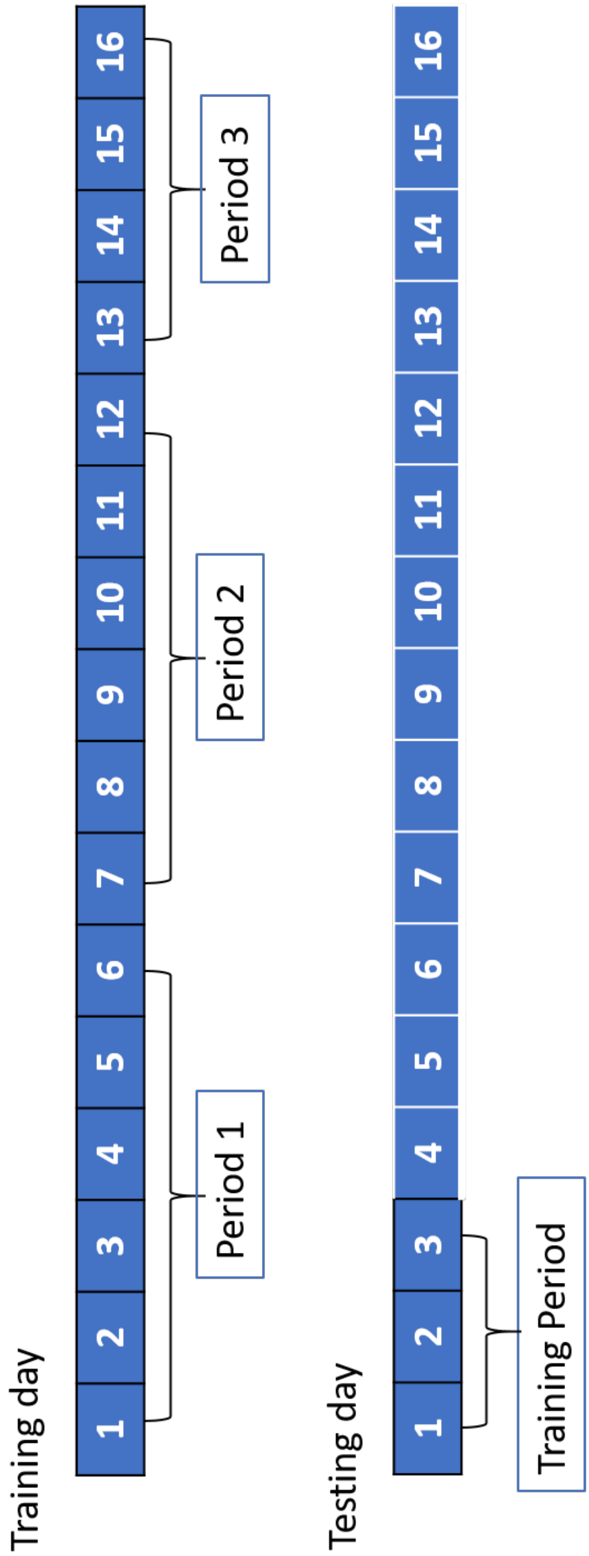

Figure 3.3: Proposed Selection Rule using 3 non-test day sessions and one testing day session

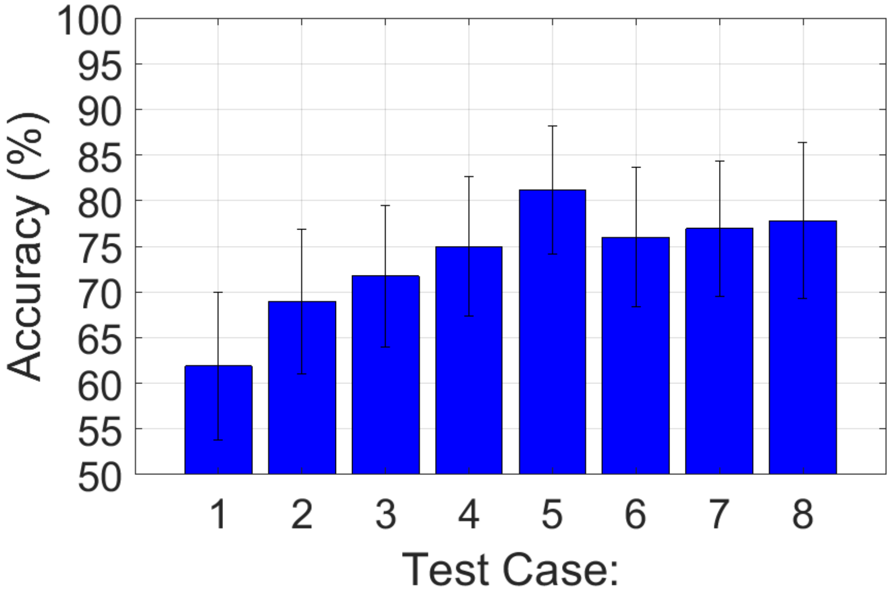

Figure 3.4: Recognition accuracy of strategies trained with non test day data only. 1: First session only 2: First 2 sessions, 3: First 3 sessions, 4: First 4 sessions. 5: Entire Day (16 Sessions), 6: 3 Spread out sessions, 7: 4 Spread out sessions, 8: Single Session from testing day only

3.5 Results

Both Fig.3.4 and Fig.3.5 show that the averaged interday performance of the four data selection methods, all are shown with and without a testing day session whereas Table.3.1 shows the complete list of accuracy and the standard deviation of each method. An immediately apparent state of both charts is that apparent state where increasing the initial dataset will provide a relative boost in accuracy, as recognized by [96]. A further aspect is that of the spaced training strategies achieving a comparative recognition accuracy without using testing day data in fig.3.4 and providing the highest recognition accuracy when testing day data is included in fig. 3.5. As demonstrated by other authors [175], the interday accuracy of a single training set is very poor at 61.9%, although this level of accuracy is very similar to that of the intraday accuracy, as an early morning session alone is unable to fully represent transient changes within the sEMG signal.

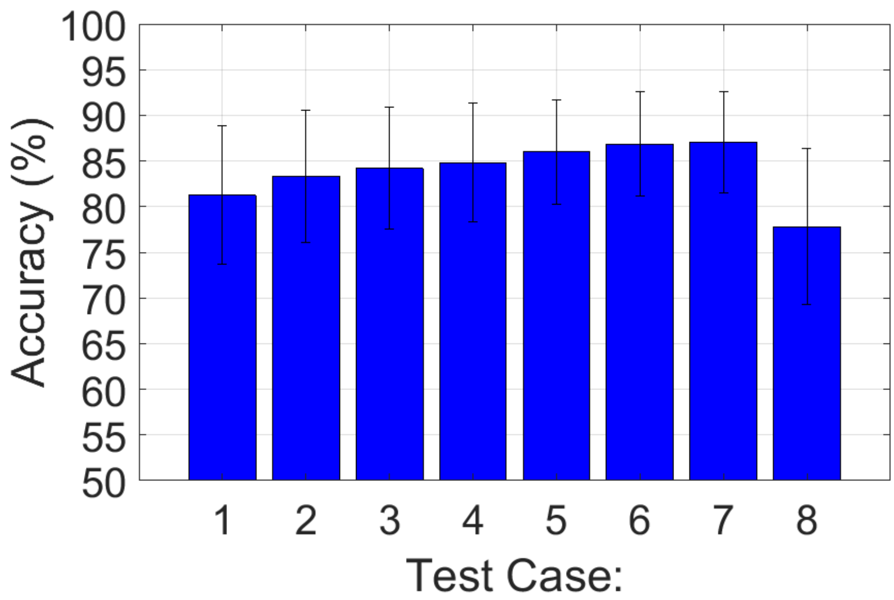

Figure 3.5: Recognition accuracy of strategies trained with test day data. 1: First session only 2: First 2 sessions, 3: First 3 sessions, 4: First 4 sessions. 5: Entire Day (16 Sessions), 6: 3 Spread out sessions, 7: 4 Spread out sessions, 8: Single Session from testing day only

Table 3.1: Results of using sessions from non-test day and first session of testing day as training data against the entirety of the testing day

Classification Results	Without Testing Day Data	With Testing Day Data
Training Day Data:	Accuracy(%)	Accuracy(%):
Testing Day data only	-	77.8±8.6
Session 1	61.9±8.0	81.2±7.6
Session 1-2	68.3±7.9	83.3±7.3
Sessions 1-3	71.7±7.8	84.2±6.7
Sessions 1-4	75.0±7.8	84.8±6.5
Entire day of 16 sessions	81.2±7.0	86.0±5.7
3 Spaced Sessions	76.0±7.6	86.9±5.7
4 Spaced sessions	76.9±7.4	87.0±5.5

The other selection methods managed to achieve constantly acceptable accuracy rates of 85% with 2% standard deviation accuracy on interday testing sets. Showing that a single days worth of data is capable of providing a good representation of a persons sEMG signals. The highest result was found with using the proposed methods of the selecting defining periods of each training day with a single early session of the testing day with an accuracy of 86.9% and 87.0%, for both the 3 and 4 session strategies. When the training set has prior knowledge of the testing day, the result reduces to 76.0% and 76.9% which is very similar to using the first session alone of any given day (77.8%). The results of the entire day could be considered to be the effect of gathering a large enough dataset to accurately represent the gradual change of the signal during an average day. Using 4 morning sessions managed achieve a reasonable amount of accuracy, although the deviation implies that it may not be fully acceptable for daily usage, the recognition accuracy also saw a large decrease when not using a testing day dataset. The reduction from removing testing day data can be assumed to stem from minor changes in the devices fitting on each day due to less controllable environmental and physiological aspects such as ambient temperature [176] and fatigue. Finally, using 3 spaced datasets and 1 testing day set as training data resulted in similar accuracy to the entire day training set.

As shown in the confusions matrix in Fig.3.5 , the proposed method achieved a high degree of accuracy on the majority of simple gestures, where the average inter-day accuracy was 90%, which poses itself as a very strong method for reliable long term sEMG prosthesis control. Generally, the majority of simple classes were easily classified. The classes which routinely scored most poorly were the two complex gestures numbered 12 and 13 in Fig.3.2, where accuracy was rarely above 70% in any test case.

3.6 Discussion

In this study, the effect of different training dataset selection strategies was investigated. The results demonstrated a stronger classifier, for inter-day sEMG gesture recognition, can be built by using data that is representative of the sEMG signal changes within a day. The novel contribution of this study is firstly relating to providing an in depth exploration of larger volumes inter session sEMG datasets than previously

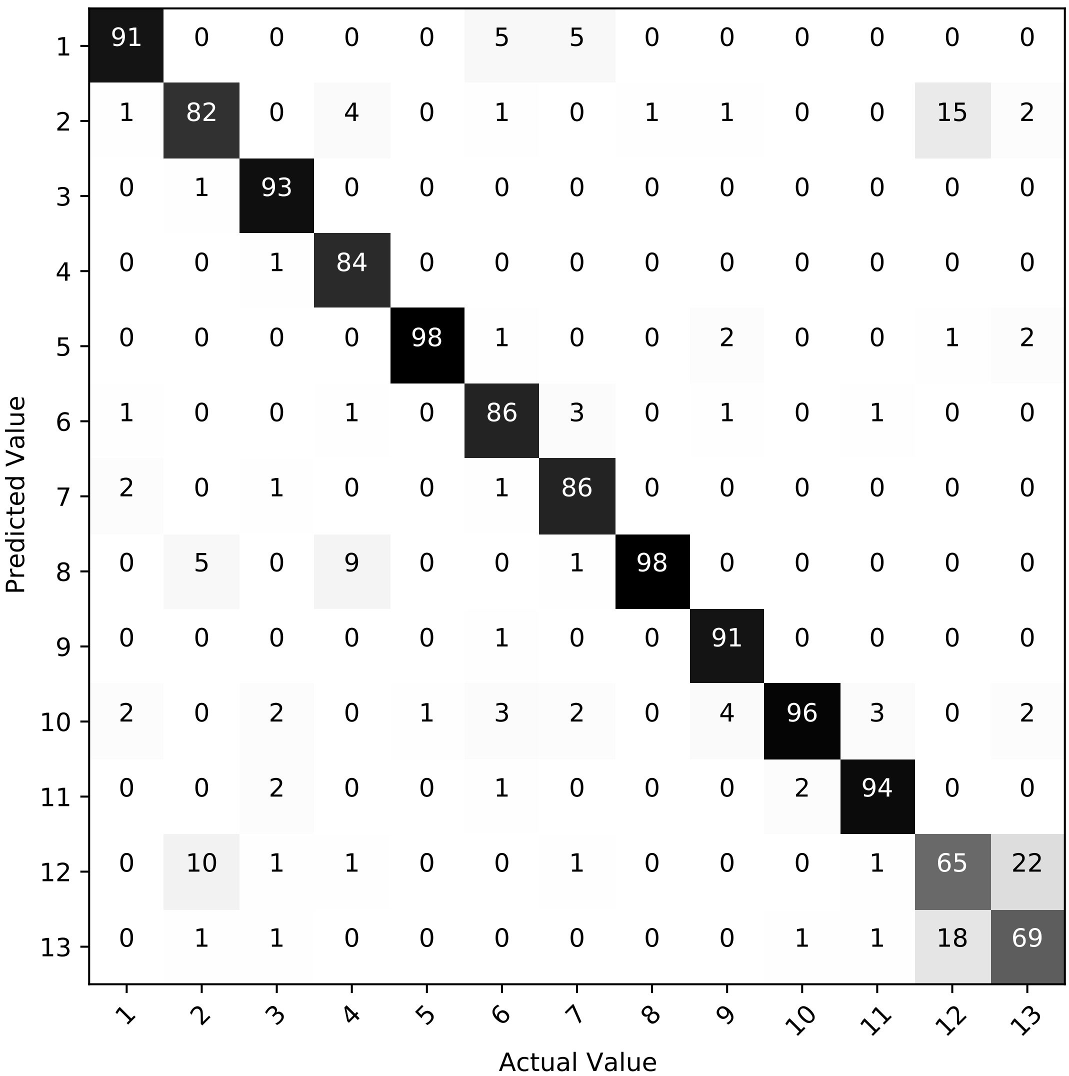

Figure 3.6: Confusion Matrix for Proposed Method of 3 Spaced Data Points

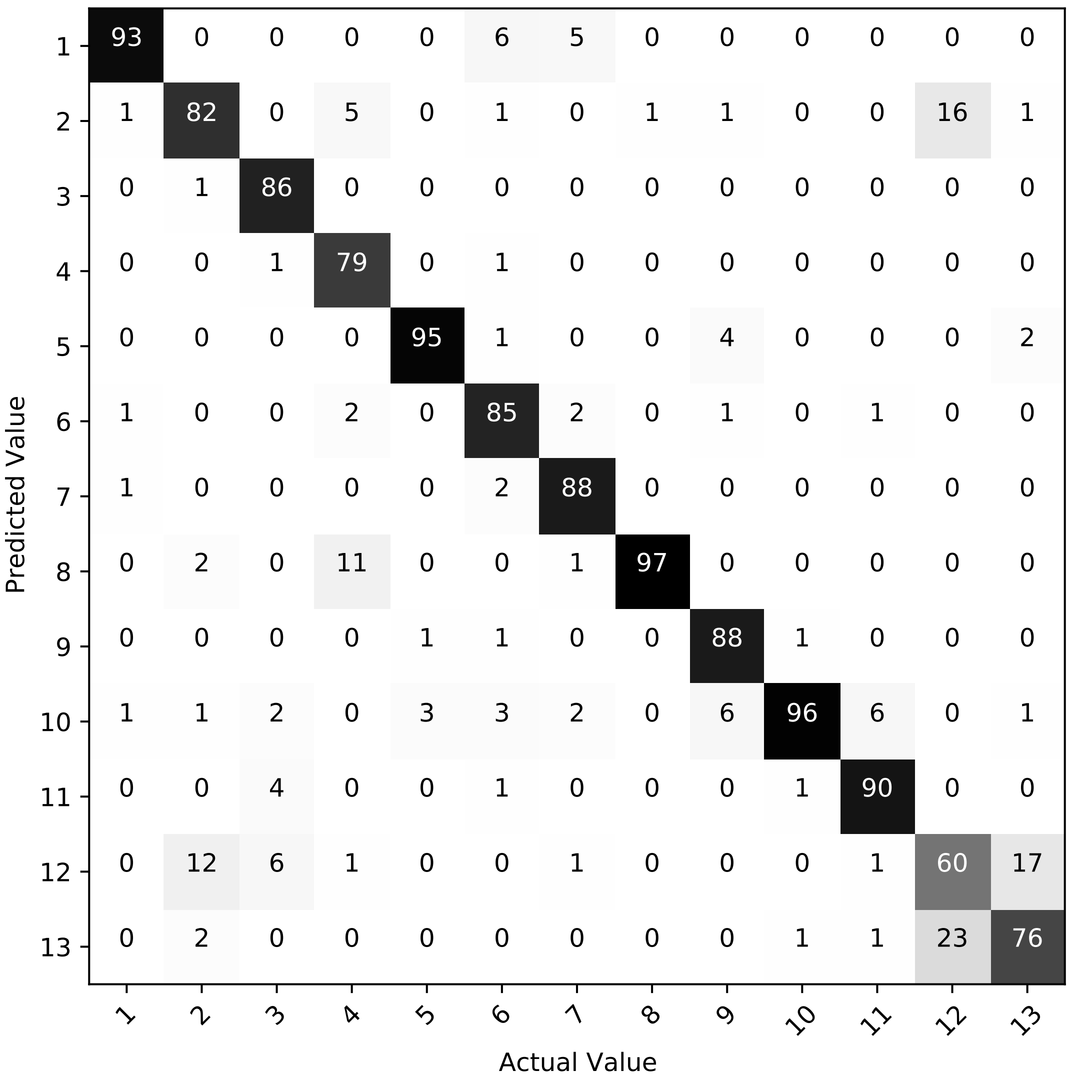

Figure 3.7: Confusion Matrix for Entire Day of Data

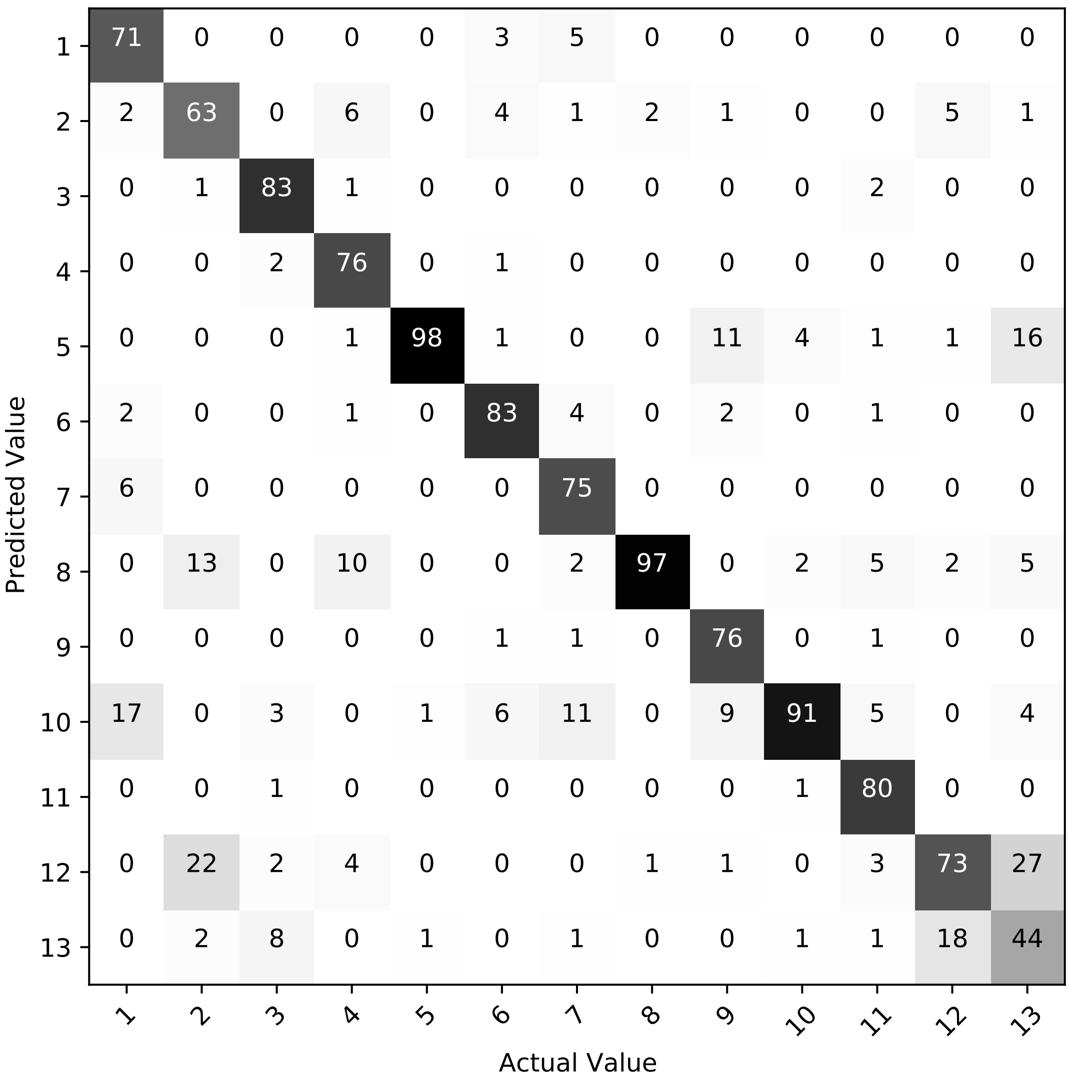

Figure 3.8: Confusion Matrix for Single Testing Day Session

collected. Secondly, through exploiting the traits of this higher density dataset, it was possible to demonstrate an initially comparative result as those shown by [97] on the CSL-HDEMG and CapgMyo DB-b datasets, with the proposed training strategies demonstrating a similar or higher recognition accuracy.

The single sessions accuracy and reduction in accuracy when excluding a testing day dataset demonstrates the previous conclusion by Amsuss et al [4] that classification accuracy decreases as a function of time. The accuracy of using 4 morning sessions is directly inline with those displayed by Kaufmann [96] when using LDA, where the error rate they had found was 21.27%, whilst this study found an error rate of 25% when using their first 5 sessions. Unfortunately, Kaufmann had not noted which periods of each day saw data collection, only that 5 datasets represented an entire day of data, whereas this study focused on the impact of when the data is collected within a day. However, when given any set of 4 consecutive hours provided similar performance on inter-day trials, suggesting that any 4 consecutive sessions will provide a seemingly reliable description of the sEMG signal. It can further be agreed that using larger quantities of data, such as an entire day of data, would provide higher classification accuracy, however, the increase in accuracy is not statistically significant enough to justify the increase in computation and burden on the user.

Although the proposed method, with no prior knowledge of the testing day, achieves a similar degree of accuracy to training the algorithm in the morning of the testing day, the removal of the requirement to train the device immediately and achieve a reasonable degree of accuracy is very promising. Through the addition of the testing day data, the proposed method provided a very good inter-day accuracy without any modification to the training dataset. The extent of the inter-day accuracy is one where it could be expected to achieve high accuracy on future datasets, regardless of time difference between the original training day and present day.

As shown in the confusion matrices in Fig.3.8, the simple gestures routinely were easy to classify from each test case, or at least represented the final accuracy best. The two complex gestures routinely scored very low, often being misclassified as one another. Due to this drop in accuracy being so localized, it could be suggested that using this method without those two classes could be more beneficial for the prosthesis user. The researcher is, however, of the opinion that it is important to promote a prosthesis control scheme which is both natural and intuitive for the amputee. Regarding the actual outputted results, differing methods would either provide higher accuracy on one complex gesture at the cost of reduced accuracy on the other gesture. Although the performance of the proposed algorithm for complex gestures is still not fully adequate for control, it displays a promising removal of the bias for either gesture.

While LDA was the only chosen classifier in this work, the results display promise towards future work with other classifiers such as MLP's or SVM. Particularly to investigate if the proposed training strategies may demonstrate similar or increased robustness to inter session usage.

It should be noted that although the performance of this method is good for the majority of presented data, it has not been tested against fatigued data or data where the presence of shift exists. Subsequently, the robustness of this method has not yet been shown to be resilient to transient changes other than those which naturally throughout a day or across a period of time.

3.7 Summary

In this chapter, the relationship between the periods of a day and the sEMG signal was investigated. The motivation of this investigation is to verify if there exists components within active daily life that may be contributory to long term sEMG based sensing as opposed to the arbitrary addition of data to a dataset, or if the decay in hand motion classification accuracy is only a function of transient changes, such as electrode shift or fatigue.

From the results of this preliminary study, there lies two main conclusions. Firstly, that selection of a data that can represent the change in the sEMG signal throughout a standard day is capable of achieving an acceptable degree of accuracy in the long term. Further to this point, it can be assumed that such data must be fully representative of the day itself, at the risk of losing stability.

Secondly, the selection strategies in this chapter suggest that usage of this studies 16 session entire days data provides minimal increase in classification accuracy when compared to less human intensive, more simplistic, and more computationally efficient methods.

The intent of this research was to investigate the changes in the sEMG signal during a day, its impact on classification accuracy over a series of days, and to find a method that was suited to promoting a robust training set for inter-day classification throughout each day.

It is suggested that future directions to expand upon this research is to look at ways of optimising or otherwise processing the original training dataset to better describe the shift in the sEMG signal, either through promoting expansion or promoting clustering. Further cases of study may also investigate the relative change in performance with days that experience high degrees of fatigue or other transient changes during a single day, where external changes may impact the quality of the sEMG signal.

Chapter 4

A-mode Ultrasound Led Sensor Fusion for Hand Gesture Recognition

In chapter 3, a training strategy to promote long term use of sEMG based sensing was proposed. This methodology contributed in expanding our understanding of the influence and relationship of time on sEMG based sensing.

This chapter attempts to approach the current limitations of sEMG based sensing through exploring the promising performance of ultrasound based sensing for hand motion recognition. It was previously highlighted in section 2.2.5 that aspects such as shift, dynamic actions, and long term use may pose issues in many forms of unimodal sensing yet also that several sensing modalities demonstrated robustness to certain transient aspects of bio-signals.

This chapter is structured as follows. Firstly, a brief introduction is given towards the challenge of sEMG sensing and the need to explore alternative modalities. Secondly, the modality of A-mode ultrasound is highlighted for its novel potential to sense deep muscle activity yet may also manifest some weaknesses in comparison to sEMG sensing. Subsequently an investigation into A-mode ultrasound prove shift is performed with an exhaustive search of applying traditional sEMG features into this domain in section. 4.2.3. The findings from this investigation are then Incorporated into a multimodal ultrasound led approach towards hand motion recognition during larger arm movements where the implemented method is compared to unimodal ultrasound and sEMG in section.4.3. Finally, a conclusion and suggestions towards future works with A-mode ultrasound is presented.

4.1 Introduction

Bio-Signal controlled prosthesis are highly important to enabling amputees to be capable of mitigating the impact on their quality of life that comes with a lost limb [106]. Whereas early prosthesis had either limited or just no functionality, modern prosthesis have seen promising growth in providing a more intuitive control system for amputees. Generally speaking, a bio-signal controlled prosthesis attempts to relate a given set of bio-input to a set of anticipated motions. The exact forms of bio-signal controlled upper limb prosthesis can be divided into two categories, conventional bio-signal prosthesis or pattern recognition based bio-Signal control strategies [177]. The most common form of these bio-signal controlled devices comes in the form of Electromyography (EMG) based bio-signal control devices. Traditionally conventional EMG controlled prosthesis followed an "on-off" switched control system, however newer conventional devices provide a more diverse series of control routines and inputs [178]. The benefit of these conventional approaches are that they are simple to implement, provide a desirable degree of robustness to transient changes in the bio-signal, and can satisfy the basic needs of an amputee for daily use. Conversely, conventional bio-signal controlled prosthesis hold limitations in several areas, such as having limited degrees of functionality and most importantly that their control scheme is unnatural in comparison to how a person would naturally move their original limb prior to amputation. Pattern Recognition based approaches, however, follow in the concept that an amputee may be able to voluntarily produce repeatable bio-signals that can be directly mapped to gestures that are best fitting to that bio-signal. Therefore, pattern recognition based approaches have seen considerable growth of interest in academia in recent years as they promise control schemes which are seemingly more natural to an amputee, whilst also providing a potentially larger pool of gestures that an amputee can perform therefore allowing a larger increase in quality of life, and finally this natural control scheme may aid in reducing the cognitive burden involved in the rehabilitative procedure of training the amputee with their new prosthesis.

4.2 Ultrasound Feature Extraction and Selection

4.2.1 Transient Changes

As with Conventional approaches, Pattern Recognition devices that utilize EMG have seen much popularity within academia, presently demonstrating highly promising results within laboratory environments. Unfortunately, EMG based pattern recognition approaches experience varying issues in their viability once applied to a clinical scenario. As for how such a dichotomy may occur a specific set of transient changes within Pattern Recognition based control systems have been cited in literature, these issues being electrode shift [179], crosstalk, fatigue [180], changes to skin conductivity, time[4, 181, 182], and concept drift.

4.2.1.1 Ultrasound

In an attempt to explore robust alternatives to SEMG motion recognition, researchers have in recent years began investigating the applicability of ultrasound sensors for the purpose of motion recognition [183] [184]. With good promise being displayed in the topics of rehabilitative Human Machine Interaction [185]. Researchers have noted that the higher resolution of Ultrasound Signal and ability to observe deeper tissue than SEMG sensors as factors that could provide more robust control schemes [186]. The usage Ultrasound (US) imaging has long been used as a non invasive method for visualizing the inside of a body. The method of action for US Imaging, in its most simple form, is by projecting a beam of high frequency sound waves from a piezoelectric transducer, where the subsequent echoes of this sound wave can then be monitored for intensity and amount of time it took for the echo to return. This common usage of ultrasound for imaging in the medical field can be tied to the capability of the ultrasonic sound waves to penetrate soft tissues without harming them, a trait long previously recognised by [187]. Methods of ultrasound data collection can utilize either Brightness Modulation (B-Mode) or Amplitude Modulation (A-mode). A-mode ultrasound uses a single ultrasound transducer and can be represented as an X and Y axis chart, where the X axis indicates depth and the Y axis indicates amplitude. B-Mode ultrasound, can be considered an array of A-mode transducers, generating an image that shows each transducers X axis to indicate depth whilst varying the brightness of each pixel to represent amplitude. Typically, Ultrasound methods used for hand motion recognition will either be the more traditional B-Mode Ultrasound, or the somewhat more compact but low resolution A-mode Ultrasound.

4.2.1.2 Area of focus - Electrode / Diode shift

As with sEMG based hand motion recognition, ultrasound diode shift may drastically impact the quality of long term hand motion recognition. Frequently with sEMG devices, a small degree of electrode shift may have an insignificant impact on the classifiers performance. The likely reasoning for this being due to area of detection of sEMG electrodes to be shallow but across a larger area, frequently meaning that the main impact of electrode shift comes in the form of reduced amplitude of the targeted muscle and increased crosstalk form neighbouring muscles. It had also been observed that shift may impact SEMG signals dependent upon if the shift is perpendicular or parallel to the original location [188].

With A-mode ultrasound, the issue of shift manifests itself in a much more noticeable fashion. It could best be considered to be from the area targeted by A-mode ultrasound diodes to be deeper than sEMG electrodes but also much more concentrated, effectively removing much of the crosstalk but providing very different signals dependant upon the sensors location.

Although it is an easy argument to make that the quality of A-mode ultrasound will be affected heavily by ultrasound shift, it is important that we quantify just what degree of performance impact can be expected from such shift such that we may make progress towards counteracting shift.

4.2.2 System and Experiments

4.2.2.1 Ultrasound System and Data representation

The ultrasound data was collected through a 2 channel A-mode Ultrasound device that collected 100 data points (or time dots) at a rate of 10MHZ. The device was placed on the muscle grouping above and below the wrist of the candidate. Transmission was performed via Ethernet.

While the hardware is capable of handling 4 channels of A-mode Ultrasound, the two channels chosen are for purposes of representation and predictability of shift. As both the top and bottom of the arm hold flat areas that hold large variations in bone and muscle formations, it is possible to map out the selected degrees of shift and reliably collected data from each location. While the sides of the arm could be used for a further two channels in this study, the full mapping and accurate movement of shift would be difficult to fit within the reliable time window of data freshness as full recording for two channels would take an average of two hours. As shown in Chapter.3 and as referenced in 3.2, classification accuracy decay can be considered as a function of time such that a much longer delay between the start and end of data collection may degrade gesture recognition accuracy for reasons other than diode shift conditions. In the absence of research into the changes in long term ultrasound based hand motion recognition, it was chosen to use the optimum number of channels that could be collected while minimizing potentials factors other than sensor shift.

For this study, a single able bodied male participant was used as a pilot to investigate the potential of applying EMG feature extraction methods to A-mode ultrasound and subsequently to evaluate if these methods could be robust to diode shift. This study was approved by the local ethics committee, ethics reference number: TECH2019-PB-03

In order to correctly model the degree of shift across the targeted muscle area, a 7 by 7 grid of 49 individual locations was marked on the top and bottom of the subjects forearm. Every location in the grid was spaced by 4mm, half of the width of the ultrasound probe. This set location of space was chosen to simulate both the potential shift from extended daily use, and the expected shift from donning and doffing the ultrasound device.

The grid was physically marked by placing a template sheet of flexible material on the arm and using pre-defined holes in the sheet to mark a pen onto the subjects arm. Mapping of the ultrasound diode to the shift location was done through aligning markers on the front and sides of the ultrasound diode with matching pen markers on the participants arm.

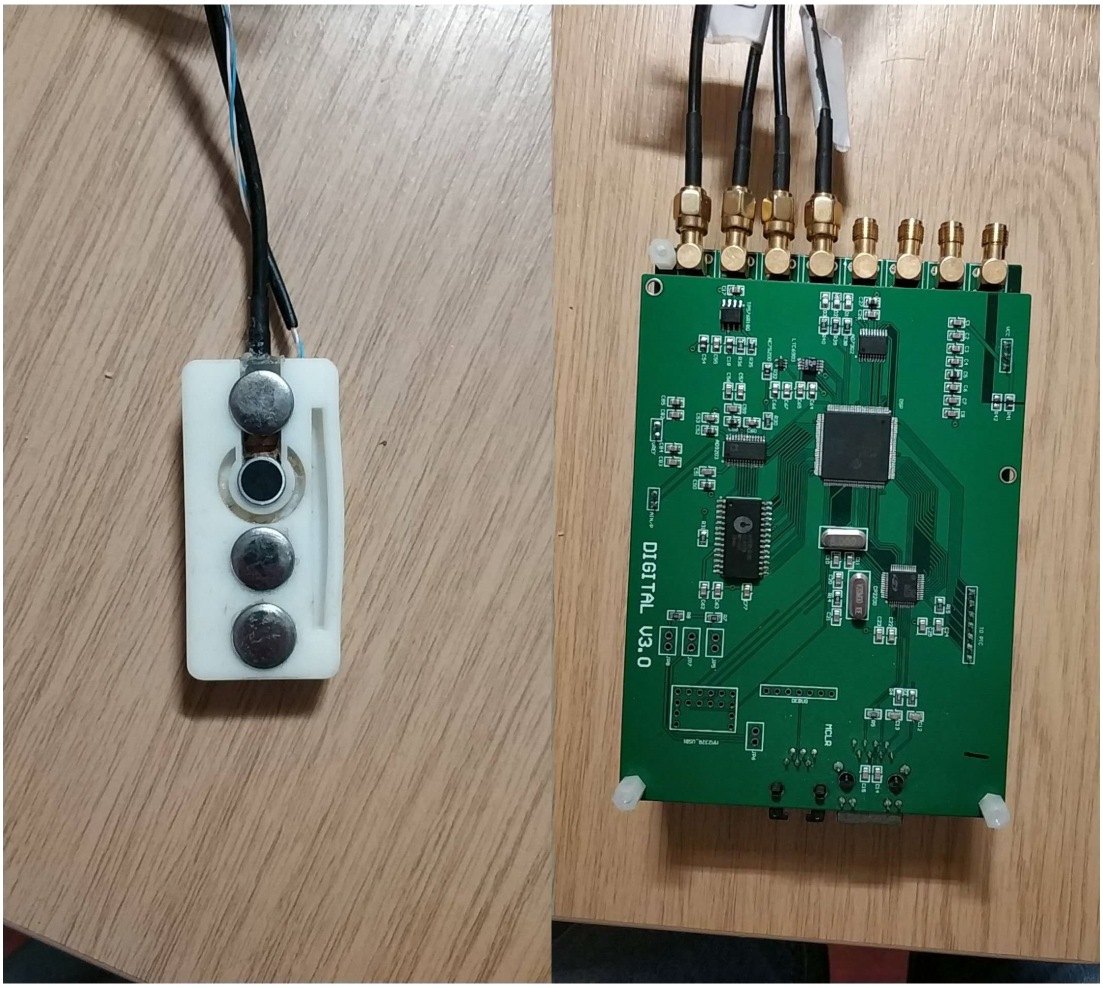

Figure 4.1: Ultrasound collection hardware, on left is the combination sEMG and A-mode ultrasound diode. The picture to the tight shows the physical hardware device. used in this study.

4.2.2.2 Motions

For this preliminary study, a single able bodied participant was used. The participant had prior experience with SEMG motion recognition. for each set of data collected, the participant would be advised to follow a set of hand motion gestures in sequence through on-screen guidance. After every set of motions was completed, both the upper and lower Ultrasound diode would be moved to a new location with ultrasound gel reapplied as necessary.

The motion collection scheme consisted of 6 gestures that involved either movement of the wrist or hand. The selected gestures were hand at rest, hand open, hand closed, wrist flexion, wrist extension, fine pinch. Each gesture was performed sequentially, for a period of 10 seconds per gesture before shifting to the next gesture. A period of 5 minutes was provided between locational shifts as to prevent fatigue. The chosen gesture pool was decided as to include typical gestures seen in sEMG and ultrasound based research to provide a reasonable metric of accuracy.

The motion collection scheme consisted of several minor and major movements involving the hand or entire arm referred to as a primitive. For every collected dataset, a particular motion and its opposite would be performed sequentially, before a period of resting time. The allocated time per gesture was 5 seconds each, with a 10 second resting period. As each set of primitives were repeated 5 times, the resulting dataset would feature 110 seconds of data with 50 seconds of motion activity.

4.2.3 Methodology

4.2.3.1 Ultrasound Feature Extraction

A-mode Ultrasound manifests itself as a linear set of time points and amplitudes that describe the echo intensity from the Ultrasound diode, as seen in figure. 4.2. These signals enable traditional sEMG feature extraction methods to be utilized as to describe the signal as each channel of A-mode ultrasound signal can behave like a single channel sEMG channel. Previously, researchers had applied Mean Square Deviation (MSD) features to A-mode Ultrasound based hand motion recognition [189]. However, there exists a gap in literature relating to feature extraction for A-mode ultrasound hand motion recognition. In this study, MSD feature extraction will be utilized alongside other typical sEMG based feature extraction techniques. The purpose of this is to compare a currently utilized feature extraction technique and to investigate the applicability of sEMG based feature extraction techniques to A-mode ultrasound signal.

4.2.3.2 Data Pre-Processing

All data processing was completed using Matlab r2017b. The pre processing for the ultrasound data firstly saw 6 seconds of stable motion data from each 10 second gesture performed, by removing 2 seconds from the beginning and end of each gesture. The intention of trimming using only the stable motion data is to the starting and ending 20 time points of each frame of data as the information carried here was not considered meaningful. A hilbert transform was subsequently applied onto the trimmed data and the envelope was extracted when viable for the chosen feature as shown in figure. 4.2.

As the A-mode ultrasound data consists of a single frame every 100ms containing 960 time points, these time points indicating the muscle activity at a given depth from the US Diode. Presently, as there exists little comparative US feature selection strategies or comparisons. Therefore, traditional feature extraction methods for EMG data were to be modified to better exploit the generalisable traits of the data. The approach to feature extraction was to operate directly on the time points within each frame, as opposed to across multiple frames, using a 120ms window and a 30ms sliding window.

4.2.3.3 Data Processing

As mentioned in the pre-processing stage, few feature selection methods for A-mode Ultrasound have been evaluated in literature. Therefore this paper shall explore the applicability of of several TD-AR methods in both the no shift and the shift conditions.

To evaluate the quality of the feature sets, several simple features shall be selected, these being Root Mean Square (RMS), Auto Regressive Coefficients (AR), Waveform Transform (WL), Slope Sign Change(SSC), Mean + Standard Deviation (MSD), Zero Crossing (ZC), and Mean Absolute Value (MAV), all of these being traditional EMG feature extraction methods that had been implemented frequently in literature. Researchers have recognized that combinations of feature extraction methods may provide more robust gesture recognition than individual features in sEMG sensing. Therefore several combinations of simple features will be evaluated alongside the individual

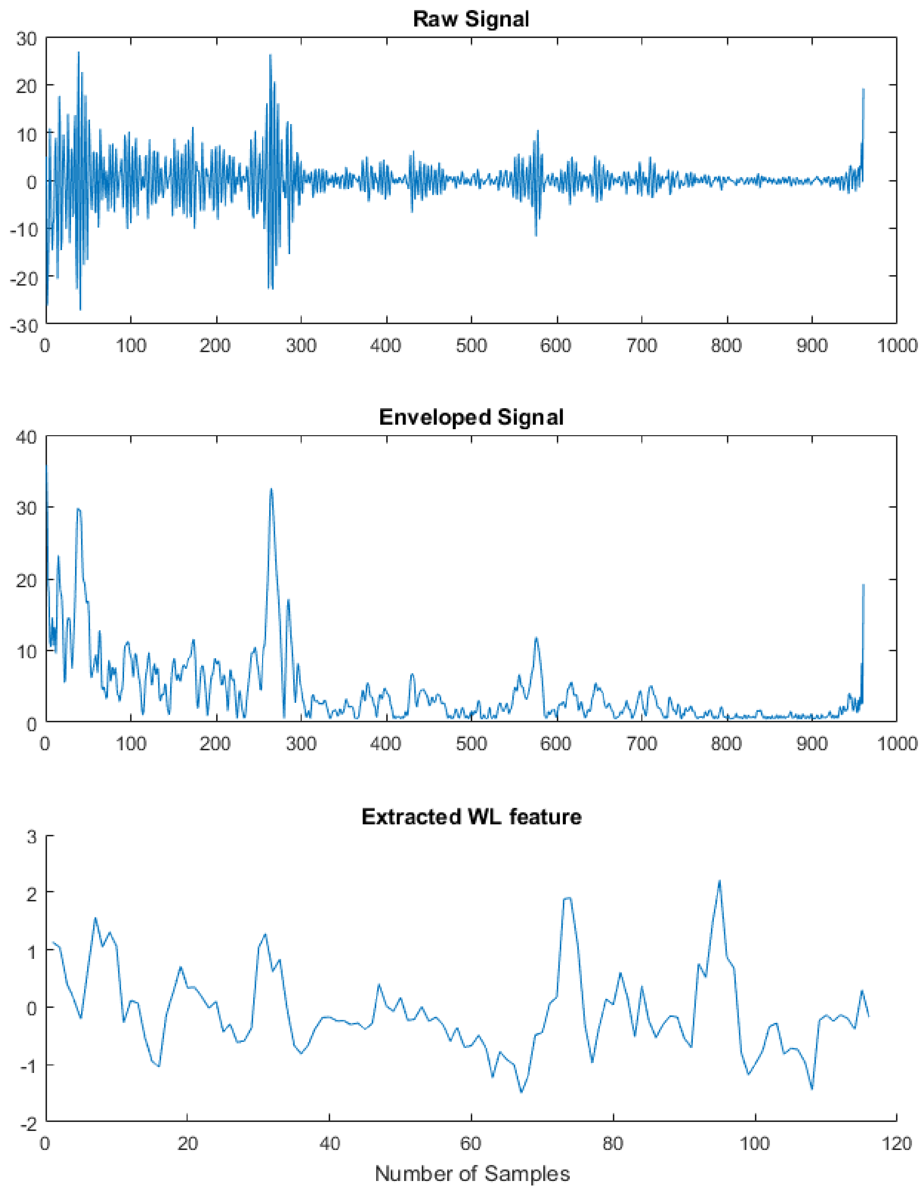

Figure 4.2: Example of feature extraction with A-mode ultrasound into a Waveform Length Feature with hilbert transform

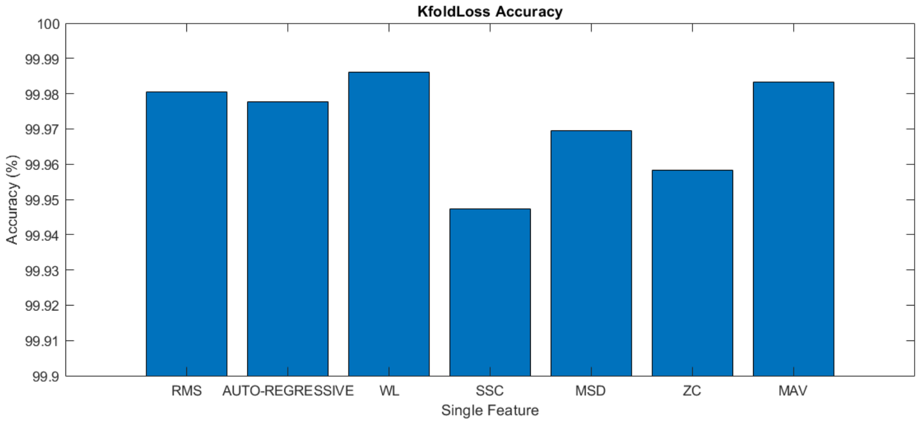

Figure 4.3: Relative Cross Validation results on the hand motion recognition Accuracy from each individual feature method

features to observe if singular features or feature sets may be better suited for A-mode based ultrasound hand motion recognition.

For classification, LDA, was used, due to this being suggested as a method that is robust to changes in the input signal [190], alongside performing well during Ultrasound Hand Motion Recognition compared to methods such as Decision trees [88].

4.2.4 Results

In fig.4.3, the results of cross validation applied for each set of single Feature case then presented as an average of all 49 locational datasets. Generally, the performance of each method provides very good responses for when there is no shift in the Ultrasound sensor. The scores under no shift frequently matching those shown in other research [39, 35, 42]. However, once shift is applied, then the rate of accuracy for all cases begin to drop at a considerable rate, as shown in fig4.4. As A-mode ultrasound projects only a single beam into the body, it is expected that larger movements across an area such as the forearm may witness larger changes than other parts of the body.

One noticeable change between the two charts is where Zero Crossing and Slope Sign change perform the worst under no shift, however, once shift is applied then both methods achieve not only a higher base accuracy, but also degrade at a similar but reduced rate in comparison to other methods. One possibility for this result is that zero

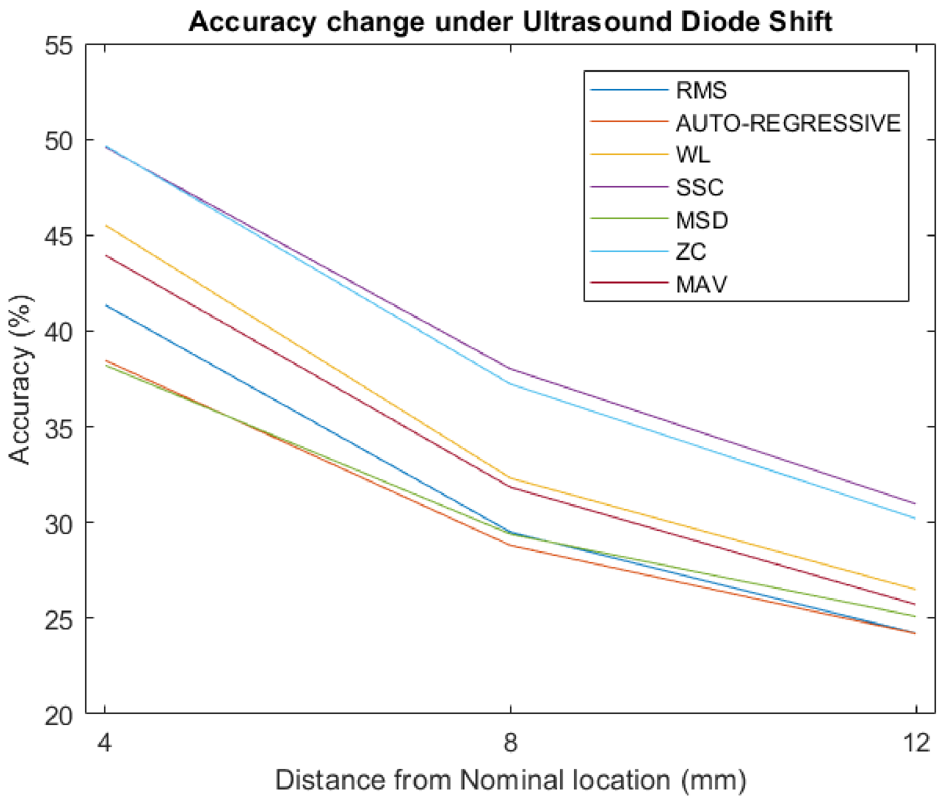

Figure 4.4: Change in Accuracy under Ultrasound Sensor Shift conditions with single features, showing the decrease in recognition accuracy the further the electrode gets from the nominal location

crossing and slope sign change features are only influenced by changes in the signal over the amplitude of the signal.

In Table 4.1, the spatial performance of all single features are displayed, alongside the top five of each increasingly large feature set upto size for features =5, then the top two sets of six feature featuresets, and finally the featureset of all features together. The most visible trait of this table is that each subsequent set of combined features perform worse than the prior best performing features, such as SSC-ZC out performing the WL-SSC-ZC combination.

4.2.5 Discussion

In this study, several feature extraction methods were analysed to observe their robustness to Ultrasound Sensor Shift. The results of this study demonstrated that, while ultrasound based methods achieve good accuracy when kept on the nominal location, there is a significant impact on performance from shift, especially when larger than 4mm shift. this would appear to be very much in-line with the findings of other researchers when experiencing transducer shift [37, 184], alongside similar reports being found in SEMG signal pattern recognition[191]. One likely factor into the heavier degrade in accuracy seen in this study is due to the nature of A-mode Ultrasound having a deeper but much more concentrated section of the arm to observe, in a sense it could be considered that the resilience to crosstalk also makes Ultrasound methods less resilient to shift. Other factors that could potentially negatively impact the performance of a Ultrasound based method is that of the subject unconsciously moving their wrist, or fingers wither when performing a movement or by not fully returning to a rest state, as noted by Li [192]. Further to this, the grip strength used in a grasp may also deteriorate a classifier, as noted by Ortenzi et al [88]. However, the most likely major factor here is directly due to the manifestation of shift itself and therefore the focus is on what feature sets may be robust to this issue.

One notable trait of the results displayed here is that the multiple feature datasets all gradually performed worse as more features were added. This could imply a degree of over training is occurring from the single nominal location datasets. In all cases, Zero Crossing, Slope sign change, and Waveform Length, constituted the three main features in any strong dataset. Therefore, it could be described that these 3 features are

Table 4.1: Comparison of Feature Extraction techniques and Feature sets under sensor Shift

Feature	Accuracy		
	4mm	8mm	12mm
Root Mean Square (RMS)	41.3502	29.4994	24.2456
AutoRegressive (AR)	38.4634	28.8036	24.2031
Waveform Length (WL)	45.5218	32.3189	26.5053
Slopesign Change (SSC)	49.5948	38.0151	30.9701
Mean + Standard Deviation (MSD)	38.2035	29.3982	25.1040
Zero Crossing (ZC)	49.6582	37.2260	30.2115
Mean Absolute Value (MAV)	43.9495	31.8411	27.7215
SSC-ZC	49.2386	37.2020	30.6760
WL-ZC	45.7314	32.4774	26.5321
WL-SSC	44.8713	32.3658	26.2964
ZC-MAV	44.1881	32.0853	26.0027
WL-MAV	43.9709	31.5118	28.9517
WL-SSC-ZC	44.8788	31.6372	25.9495
SSC-ZC-MAV	43.7783	31.6879	25.7942
WL-ZC-MAV	43.5127	31.1777	25.6881
WL-SSC-MAV	43.1884	31.3576	26.1230
WL-MSD-ZC	43.1755	31.5351	25.9677
SSC-MSD-ZC-MAV	42.2245	30.0888	25.3892
WL-MSD-ZC-MAV	42.0067	30.1947	24.7848
WL-SSC-MSD-ZC	41.9771	30.5604	25.4144
WL-SSC-MSD-MAV	41.9579	30.5913	25.0622
WL-SSC-ZC-MAV	41.4526	30.4854	25.6745
AUTO-REGRESSIVE-WL-SSC-ZC-MAV	42.6839	30.8301	25.3570
AUTO-REGRESSIVE-WL-SSC-MSD-ZC	42.3035	31.3956	25.6678
RMS-AUTO-REGRESSIVE-SSC-ZC-MAV	41.9753	30.3633	25.1596
AUTO-REGRESSIVE-SSC-MSD-ZC-MAV	41.9150	30.0390	24.9601
RMS-AUTO-REGRESSIVE-WL-SSC-ZC	41.8352	31.0312	25.4697
AUTO-REGRESSIVE-WL-SSC-MSD-ZC-MAV	43.7954	32.0128	26.3671
RMS-AUTO-REGRESSIVE-WL-SSC-MSD-ZC-MAV	43.7206	32.5627	26.7492

far more robust to the occurrence of Sensor shift in Ultrasound hand motion recognition. This could suggest that these methods are stronger at defining the spikes within the ultrasound signal, while other approaches are likely to smooth the signal and bring forward minor changes in signal that don't relate directly to expected signal. Moving forward, there could be great promise in combining these existing features with methods that promote retraining, or the construction of robust datasets that anticipate the impact of shift or other transient changes in signal [63, 193].

As described in section 4.2.3, A-mode ultrasound based hand motion recognition can be extremely accurate for deep muscle activity, however, certain implementations may be more susceptible to shift although correct selection of features may provide a more robust interface. Considering that the degree of shift applied also extends beyond that which can be anticipated during use then it shows good promise to the viability of a mode ultrasound sensing for hand motion recognition. This novel investigation into A-mode ultrasound shift can provide good guidance to future researchers.

A further consideration is that the results displayed here are on a two channel system, whilst prior studies used a 4 channel device. It is likely that a 4 channel device could only serve to further improve the accuracy demonstrated in this study.

4.3 Ultrasound Led Hand Motion Recognition

Previously researchers have attempted to resolve limitations in sEMG sensing through the combination of sEMG based unimodal sensing through the addition of additive sensing modalities which were investigated in section 2.2.5 and have shown good promise in fusion modality sensing. Expanding on the promising directions shown for fusion modality sensing, this section shall attempt to explore improving the quality of sEMG based hand motion recognition through utilizing A-mode ultrasound led sensing.

A common challenge found in sEMG based is that of large arm movements and in situations where the location of an arm is not in the comfortable position frequently seen within laboratory experiments. It can be considered that a factor which inhibits the capability of sEMG based sensing with pattern recognition is that of crosstalk. As the arm moves into dynamic poses there exists a degree of shift and co-activation of muscle groupings surrounding the targeted muscles which subsequently impact recognition accuracy. The issue is further amplified when considering larger muscle groups in the biceps.

As ultrasound based sensing is capable of detection only the activity of the targeted muscle boundaries then this degree of crosstalk may be possible to be avoided or at least minimized through introducing ultrasound as the dominant sensing medium for hand motion recognition with sEMG based sensing to provide context to larger arm muscle activation.

4.3.1 Hypothesis

The Hypothesis of this study is therefore that the addition of A-mode ultrasound based sensing to sEMG based sensing can provide a meaningful increase to hand motion recognition with larger arm movements.

4.3.2 Experimental Setup

As with the prior work, an A-mode ultrasound capturing device was used to retrieve the subjects bio-signals. However, an additional two channels were implemented as to gain a deeper insight into the muscle activity across the subjects forearm bringing the total quantity of ultrasound channels to 4. To maintain a secure fitting for the US sensors, an elastic skin tape was used to secure the sensors in their correct location along the subjects arm. Hypoallergenic Ultrasound gel, Anagel ultrasound gel, was applied prior to each set of data collection as to ensure improve the transmission quality of the ultrasound signals and to reduce interference from air gaps.

The sEMG hardware described in section 3.3.1 was used however, the sEMG 16 channel elasticated armband was replaced for 6 pairs of wet electrodes. As this study focuses on A-mode ultrasound led hand motion recognition, the 6 pairs of bi polar electrodes were instead distributed on the major muscle sites of the arm as to provide muscle activation information during larger arm movements. The chosen electrode locations are the lateral deltoid, biceps bracchii shorthead, supinator, and pronator teres and ticeps bacchii. The fitting of the wet electrodes and A-mode ultrasound hardware can be seen in figure 4.5. Two able bodied participants aged between 26 and 32 were used in this study. The experiments carried out were confirmed by the local ethics committee, reference number: TECH2019-PB-03.

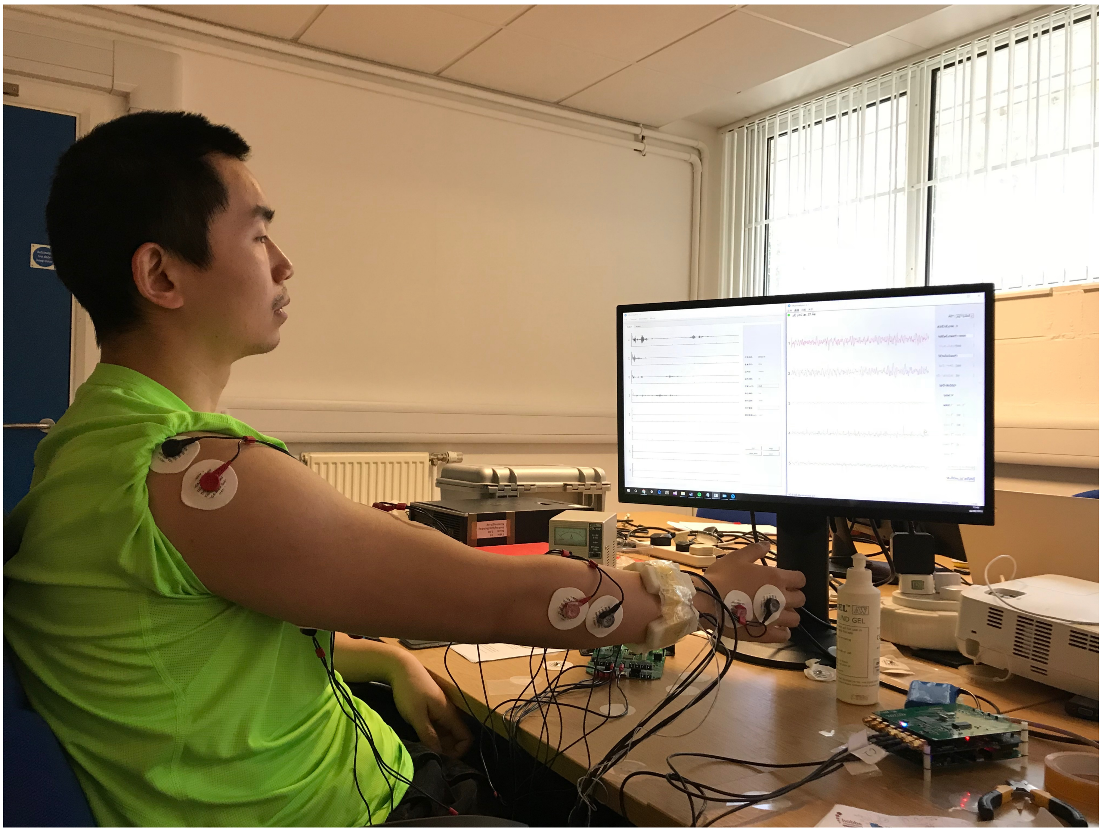

Figure 4.5: Multimodal Ultrasound and sEMG experimental setup

4.3.2.1 Data capture

The data capture was divided into 5 trials with ten gestures performed per trial. In order to acquire a dynamic range of motion activity across the whole arm five motion primitives were selected and performed in their open pose and inverse totalling in ten hand and arm motions. The chosen primitives were as follows in order Hand Open (HO), Hand Closed (HC), Forearm Pronation (FP), Forearm Supination (FS), Rotation In (RI), Rotation Out (RO), Humerus Forward (HF), Humerus Backward (HB), Wrist Flexion (WF), Wrist Extension (WE). Each individual motion was performed for five seconds before shifting to its inverse motion and then a rest period of ten seconds between motion primitive. Each trial lasted for a total of 110 seconds including the initial rest period with a total of 50 seconds of motion activity. There was no change of the electrode or ultrasound sensor placement between trials as to introduce a degree of the natural shift that may form with daily use of this combined sensing modality.

No shift conditions were applied during this condition, as this section focuses on the capability of recognizing large arm movements where shift may naturally exist due to larger arm changes that may be experienced during daily use, whilst the previous study focused on gesture shift within hand movements alone inline with typical sEMG gesture recognition schemes.

4.3.3 Data Processing

The approach to processing the collected ultrasound signals was very much similar to that in section 4.2.3.2 while synchronising the sEMG signal and ultrasound signal was performed through manual recognition of the first muscle activation. sEMG signals were filtered and processed much in accordance to the manner used in section 3.4.1. Using the information displayed in the Table 4.1, the waveform length feature was selected to represent the ultrasound signals due to the strong performance shown under both no shift and shift scenarios. sEMG signals were represented by the RMS feature. The fusion scheme consisted of appending the sEMG signal data to the A-mode ultrasound data after feature extraction. The rationale behind this decision is that the while ultrasound data may provide accurate recognition of the hand gesture, the supplemental information from the sEMG signal will provide information about the larger arm motion. All classification was performed using LDA with naive bayes due to the classifiers robustness. Classifier training was performed using a single trial that was evaluated with cross validation against the other 4 trials.

4.3.4 Results and discussion

To verify the performance of the ultrasound led method, each set of 5 trials were evaluated on the basis of sEMG alone, A-mode ultrasound alone, and finally the A-mode ultrasound led approach.

As seen in Fig.4.6, the sEMG unimodal approach demonstrated the poorest performance overall, achieving an accuracy of 74.51%. The strongest modality for performance was the ultrasound unimodal approach with an accuracy of 82.91% which was closely followed by the multimodal ultrasound led approach at 78.65%. It can be inferred from this result that sEMG unimodal sensing is more susceptible to reduced classification accuracy during larger arm motions where crosstalk and interference from cabling may be more apparent. An interesting result is that of the performance from the unimodal ultrasound approach, which although only focused on the forearm area had managed to achieve reasonable accuracy during larger arm motions. The cause of this performance increase may likely come from smaller muscle changes that occur due to physiological changes of the arm as opposed to active MU activity. The potential for ultrasound to better recognize subtle changes in muscle boundaries is promising for future usage of A-mode ultrasound.

Subsequently, the capability of A-mode ultrasound to provide robust sensing to larger arm movements, the capabilities of sEMG based sensing was improved, albeit to a lesser degree than unimodal ultrasound. When placed in context of the investigation into ultrasound diode shift in section 4.2.4 and present research into sEMG sensor shift [194], there exists an argument that the ultrasound based approach provides robustness to larger arm movements, whereas sEMG based sensing may improve the robustness to sensor shift during daily use.

Future work in this in this direction would seek to exploring ultrasound based sensing in active dynamic tasks as to explore it's robustness to aspects of muscle crosstalk and dynamic muscle contractions which are challenges in sEMG based sensing. Moreover further exploration should be conducted towards long term use of multimodal A-mode ultrasound led sensing with sEMG such as in inter day use.

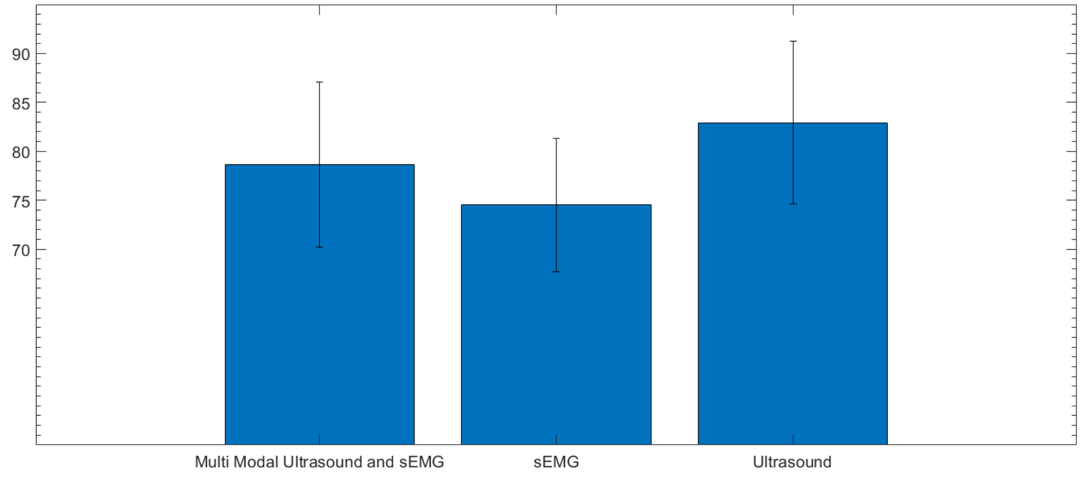

Figure 4.6: Multimodal hand motion recognition results

4.4 Summary

In this section, the robustness of traditional sEMG feature extraction techniques were explored when applied to Ultrasound Sensor based Hand motion recognition.From the results of this study, there are two major conclusions. Firstly: the main feature Extraction methods demonstrated that the quality of Ultrasound based hand motion recognition is extremely high under no shift conditions. However, it can be recognised that Ultrasound sensor shift can significantly affect the quality of the classification result, especially at larger ranges.

Secondly, the results that are demonstrated in this section indicate that combined feature sets seemingly do not perform as well as individual features. This could suggest that the matter comes to being related specifically to the representation of the ultrasound data , or potentially as a consequence of over training in the cases of combined feature sets.

Thirdly, a multi modal A-mode ultrasound led sensing platform was implemented and demonstrated to be feasible during larger arm motions particularly in comparison to unimodal sEMG and furthermore was shown to contribute to improving the quality of sEMG based sensing in this area.

It is suggested that future directions in Ultrasound hand motion recognition is to investigate whether the inclusion of more channels when considering sensor shift may further improve the classification accuracy alongside the impact of larger arm motions. To expand the features tested here on other traditional feature selection methods. Further to this, to investigate training strategies that may improve the robustness to sensor shift in Ultrasound. Furthermore, it is suggested to further investigate the relative comparison of Ultrasound based hand Motion Recognition, in comparison to EMG when considering Long Term Use. Finally, it is suggested to explore the capability of ultrasound led hand and arm motion recognition during more dynamic tasks as a multi modal approach with sEMG sensing.

The intent of this research was firstly to explore the relative robustness of different Ultrasound feature extractions methods under the situation of sensor shift and to find a feature or set of features that can provide a meaningful representation of the Ultrasound Signal for hand motion recognition. The second contribution of this research was to investigate the capability of ultrasound led sensing during larger arm motions, where the implemented ultrasound method was shown to outperform sEMG and to provide important muscle activation activity when fused with sEMG sensing.

Chapter 5

Virtual Environment Assisted Rehabilitation System for Precise sEMG Control and Repeatability

In Chapter 3 a novel methodology to examine the changing state of sEMG signals over time and during inter day use was explored where a subsequent training strategy that exploited the variable traits of sEMG signal in order to better define the invariant state of sEMG signal was proposed. Within chapter 4 the nature of ultrasound based hand motion recognition was explored in terms of robustness to shift and finally was used in a multimodal approach with sEMG based signal as a supporting signal trait. The unison of ultrasound for deep muscle activity and sEMG for wider area surface level sensing was demonstrated.

While the previous research works have their own novelty and demonstrate benefit towards sensing, they mainly focus on the sensing and adaptive state where observation of the user is performed with ideally minimal input from the user. Although these methods work well for their proposed purposes the scope of adaptability extends beyond that of just sensing and algorithm based hand motion recognition specifically towards that of rehabilitation.

During rehabilitation and long term use, a sensing modality and related recognition algorithms may only be capable of performing with a level of quality related to the data provided to them which in this case would be bio signals whether ultrasound or sEMG in the research conducted. For an amputee, the capability to reliably produce bio signals to a consistent degree is one of the early challenges for the rehabilitative process. Provided a user can produce consistent and repeatable signals then the quality of the sensing hardware and recognition algorithms outside of transient changes in signal can be assured.

Therefore, this chapter describes the development, implementation, and validation of a Virtual environment assisted rehabilitation system to enable precise sEMG control and reliability. The proposed system investigates the impact on the rehabilitative process towards learning fine grasping and being able to accurately grasp a virtual object without dropping or breaking the object. Most importantly, the proposed rehabilitative system attempts to close the loop of grasping control through the provision of feedback through virtual feedback and also through electrotactile feedback. The following chapter is structured as follows. The proposed rehabilitative system is then described in terms of the virtual environment, hardware utilized, and the interactions between each component. The methodology of the experiments and the evaluation criteria as to validate the rehabilitative system are described. Finally the results of the conducted experiments are discussed regarding their comparative performance metrics based on the criteria used to quantify the change to the training period and to the success in the testing period. Finally, the overall conclusions to the works in this chapter are described.

5.1 Introduction

5.1.1 Hypothesis

The hypothesis of this experiment is to find if Virtual and Electrotactile feedback can improve the repeatability of a grasping exercise when performed by a patient during rehabilitation. Specifically when the patient is required to maintain a specific quantity of voluntary contraction for a short period of time in order to grasp a virtual object.

5.2 System & Data Representation

5.2.1 Functional Modules

This study implemented a combination of 3 modules, Firstly an sEMG capture module, a Virtual Hand environment which includes fingertip deformation, and an electrotactile feedback module.

5.2.1.1 sEMG Capture Module

The sEMG signals were captured using a multi channel sEMG acquisition system, that enables up to 16 channels of sEMG signal capture, previously described in Chapter.3. This particular research only utilized two bi polar sEMG electrodes with one pair of electrodes for signal extraction and a secondary pair as a reference signal to remove noise. The minimal electrode setup was chosen as the targeted muscle activation is limited to that of an individual grasping exercise to support fine sEMG control in a single gesture as opposed to a pattern recognition approach. Moreover the focus of this study is on training to achieve specific grasping forces. Were this study to focus on a larger array of gestures beyond simple open / close grasping then 16 channels may be preferential. However, this work is focused specifically on verifying the feedback platform in a basic scenario.

The sampling rate used remained at 1KHz and sensing of this system utilized a standard powerline noise filter. A change with the hardware used in this study was for the sensing hardware to use bluetooth for data transfer whereas the device used in chapter 3 used a wired connection. The change in transmission medium had minimal impact on the captured signals for real time use. Processing of the captured signal used a simple median signal amplitude across a designated window of 150ms as the feature for recognition of grasping force. The reduced window compared to chapter 3 is due to the focus of this study utilizing direct sEMG activation as opposed to any pattern recognition, where a larger window may provide a more robust classification.

5.2.1.2 Electrotactile Stimulation Module

As previously discussed in chapter 2 there exists many forms of feedback methods to enable haptic responses to a prosthesis user that may utilize moving components to enact a sense of touch such as stretch, squeeze, or vibrotactile alongside feedback methods that use non moving components such as thermal or electrotactile. Based on the findings within the state of the art it can be concluded that electrotactile has numerous advantages such as low power consumption, lightweight, minimal noise, can have an almost instantaneous response, have a small form factor, and moreover can assist in recovering a natural sense of touch [195] .

The specific form of electrotactile simulator (ETS) used in this research was previously proposed in [196] towards the implementation of force feedback in a rehabilitative platform. The full range of the simulator used in this research can facilitate up to 16 channels of output with adjustable outputs including amplitude (0-100mA), frequency (1-200Hz), and pulse width (0-500 μs). Although the simulator is capable of various wave-forms as feedback, symmetric biphasic square pulses are chosen as the output signal. The selection of biphasic waves are due to the negative pulses produced being able to neutralize the charge accumulation on the users skin, the polarization effect on skin caused by positive pulses and prevents tissue damage [197]. While there exists research that uses many electrotactile feedback channels and the hardware used can support up to 16 channels, the usage of the electrotactile feedback system in this work only utilizes three channels with three levels of feedback per channel totalling at 9 feedback levels to represent force intensity.

5.2.1.3 Real Time Virtual Control System

In order to provide a Virtual system that can simulate human interaction in a realistic manner a physics based Virtual hand grasping task was developed within the Unity Engine. While there exists several platforms built specifically for medical simulation, the Unity engine was chosen for purposes of development, experiment modification, and finally for potential deployment outside of this study. For developmental reasons Unity provided ease of integration with the various hardware devices in use for this study and may be easily modified to accommodate alternative sensor devices due to interaction being handled in a C# back-end. The experiment based considerations for Unity were due to speed of changing experimental designs and experimental parameters. Other experiment based aspects for choosing unity were so that the various data collection needs and outputs could be modified easily through unities editor menu. The deployment related aspects behind selecting the unity engine is that the Unity based system can be deployed on desktop, mobile, and potentially VR applications. The freedom in deployment method can subsequently reduce the cost of a final system in terms of hardware requirements or potentially provide an enhanced rehabilitative experience through Virtual Reality. Furthermore, it was considered that the Unity engine having an easily customized user interface that can be either opened or reduced based on the experiments conditions would allow precise yet simple control of a virtual hand and therefore training for people who would administer experiments using the system. Although the Unity engine does not provide perfect physics based biomedical simulation, for the purposes of providing easily controlled realistic interaction within a virtual environment that does provide various degrees of modelled visual feedback then the Unity engine is relatively fit for purpose. The developed platform as shown in fig.5.1 is integrated with the sEMG sensing module and ETS feedback module to provide control and feedback in realtime. The hand itself holds the same 27 degrees of freedom as the typical human hand while the virtual implementation avoids the difficult challenge of creating a natural sense of movement from traditional mechanical actuators therefore allowing users to feel a natural and intuitive sense of fluid motion when controlling the virtual hand. To further simulate physical grasping, each fingertip of the virtual hand is deformable using the Gaussian distribution based haptic model for fingertip deformation described [198].

To model the relationship of sEMG amplitude to simulated force intensity, a linear relationship was formed. As described by Yang et al. [199], force measurements can be linearly scaled to the scope of the sEMG signal. As this study attempts to map an unknown scale of sEMG signal to a known scope of force, an inverse measure was taken. By calculating the participants sustained Maximum Voluntary Contraction (sMVC) to the maximum simulated force output of the virtual prosthesis through linear mapping it was possible to provide an intuitive measure of the participants imparted effort to the virtual prosthesis. This linear mapping, as also stated by Yang [199] further reduces computational complexity for the platform alongside ensuring that the platform is adequately scaled to the participants needs.

Within this virtual environment the grasping force of the virtual hand is directly controlled by the detected sEMG signals while the fingertip deformation is directly corresponding to the virtual force imparted on the object within the environment. As the grasping force increased the degree of fingertip deformation would increase accordingly within a range of 0-5mm. Much like human skin, the degree of fingertip deformation has a maximum value when a certain quantity of force is exerted upon the object it grasping regardless of any further grasping force exerted. It is through this combined virtual force feedback and visual fingertip deformation that a two tiered hierarchical feedback system is developed that realizes an enhanced feedback strategy over previous single structured visual feedback strategies.

The simulated virtual object in this grasping exercise was that of a ball which would have adjustable weight and rigidity according to the desired force control parameters. The visible state of the virtual object in this research was kept identical as to ensure that only the knowledge of the desired force input and whichever feedback method selected would be guiding the users force input. For the visual on screen feedback a force bar would display the present level of detected sEMG signal amplitude. A deformation bar would also exist as to infer the degree of finger deformation currently experienced alongside a numerical listing of the sEMG input and deformation experienced by the finger tips, in this case being the thumb. While the trial continues the quantity of successful or failed grasping attempts are shown in the top left alongside the time per trial and control buttons for the investigator. Upon completion of each set of trials, a document would be created that details several statistics related to the feedback methodology, object weightings per each trial, time of each trial, the trial outcomes, and information related to the sEMG signals detected during the trials. The implementation and structure of the Virtual environment is shown in fig.5.3.

It is through the above described aspects of the virtual environment that this focused on implementing a platform that can provide the three experimental feedback approaches of a hand grasping without feedback, a hand grasping with electrotactile feedback, and finally a hand grasping with virtually displayed feedback such visual representations of the sEMG's intensity and translated force to the object using the force model described in [198]. Every aspect of the experiment could be modified directly through the unity engines editor panel or through provided utility tools within the virtual environment. Such changes could include modifying the objects shape, size, and simulated properties of weight or strength. As mentioned previously, output data could be selected through tick boxes in the editor panel to modify the output to the researchers preferred data description, such as XML or csv. Utility tools within the

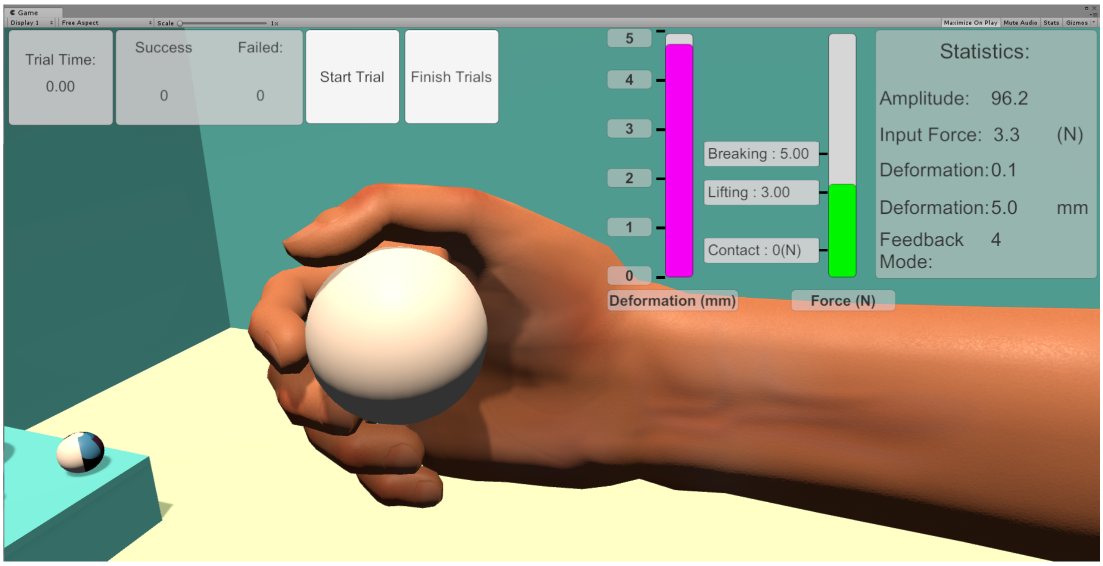

Figure 5.1: Virtual grasping rehabilitation environment during an example grab task. The top left of the screen displays that trials time per trial, successful grasps, and failed grasps. In the right of the screen, the deformation model is represented by the pink bar to indicate mm's of thumb deformation. The green bar represents the current amplitude of the sEMG signal with indicators for the level of imparted effort by the participant to make contact with the object, lift the object, and to break the object. On the top right is a Statistic chart to show the input amplitude, the predicted force imparted degree of thumb deformation, and the electrotactile feedback mode.

virtual environment for functions such as setting an individual participants electrotactile feedback parameters could be directly modified through a simple GUI and output user specific XML files for the researcher to select prior to the experiment.

To summarise, the proposed virtual rehabilitation platform combines a biological signal acquisition platform through sEMG sensing, an electrotactile stimulation module, and interactive interface within a realistic virtual simulation environment that attempts to combined biological engineering and virtual reality within a platform for upper limb rehabilitation, specifically for hand rehabilitation in this research.

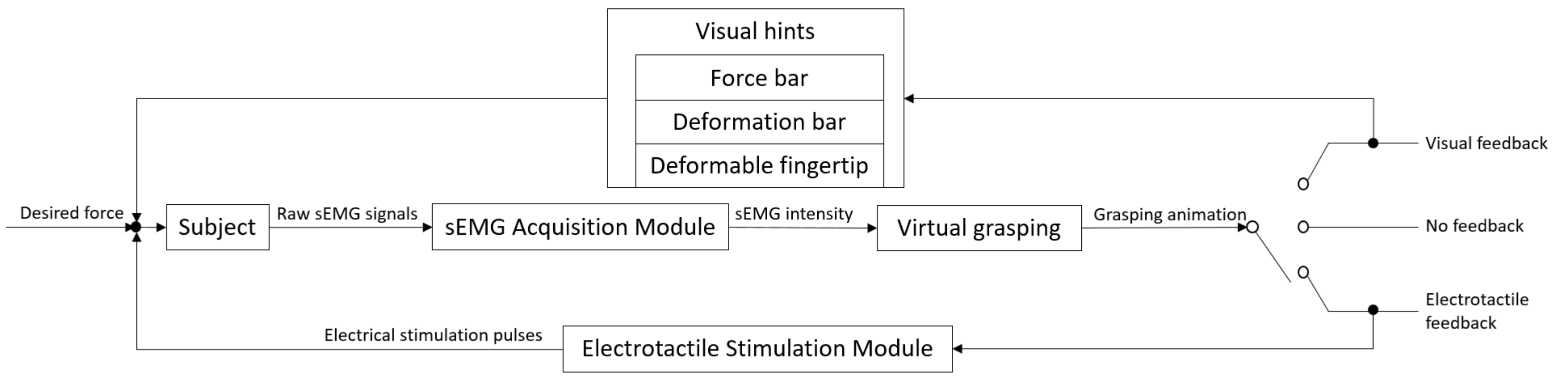

Figure 5.2: Schematic diagram of the hand rehabilitation platform, core path is that of the participants effort and subsequent virtual representation of their imparted effort. The top part indicates the changing aspects which can be perceived within the virtual system by the participant. The bottom path shows the process of electrotactile feedback to the participant.

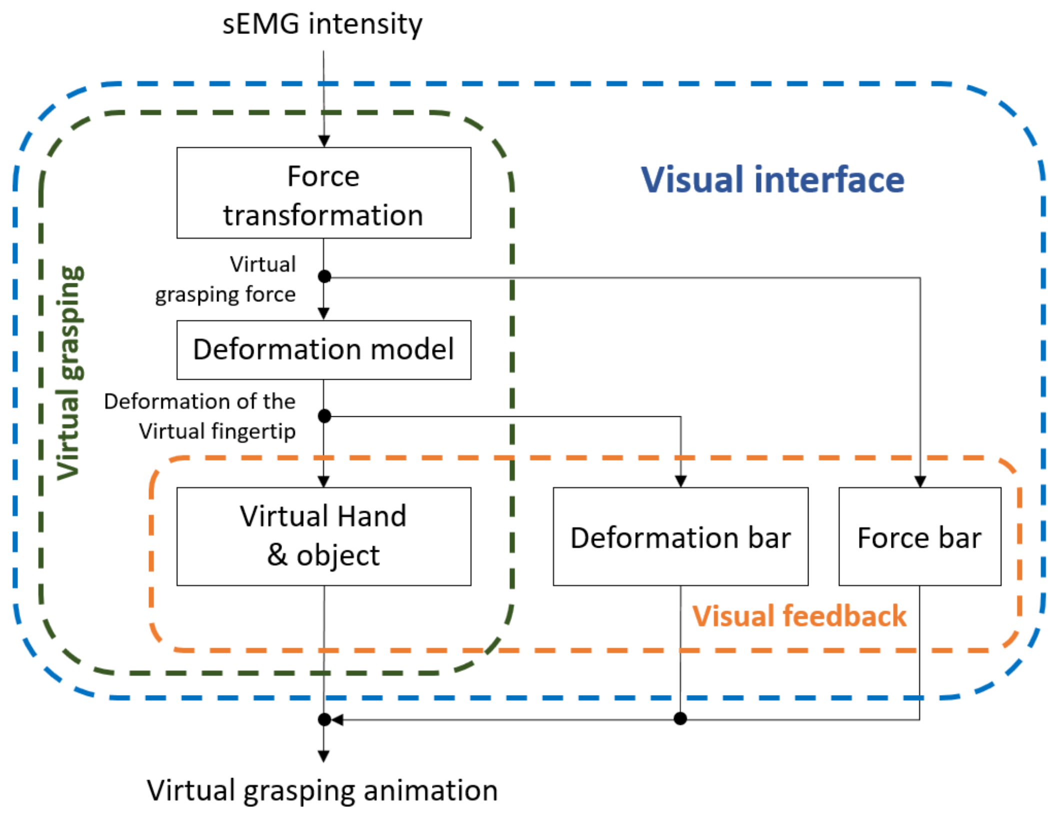

Figure 5.3: Virtual environment schematic, demonstrating the interpretation from the participants imparted sEMG intensity into the virtual hand with the simulated deformation model two changing bars that indicate the perceived force from the participants effort and the degree of deformation imparted from the hands interaction with the virtual object.

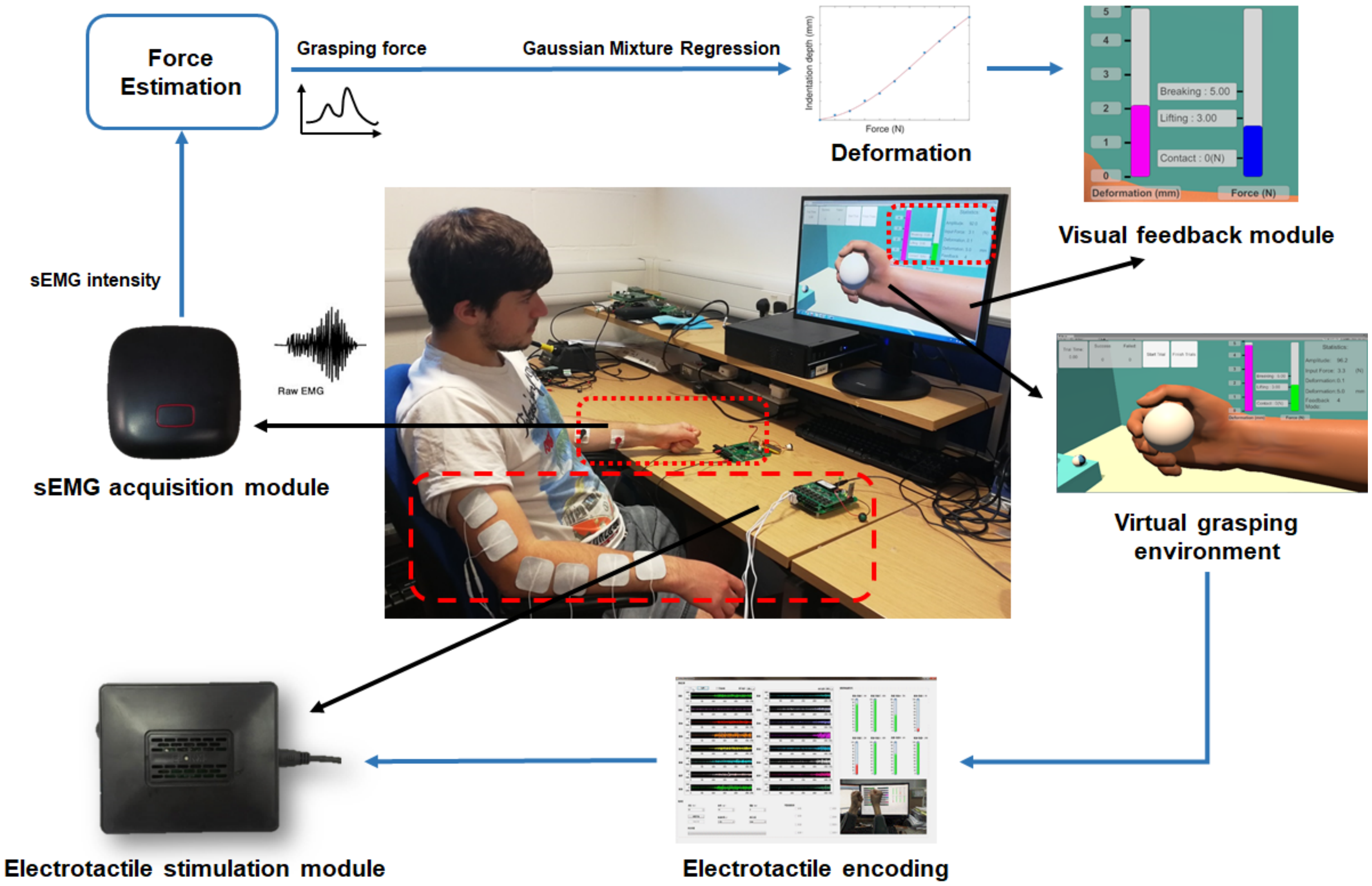

Figure 5.4: The experimental setup, demonstrating each module utilized in this experiment, the aspects of the virtual environment interacted with, and the manner that feedback is provided to the participant.

5.3 Experimental setup

Within the experiments defined below the aim is as stated in the hypothesis to evaluate the feasibility of the constructed virtual rehabilitate system and the impact of closed loop feedback on the rehabilitative process. Firstly the participant recruitment process is described, secondly the metrics of grasping success or failure are defined. Thirdly the process of feedback in the open loop, virtual feedback, and electrotactile feedback are detailed in their methodology. Finally this section concludes with the description of how the experimental protocol is performed under each feedback condition and the evaluation criteria used to analyze grasping performances are described.

5.3.1 Subjects

The subjects used in this experiment were 6 able bodied participants who ranged between 24-29 years old. Participants included 2 females and 4 males and all participants were able bodied. All participants were recruited within the University. The study was approved by the local ethics committee, ethics reference number: TECH2019-PB-03. Prior to each experiment, the participant was informed of the experimental process, reminded that they could stop the study at any time to rest or withdraw, and that they could withdraw at any point during the study and within a period of 3 months after the study, with destruction of any collected data at the participants request. Following this the participant signed the study consent forms and reminded of their right to withdraw as per ethics policy.

5.3.2 Measure of Task Success or Failure

In order to support the above hypothesis the following conditions were implemented into the study. Firstly the object that is to be grasped was divided into 3 separate weight classes, the weight classes being ”light”, ”medium”, and ”heavy”. Each object subsequently had 3 thresholds: ”Hand Activation”, ”Object Lifting”, and ”Object Breaking” that would vary between object weighting. Therefore requiring a finite degree of force for each object. A further aspect of the weighting is that the ball was considered ”Lifted” once the participant maintained a lifting force for more than 1 s.

A successful grasp was considered to be when the participant was able to maintain a grasp between the ”Object Lifting” and ”Object Breaking” thresholds for a period of 2 s minimum, otherwise the trial was considered failed. Other fail conditions included:

- If the Grasping Force is below the minimum lifting force for 5 s.
- If the Grasping Force exceeds the ”Object Breaking” threshold for 300ms.
- If the object is considered ”Lifted” and the Grasping Force either exceeds or drops below the safe region for a period of 300ms.

5.3.3 Virtual Feedback Setup

The Visual feedback in the study was provided by the environment previously introduced in section []. Each trial begun with the Virtual Hand in an open hand pose. When the minimum required Grasping Force intensity was reached then the hand would begin to grasp around the virtual ball. As the Grasping Force increased, the Virtual Hands fingertip would deform as per a function of deformation described by [198]. Accordingly the ball would provide Visual feedback in the situation of the grasp success or failure, by changing colour or visually ”breaking” if the grasping force is exceeded for the required period.

While the deformation implemented in this study does behave inline with real world expectation, it is realized that fingertip deformation may not be immediately observable to participants. Therefore deformation information was provided by the deformation bar.

During the virtual feedback condition, the participant was allowed to practice and perform as many successful grasps as possible prior to beginning of the formal experiment to mirror the learning process. Virtual Feedback in this condition was provided by the Virtual Grasping force bar that would directly reflect the raw sEMG input of the participant. The participant would also be able to monitor the deformation bar during this condition. Each trial under this condition ended by returning the environment to its initial state and requesting the participant to relax their arm.

5.3.4 Electrotactile Feedback Setup

In the Electrotactile feedback condition, distinct modes of electrical stimulation were applied in a multi channel setup. The logic behind this decision is that two to fifteen outputs of feedback were used in previous studies. While it is believed that fifteen outputs could be provided with a single channel, it was considered that the cognitive accuracy and perceptive burden of the participant would be negatively impacted by the potential lack of clear variation between impulses. To reconcile the possible issue of indistinguishable outputs and burden on the participant, only nine stimulation outputs were utilized the better represent the real-time intensity of sEMG signals / grasping force from light to hard. In order to ensure the nine outputs are easily distinguishable and recognisable, a combination of mixed and spatial coding were applied. This is to say that 3 sites from the bicep to forearm were employed, with each site providing a modulating combination of parameters consisting of amplitude, frequency, and pulse width. The modulation parameters for the electrotactile feedback was firstly based on the known stable feedback rates with spatial encoding from the methods using 15 levels referenced in 2.7. The further modulation parameters were modeled off those previously used in literature for single location electrotactile feedback modulation [200]. Each locations upper bound would be based on known comfortable levels, such as those used by Dosen et al [138]. The lower levels of modulation were found by finding the minimal recognizable signal and the middle level was placed as a mid point between the upper and lower bound with light changes performed to ensure that the three levels were easily identified by the participant. The subsequent feedback pattern would be that three electrodes would be utilized with each electrode providing three levels of electrical stimulation from low intensity to high intensity. The decision for three levels of feedback per each of three the electrodes was based on the review in 2.7 on mixed and spaced encoding. It was found that a single arm band of electrodes could provide over 15 levels of electrotactile feedback during a grasping exercise [135, 137, 138], alongside distribution along the arm [136]. While much of the research for 15 levels focused on five locations with three levels, this study reduced the electrode quantity to three while maintaining the three levels. The decision to utilize only three locations was based on an attempt to simplify the feedback scheme and subsequently training speed. Although the simulated environment could provide a simple on/off control to the imparted sEMG intensity being within the grasping range, the intention of this work is to simulate a potential feedback application for daily use. That is to say, the training setup is for the participant to be familiar with each of the nine feedback levels to represent a different quantity of force imparted by a real or virtual prosthesis. Although out of this studies scope, these 9 levels of feedback could subsequently be used with intermediate weights between the current weighted objects.

As individual responses to the electrotactile feedback would vary vastly across the participant population, each set of stimulation parameters were modulated specifically to the participants requirements as to maintain both comfort and distinguishable between the stimulation conditions. during the experiment, the participant would be able to modify their grasping force according to the feedback at each stimulation level.

The finalized experimental setup used during this study can be seen in fig.5.4 for the complete system.

5.3.5 Experimental Protocol

The experiment itself consisted of three independent stages: preparation, training, and testing. The study itself was approved by the University ethics committee. To be in compliance with ethical conduction of the study, participants were informed of the experiment, experimental procedure and aim of the study before any experiments could be conducted. Upon the participants willingness to continue and signing of the consent forms, the study could begin.

For each subject, the study continued in the follow states:

1. Preparation: Before the study could begin, the subject needed to be acquainted with the rehabilitation system. This required familiarising the subject with EMG input, assigning the parameters of electrotactile feedback, and finally linking these together with the virtual environment. The initial stage is for the subject to be seated in a comfortable manner, such that they would not feel discomfort during the experiment. sEMG signals were gathered through placement of two pairs of wet sEMG electrodes on the subjects left arm. The electrotactile stimulation electrodes were placed on the subjects right arm. The purpose behind this is to minimize the potential for electrical interference between the sEMG electrodes and electrotactile stimulation electrodes as to enable synchronized capture

and stimulation. It was considered to filter out the incoming electrotactile signals. However, filtering the electrotactile feedback was deemed too costly and inconsistent of a method due to the varying nature of the electrotactile feedback in the study and the inter subject variability with regards to the propagation of electrical signals through their bodies.

Once the electrodes were in place, the sEMG parameters would be the first parameter to set. The subject was asked to contract their left forearm muscles as much as possible three times for a single second each time. The raw intensity of the three contractions was averaged and then sixty percent of the averaged intensity was considered the upper limit of the subjects sEMG signal. The logic behind this decision is to observe the subjects maximum contraction and to then use a reduced intensity that the subject can hold for a prolonged period of time, even when experience a degree of fatigue.

Secondly, the electrotactile stimulation parameters were to be established. Initially an acceptable set of parameters were used, these parameters were dictated by literature and the researchers own experience. The general ruling in past experience was to acquire the average of several responses for each electrotactile feedback setting from two of the researchers involved. As to avoid discomfort, the testing for feedback parameters would begin from the lowest setting to the highest setting on each channel. Provided the participant can experience sensation from the lowest setting then the intensity shall be reduced until they can only just distinguish it while the intensity will be gradually increased if the participant experiences no sensation. Each feedback level would be tested under the same approach, as to minimize the feedback settings whilst being discernible from the setting below. This process was repeated until the highest setting for each channel, then verified both once the highest channel is set and once all channel feedback levels had been set. This process is modelled around minimizing discomfort in the participant. This process may also be repeated during the study, as it had been found that prolonged sessions may reduce sensitivity to the feedback, which may pose issues with the minimal feedback approach.

Finally, the participant was provided one minute to experience the environment with both the visual feedback and electrotactile feedback settings. This process is used to both provide a first connection between the participants physical effort in grasping and the feedback they would receive from the environment. After this period the participant would only experience individual feedback methods or no feedback.

2. *Training and Testing:* The training and testing process were conducted under three feedback conditions, which included a) feed-forward control with no feedback (NF); b) closed-loop control with Visual Feedback (VF); c) closed-loop control with electrotactile feedback (EF) shown in the schematic in fig.5.2.

    - Feed-Forward with No Feedback (NF)

      The process for the No-Feedback scenario in both testing and training was to advise the participant to close their eyes. They would then be advised of the object type and when tp begin their grasp attempt. This process attempts to exclude any potential feedback from the scenario beyond verbal feedback after each grasp of the grasping result, such that the participant can tune their grasping strength.

    - Closed-loop Control with Visual Feedback (VF)

      The procedure for the visual Feedback scenario follows a similar trend as the No Feedback Scenario. The participant would be advised of the object to grasp, the start of the grasping attempt, and the result of each grasp. The main difference being a visual identifier on the screen in the form of a force bar and the actual Virtual Scenario. The Force Bar would, in theory, provide the participant real-time feedback of their virtual grasping attempt, such that they can fine tune their grasp during the exercise. The participant would also be able to view each attempt result for themselves.

    - Closed-loop Control with Electrotactile Feedback (EF)

      Due to the nature of electrotactile feedback, this third scenario requires some preparation before proceeding into the training or testing phase. This preparation stage largely focused on testing the electrotactile stimulation parameters, using the settings form the participants prior response and fine tuning them to participants needs. The intent of this process is to ensure that the participant has not adjusted to the prior settings or that no change in skin

/ electrode connection has occurred. The participant would be put through the calibration process to adjust any parameters if necessary. Following the participants happiness to proceed, the researcher provided stimulation of different feedback levels and requested the participant to respond on which feedback level they experienced. This process was repeated, with any extra fine tuning, until such a time that the participant could provide accurate response for each feedback level in a row. Following this preparation stage, the remaining experiment would proceed akin to the No feedback condition. That is to say, the participant was requested to close their eyes, as to allow any grasping force and fine adjustments to their grasping force to be dictated by the electrotactile feedback provided to them. the only external cues would be from the researcher informing the participant of the grasping attempt beginning and the grasping result.

Through the above control and feedback approaches, it is anticipated that the first approach will reflect the current implementation of prosthesis control where the voluntary contraction is the only factor utilized in controlling the prosthesis. The two feedback approaches aim to provide a sense of closed loop control such that the voluntary contraction performed by the participant can be better guided based on the feedback provided to them during a grasp exercise.

During the training process, the participant would provided objects of 3 different weightings and breaking point, for virtual grasping. The weightings of the objects had a threshold of raw EMG input that would be considered high enough to activate the virtual hand, pick up the object, and then to break the object. The weightings would stagger from object 1 - a light object, object 2 - a medium weighted object, object 3 - a heavy weighted objects. The breaking point for each object was modeled to climb at the same rate as the lifting point. The participants were provided one minute prior to any training period for each object to acclimatize themselves to the objects parameters, this process would be facilitated with the ability to see the force bar within the visual interface, as to provide initial relations of their input force before proceeding. Following each attempt, the participant would be informed of the result of their grasp, dependant upon the states available. This would provide a form of guidance as the the subjects input effort, such that it can be adjusted in the next attempt, whether they need to increase their force, improve maintaining their force, or to reduce their inputted grasping force. Visual Feedback of the grasp result is also available in the VF and EF scenarios in the form of the ball colouring red from either a failed grasp or dropped ball, the ball would appear cracked if it was broken, and would be coloured green if the grasp was successful. Through this process the participant could adjust their grasp intensity and learn the required amount of force required to pick up the object successfully. Upon the subject being able to grasp the object two times in a row, another object would be shown to the participant, scaling from lightest to heaviest. Each attempt performed during this training phase would be recorded. Once two consecutive successful grasps are performed then the participant moves to the testing phase.

The testing phase proceeded by the participant having 10 opportunities to grasp each object. As to ensure the training was a success, the objects would not be presented in order, but instead in a random order. This therefore should ensure that the participants response to each presented object will come from recalling the force required to grasp the object, as opposed to learning the sequence of objects.

For each participant, the entire experiment would last an average period of two hours. It was anticipated that this extended period of grasping could impart muscle fatigue upon the participant, alongside the potentially fatigue from the electrotactile feedback. Subsequently, the participant was afforded every opportunity to rest during the study, as to prevent fatigue or discomfort. Throughout the training and the testing phase several metrics were recorded, these include the attempt result (success or failure), grasping force, and the time taken during each grasping exercise. These metrics were considered satisfactory for ample evaluation of performance across the multiple object and feedback types.

5.3.6 Data Analysis Criteria

As highlighted in the experimental protocol, several metrics were taken during both the training and testing periods as to evaluate the rehabilitative performance in terms of the

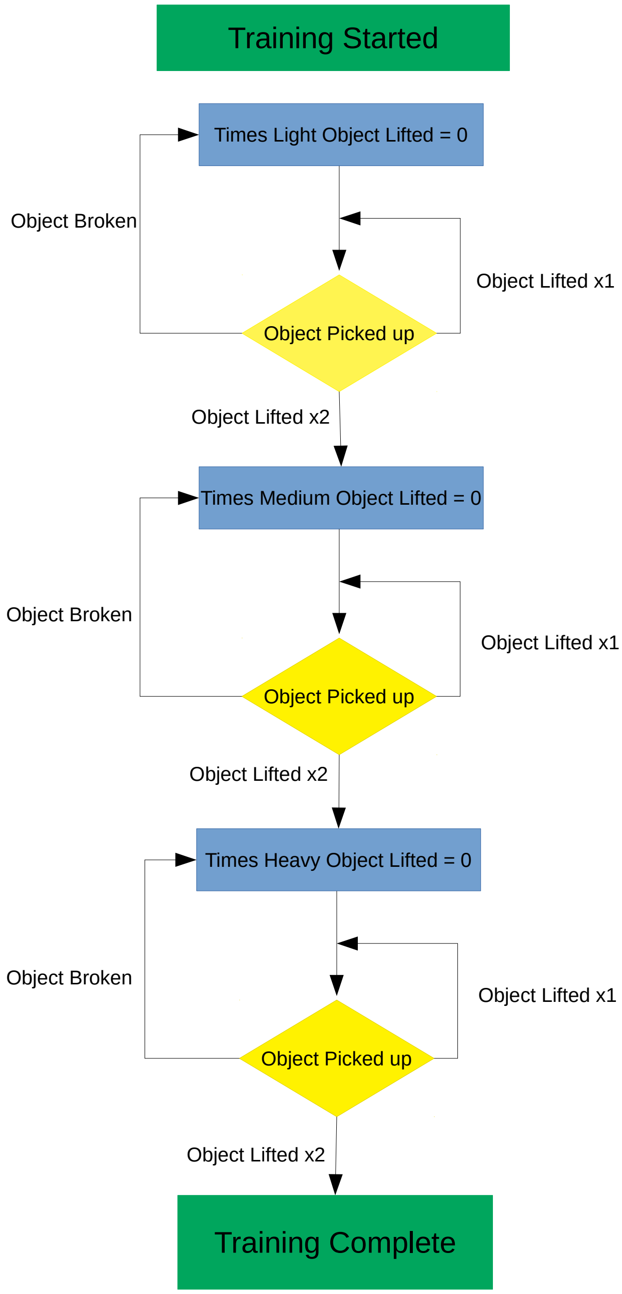

Figure 5.5: Example flow chart of training process prior to testing. Each stage of process would continue until two consecutive successful grasps of each object was achieved

speed of training and the effectiveness of the training. These criteria are as follows:

1. Number of Attempts (NoA): The number of attempts indicates the total number of grasping attempts performed by the participant until they were able to successfully grasp the object twice in a row. Therefore this value contains the total number of grasping attempts performed during the training period. Through this criteria it is possible to evaluate the impact of each feedback condition on the participants ability to learn the required amount of fine control force and to demonstrate repeatable control.

2. Duration of Training (DoT): The value represented by the duration of training is used as a complimentary value to the number of attempts. This value represents the sum of every grasping attempts time. Therefore this value will be able to inform on the total quantity of time required in the training process to demonstrate any potential relationship between the number of attempts and total time required in each feedback condition.

3. Duration of Attempt (DoA): Akin to the duration of training criteria, this criteria represents the average amount of time used across every attempted grasp performed by the participant in the testing phase. Therefore this criteria can be used to evaluate the participants relative speed to grasping the virtual object in each feedback condition.

4. Success Rate (SR): The success rate represents every successful grasp during testing phase without the object breaking or slipping. Through the success rate, the effectiveness of each feedback conditions rehabilitative performance when grasping each of the weighted objects can be evaluated.

5.3.7 Results

5.3.7.1 Setting Of Parameters

With relation to the EMG intensity observed during the study across each participant, a transient upper limit between 400 and 600 was observed. As the participant would be required to maintain a muscle contraction repeatedly throughout the course of the experiments it would be unlikely that such an upper limit could be realistically maintained throughout. Subsequently the long-lasting upper limits of all participant were tested from extended grasps. Across all participants there was little visible difference in the long-lasting upper limited where an average of 210 was observed.

The electrotactile stimulation parameters, however, observed a very noticeable amount of variation across the participant population. Individual responses to the electrotactile stimulation varied between sensitivity to the stimulation on the upper and lower ends, alongside varying ability to discern the stimulation. The two typical coding schemes used in the experiment can be seen in 5.1. The values on the left indicate the parameters used by a participant who demonstrated high sensitivity to the electrotactile stimulation at lower intensities. In contrast, the values on the right demonstrate the electrotactile stimulation parameters that were used with a participant who was able to experience the electrotactile stimulation at a higher intensity. Across the participant population, the preparation and testing of suitable parameters took a period of on average 30-40 minutes. Within this period of time it could be verified that the stimulation parameters are comfortable for the participant and that the participant can demonstrate effortless recognition of the 9 stimulation parameters.

5.3.8 Number of Attempts (NoA)

The average number of attempts (NoA) per object in different conditions are shown in Figure. 5.6. When grasping the lightest object, the subjects' learning performance in different feedback conditions is similar. Across the objects, subjects spent comparable NoA in VF and EF conditions. However, it took approximately twice NoA to grasp a heavier object (medium, heavy) in NF condition comparing with the NoAs of the other two conditions. The overall average NoAs across conditions as shown in Figure. 5.7 also indicate the same information that the VF and EF help to save about half NoA comparing with the training in NF condition.

5.3.9 Duration of Training (DoT) and Duration of an Attempt (DoaA)

The average duration of training (DoT) as shown in Fig. 5.8 presents a similar trend with the NoA in Fig. 5.6. It is reasonable that the DoT is positively correlated with the

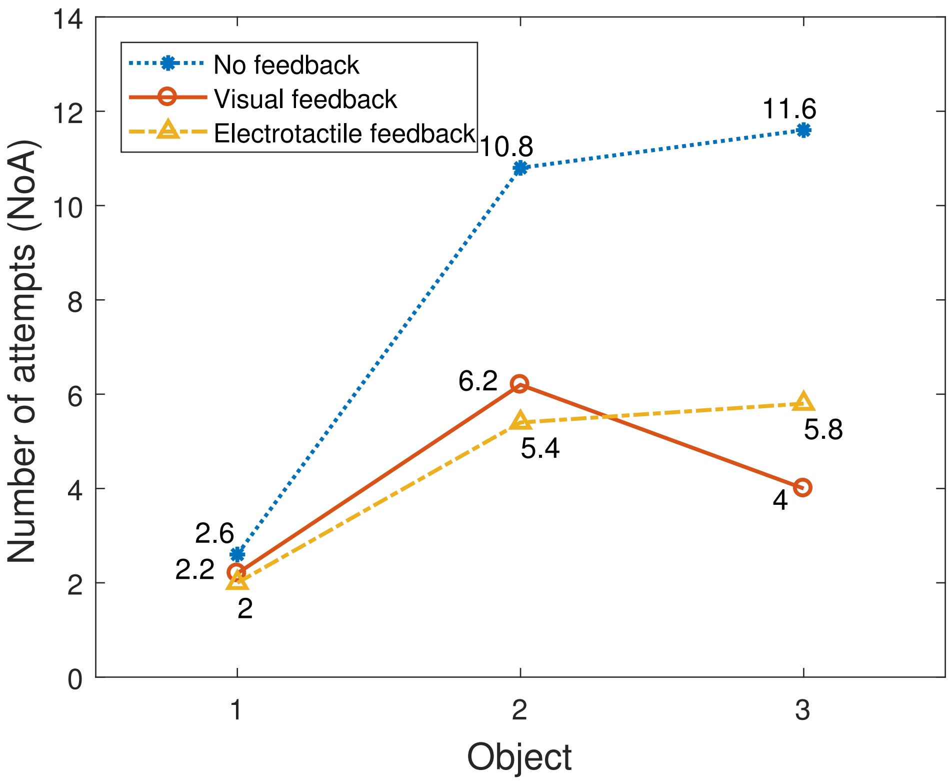

Figure 5.6: Average number of attempts (NoA) of each object in different feedback conditions to complete the experiment. Each object value represents the objects simulated weight: 1- ”Light”, 2 - ”Medium”, and 3 - ”Heavy”. It can be seen how the number of attempts required to complete the experiment with the Medium and Heavy objects is highest in the no feedback condition. The two feedback conditions provided similar performance, although the electrotactile feedback condition performed better with a medium object while the visual feedback condition performed better with the heavy object.

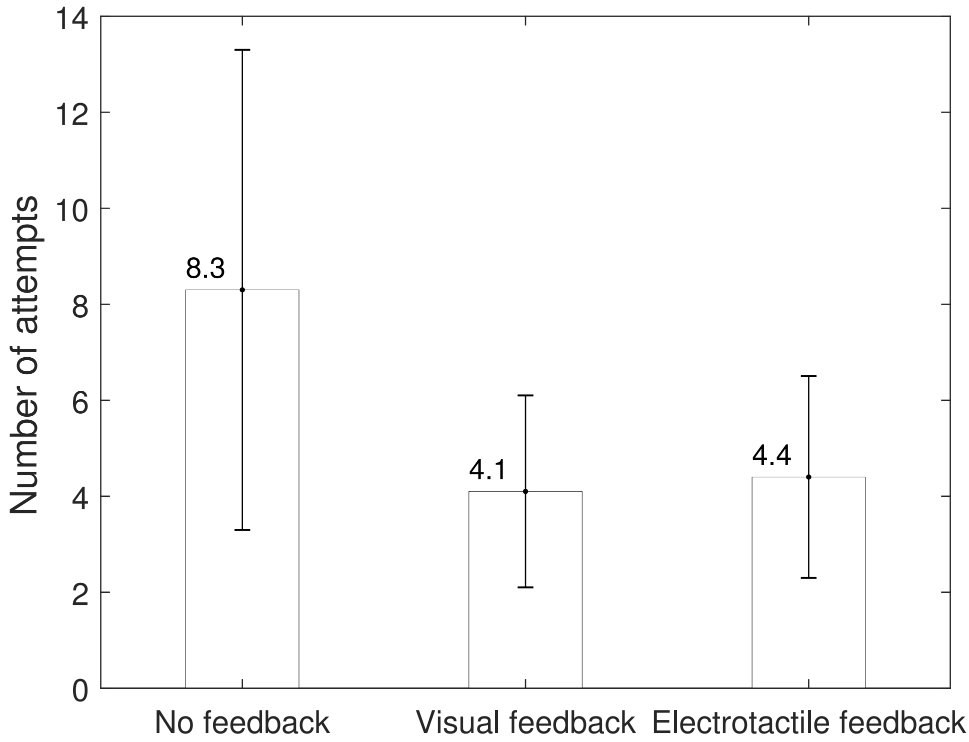

Figure 5.7: Average number of attempts (NoA) of all objects in different feedback conditions. It can be seen above that the no feedback condition not only required the highest number of attempts but also had the largest deviation in performance across all object settings. The two feedback conditions performed within a similar bounds, although visual feedback performed slightly better than electrotactile.

Table 5.1: Coding scheme of electrotactile feedback. Within this table, the ranges for each level on every channel is displayed in terms of the lowest observed stimulation parameters to the highest stimulation parameters.

	Stimulation Parameter	Amplitude (mA)	Frequency (Hz)	Pulse width (us)
	Level 1	3 / 3	10 / 10	50 / 180
Channel 1	Level 2	2 / 2	30 / 61	50 / 50
	Level 3	2 / 2	45 / 62	70 / 50
	Level 4	2 / 3	10 / 10	40 / 180
Channel 2	Level 5	2 / 2	25 / 60	40 / 50
	Level 6	3 / 2	35 / 61	60 / 45
	Level 7	1 / 3	10 / 10	20 / 160
Channel 3	Level 8	1 / 2	20 / 56	20 / 60
	Level 9	1 / 2	35 / 58	20 / 100

NoA. The training periods in EF and VF condition are less than half of the NF training period, although training with EF took a little longer than training in VF condition.

Fig. 5.9 presents the average duration of an attempt (DoaA) in different feedback conditions during the testing process. The conditions with feedback (VF and EF) took a longer duration to accomplish one attempt than the condition of NF. The condition with EF shows the longest DoaA and the largest standard deviation, while the condition with NF shows the least.

5.3.10 Success Rate (SR)

The average success rate (SR) across different objects and feedback conditions are shown in Fig. 5.3.10. It can be seen that the SR of both EF and VF outperforms that of NF. The SR in EF condition is comparable with that in VF condition when grasping object 1 (light) and object 2 (medium) and is even observably higher than the SR in the condition of VF when grasping object 3 (heavy). Fig. 5.10 presents the overall average SR of each condition. Grasping with EF shows the highest SR, and the standard deviations in different feedback conditions are comparable. It indicates that

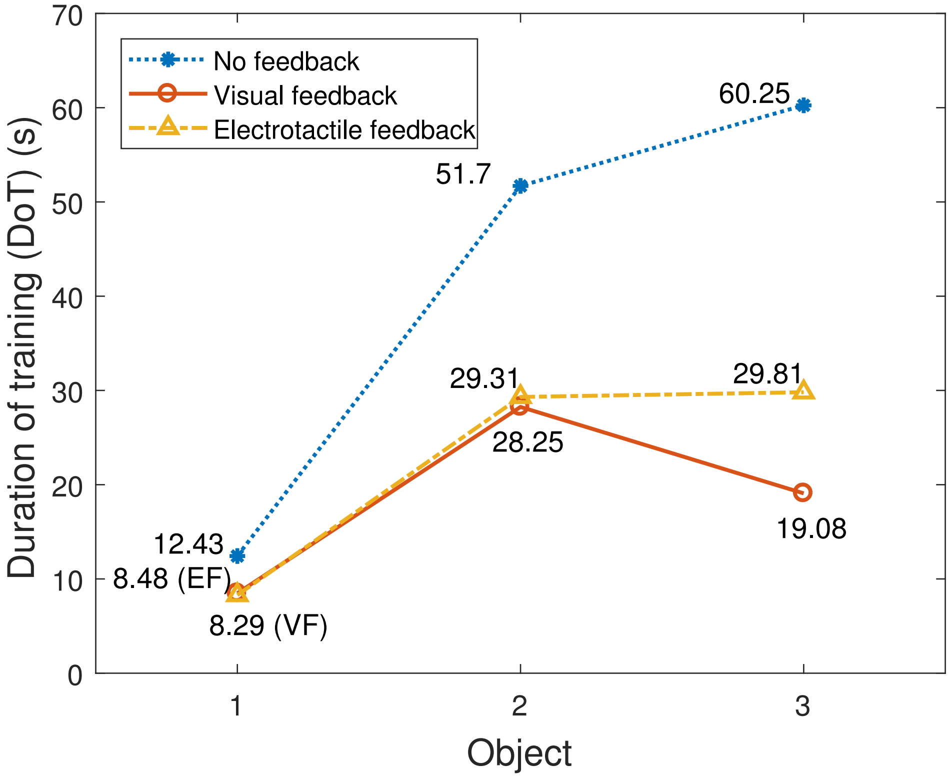

Figure 5.8: Average duration of training (DoT) of each object in different feedback conditions. The above figure displays the total period of time required for the participant to be able to successfully grasp the object repeatedly prior to the main experiment under each object scenario. It is clear that the no feedback condition had little issue with the lighter object but would then require almost double the training time of the two feedback conditions before the pre-experiment training could be considered complete. As with the number of attempts figure 5.6, the visual feedback condition performed better under the heavy object condition

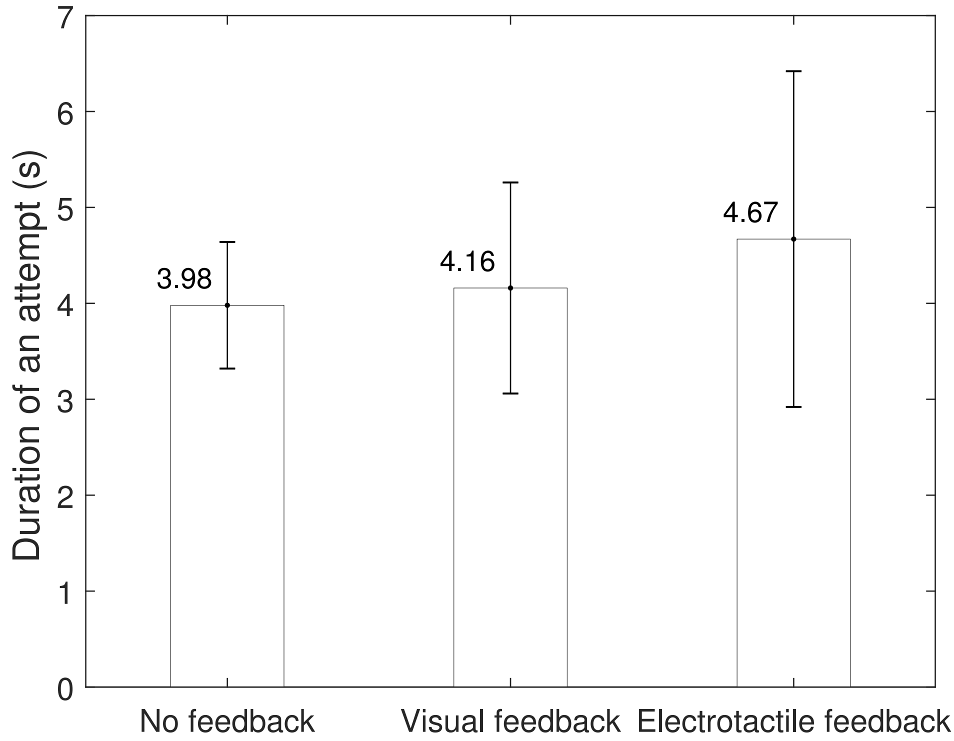

Figure 5.9: Average duration of an attempt (DoaA) in different feedback conditions. Each bar of the above figure represents the average duration across each object class. It is noticeable that the no feedback condition in this figure would appear to outperform the two feedback conditions. However, this faster performance would be counter-intuitive given the considerably lower success rate of the no feedback condition. The slower average duration of the feedback conditions would seem to indicate the participant acting slower to utilize the feedback conditions

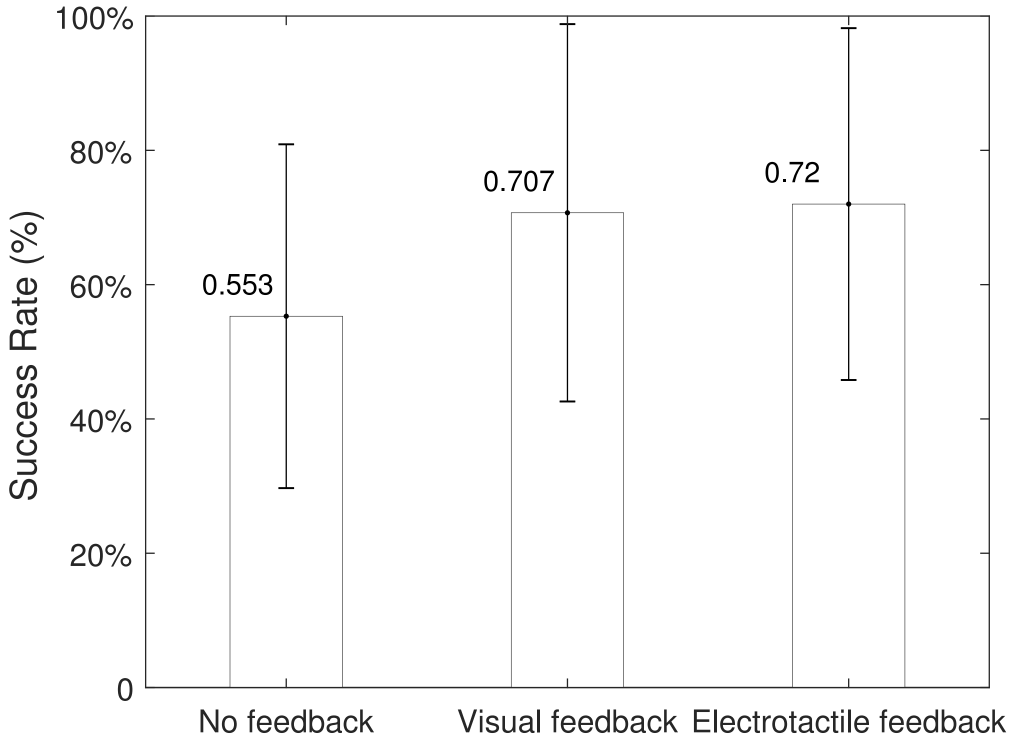

Figure 5.10: Average success rate (SR) during testing process across each object class. As with the success rate during the experiment, the no feedback condition performed worst, while the two feedback conditions obtained a reasonable success rate given for training alone

the percentage of standard deviation out of the average SR in EF condition is lower than those of VF and NF.

5.4 Discussion

As demonstrated in the above results section, the experiments conducted on 6 participants demonstrate that both the visual feedback and electrotactile feedback methods contributed to an improve training efficiency in terms of time and number of attempts. Further to this, the closed loop feedback conditions also demonstrated better fine grasp

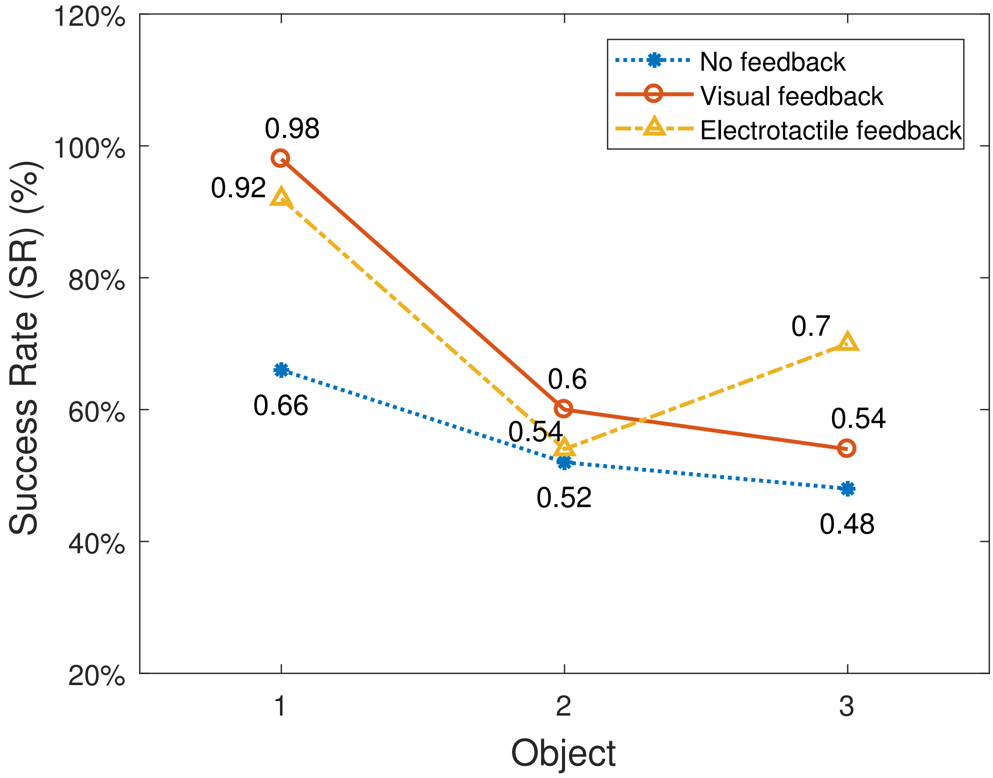

Figure 5.11: Average success rate (SR) of per object in different feedback conditions during experiment. As before, the objects are represented by their simulated weight: 1- ”Light”, 2 - ”Medium”, and 3 - ”Heavy”. A noticeable element of this figure is the high success rate with the light object for both feedback conditions, while the non feedback condition is at best achieves 66% accuracy and only decreases. While the two feedback conditions decrease with heavier objects, it is also apparent that the electrotactile feedback condition improves with the heavy object.

control. given the comparative performance of each testing condition, it could be inferred that the incorporated feedback modules manage to provide a reference signal for the participant to actively learn and adjust their voluntary grasping effort in a closed loop manner when compared to the open-loop control with no feedback. Within the virtual environment the closed loop feedback methods displayed an improved rehabilitation approach for fine hand grasp control against the evaluation criteria of number of attempts, duration of training, and the success rate of the testing. When observing the training period, the number of attempts can be used as a reasonable measure of how quickly the participant could relate their grasping effort to the amount of force required within the virtual environment such that they could successfully grasp an object twice sequentially. With object 1, all grasping methods were largely comparable in their number of attempts. The similar performance in the object 1 condition can be explained as having a form of innate closed loop feedback in each condition for this object, as the object 1 parameters are within a small range directly from the participants minimal grasping effort, allowing the participant to gently amplify their grasp until a success condition is met. this may subsequently describe why there is a longer training period for a similar number of attempts. The impact from lack of any feedback is seen very clearly when increasing the complexity of the task through higher weight thresholds. During lifting exercises with heavier weighted virtual objects it was visible that the number of attempts required by the participant was almost double that of either feedback condition. In other words, both the visual and electrotactile feedback conditions reduced the quantity of training required and the duration of these training periods by half when compared to open loop control. This change in the burden imposed during the rehabilitative process is vital for enabling improved rehabilitative results. Within the 2 hour period used for the experiments in this research it could be stated that a large volume of that time was focused on the open loop feedback training scenario.

While it is notable that the overall duration of attempt between each feedback condition was largely similar, the overall number of attempts required in order to provide adequate results in the training period was considerably higher. However, a notable aspect in the duration of each attempt is that of the closed loop feedback conditions taking almost a second longer to complete an attempt. It can be inferred that the phenomenon of increased time to perform an attempt and the relatively reduced training period describes the state of the user dynamically adjusting their force in accordance to the feedback received whereas open loop feedback could be considered to display relatively little adjustment. Furthermore the relative changed in attempt duration can be considered to align with the cognitive interpretation of the feedback form such that open loop feedback experiences minimal delay yet this delay may manifest largely in failed attempts where the object could be considered broken or dropped. The visual feedback condition sat between the open loop feedback and electrotactile feedback in attempt duration while experiencing a low degree of training burden inline with that of the electrotactile feedback approach. It could therefore be conceived that the visual feedback approaches faster duration of attempt and perhaps adaption rate is from an inherently faster interpretation of the on screen force bar to the imparted effort by the participant due to familiarity with the concept of visual bars to represent input whereas many participants had minimal previous experience with electrotactile feedback of any nature. Although it is typically assumed that touch stimuli has a faster reaction time than visual stimuli, aspects of the delay may decrease were the study to be conducted across a longer period of time as to allow the participant to grow familiar with interpreting the electrotactile feedback condition.

When looking towards the relative success rate of each method there existed a similar display of improved results during closed feedback conditions such that the relative success rate across the three objects saw an increase of 15% and 17% of the closed loop feedback conditions compared to the open loop feedback condition. A subsequent result of the improvement to grasping weighted objects as displayed in this research is that of how the proposed closed loop feedback approaches may support bridging the gap between initiating rehabilitation to being capable of reliably performing grasping actions during real life use of a prosthesis. Therefore the conducted research here can be summarized as demonstrating the feasibility and applicability of closed loop feedback enabling a stable and successful control scheme during hand rehabilitation for finite sEMG based grasps in a virtual environment. The inherent challenges of interpreting sEMG imparted by a participant to force in the prosthesis can therefore be resolved to enable better formed decision making and adaption by a prosthesis user.

When considering the application of this virtual environment,the purpose is to train a relationship between the users voluntary contraction and the force imparted by the prosthesis. As described in section 5.2.1.3, the system maps the users sMVC to the scope of potential force that can be deployed by either a virtual or real prosthesis. It is therefore possible to train a user to enact precise control of their imparted sEMG signal. Provided the scope of force imparted by the virtual environment is modified to match the desired scope of force imparted by end prosthesis prior to training.

Through the above mapping of sEMG amplitude to potential force from a prosthesis, it may be possible to further simplify switching between prosthesis provided the degree of force the amputee is trained with is within the scope of the new prosthesis. The beneficial aspect of electrotactile feedback during user training on a participants prior perception was highlighted by Strbac et al. [137] as something that may further benefit rehabilitation, even if not used in a final prosthesis.

Although the proposed feedback conditions demonstrate promising results towards improving the rehabilitative process through closed loop feedback guided adaption there still exists some limitations and challenges. Although the visual feedback scenarios displayed faster response and adaption times than the electrotactile feedback condition there does exist the argument that visual feedback as used in this scenario is largely limited to a laboratory scenario. While it may be possible to impart visual feedback through prosthesis mounted interfaces or through a form of augmented reality based system such methodologies are not presently implemented in commercial prosthesis and research into such systems is scarce. In the absence of a prosthesis based implementation of the sEMG bar used in this study, this approach to training for precise sEMG based control can still be useful in improving the rehabilitative process. Specifically by better relating the imparted force to a visible stimuli other than a binary hand open/closed actions. While further studies may be necessary to quantify the degree of impact, it is believed that the demonstrated visual feedback results are promising for their contribution to rehabilitation.

Therefore it can be concluded that currently electrotactile feedback may be the more promising method if the feedback condition is considered to be utilized for daily use outside of the rehabilitative process. Electrotactile feedback based approach's can readily be implemented into prosthesis hardware although such systems may interfere with sEMG based sensing therefore feedback may mirror that of this study where feedback was provided to the non grasping arm. Potentially ultrasound or NIRS based sensing may provide a pathway to achieve same arm sensing and feedback for prosthesis control. Furthermore, increased exposure to the electrotactile feedback condition and a same arm fitting of feedback and sensing may further contribute to decreasing the duration of attempts seen in this study to be inline with that of the visual feedback condition.

While this study focused on investigating the training for repeatability in finite sEMG based control of a virtual prosthesis, a potential limitation is that to ensuring long term repeatability. The training section of this study focused on the participants grasping the virtual objects until they could repeatedly achieve the goal, before moving forward to the validation phase. The results demonstrated that the feedback conditions were useful in reducing this training phase and more importantly demonstrating that this training could be adequately utilized in the testing phase of the study. It is through this short term improvement in both repeatability and reduction in training time that a longer term study would be capable of demonstrating both an improvement in the participants success rate and a reduction in overall repeated trial time. However, it is recognized that, while the short term results are promising, a longer term study would be required to validate this platform as a long term rehabilitation tool.

In summary, the proposed methodology of a virtual rehabilitation system that utilizes closed loop feedback displayed that not only does the average performance during testing exercises improve through the provision of closed loop feedback but also that a substantial increase in the relative speed of training and reduction in amount of attempts required during the training stage can be achieved through closed loop feedback. While it can be assumed that the simple feedback of grasping for a light object may be a simple task, it is with heavier objects where the most notable change from being capable of successfully grasping an object is seen. The visual feedback condition demonstrated a faster response time and relatively improved grasping for medium weighted objects yet the electrotactile feedback method displayed higher success during grasping of a heavier object. It could be considered that the active physical sensation of the electrotactile feedback may be assist in evoking the necessary sense of agency required for this task.

5.5 Summary

Within this chapter a novel Virtual environment enhanced hand rehabilitation system was proposed which utilized both Virtual and Electrotactile feedback. The performance of this proposed platform was demonstrated in comparison to an open loop form of control during a grasping exercise of 3 separate weighted virtual objects. The contribution of this chapter is specifically the virtual rehabilitation environment proposed, which can provide closed loop feedback to the user through virtual and electrotactile feedback. The specific benefits from this platform is through the ease of customisation and adaptability to the patients rehabilitation requirements, the benefits of the closed feedback methods, and importantly in the ease of implementation prior to fitting with a prosthesis.

This contribution is further reinforced by the results which show how the virtual environment with closed loop feedback can be helpful in reducing the time required to train a user to perform precision control of a prosthesis and showed improvement in successfully grasping an object displaying good promise for future integration in a clinical scenario.

Chapter 6

Conclusions

6.1 Overview

The focus of this thesis is on the research of upper limb based bio-signal sensing modalities and their application into the rehabilitative process to promote long term use of prosthesis with a focus on challenges related to the robustness of sEMG sensing during both intra and inter day usage. Specifically the human factor when relating to sensing and adaption for long term use where challenges revolve around inherent bottlenecks in present sEMG implementations and enabling long term robust control of a prosthesis. This thesis highlighted three core components to enabling long term hand rehabilitation. Firstly through training strategies for robust long term prosthesis control. Secondly, by providing better hand motion sensing through a multimodal A-mode ultrasound led approach, and thirdly the rehabilitative challenge of closing the loop in precise prosthesis control and rehabilitation through a virtual environment.

6.2 Contributions

6.2.1 Training Strategy for Improving Long Term Robust Usage of Prosthesis

Firstly, training strategies that attempt to exploit temporal aspects of sEMG data are developed to improve long term use. These methods initially performed a novel exploration into the intraday time sensitivity and concept of sEMG freshness from a given period of a given day. The anticipated temporal decay of the sEMG data is then utilized in a training strategy based on an LDA with naive bayes classifier. The training strategy is compared against a training strategy that requires data collection every 30 minutes and shown to provide similar results with heavily decreased training burden through qualitative dataset collection as opposed to quantitative. The training strategies are then shown to be improved through the addition of a single set of testing day data as a form of calibration data. Finally, a strategy that utilizes increasing degrees of intraday data with the initial training strategy is explored.

6.2.2 Multimodal A-mode Ultrasound led Hand Motion Recognition

As sEMG sensing is limited by lack of deep muscle activity, crosstalk from surrounding muscles, and finally electrical fluctuations in the sEMG signal from external factors, a multimodal Ultrasound led sensing approach is developed. The fusion of ultrasound and sEMG signals enables robustness against agitating factors such as crosstalk and electrical interference with the addition of higher resolution understanding of deep muscle activity. The complication of ultrasound probe shift is explored and highlighted for existing unimodal robustness through handcrafted feature selection strategies. The addition of sEMG signals further assists by providing detailed muscle activation to provide robustness to potential probe shift and to guide in larger arm motions. This contribution provides a novel ultrasound led control scheme and focused analysis on the concept of ultrasound probe shift.

6.2.3 Virtual Environment Based Hand Rehabilitation Platform

Finally, in order to reduce the burden of the rehabilitative process and to combine this with improving the quality of life for a prosthesis user, a Virtual Environment based rehabilitation platform is proposed, that utilizes both virtual and electrotactile feedback. As present open loop based control schemes in hand rehabilitation are not fully sufficient in providing an accurate depiction of the relationship between interaction and patient exerted effort a haptic based control scheme is proposed to close the loop in proportional force control. This control scheme is achieved through introducing both visual feedback and electrotactile feedback in an environment where a subject is expected to provide a precise quantity of muscle contraction effort during three forms of virtual grasping exercise. This contribution demonstrates that the inclusion of closed loop feedback improves the speed of the rehabilitative process in proportional control and also increases the success rate during grasping exercises when compared to open loop control.

6.3 Further Work

In this concluding section, the limitations of the works performed in this thesis are discussed and the potential directions of future research.

Temporal sEMG training strategies are a promising concept for enabling improved long term prosthesis control. This thesis demonstrates the value of sEMG signal freshness, the decay of sEMG data in intraday scenarios, and how such information may be exploited. However, there exists more work to be conducted towards verifying the strategies proposed for clinical use. Firstly, although the work presented focused on the temporal nature of signal decay and exploitation in a training strategy for long term use, the work done is using laboratory scenarios where subject data collection is performed in a comfortable position and dynamic transition data removed to provide best example data of each motion although the density and length of data collection did provide some real-world issues such as electrode shift, sweat, and fatigue. Future work would look further to evaluating these strategies in dynamic contractions where the residual limb may not always be in an ideal relaxed position. Secondly, while it is demonstrated that there exists temporal qualities of sEMG data that may be exploited it still is very much the case as with Amssus et al [155] that there still remains qualities of sEMG signal across time that are not yet known. The proposed concept of signal freshness indicates a quantifiable period of classification decay which could provide guidance into methods to better analysing the impact of time on sEMG signals. Within this there is a question on whether a focused subset of gestures may be capable of providing reference signals to maintain the quality of a trained model. Therefore future work towards understanding the temporal nature of sEMG data for long term use would explore reduced dataset calibration to propose strategies which require less direct intervention on the subjects behalf and to furthermore form an anatomical model to better describe the change in sEMG signal over time.

MultiModal Sensing based hand motion recognition through using both ultrasound and sEMG with ultrasound led control has been proposed in this thesis. Although the aspect of ultrasound probe shift has been investigated and reasonably rectified through the addition of sEMG, there still remains the issue in how best to resolve probe and electrode shift in a dynamic or robust manner. Therefore it firstly should be investigated as to the best integration and fitting sites of a combined ultrasound and sEMG sensing platform and targeting as to provide high quality signal information that is robust to shift and in the least disruptive manner possible to the user or whether there exists training strategies to better prepare for probe shift.

Secondly, the work demonstrated in this thesis investigated the combined modalities of ultrasound and sEMG in only probe shift conditions or same session conditions. Although present results are very promising for this combined modality, the long term robustness of this combined modality should be investigated across interday use.

Virtual Environment assisted hand rehabilitation platform Although closed loop feedback has been demonstrated as an effective tool within this thesis. However, there exists several limitations and future directions to the contributions in this thesis. Although it is clear that electrotactile feedback has many benefits in terms of speed of response and in terms of being very wearable, the calibration stage of electrotactile feedback is presently a slow process that would need investigation into methods that can reduce the length of the calibration stage and furthermore to make it a process that can be completed by a patient without practitioner intervention. Furthermore, many haptic feedback approaches are yet to be perfected for usage over long duration's, where squeeze and stretch methods may incur damage or discomfort during prolonged use and where vibrotactile and electrotactile methods experience reduced sensitivity during prolonged use. Future directions could focus on strategies that enable adaptive feedback based on patient specific responses over prolonged use.

Moreover, an inherent limitation of electrotactile feedback in this work is that of using sEMG signals as input. As the nature of electrotactile feedback will produce noise during sEMG data capture it is necessary for current systems to use one arm for feedback and one arm for data capture. Although using a single arm for sEMG and one for feedback is shown to be viable for providing feedback, an ideal prosthesis would embed the feedback and data capture on the same arm. A potential solution to this problem would be that of implementing ultrasound based sensing. As ultrasound based sensing observes the nature of muscle boundaries it would be very possible for near site sensing and feedback. Therefore future work will seek to exploit the multimodal sensing proposed above to implement a multimodal approach to prosthesis control land haptic feedback through an ultrasound led hand motion recognition approach.

Bibliography

[1] D. Novak and R. Riener, "A survey of sensor fusion methods in wearable robotics," in *Robotics and Autonomous Systems*, vol. 73. Elsevier, nov 2015, pp. 155–170. ix, 20, 22

[2] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, "Target Achievement Control Test: evaluating real-time myoelectric pattern-recognition control of multifunctional upper-limb prostheses." *Journal of rehabilitation research and development*, vol. 48, no. 6, pp. 619–27, 2011. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/21938650http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC4232230 ix, 31, 32

[3] F. Cordella, A. L. Ciancio, R. Sacchetti, A. Davalli, A. G. Cutti, E. Guglielmelli, and L. Zollo, "Literature review on needs of upper limb prosthesis users," *Frontiers in neuroscience*, vol. 10, pp. 209–209, May 2016, 27242413[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/27242413 1

[4] S. Amsuss, L. P. Paredes, N. Rudigkeit, B. Graimann, M. J. Herrmann, and D. Farina, "Long term stability of surface EMG pattern classification for prosthetic control," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2013, pp. 3622–3625. 5, 52, 54, 55, 65, 73, 78

[5] E. Todorov, "Optimality principles in sensorimotor control," 2004. 13

[6] E. Todorov and M. I. Jordan, "Optimal feedback control as a theory of motor coordination," *Nature Neuroscience*, 2002. 13

[7] E. M. Summerside, R. Shadmehr, and A. A. Ahmed, "Vigor of reaching movements: Reward discounts the cost of effort," *Journal of Neurophysiology*, 2018. 13

[8] P. J. Kerry, "The ABC of EMC," 2005. 14

[9] K. Kanosue, M. Yoshida, K. Akazawa, and K. Fujii, "The Number of Active Motor Units and Their Firing Rates in Voluntary Contraction of Human Brachialis Muscle," *Japanese Journal of Physiology*, 1979. 15

[10] R. H. Chowdhury, M. B. Reaz, M. A. Bin Mohd Ali, A. A. Bakar, K. Chellappan, and T. G. Chang, "Surface electromyography signal processing and classification techniques," pp. 12 431–12 466, sep 2013. 15

[11] S. H. Nawab, S. S. Chang, and C. J. De Luca, "High-yield decomposition of surface EMG signals," *Clinical Neurophysiology*, vol. 121, no. 10, pp. 1602–1615, oct 2010. 15

[12] M. Kim, G. Gu, K. J. Cha, D. S. Kim, and W. K. Chung, "Wireless semg system with a microneedle-based high-density electrode array on a flexible substrate," *Sensors (Basel, Switzerland)*, vol. 18, no. 1, p. 92, Dec 2017, 29301203[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/29301203 15

[13] K. Englehart and B. Hudgins, "A Robust, Real-Time Control Scheme for Multifunction Myoelectric Control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, 2003. 15

[14] J. Robertson, "Effects of Confidence-Based Rejection on Usability and Error in Pattern Recognition-Based Myoelectric Control Confidence-Based Rejection Threshold and User Error View project Myoelectric Control View project," *Article in IEEE Journal of Biomedical and Health Informatics*, 2018. [Online]. Available: https://www.researchgate.net/publication/328597123 15

[15] D. Farina, R. Merletti, R. M. Enoka, M. Amann, G. M. Blain, L. T. Proctor, J. J. Sebranek, D. F. Pegelow, and J. A. Dempsey, "The extraction of neural strategies from the surface EMG Neural Control of Movement The extraction of neural strategies from the surface EMG," pp. 1486–1495, 2012. 15

[16] G. Li, Y. Li, L. Yu, and Y. Geng, "Conditioning and sampling issues of EMG signals in motion recognition of multifunctional myoelectric prostheses," *Annals of Biomedical Engineering*, vol. 39, no. 6, pp. 1779–1787, jun 2011. 15

[17] J. C. Ives and J. K. Wigglesworth, "Sampling rate effects on surface EMG timing and amplitude measures," *Clinical Biomechanics*, vol. 18, no. 6, pp. 543–552, 2003. 15

[18] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 1, pp. 82–94, Jan 1993. 16

[19] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848–854, July 2003. 16

[20] J. Vinstrup, J. Calatayud, M. D. Jakobsen, E. Sundstrup, J. R. Jørgensen, J. Casaña, and L. L. Andersen, "Hand strengthening exercises in chronic stroke patients: Dose-response evaluation using electromyography," *Journal of Hand Therapy*, vol. 31, no. 1, pp. 111–121, jan 2018. 16

[21] L. Wei, H. Hu, and K. Yuan, "Use of forehead bio-signals for controlling an intelligent wheelchair," in *2008 IEEE International Conference on Robotics and Biomimetics, ROBIO 2008*, 2008, pp. 108–113. 16

[22] C. J. De, "THE USE OF SURFACE ELECTROMYOGRAPHY IN BIOMECHANICS," Tech. Rep., 1993. 16

[23] B. Hudgins, P. Parker, and R. N. Scott, "A New Strategy for Multifunction Myoelectric Control," *IEEE Transactions on Biomedical Engineering*, vol. 40, no. 1, pp. 82–94, 1993. 17

[24] A. Phinyomark, P. Phukpattaranont, and C. Limsakul, "Feature reduction and selection for EMG signal classification," *Expert Systems with Applications*, vol. 39, no. 8, pp. 7420–7431, jun 2012. 17

[25] R. S. C. Cobbold, "Foundations of Biomedical Ultrasound," *Oxford University Press*, 2007. 17

[26] P. C. Ramos, "Ultrasound imaging in juvenile idiopathic arthritis for the rheumatologist," *Clinical and Experimental Rheumatology*, 2014. 17

[27] R. D. Herbert and S. C. Gandevia, "Changes in pennation with joint angle and muscle torque: in vivo measurements in human brachialis muscle." *The Journal of Physiology*, vol. 484, no. Pt 2, p. 523, 1995. 17

[28] D. Critchley, "Instructing pelvic floor contraction facilitates transversus abdominis thickness increase during low-abdominal hollowing." *Physiotherapy research international : the journal for researchers and clinicians in physical therapy*, 2002. 17

[29] P. W. Hodges, L. H. M. Pengel, R. D. Herbert, and S. C. Gandevia, "Measurement of muscle contraction with ultrasound imaging," *Muscle and Nerve*, 2003. 17

[30] J. Shi, Y. P. Zheng, X. Chen, and Q. H. Huang, "Assessment of muscle fatigue using sonomyography: Muscle thickness change detected from ultrasound images," *Medical Engineering and Physics*, vol. 29, no. 4, pp. 472–479, may 2007. 17

[31] J.-Y. Guo, Y.-P. Zheng, Q.-H. Huang, and X. Chen, "Dynamic monitoring of forearm muscles using one-dimensional sonomyography system." *Journal of rehabilitation research and development*, vol. 45, no. 1, pp. 187–95, 2008. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/18566937 18

[32] Q. Chang, J. Shi, Z. Xiao, and Y. Zheng, "A research of SMG controlled prosthetic hand with SSE2 acceleration," in *International Conference on Signal Processing Proceedings, ICSP*, 2008, pp. 2146–2149. 18

[33] J. Shi, S. X. Hu, Z. Liu, J. Y. Guo, Y. J. Zhou, and Y. P. Zheng, "Recognition of finger flexion from ultrasound image with optical flow: A preliminary study," in *2010 International Conference on Biomedical Engineering and Computer Science, ICBECS 2010*, 2010. 18

[34] J. Shi, J. Y. Guo, S. X. Hu, and Y. P. Zheng, "Recognition of Finger Flexion Motion from Ultrasound Image: A Feasibility Study," *Ultrasound in Medicine and Biology*, vol. 38, no. 10, pp. 1695–1704, oct 2012. 18

[35] S. Sikdar, H. Rangwala, E. B. Eastlake, I. A. Hunt, A. J. Nelson, J. Devanathan, A. Shin, and J. J. Pancrazio, "Novel method for predicting dexterous individual finger movements by imaging muscle activity using a wearable ultrasonic system," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 1, pp. 69–76, jan 2014. 18, 85

[36] C. Castellini and G. Passig, "Ultrasound image features of the wrist are linearly related to finger positions," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, sep 2011, pp. 2108–2114. [Online]. Available: http://ieeexplore.ieee.org/document/6094831/ 18

[37] C. Castellini, G. Passig, and E. Zarka, "Using ultrasound images of the forearm to predict finger positions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 6, pp. 788–797, 2012. 18, 87

[38] C. Castellini and D. S. Gonzalez, "Ultrasound imaging as a human-machine interface in a realistic scenario," in *IEEE International Conference on Intelligent Robots and Systems*, 2013, pp. 1486–1492. 18

[39] Y. Huang, X. Yang, Y. Li, D. Zhou, K. He, and H. Liu, "Ultrasound-Based Sensing Models for Finger Motion Classification," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 5, pp. 1395–1405, sep 2018. 18, 20, 85

[40] X. Chen, Y. P. Zheng, J. Guo, Z. Zhu, S. C. Chan, and Z. Zhang, "A novel approach for detection of muscle boundary in ultrasound images," in *Proceedings - 2011 4th International Conference on Biomedical Engineering and Informatics, BMEI 2011*, vol. 1, 2011, pp. 56–59. 18

[41] J. Li, Y. Zhou, X. Chen, G. Dan, and Y. P. Zheng, "Characterization of individual muscle activities during isometric contraction using ultrasound imaging," in *International Conference on Digital Signal Processing, DSP*, vol. 2014-January. Institute of Electrical and Electronics Engineers Inc., 2014, pp. 162–166. 18

[42] N. Hettiarachchi, Z. Ju, and H. Liu, “A New Wearable Ultrasound Muscle Activity Sensing System for Dexterous Prosthetic Control,” in *Proceedings - 2015 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2015*. Institute of Electrical and Electronics Engineers Inc., jan 2016, pp. 1415–1420. 18, 85

[43] H. B. Xie, Y. P. Zheng, and J. Y. Guo, “Classification of the mechanomyogram signal using a wavelet packet transform and singular value decomposition for multifunction prosthesis control,” *Physiological Measurement*, vol. 30, no. 5, pp. 441–457, 2009. 20

[44] T. W. Beck, “Technical aspects of surface mechanomyography,” *Applications of Mechanomyography for examining muscle function. Kerala: Transworld Research Network*, pp. 95–107, 2010. 20

[45] N. Lan, C. M. Niu, M. Hao, C.-H. Chou, and C. Dai, “Achieving Neural Compatibility with Human Sensorimotor Control in Prosthetic and Therapeutic Devices,” *IEEE Transactions on Medical Robotics and Bionics*, pp. 1–1, jul 2019. 20

[46] L. Zhengyi, Z. Hui, Y. Dandan, and X. Shuiqing, “Multimodal deep learning network based hand adls tasks classification for prosthetics control,” in *2017 International Conference on Progress in Informatics and Computing (PIC)*, 2017, pp. 91–95. 21

[47] Z. Ju and H. Liu, “Human hand motion analysis with multisensory information,” *IEEE/AsMe Transactions on Mechatronics*, vol. 19, no. 2, pp. 456–466, 2013. 21, 23

[48] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, and K. B. Englehart, “Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 10, pp. 2867–2875, 2011. 21

[49] W. Guo, X. Sheng, D. Zhang, and X. Zhu, “Development of a hybrid surface emg and mmg acquisition system for human hand motion analysis,” 08 2015, pp. 329–337. 21

[50] K. Kiguchi and Y. Hayashi, “A study of emg and eeg during perception-assist with an upper-limb power-assist robot,” in *2012 IEEE International Conference on Robotics and Automation*, 2012, pp. 2711–2716. 21

[51] E. A. Kirchner, M. Tabie, and A. Seeland, “Multimodal movement prediction - towards an individual assistance of patients,” *PloS one*, vol. 9, no. 1, pp. e85 060–e85 060, Jan 2014, 24416341[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/24416341 21

[52] R. Leeb, H. Sagha, R. Chavarriaga, and J. d. R. Millan, “A hybrid brain-computer interface based on the fusion of electroencephalographic and electromyographic activities,” *Journal of neural engineering*, vol. 8, p. 025011, 03 2011. 21

[53] A. Presacco, L. W. Forrester, and J. L. Contreras-Vidal, “Decoding intra-limb and inter-limb kinematics during treadmill walking from scalp electroencephalographic (eeg) signals,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 2, pp. 212–219, 2012. 21

[54] T. P. Luu, Y. He, S. Nakagame, J. Gorges, K. Nathan, and J. L. Contreras-Vidal, “Unscented kalman filter for neural decoding of human treadmill walking from non-invasive electroencephalography,” in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2016, pp. 1548–1551. 21

[55] S. Nakagome, T. P. Luu, J. A. Brantley, and J. L. Contreras-Vidal, “Prediction of emg envelopes of multiple terrains over-ground walking from eeg signals using an unscented kalman filter,” in *2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2017, pp. 3175–3178. 21

[56] F. Widjaja, C. Shee, W. Tun Latt, W.-L. Au, P. Poignet, and W. Ang, “Kalman filtering of accelerometer and electromyography (emg) data in pathological tremor sensing system,” 05 2008, pp. 3250–3255. 21

[57] H. ElMohandes, S. Eldawlatly, J. M. C. Audí, R. Ruff, and K.-P. Hoffmann, “Decoding arm kinematics from emg signals using kalman filter,”

in *Proceedings of the 2018 8th International Conference on Biomedical Engineering and Technology*, ser. ICBET '18. New York, NY, USA: Association for Computing Machinery, 2018, p. 96–102. [Online]. Available: https://doi.org/10.1145/3208955.3208966 21

[58] E. Okorokova, M. Lebedev, M. Linderman, and A. Ossadtchi, "A dynamical model improves reconstruction of handwriting from multichannel electromyographic recordings," *Frontiers in neuroscience*, vol. 9, pp. 389–389, Oct 2015, 26578856[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/26578856 21

[59] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and O. Stavdahl, "A multi-modal approach for hand motion classification using surface EMG and accelerometers," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2011, pp. 4247–4250. 22

[60] A. Gijsberts and B. Caputo, "Exploiting accelerometers to improve movement classification for prosthetics," in *IEEE International Conference on Rehabilitation Robotics*, 2013. 22

[61] Y. Geng, P. Zhou, and G. Li, "Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, no. 1, 2012. 23

[62] P. C. Hsiao, S. Y. Yang, B. S. Lin, I. J. Lee, and W. Chou, "Data glove embedded with 9-axis IMU and force sensing sensors for evaluation of hand function," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2015-November. Institute of Electrical and Electronics Engineers Inc., nov 2015, pp. 4631–4634. 23

[63] J. Liu, X. Sheng, D. Zhang, N. Jiang, and X. Zhu, "Towards Zero Retraining for Myoelectric Control Based on Common Model Component Analysis," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2016. 23, 89

[64] J. Wang and Z. Ting, "An ARM-based embedded gesture recognition system using a data glove," in *26th Chinese Control and Decision Conference, CCDC 2014*. IEEE Computer Society, 2014, pp. 1580–1584. 23

[65] Y. Xue, Z. Ju, K. Xiang, C. Yang, and H. Liu, "Dexterous hand motion classification and recognition based on multimodal sensing," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10462 LNAI. Springer Verlag, 2017, pp. 450–461. 23

[66] J. P. Dewald, P. S. Pope, J. D. Given, T. S. Buchanan, and W. Z. Rymer, "Abnormal muscle coactivation patterns during isometric torque generation at the elbow and shoulder in hemiparetic subjects," *Brain*, vol. 118, no. 2, pp. 495–510, apr 1995. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/7735890 23

[67] S. Park, C. Meeker, L. M. Weber, L. Bishop, J. Stein, and M. Ciocarlie, "Multimodal Sensing and Interaction for a Robotic Hand Orthosis," *IEEE Robotics and Automation Letters*, vol. 4, no. 2, pp. 315–322, apr 2019. 23

[68] N. Jaquier, M. Connan, C. Castellini, and S. Calinon, "Combining Electromyography and Tactile Myography to Improve Hand and Wrist Activity Detection in Prostheses," *Technologies*, vol. 5, no. 4, p. 64, oct 2017. 24

[69] S. Herrmann and K. Buchenrieder, "Fusion of myoelectric and near-infrared signals for prostheses control," in *Proceedings of the 4th International Convention on Rehabilitation Engineering & Assistive Technology*. Singapore Therapeutic, Assistive & Rehabilitative Technologies (START) Centre, 2010, p. 54. 24

[70] M. Paleari, R. Luciani, and P. Ariano, "Towards NIRS-based hand movement recognition," in *IEEE International Conference on Rehabilitation Robotics*. IEEE Computer Society, aug 2017, pp. 1506–1511. 24

[71] W. Guo, X. Sheng, H. Liu, and X. Zhu, "Development of a Multi-Channel Compact-Size Wireless Hybrid sEMG/NIRS Sensor System for Prosthetic Manipulation," *IEEE Sensors Journal*, vol. 16, no. 2, pp. 447–456, jan 2016. 24

[72] S. Herrmann, A. Attenberger, and K. Buchenrieder, “Prostheses control with combined near-infrared and myoelectric signals,” in *International Conference on Computer Aided Systems Theory*. Springer, 2011, pp. 601–608. 24

[73] A. Botter, T. M. M. Vieira, I. D. Loram, R. Merletti, and E. F. Hodson-Tole, “A novel system of electrodes transparent to ultrasound for simultaneous detection of myoelectric activity and B-mode ultrasound images of skeletal muscles,” *Journal of Applied Physiology*, vol. 115, no. 8, pp. 1203–1214, oct 2013. 24

[74] A. Botter, M. Beltrandi, G. L. Cerone, M. Gazzoni, and T. M. Vieira, “Development and testing of acoustically-matched hydrogel-based electrodes for simultaneous EMG-ultrasound detection,” *Medical Engineering and Physics*, vol. 64, pp. 74–79, feb 2019. 25

[75] W. Xia, Y. Zhou, X. Yang, K. He, and H. Liu, “Toward portable hybrid surface electromyography/a-mode ultrasound sensing for human-machine interface,” *IEEE Sensors Journal*, vol. 19, no. 13, pp. 5219–5228, jul 2019. 25

[76] M. A. Oskoei and H. Hu, “Support vector machine-based classification scheme for myoelectric control applied to upper limb,” *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 8, pp. 1956–1965, aug 2008. 26

[77] Q. Ding, X. Zhao, Z. Li, and J. Han, “An incremental EMG classification model to detect and recognize randomly-occurred outlier motion,” in *2017 IEEE International Conference on Robotics and Biomimetics, ROBIO 2017*, vol. 2018-January. Institute of Electrical and Electronics Engineers Inc., mar 2018, pp. 1–6. 26

[78] T. Matsubara and J. Morimoto, “Bilinear modeling of EMG signals to extract user-independent features for multiuser myoelectric interface,” *IEEE Transactions on Biomedical Engineering*, vol. 60, no. 8, pp. 2205–2213, 2013. 26

[79] Z. Li, X. Zhao, J. Han, and G. Liu, “Comparisons on different sEMG-features with dimension-reduction methods in hand motion recognition,” in *ICARM 2016 - 2016 International Conference on Advanced Robotics and Mechatronics*. Institute of Electrical and Electronics Engineers Inc., oct 2016, pp. 631–634. 26

[80] Y. Narayan, L. Mathew, and S. Chatterji, "SEMG signal classification with novel feature extraction using different machine learning approaches," *Journal of Intelligent and Fuzzy Systems*, vol. 35, no. 5, pp. 5099–5109, 2018. 26

[81] E. N. Kamavuako, J. C. Rosenvang, R. Horup, W. Jensen, D. Farina, and K. B. Englehart, "Surface versus untargeted intramuscular EMG based classification of simultaneous and dynamically changing movements," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, no. 6, pp. 992–998, 2013. 26

[82] S. Raurale, J. McAllister, and J. M. Del Rincon, "Emg acquisition and hand pose classification for bionic hands from randomly-placed sensors," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, vol. 2018-April. Institute of Electrical and Electronics Engineers Inc., sep 2018, pp. 1105–1109. 26

[83] J. A. Mendes, R. R. Robson, S. Labidi, and A. K. Barros, "Subvocal speech recognition based on EMG signal using independent component analysis and neural network MLP," in *Proceedings - 1st International Congress on Image and Signal Processing, CISP 2008*, vol. 1, 2008, pp. 221–224. 26

[84] Y. Chen, L. Liang, M. Wu, and Q. Dong, "A SEMG-angle model based on HMM for human robot interaction," in *Technology and Health Care*, vol. 27, no. S1. IOS Press, 2019, pp. S383–S395. 26

[85] C. L. Pulliam, J. M. Lambrecht, and R. F. Kirsch, "Electromyogram-based neural network control of transhumeral prostheses." *Journal of rehabilitation research and development*, vol. 48, no. 6, pp. 739–54, 2011. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/21938659http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3579560 26

[86] J. Yang, J. Pan, and J. Li, "SEMG-based continuous hand gesture recognition using GMM-HMM and threshold model," in *2017 IEEE International Conference on Robotics and Biomimetics, ROBIO 2017*, vol. 2018-January. Institute of Electrical and Electronics Engineers Inc., mar 2018, pp. 1509–1514. 26

[87] T. D. Lalitharatne, Y. Hayashi, K. Teramoto, and K. Kiguchi, "Compensation of the effects of muscle fatigue on emg-based control using fuzzy rules based scheme," in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, July 2013, pp. 6949–6952. 27, 55

[88] V. Ortenzi, S. Tarantino, C. Castellini, and C. Cipriani, "Ultrasound imaging for hand prosthesis control: A comparative study of features and classification methods," in *IEEE International Conference on Rehabilitation Robotics*, 2015. 27, 85, 87

[89] M. Atzori, A. Gijsberts, S. Heynen, A. M. Hager, O. Deriaz, P. van der Smagt, C. Castellini, B. Caputo, and H. Müller, "Building the ninapro database: A resource for the biorobotics community," in *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2012, pp. 1258–1265. 27

[90] H.-m. Shim and S. Lee, "Multi-channel electromyography pattern classification using deep belief networks for enhanced user experience," *Journal of Central South University*, vol. 22, no. 5, pp. 1801–1808, May 2015. [Online]. Available: https://doi.org/10.1007/s11771-015-2698-0 28

[91] K.-H. Park and S.-W. Lee, "Movement intention decoding based on deep learning for multiuser myoelectric interfaces," in *2016 4th International Winter Conference on Brain-Computer Interface (BCI)*. IEEE, 2016, pp. 1–2. 28

[92] W. Geng, Y. Du, W. Jin, W. Wei, Y. Hu, and J. Li, "Gesture recognition by instantaneous surface emg images," *Scientific Reports*, vol. 6, no. 1, p. 36571, Nov 2016. [Online]. Available: https://doi.org/10.1038/srep36571 28

[93] Y. Du, W. Jin, W. Wei, Y. Hu, and W. Geng, "Surface emg-based inter-session gesture recognition enhanced by deep domain adaptation," *Sensors (Basel, Switzerland)*, vol. 17, no. 3, p. 458, Feb 2017, 28245586[pmid]. [Online]. Available: https://doi.org/10.3390/s17030458 28

[94] M. Zia Ur Rehman, A. Waris, S. O. Gilani, M. Jochumsen, I. K. Niazi, M. Jamil, D. Farina, and E. N. Kamavuako, "Multiday emg-based classification of hand motions with deep learning techniques," *Sensors (Basel, Switzerland)*, vol. 18, no. 8, p. 2497, Aug 2018, s18082497[PII]. [Online]. Available: https://doi.org/10.3390/s18082497 28

[95] M. Atzori, A. Gijsberts, S. Heynen, A. M. Hager, O. Deriaz, P. van der Smagt, C. Castellini, B. Caputo, and H. Müller, "Building the ninapro database: A resource for the biorobotics community," in *2012 4th IEEE RAS EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, 2012, pp. 1258–1265. 29

[96] P. Kaufmann, K. Englehart, and M. Platzner, "Fluctuating EMG Signals : Investigating Long-term Effects of Pattern Matching Algorithms," pp. 6357–6360, 2010. 29, 52, 55, 56, 63, 65, 67, 73

[97] Y. Du, W. Jin, W. Wei, Y. Hu, and W. Geng, "Surface EMG-based inter-session gesture recognition enhanced by deep domain adaptation," *Sensors*, vol. 17, no. 3, p. 458, 2017. 30, 56, 73

[98] C. Amma, T. Krings, J. Böer, and T. Schultz, "Advancing muscle-computer interfaces with high-density electromyography," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, ser. CHI '15. New York, NY, USA: ACM, 2015, pp. 929–938. [Online]. Available: 10.1145/2702123.2702501"⟩http://doi.acm.org/10.1145/2702123.2702501 30

[99] M. Ortiz-Catalan, F. Rouhani, R. Branemark, and B. Hakansson, "Offline accuracy: A potentially misleading metric in myoelectric pattern recognition for prosthetic control," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2015-November. Institute of Electrical and Electronics Engineers Inc., nov 2015, pp. 1140–1143. 30

[100] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, and K. B. Englehart, "Targeted muscle reinnervation for real-time myo-

electric control of multifunction artificial arms," *JAMA - Journal of the American Medical Association*, vol. 301, no. 6, pp. 619–628, feb 2009. 30

[101] J. Park, W. Bae, H. Kim, and S. Park, "EMG - Force correlation considering Fitts' law," in *IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems*, 2008, pp. 644–649. 31

[102] E. N. Kamavuako, E. J. Scheme, and K. B. Englehart, "On the usability of intramuscular EMG for prosthetic control: A Fitts' Law approach," *Journal of Electromyography and Kinesiology*, vol. 24, no. 5, pp. 770–777, 2014. 33

[103] E. J. Scheme and K. B. Englehart, "Validation of a selective ensemble-based classification scheme for myoelectric control using a three-dimensional fitts' law test," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, no. 4, pp. 616–623, 2013. 33

[104] C. Castellini, P. Artemiadis, M. Wininger, A. Ajoudani, M. Alimusaj, A. Bicchi, B. Caputo, W. Craelius, S. Dosen, K. Englehart, D. Farina, A. Gijsberts, S. B. Godfrey, L. Hargrove, M. Ison, T. Kuiken, M. Marković, P. M. Pilarski, R. Rupp, and E. Scheme, "Proceedings of the first workshop on peripheral machine interfaces: Going beyond traditional surface electromyography," 2014. 33

[105] C. Ahmadizadeh, L. K. Merhi, B. Pousett, S. Sangha, and C. Menon, "Toward Intuitive Prosthetic Control: Solving Common Issues Using Force Myography, Surface Electromyography, and Pattern Recognition in a Pilot Case Study," *IEEE Robotics and Automation Magazine*, vol. 24, no. 4, pp. 102–111, dec 2017. 33

[106] E. a. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: a survey of the last 25 years." *Prosthetics and orthotics international*, vol. 31, no. 3, pp. 236–257, 2007. 33, 35, 77

[107] L. A. Miller, K. A. Stubblefield, R. D. Lipschutz, B. A. Lock, and T. A. Kuiken, "Improved myoelectric prosthesis control using targeted reinnervation surgery: A case series," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 1, pp. 46–50, feb 2008. 34

[108] T. Kuiken, L. Miller, R. Lipschutz, K. Stubblefield, and G. Dumanian, "Prosthetic Command Signals Following Targeted Hyper-Reinnervation Nerve Transfer Surgery," in *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. IEEE, 2005, pp. 7652–7655. [Online]. Available: http://ieeexplore.ieee.org/document/1616284/ 34

[109] O. C. Aszmann, I. Vujaklija, A. D. Roche, S. Salminger, M. Herceg, A. Sturma, L. A. Hruby, A. Pittermann, C. Hofer, S. Amsuess, and D. Farina, "Elective amputation and bionic substitution restore functional hand use after critical soft tissue injuries," *Scientific Reports*, vol. 6, oct 2016. 34

[110] A. Sturma, P. Göbel, M. Herceg, N. Gee, A. Roche, V. Fialka-Moser, and O. C. Aszmann, "Advanced rehabilitation for amputees after selective nerve transfers: EMG-guided training and testing," *Biosystems and Biorobotics*, vol. 7, pp. 169–177, 2014. 34

[111] K. A. Stubblefield, L. A. Miller, R. D. Lipschutz, and T. A. Kuiken, "Occupational therapy protocol for amputees with targeted muscle reinnervation." *Journal of rehabilitation research and development*, vol. 46, no. 4, pp. 481–8, 2009. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/19882483http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=PMC3031096 34

[112] T. A. Kuiken, G. A. Dumanian, R. D. Lipschutz, L. A. Miller, and K. A. Stubblefield, "The use of targeted muscle reinnervation for improved myoelectric prosthesis control in a bilateral shoulder disarticulation amputee," *Prosthetics and Orthotics International*, vol. 28, no. 3, pp. 245–253, 2004. 34

[113] M. A. Schweisfurth, J. Ernst, I. Vujaklija, A. F. Schilling, D. Farina, O. C. Aszmann, and G. Felmerer, "Longitudinal high-density EMG classification: Case study in a glenohumeral TMR subject," in *IEEE International Conference on Rehabilitation Robotics*. IEEE Computer Society, aug 2017, pp. 1–6. 34

[114] U. Wijk and I. Carlsson, "Forearm amputees' views of prosthesis use and sensory feedback," *Journal of Hand Therapy*, vol. 28, no. 3, pp. 269–278, jul 2015. 35

[115] J. M. Fontana, R. O'Brien, E. Laciar, L. S. Maglione, and L. Molisani, "Vibrotactile Stimulation in the Upper-Arm for Restoring Individual Finger Sensations in Hand Prosthesis," *Journal of Medical and Biological Engineering*, vol. 38, no. 5, pp. 782–789, oct 2018. 35, 37

[116] J. Bimbo, C. Pacchierotti, M. Aggravi, N. Tsagarakis, and D. Prattichizzo, "Teleoperation in cluttered environments using wearable haptic feedback," in *IEEE International Conference on Intelligent Robots and Systems*, vol. 2017-September. Institute of Electrical and Electronics Engineers Inc., dec 2017, pp. 3401–3408. 36, 37

[117] H. Huang, T. Li, C. Antfolk, C. Enz, J. Justiz, and V. M. Koch, "Experiment and investigation of two types of vibrotactile devices," in *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, vol. 2016-July. IEEE Computer Society, jul 2016, pp. 1266–1271. 36, 37

[118] T. Li, H. Huang, C. Antfolk, J. Justiz, and V. M. Koch, "Tactile display on the remaining hand for unilateral hand amputees," *Current Directions in Biomedical Engineering*, vol. 2, no. 1, pp. 399–403, sep 2016. 36, 37

[119] M. D'Alonzo, F. Clemente, and C. Cipriani, "Vibrotactile stimulation promotes embodiment of an Alien hand in amputees with phantom sensations," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 3, pp. 450–457, may 2015. 36, 37

[120] M. Nabeel, K. Aqeel, M. N. Ashraf, M. I. Awan, and M. Khurram, "Vibrotactile stimulation for 3D printed prosthetic hand," in *2016 2nd International Conference on Robotics and Artificial Intelligence, ICRAI 2016*. Institute of Electrical and Electronics Engineers Inc., dec 2016, pp. 202–207. 36, 37

[121] C. Antfolk, C. Balkenius, G. Lundborg, B. Rosén, and F. Sebelius, "Design and technical construction of a tactile display for sensory feedback in a hand prosthesis system," *BioMedical Engineering Online*, vol. 9, sep 2010. 36, 38

[122] C. Antfolk, C. Cipriani, M. C. Carrozza, C. Balkenius, A. Björkman, G. Lundborg, B. Rosén, and F. Sebelius, “Transfer of tactile input from an artificial hand to the forearm: Experiments in amputees and able-bodied volunteers,” *Disability and Rehabilitation: Assistive Technology*, vol. 8, no. 3, pp. 249–254, may 2013. 36, 38

[123] K. Kim and J. E. Colgate, “Haptic feedback enhances grip force control of sEMG-controlled prosthetic hands in targeted reinnervation amputees,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 6, pp. 798–805, 2012. 37, 38

[124] K. Bark, J. Wheeler, G. Lee, J. Savall, and M. Cutkosky, “A wearable skin stretch device for haptic feedback,” in *Proceedings - 3rd Joint EuroHaptics Conference and Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems, World Haptics 2009*, 2009, pp. 464–469. 37, 39

[125] K. Bark, J. Wheeler, P. Shull, J. Savall, and M. Cutkosky, “Rotational skin stretch feedback: A wearable haptic display for motion,” *IEEE Transactions on Haptics*, vol. 3, no. 3, pp. 166–176, 2010. 37, 39

[126] J. Wheeler, K. Bark, J. Savall, and M. Cutkosky, “Investigation of rotational skin stretch for proprioceptive feedback with application to myoelectric systems,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 1, pp. 58–66, feb 2010. 37, 39

[127] F. Chinello, C. Pacchierotti, J. Bimbo, N. G. Tsagarakis, and D. Prattichizzo, “Design and Evaluation of a Wearable Skin Stretch Device for Haptic Guidance,” *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 524–531, jan 2018. 38, 39

[128] S. Casini, M. Morvidoni, M. Bianchi, M. Catalano, G. Grioli, and A. Bicchi, “Design and realization of the CUFF - Clenching upper-limb force feedback wearable device for distributed mechano-tactile stimulation of normal and tangential skin forces,” in *IEEE International Conference on Intelligent Robots and Systems*, vol. 2015-December. Institute of Electrical and Electronics Engineers Inc., dec 2015, pp. 1186–1193. 38, 40

[129] M. Bianchi, G. Valenza, A. Serio, A. Lanatà, A. Greco, M. Nardelli, E. P. Scilingo, and A. Bicchi, "Design and preliminary affective characterization of a novel fabric-based tactile display," in *IEEE Haptics Symposium, HAPTICS*. IEEE Computer Society, 2014, pp. 591–596. 39, 40

[130] D. D. Damian, M. Ludersdorfer, Y. Kim, A. Hernandez Arieta, R. Pfeifer, and A. M. Okamura, "Wearable haptic device for cutaneous force and slip speed display," in *Proceedings - IEEE International Conference on Robotics and Automation*. Institute of Electrical and Electronics Engineers Inc., 2012, pp. 1038–1043. 39, 40

[131] Y. Ueda and C. Ishii, "Development of a feedback device of temperature sensation for a myoelectric prosthetic hand by using Peltier element," in *International Conference on Advanced Mechatronic Systems, ICAMechS*. IEEE Computer Society, jan 2017, pp. 488–493. 39, 41

[132] S. Gallo, C. Son, H. J. Lee, H. Bleuler, and I. J. Cho, "A flexible multimodal tactile display for delivering shape and material information," *Sensors and Actuators, A: Physical*, vol. 236, pp. 180–189, dec 2015. 40, 41

[133] M. Nakatani, K. Sato, K. Sato, Y. Kawana, D. Takai, K. Minamizawa, and S. Tachi, "A novel multimodal tactile module that can provide vibro-thermal feedback," in *Lecture Notes in Electrical Engineering*, vol. 432. Springer Verlag, 2018, pp. 437–443. 40, 41

[134] M. Gabardi, D. Leonardis, M. Solazzi, and A. Frisoli, "Development of a miniaturized thermal module designed for integration in a wearable haptic device," in *IEEE Haptics Symposium, HAPTICS*, vol. 2018-March. IEEE Computer Society, may 2018, pp. 100–105. 40, 41

[135] M. Štrbac, M. Belić, M. Isaković, V. Kojić, G. Bijelić, I. Popović, M. Radotić, S. Došen, M. Marković, D. Farina, and T. Keller, "Integrated and flexible multichannel interface for electrotactile stimulation," *Journal of Neural Engineering*, vol. 13, no. 4, jun 2016. 41, 43, 108

[136] M. Franceschi, L. Seminara, S. Dosen, M. Strbac, M. Valle, and D. Farina, "A System for Electrotactile Feedback Using Electronic Skin and Flexible Matrix Electrodes: Experimental Evaluation," *IEEE Transactions on Haptics*, vol. 10, no. 2, pp. 162–172, apr 2017. 41, 43, 108

[137] M. Štrbac, M. Isaković, M. Belić, I. Popović, I. Simanić, D. Farina, T. Keller, and S. Došen, "Short-and long-term learning of feedforward control of a myoelectric prosthesis with sensory feedback by amputees," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 11, pp. 2133–2145, 2017. 41, 43, 108, 126

[138] S. Dosen, M. Markovic, M. Strbac, M. Belic, V. Kojic, G. Bijelic, T. Keller, and D. Farina, "Multichannel electrotactile feedback with spatial and mixed coding for closed-loop control of grasping force in hand prostheses," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 3, pp. 183–195, mar 2017. 42, 43, 108

[139] G. H. Chai, S. Li, X. H. Sui, Z. Mei, L. W. He, C. L. Zhong, J. W. Wang, D. G. Zhang, X. Y. Zhu, and N. Lan, "Phantom finger perception evoked with transcutaneous electrical stimulation for sensory feedback of prosthetic hand," in *International IEEE/EMBS Conference on Neural Engineering, NER*, 2013, pp. 271–274. 42, 43

[140] E. I. Germany, E. J. Pino, and P. E. Aqueveque, "Myoelectric intuitive control and transcutaneous electrical stimulation of the forearm for vibrotactile sensation feedback applied to a 3D printed prosthetic hand," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, vol. 2016-October. Institute of Electrical and Electronics Engineers Inc., oct 2016, pp. 5046–5050. 42, 43

[141] C. Cipriani, F. Zaccone, S. Micera, and M. C. Carrozza, "On the shared control of an EMG-controlled prosthetic hand: Analysis of user-prosthesis interaction," *IEEE Transactions on Robotics*, vol. 24, no. 1, pp. 170–184, feb 2008. 42

[142] F. De Vignemont, "Embodiment, ownership and disownership," *Consciousness and Cognition*, vol. 20, no. 1, pp. 82–93, 2011. [Online]. Available: https://jeannicod.ccsd.cnrs.fr/ijn{_}00526983 42

[143] E. A. Caspar, A. Cleeremans, and P. Haggard, "The relationship between human agency and embodiment," *Consciousness and Cognition*, vol. 33, pp. 226–236, may 2015. 42

[144] F. Argelaguet, L. Hoyet, M. Trico, and A. Lécuyer, "The role of interaction in virtual embodiment: Effects of the virtual hand representation," in *Proceedings - IEEE Virtual Reality*, vol. 2016-July. IEEE Computer Society, jul 2016, pp. 3–10. 42

[145] A. W. Wilson, D. H. Blustein, and J. W. Sensinger, "A third arm - Design of a bypass prosthesis enabling incorporation," in *IEEE International Conference on Rehabilitation Robotics*. IEEE Computer Society, aug 2017, pp. 1381–1386. 42

[146] M. Tsakiris, G. Prabhu, and P. Haggard, "Having a body versus moving your body: How agency structures body-ownership," *Consciousness and Cognition*, vol. 15, no. 2, pp. 423–432, jun 2006. 42

[147] A. Kalckert and H. Ehrsson, "Moving a rubber hand that feels like your own: A dissociation of ownership and agency," *Frontiers in Human Neuroscience*, vol. 6, p. 40, 2012. [Online]. Available: https://www.frontiersin.org/article/10.3389/fnhum.2012.00040 43

[148] W. Wen, "Does delay in feedback diminish sense of agency? A review," aug 2019. 44

[149] V. Huynh, R. Bekrater-Bodmann, J. Fröhner, J. Vogt, and P. Beckerle, "Robotic hand illusion with tactile feedback: Unravelling the relative contribution of visuotactile and visuomotor input to the representation of body parts in space," *PLoS ONE*, vol. 14, no. 1, jan 2019. 44

[150] M. Keetels and J. Vroomen, “Exposure to delayed visual feedback of the hand changes motor-sensory synchrony perception,” *Experimental Brain Research*, vol. 219, no. 4, pp. 431–440, 2012. 44

[151] M. A. F. Ismail and S. Shimada, “’Robot’ hand illusion under delayed visual feedback: Relationship between the senses of ownership and agency,” *PLoS ONE*, vol. 11, no. 7, jul 2016. 44

[152] S. Shimada, K. Fukuda, and K. Hiraki, “Rubber hand illusion under delayed visual feedback,” *PLoS ONE*, vol. 4, no. 7, jul 2009. 44

[153] M. M. C. Vidovic, H. J. Hwang, S. Amsüss, J. M. Hahne, D. Farina, and K. R. Müller, “Improving the robustness of myoelectric pattern recognition for upper limb prostheses by covariate shift adaptation,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 9, pp. 961–970, Sept 2016. 55

[154] A. J. Young, L. J. Hargrove, and T. A. Kuiken, “The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2537–2544, Sept 2011. 55

[155] S. Amsüss, L. P. Paredes, N. Rudigkeit, B. Graimann, M. J. Herrmann, and D. Farina, “Long term stability of surface emg pattern classification for prosthetic control,” in *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, July 2013, pp. 3622–3625. 55, 131

[156] A. M. Simon, L. J. Hargrove, B. A. Lock, and T. A. Kuiken, “A decision-based velocity ramp for minimizing the effect of misclassifications during real-time pattern recognition control,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 8, pp. 2360–2368, Aug 2011. 56

[157] C. L. Chicoine, A. M. Simon, and L. J. Hargrove, “Prosthesis-guided training of pattern recognition-controlled myoelectric prosthesis,” in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Aug 2012, pp. 1876–1879. 56

[158] F. Orabona, C. Castellini, B. Caputo, A. E. Fiorilla, and G. Sandini, "Model adaptation with least-squares svm for adaptive hand prosthetics," Idiap, Idiap-RR Idiap-RR-05-2009, 3 2009, accepted in ICRA09. 56

[159] P. M. Pilarski, M. R. Dawson, T. Degris, J. P. Carey, K. M. Chan, J. S. Hebert, and R. S. Sutton, "Adaptive artificial limbs: a real-time approach to prediction and anticipation," *IEEE Robotics Automation Magazine*, vol. 20, no. 1, pp. 53–64, March 2013. 56

[160] Y. Zhang, Z. Wang, Z. Zhang, Y. Fang, and H. Liu, "Comparison of online adaptive learning algorithms for myoelectric hand control," in *2016 9th International Conference on Human System Interactions (HSI)*, July 2016, pp. 69–75. 56

[161] J. W. Sensinger, B. A. Lock, and T. A. Kuiken, "Adaptive pattern recognition of myoelectric signals: Exploration of conceptual framework and practical algorithms," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 17, no. 3, pp. 270–278, June 2009. 56

[162] J.-Y. Hogrel, J. Duchêne, and J.-F. Marini, "Variability of some semg parameter estimates with electrode location," *Journal of Electromyography and Kinesiology*, vol. 8, no. 5, pp. 305 – 315, 1998. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1050641197000436 57

[163] Y. Fang and H. Liu, "Robust semg electrodes configuration for pattern recognition based prosthesis control," in *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. IEEE, 2014, pp. 2210–2215. 58

[164] I. Veldhuizen, A. Gaillard, and J. de Vries, "The influence of mental fatigue on facial emg activity during a simulated workday," *Biological Psychology*, vol. 63, no. 1, pp. 59 – 78, 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0301051103000255 58

[165] B. Pageaux, S. Marcora, V. Rozand, and R. Lepers, "Mental fatigue induced by prolonged self-regulation does not exacerbate central fatigue during subsequent whole-body endurance exercise," *Frontiers in Human Neuroscience*, vol. 9, 02 2015. 58

[166] J. Van Cutsem, S. Marcora, K. De Pauw, S. Bailey, R. Meeusen, and B. Roelands, "The effects of mental fatigue on physical performance: A systematic review," *Sports Medicine*, vol. 47, 01 2017. 58

[167] Q. Huang, D. Yang, L. Jiang, H. Zhang, H. Liu, and K. Kotani, "A novel unsupervised adaptive learning method for long-term electromyography (emg) pattern recognition," *Sensors (Basel, Switzerland)*, vol. 17, no. 6, p. 1370, Jun 2017, 28608824[pmid]. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/28608824 58

[168] Y. Fang, X. Zhu, and H. Liu, *Development of a Surface EMG Acquisition System with Novel Electrodes Configuration and Signal Representation*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 405–414. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-40852-6_41 59

[169] Y. Fang, H. Liu, G. Li, and X. Zhu, "A multichannel surface emg system for hand motion recognition," *International Journal of Humanoid Robotics*, vol. 12, no. 02, p. 1550011, 2015. [Online]. Available: http://www.worldscientific.com/doi/abs/10.1142/S0219843615500115 59

[170] Y. Fang and H. Liu, "Robust semg electrodes configuration for pattern recognition based prosthesis control," in *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Oct 2014, pp. 2210–2215. 59

[171] X. Chen, D. Zhang, and X. Zhu, "Application of a self-enhancing classification method to electromyography pattern recognition for multifunctional prosthesis control," *Journal of neuroengineering and rehabilitation*, pp. 1–13, 2013. 63

[172] Y. Huang, K. B. Englehart, B. Hudgins, and A. D. C. Chan, "A Gaussian mixture model based classification scheme for myoelectric control of powered upper limb prostheses," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 11, pp. 1801–1811, 2005. 63

[173] A. A. Adewuyi, L. J. Hargrove, and T. A. Kuiken, "Evaluating emg feature and classifier selection for application to partial-hand prosthesis control," *Frontiers in Neurorobotics*, vol. 10, p. 15, 2016. [Online]. Available: https://www.frontiersin.org/article/10.3389/fnbot.2016.00015 63

[174] S. Jain, G. Singhal, R. J. Smith, R. Kaliki, and N. Thakor, “Improving long term myoelectric decoding, using an adaptive classifier with label correction,” in *Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics*, 2012, pp. 532–537. 64

[175] M. M. Vidovic, H.-j. Hwang, S. Amsüss, J. M. Hahne, D. Farina, and K.-r. Müller, “Improving the Robustness of Myoelectric Pattern Recognition for Upper Limb Prostheses by Covariate Shift Adaptation,” vol. 24, no. 9, pp. 961–970, 2016. 67

[176] B. Cornish, B. Thomas, and L. Ward, “Effect of temperature and sweating on bioimpedance measurements,” *Applied Radiation and Isotopes*, vol. 49, no. 5, pp. 475 – 476, 1998, international Symposium on In Vivo Body Comparison Studies. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0969804397000572 69

[177] C. Toledo, A. Simon, R. Muñoz, A. Vera, L. Leija, and L. Hargrove, “A comparison of direct and pattern recognition control for a two degree-of-freedom above elbow virtual prosthesis,” in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2012. 77

[178] E. Scheme and K. Englehart, “Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use,” *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 643–660, 2011. [Online]. Available: http://www.rehab.research.va.gov/jour/11/486/pdf/scheme486.pdf 77

[179] A. J. Young, L. J. Hargrove, and T. a. Kuiken, “The effects of electrode size and orientation on the sensitivity of myoelectric pattern recognition systems to electrode shift,” *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 9, pp. 2537–2544, 2011. 78

[180] T. D. Lalitharatne, Y. Hayashi, K. Teramoto, and K. Kiguchi, “Compensation of the effects of muscle fatigue on EMG-based control using fuzzy rules based

scheme," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2013, pp. 6949–6952. 78

[181] P. Kaufmann, K. Englehart, and M. Platzner, "Fluctuating EMG signals: Investigating long-term effects of pattern matching algorithms," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010. 78

[182] P. Boyd, Y. Fang, and H. Liu, "Preliminary results of emg-based hand gestures for long term use," in *Intelligent Robotics and Applications*, Y. Huang, H. Wu, H. Liu, and Z. Yin, Eds. Cham: Springer International Publishing, 2017, pp. 98–108. 78

[183] N. Akhlaghi, C. A. Baker, M. Lahlou, H. Zafar, K. G. Murthy, H. S. Rangwala, J. Kosecka, W. M. Joiner, J. J. Pancrazio, and S. Sikdar, "Real-time classification of hand motions using ultrasound imaging of forearm muscles," *IEEE Transactions on Biomedical Engineering*, 2016. 78

[184] X. Yang, X. Sun, D. Zhou, Y. Li, and H. Liu, "Towards wearable a-mode ultrasound sensing for real-time finger motion recognition," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2018. 78, 87

[185] D. S. González and C. Castellini, "A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees," *Frontiers in Neurorobotics*, 2013. 78

[186] X. Yang, Y. Li, Y. Fang, and H. Liu, "A preliminary study on the relationship between grip force and muscle thickness," in *International IEEE/EMBS Conference on Neural Engineering, NER*, 2017, pp. 118–121. 78

[187] I. Donald, J. Macvicar, and T. G. Brown, "INVESTIGATION OF ABDOMINAL MASSES BY PULSED ULTRASOUND," *The Lancet*, 1958. 78

[188] J. He, X. Sheng, X. Zhu, and N. Jiang, "Electrode density affects the robustness of myoelectric pattern recognition system with and without electrode shift," *IEEE Journal of Biomedical and Health Informatics*, 2019. 79

[189] X. Yang, J. Yan, Z. Chen, H. Ding, and H. Liu, “A proportional pattern recognition control scheme for wearable a-mode ultrasound sensing,” *IEEE Transactions on Industrial Electronics*, vol. 67, no. 1, pp. 800–808, 2020. 82

[190] P. Kaufmann, K. Englehart, and M. Platzner, “Fluctuating EMG signals: Investigating long-term effects of pattern matching algorithms,” in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC'10*, 2010. 85

[191] A. J. Young, L. J. Hargrove, and T. A. Kuiken, “Improving myoelectric pattern recognition robustness to electrode shift by changing interelectrode distance and electrode configuration,” *IEEE Transactions on Biomedical Engineering*, 2012. 87

[192] Y. Li, K. He, X. Sun, and H. Liu, “Human-machine interface based on multichannel single-element ultrasound transducers: A preliminary study,” in *2016 IEEE 18th International Conference on e-Health Networking, Applications and Services, Healthcom 2016*, 2016. 87

[193] L. Hargrove, K. Englehart, and B. Hudgins, “A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control,” *Biomedical Signal Processing and Control*, 2008. 89

[194] L. Pan, D. Zhang, N. Jiang, X. Sheng, and X. Zhu, “Improving robustness against electrode shift of high density EMG for myoelectric control through common spatial patterns,” *Journal of NeuroEngineering and Rehabilitation*, vol. 12, no. 1, dec 2015. 93

[195] K. Li, Y. Fang, Y. Zhou, and H. Liu, “Non-Invasive Stimulation-Based Tactile Sensation for Upper-Extremity Prosthesis: A Review,” *IEEE Sensors Journal*, vol. 17, no. 9, pp. 2625–2635, may 2017. 99

[196] Y. Zhou, Y. Fang, K. Gui, K. Li, D. Zhang, and H. Liu, “SEMG Bias-Driven Functional Electrical Stimulation System for Upper-Limb Stroke Rehabilitation,” *IEEE Sensors Journal*, vol. 18, no. 16, pp. 6812–6821, aug 2018. 99

[197] L. Baker, C. Wederich, D. McNeal, C. Newsam, and R. Waters, *Neuro Muscular Electrical Stimulation - A practical Guide*. Las Amigos Research & education institute, 1993. 99

[198] K. Li, Y. Fang, Y. Zhou, Z. Ju, and H. Liu, "Haptics model for human fingertips based on Gaussian distribution," *Journal of Intelligent and Fuzzy Systems*, vol. 36, no. 5, pp. 3945–3955, 2019. 100, 101, 107

[199] D. Yang, J. Zhao, Y. Gu, L. Jiang, and H. Liu, "Estimation of hand grasp force based on forearm surface emg," in *2009 International Conference on Mechatronics and Automation*, 2009, pp. 1795–1799. 100

[200] N. Jorgovanovic, S. Dosen, D. J. Djozic, G. Krajoski, and D. Farina, "Virtual grasping: Closed-loop force control using electrotactile feedback," *Computational and Mathematical Methods in Medicine*, vol. 2014, p. 120357, Jan 2014. [Online]. Available: https://doi.org/10.1155/2014/120357 108

FORM UPR16

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UNIVERSITY OF PORTSMOUTH

Postgraduate Research Student (PGRS) Information		**Student ID:**	658763
PGRS Name:	Peter Boyd		
Department:	School Of Computing	**First Supervisor:**	Honghai Liu
Start Date: (or progression date for Prof Doc students)		01/10/2015	

Study Mode and Route:	Part-time ☐	MPhil ☐	MD ☐
	Full-time ☒	PhD ☑	Professional Doctorate ☐

Title of Thesis:	Sensing and Adaption for Long Term Hand Rehabilitation
Thesis Word Count: (excluding ancillary data)	31029

If you are unsure about any of the following, please contact the local representative on your Faculty Ethics Committee for advice. Please note that it is your responsibility to follow the University's Ethics Policy and any relevant University, academic or professional guidelines in the conduct of your study

Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

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(If you would like to know more about the checklist, please see your Faculty or Departmental Ethics Committee rep or see the online version of the full checklist at: http://www.ukrio.org/what-we-do/code-of-practice-for-research/)

a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame?	YES ☒ NO ☐
b) Have all contributions to knowledge been acknowledged?	YES ☒ NO ☐
c) Have you complied with all agreements relating to intellectual property, publication and authorship?	YES ☒ NO ☐
d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration?	YES ☒ NO ☐
e) Does your research comply with all legal, ethical, and contractual requirements?	YES ☒ NO ☐

Candidate Statement:

I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)

Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):	TECH2019- P.B -03

If you have *not* submitted your work for ethical review, and/or you have answered 'No' to one or more of questions a) to e), please explain below why this is so:

Signed (PGRS):		**Date:** 30/09/2019