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Doctor of Philosophy

Training, Retaining and Transferring Novel Myoelectric Skills for Prosthetic Hand Control

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Declaration

I hereby declare that this thesis is my own work except where specific reference is made to the work of others. The contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university.

Simon Stuttaford
December 2023

Dedication

In dedication to:

René Stuttaford
"Ek boudtjies warm klap"

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Abstract

Recent advancements in robotics have led to the creation of highly dexterous multi-articulating hands that can mimic human capabilities. Despite this achievement, high rates of prosthesis abandonment persist in the field of upper-limb prosthetics, with control issues and limited functionality often cited as key reasons. Although various solutions have been attempted, there remains a critical gap between the capabilities of modern artificial hands and the means to effectively operate them.

Until prosthetic systems can perfectly interpret user intent, prosthesis control will always involve an aspect of motor-learning, as users naturally adapt their motor behaviour when they encounter an error. Various studies have inadvertently provided evidence that human motor learning actively compensates for inaccuracies in prosthetic systems. However, serious exploration of the impact of the human element within the control loop has only recently begun. This thesis investigates the integration of neuroscience and motor learning principles to enhance prosthesis control and system robustness. Moreover, it emphasises the often-overlooked role of user learning in optimising pre-device training for improved control experiences.

Four studies form the core contributions of this work. Two multi-day studies, one lab-based and one home-based, comprise the first two studies that analyse the effects of different feedback mechanisms on the permanency of learned myoelectric skills. In total, ~35,000 trials were collected, yielding one of the largest myoelectric datasets in the field. The findings highlight the importance of utilising appropriate feedback mechanisms during user learning and provides a novel method of myoelectric training that leads to improved skill permanency in the absence of artificial feedback. The third study focused on the transferability of these findings to actual prosthesis

use, which showed improved prosthesis control following myoelectric training with delayed feedback, highlighting the method's efficacy in pre-device rehabilitation. The fourth study examined the impact of arm position changes on muscle activity, showcasing the benefits of delayed feedback training in enhancing muscle activation consistency which generalised to untrained positions. These findings offer the field a novel tool for combatting the limb position effect. Collectively, they underscore the potential of human motor learning to optimise rehabilitation protocols and enhance prosthesis control performance.

Contents

Chapter 1

Introduction

1.1 Motivation

Projections estimate that more than 2.5 million people worldwide are currently living with limb difference [1]. Adding to this population, each year one in 2,500 infants are born with upper-limb difference [2]. Although trauma from recent wars is often the most common cause of limb loss, vascular disease and workplace accidents due to industrial advancement in developing countries have started to claim a larger percentage of amputations [1]. The loss of a hand is perceived as being particularly devastating due to the impact it can have on work, social life, and independence. Unfortunately, the World Health Organization estimates that only 1 in 10 people in need has access to prostheses and orthoses, due to their high cost and low availability [3]. Equipping people with an amputation with purpose-fit and affordable prosthetics can be better enable them to regain their independence and return to work and social life, thus improving their overall quality of life.

Despite the promise of modern myoelectric prostheses, studies indicate that around 29% - 44% of users stop using their devices [4]–[6]. Additionally, an estimated 20% of individuals with limb deficiencies choose not to seek any form of prosthetic device at all [7]. Among those who do adopt myoelectric prostheses, many primarily rely on their intact hand for most tasks [8], [9]. Consequently, it is not surprising that users often report feeling more functional without a device [10]. While myoelectric hand prostheses may enhance feelings of social acceptance, they are frequently criticized for being less robust, difficult to control [11]. As a result, these prosthetic devices are often repurposed for solely cosmetic purposes [12]. Unfortunately, the advancement of electro-mechanical hands has far outpaced development of the control methods to drive them. Although myoelectric prostheses have the potential to restore multiple movements, even state-of-the-art control methods cannot exploit the full range of motion offered by modern electro-mechanical hands.

An ideal upper-limb prosthesis would provide high-fidelity feedback of the user's control signals in real time, mimicking human physiology. The delay between intent and grasp actuation would also resemble that of an intact hand. Unfortunately, this is far from what is clinically or commercially available - in reality, users must rely on visual feedback of the hand moving. However, there is a relatively large delay between user intent and activation of the prosthetic hand. Consequently, it is difficult to adapt input signals on the fly, such as in response to a prosthetic hand performing the wrong grasp. Until such idealised prostheses exist it is crucial that users generate consistent and accurate control signals in the absence of external feedback mechanisms. In order to achieve this, users must learn to control their muscle activity in a novel manner.

Previous research on motor learning-based myoelectric control systems have traditionally presented concurrent feedback of the user's control signals in real-time [13]–[20]. This alone does not a pose problem - feedback is a necessary part of learning. However, the motor skills demanded by this task may be fundamentally distinct to those required for controlling an existing prosthesis. For example, existing literature in the field of applied motor learning suggests that traditional feedback mechanisms (i.e. those used throughout myoelectric research) may actually reinforce counterproductive skills by encouraging the user to rely on concurrent feedback, which is not present during actual prosthesis control [21]–[27]. Therefore, extrapolating the myoelectric performance observed in the laboratory to real world prosthesis control is challenging. This makes it difficult to evaluate the viability of some rehabilitation training protocols or myoelectric control schemes. Previous prosthesis control literature has not investigated this perspective of motor learning. To fill that research gap, this thesis intends to explore the applicability of findings from the fields of neuroscience and motor learning to training users to produce novel muscle activity to control a prosthesis.

Furthermore, there is evidence to suggest that improvements in prosthesis control occur when users interact with the system over time [28]–[35]. Often, these control systems have roots in the numerical sciences; therefore, the involvement of user learning has not been a primary focus. This thesis argues that if learning occurs when users interact with any system, it stands to reason that the user aspect of the control loop must be optimised with training protocols.

1.2 Aims and Objectives

This work was done in collaboration with Newcastle University, The University of Edinburgh and University College Dublin.

The overall aims of this thesis were twofold:

1. Improve the quality of prosthesis users' control signals through practice to enable them to benefit more from the devices currently available to them.
2. Inform future myoelectric training protocols to assist in the retention and transfer of myoelectric skill, prior to receiving a device.

1.2.1 Study 1: The Effects of Delayed Feedback Training on Myoelectric Skill Retention

This study aimed to demonstrate that four grasp classes could feasibly be restored without any algorithmic assistance or hardware beyond the current clinical standard. This study consisted of a rigorous laboratory experiment, conducted over 4 consecutive days, and included a follow-up after an 18-day hiatus. The objectives were as follows:

- Investigate the retention of myoelectric skill after concurrent and delayed feedback training.
- Compare the permanency of this skill over days and weeks, as measured by two commonly used methods intended to probe the state of learning: catch trials and zero-feedback blocks.

1.2.2 Study 2: Myoelectric Skill Training in The Home Environment

This study used remote data collection methods while participants underwent myoelectric training in their homes over a 5-day period. The specific objectives for each part of this study were as follows:

- Assess the feasibility of using bespoke, home-based protocols to train participants within suitable time frames.
- Investigate whether participants trained with delayed feedback can match the high level of performance achieved by concurrent feedback trained participants.

1.2.3 Study 3: The Effects of Myoelectric Training on Skill Transfer to Prosthesis Control

This study aimed to demonstrate skill transfer from myoelectric control to prosthesis control. Participants underwent myoelectric training with the protocol devised in the home-based retention study. A prosthesis control task was carried out pre- and post-training to assess the proportion of the retained myoelectric skill translated to real-world prosthesis control. The two main objectives were as follows:

- Demonstrate skill transfer from myoelectric control to prosthesis control.
- Understand how performance in laboratory settings translates to prosthesis control.

1.2.4 Study 4: The Impact of Reducing Motor Variability on The Limb Position Effect

This study aimed to explore the impact of the limb position effect on the performance of participants trained with either concurrent or delayed feedback within a myoelectric task. The lab-based retention study showed that the type of feedback used during training led to fundamentally different myoelectric skills. This study was conducted with participants from the lab-based retention study, all of whom had conducted 4 days of training in a single arm position. The objectives of this study were as follows:

- Investigate whether improved muscle output consistency observed during prolonged training in a single position generalises to untrained arm positions.
- Explore the structural changes of muscle activity, across multiple recording sites, following a change in arm position.

1.2.5 Appendices

Finally, the findings from two pilot studies are presented. Although both are relevant to the overall message of this thesis, they are included in the appendices to maintain focus on the core studies.

Study A1: The Application of User Adaptation On Pattern Recognition

The findings from the lab-based retention study demonstrated that users can learn to improve their myoelectric performance in a two-dimensional task space. The results from the limb position study suggested that user learning led to reduced contraction pattern variability, which in turn yielded gains in decoding robustness under novel conditions. This study aimed to investigate how to apply user learning in high-dimensional pattern recognition based systems. The objectives were as follows:

- Assess the feasibility and efficacy of training users to increase contraction pattern consistency.
- Investigate the impact of reduced motor output variability on static decision boundaries.

Study A2: Exploiting Iterative Biofeedback for Automatic Control-site Detection

This study aimed to assess the applicability of an algorithm in terms of its ability to detect viable contraction strategies in real time. An iterative variant of principal component analysis, called Candid Covariance-free Incremental Principal Component Analysis (CCIPCA), was applied to offline muscle activity data of participants learning a novel myoelectric task. This study was a proof of concept for use as a clinical tool. The objectives were as follows:

- Compare CCIPCA's convergence to the 'gold standard' of batch principal component analysis (PCA).
- Illustrate the usefulness of the biofeedback provided by CCIPCA.

1.3 Publications

Journal Publications

- **S. A. Stuttaford**, S. S. G. Dupan, K. Nazarpour, and M. Dyson, "Delaying feedback during pre-device training facilitates the retention of novel myoelectric skills: A laboratory and home-based study," *Journal of Neural Engineering*, vol. 20, no. 3, p. 036 008, 2023
- **S. A. Stuttaford**, M. Dyson, K. Nazarpour, and S. S. G. Dupan, "Reducing motor variability enhances myoelectric control robustness across untrained limb positions," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2023

Conference Publications

- **S. A. Stuttaford**, A. Krasoulis, S. Dupan, K. Nazarpour, and M. Dyson, "Automatic myoelectric control site detection using candid covariance-free incremental principal component analysis," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, IEEE, 2020, pp. 3497–3500
- **S. A. Stuttaford**, S. Dupan, K. Nazarpour, and M. Dyson, "Long-term myoelectric training with delayed feedback in the home environment," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, IEEE, 2021, pp. 6437–6440
- S. S. G. Dupan, **S. A. Stuttaford**, K. Nazarpour, and M. Dyson, "Transfer of abstract control skills to prosthesis use," in *Proc. Myoelectric Controls Symp. (MEC)*, 2022, pp. 94–97

1.4 Thesis Organisation

This document is organised as follows:

- **Chapter 2** provides a background of the relevant literature on myoelectric prosthetics and motor learning.
- **Chapter 3** describes the methods used for collecting data in each study.
- **Chapter 4** introduces the Study 1. This study was conducted under laboratory conditions and investigates the effect of feedback provided during training on myoelectric skill.
- **Chapter 5** introduces Study 2, which was conducted in the participants' homes.
- **Chapter 6** presents Study 3, which builds upon the findings from Study 1 and demonstrates the transfer of myoelectric skills to prosthesis control.
- **Chapter 7** describes the findings from Study 4. Participants from Study 1 were tested under multiple arm positions.
- **Chapter 8** summarises the findings from each study and discusses potential avenues for future work.
- **Appendices** introduces two studies: Study A1, which applies user learning within the context of pattern recognition, and Study A2, which demonstrates a proof of concept for an algorithmic tool intended to detect suitable muscle contraction patterns by providing real-time biofeedback.

Chapter 2

Background

2.1 Limb Difference

In upper-limb prosthetics, the term *limb difference* is often used to describe deviations from the typical function or form of a limb [41]. Limb difference can be acquired via amputation, following a traumatic injury or through vascular disease. It can also be present at birth, which is referred to as *congenital* limb difference [41]. There are several levels of limb difference, which are categorised in Figure 2.1. The cause, level, and structure of the limb can impact a person's desire or ability to use certain prosthetic devices.

Prostheses can be split in to two categories: active and passive [42]. Passive prostheses are typically used for cosmetic purposes and are often made to look like a natural limb. Although some may have posable joints, which can help in stabilising objects, these prostheses do not actively move. By contrast, active prostheses enable operation of a grasping mechanism by utilising either electric motors or body power (i.e. by changing the tension on a cable connected to the gripper). Active hand prostheses are one option available to people with limb difference to assist in restoring function.

2.2 Prosthesis Control

The most common way of controlling a modern electro-mechanical prosthetic hand is by using the electrical impulses generated by muscles in the residual

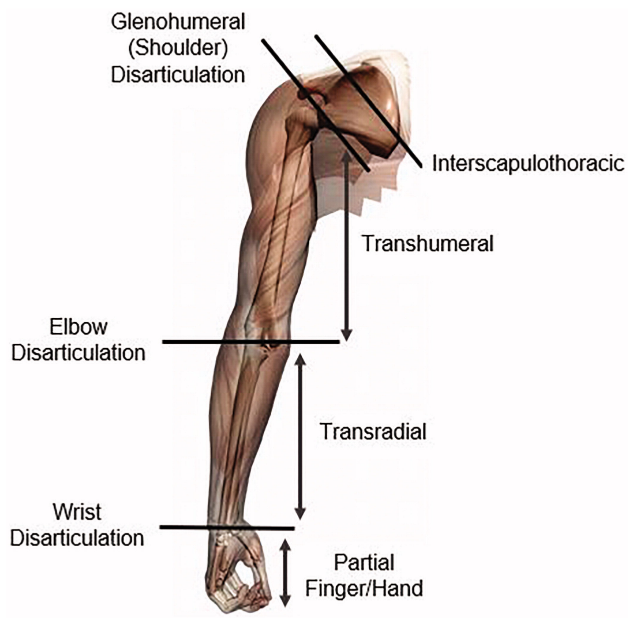

Figure 2.1: The naming convention for different levels of upper-limb amputation. Figure sourced from [41]

limb [43]. Prostheses that operate in this way are aptly named *myoelectric*, which translates from Greek as 'electric muscle'. Progress in electromyography (i.e. the recording and interpretation of muscle activity) has played a pivotal role in enhancing myoelectric prostheses [44].

2.2.1 Electromyography

Signals related to movement intent are generated through a series of action potential pulses from the motor cortex [45]. 'Action potential', which refers to the momentary depolarisation in the membrane potential of a cell, is the basis for electrical signalling between neurons [46]. These signals travel down the spinal cord to muscles innervated by motor neurons. Because one nerve can innervate many muscle fibres, the neural signals are effectively amplified, allowing them to be easily sampled with electrodes placed on the surface of the skin [47]. Therefore, the resulting electromyography (EMG) signals reflect the superposition of action potentials from many muscle fibres, which are organised into groups called motor units [47]. Alternatively, EMG can also be measured invasively with intramuscular electrodes. This enables recordings that have greater spatial resolution and allows identification of individual 'motor units' [48]. However, because of its ease of use and non-invasiveness, surface electromyography (sEMG) is generally preferred for real-world applications of the approach [43]. An illustration of the composition and detection of EMG signals is shown in Figure 2.2.

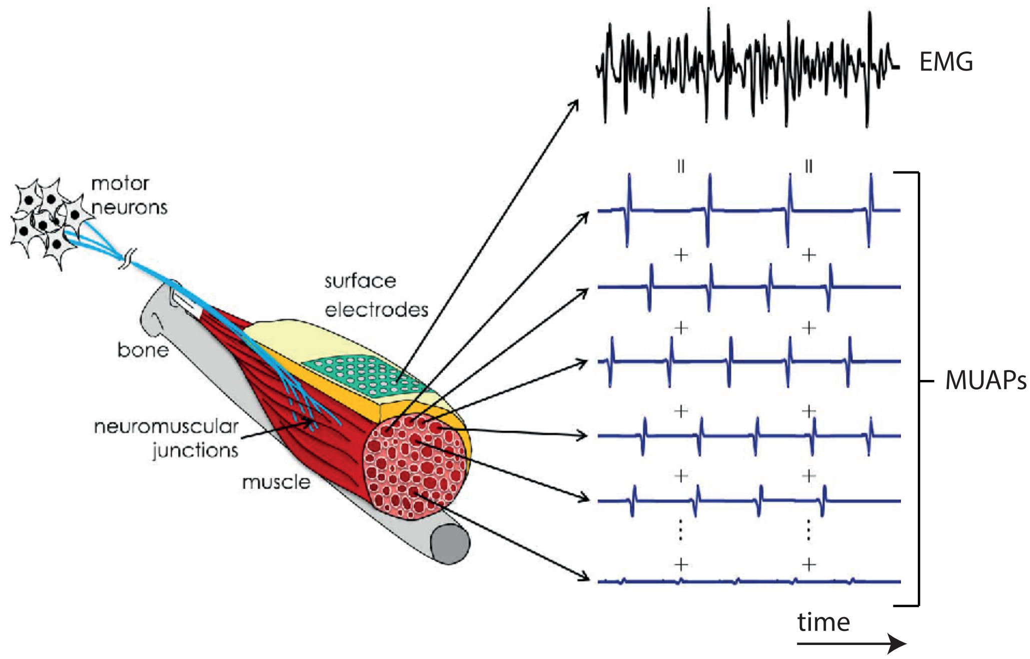

Figure 2.2: The generation and composition of an EMG signal. Motor neurons in the spinal cord cause muscle fibres to activate. The EMG signal detected on the surface of the skin is a sum of individual motor unit action potentials (MUAPS). Figure edited from [47]

The information inherent over a window of EMG can be used to estimate joint positions and force production of an intact limb [49], [50]. In the case of limb difference, the neural signals still remain and are amplified by the remnant muscles in the residual limb. This enables user intent to be estimated for non-existent joints as well. The most common method of controlling active hand prostheses is by recording muscle activity from the residual limb with EMG [43]. The information acquired from EMG signals can then be mapped to a prosthesis output via a control scheme, of which many types exist [51].

2.2.2 Forearm Biomechanics

Despite not being connected to a joint after amputation, as long as the neural pathways remain intact, residual muscles can still be contracted isometrically, and therefore EMG signals can be acquired [52]. As the ECR and FCR are the largest muscles in the forearm, they are likely to remain after amputations below the elbow [52]. In addition, since they are also superficial muscles, their respective EMG activity can be easily detected via surface electrodes for prosthesis control [53]. The ECR and FCR muscles are an agonist-antagonist pair, enabling extension and flexion of the wrist. In an intact arm, the ECR and FCR muscles run along the length of the posterior and anterior sides of the forearm, respectively [52]. The ECR muscle originates on the lateral side of the humerus and inserts at the base of the second metacarpal bone [54]. Whereas the FCR muscle originates from the medial epicondyle of the humerus and inserts to the second and third metacarpal bones [54]. There are 20 other predominant muscles in the forearm that support wrist, finger, and elbow movement [55], [56]. The close proximity of muscle groups can make precise targeting of muscle activity with non-invasive sensors challenging, potentially leading to uncertainty in the validity of the recorded data.

2.2.3 Conventional Control Schemes

In an intact limb, the signal latency from brain to movement output can take up to 150 ms [57]. Due to the additional processing steps, typical myoelectric prostheses can add an additional delay of up to 300 ms [58]. Figure 2.3 demonstrates the general flow structure of controlling a myoelectric prosthesis.

1. Neural commands, in the form of action potentials, are sent from the central nervous system to the remnant muscles in the residual limb.
2. The resulting EMG signals are detected by electrodes housed inside the prosthetic socket.
3. The user receives noisy proprioceptive feedback from their muscles contracting.
4. The EMG signals undergo signal processing; data are windowed so that features can be extracted.

5. This information is passed to a decoder, which maps it to a prosthesis output.
6. The motors in the prosthetic hand begin to actuate the decoded grasp.
7. Finally, the user receives visual feedback from the prosthesis movement, which can then be used to inform their next control decision.

The recording method, signal processing and decoding steps can vary drastically depending on the requirements of the control scheme. Figure 2.4 shows an overview of common approaches used to control a prosthesis as well as the differing hardware requirements for each approach. For example, Figure 2.4a depicts a relatively simple decoder. It works by receiving muscle activity data, which is typically the envelope of the EMG profile from a single electrode, and outputs a grasp if activity surpasses a certain threshold. A decoder can also be more complex, however. Figures 2.4c and 2.4d illustrate two control schemes that require several input channels and multiple features per channel. A machine-learning-based algorithm is then applied to the incoming data to predict an output.

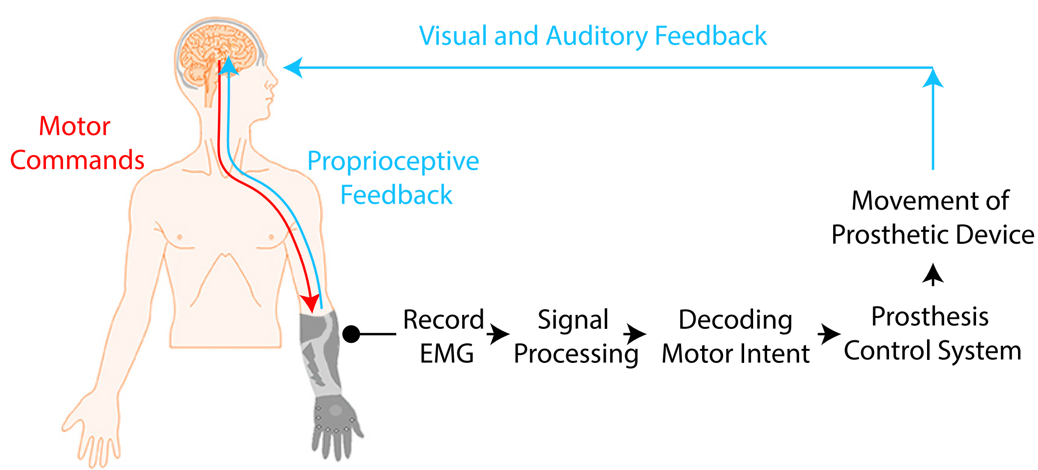

Figure 2.3: The control and feedback loops available to users during the operation of a typical prosthetic device. Figure edited from [59].

The final output can be discrete (such as a grip that the hand is instructed to complete, as is the case in Figure 2.4c) or it can be continuous (which can be used for proportional control of single or multiple degrees of freedom, as shown in Figure 2.4d). Proportional control is defined as users having access to ‘at least one mechanical output quantity of the prosthesis (e.g. force, velocity, position, or any function thereof) within a finite, useful, and essentially continuous interval by varying his/her control input within a corresponding continuous interval’ [60]. All control schemes aim to interpret the motor control signals sent by the central nervous system. However, the control scheme can also demand fundamentally different muscle behaviour from the user. Two mainstream control schemes that exemplify this difference are: dual-site control (with mode switching) and pattern recognition.

Dual-site Control

For users with trans-radial (below-elbow) limb difference, the most commonly deployed control scheme is ‘dual-site’ or ‘direct’ control [61]. This approach uses EMG signals from a pair of residual muscles to provide bidirectional, proportional control of one degree of freedom (DoF) at a time. This control scheme is depicted in Figure 2.4b. In order to access additional degrees of freedom or specific hand grasps, the user must provide a co-contraction, which cycles through a series of preset grasps or controllable joints that can then be actuated by the pair of residual muscles. Due to its simplicity, dual-site control is relatively robust. However, it is limited by its sequential nature and cumbersome mode switching [62].

Pattern Recognition

Pattern recognition offers an alternative to dual-site control and is regarded as the likely successor to sequential control [35]. Pattern recognition was first applied to prosthetic control during the 1970s [63]–[65]. However, the approach gained mainstream attention only in the 1990s, when advancements in micro-processors and multi-articulating prosthetic hands made it possible to fully realise its potential [44], [66].

Various algorithms have been proposed for this approach, but the underlying premise of pattern recognition remains the same. In general, at least eight electrode channels are used to record EMG signals from around the residual limb. Features are extracted from the EMG signal and passed to a classifier. The classifier is a mathematical function that takes the input data and assigns it a label corresponding to a single movement class. Before the system can be used, however, it is first necessary to train the classifier with labelled example data. Figure 2.4c highlights that the output of the classifier is discrete, corresponding to one specific grasp or movement class at a time.

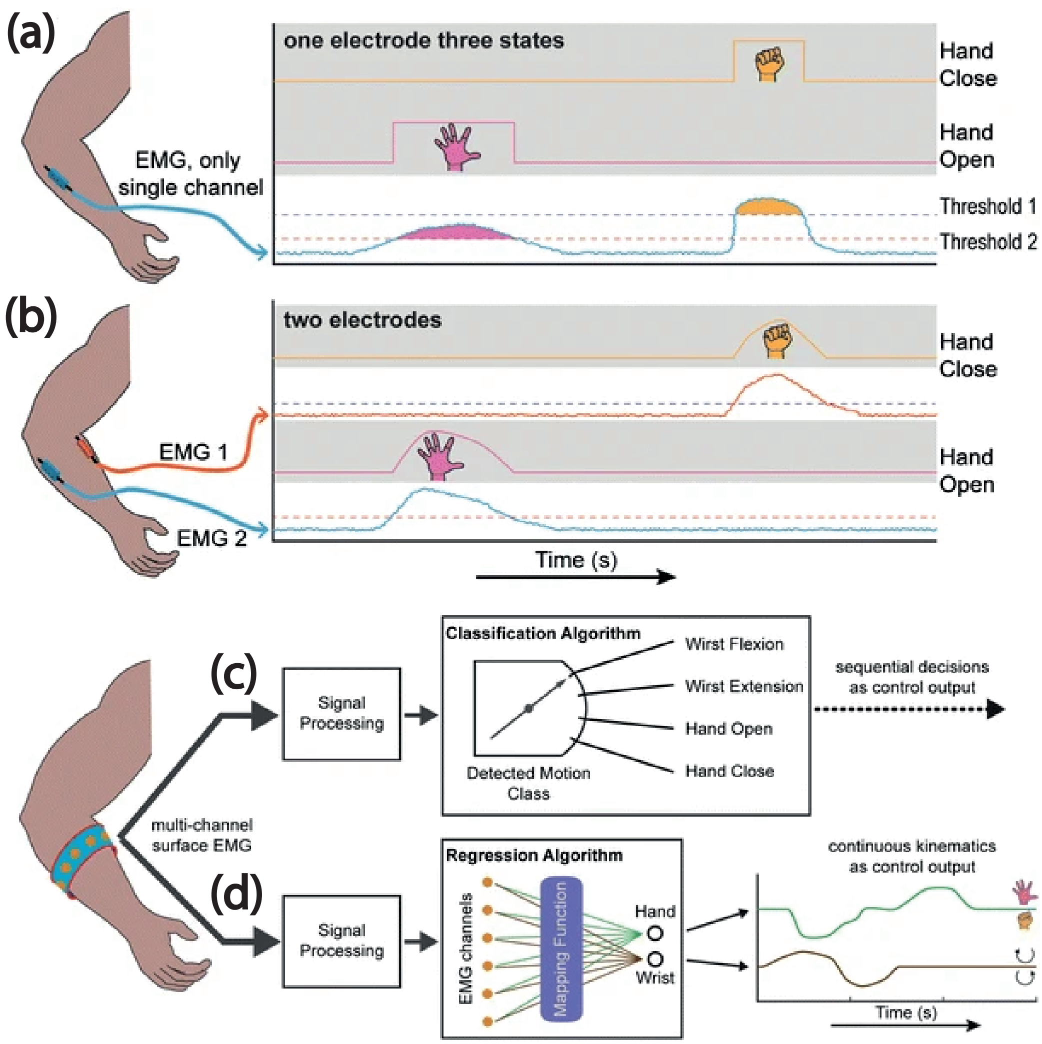

Figure 2.4: Illustration of the different control strategies used to control a myoelectric device. (a) Single channel control. Discrete prosthesis grasp is determined by the activity of a single EMG channel overcoming predefined thresholds. (b) Dual-site control. The aperture of a grip is controlled proportionally using muscle activity from two electrodes. (c-d) Multi-channel control. (c) Classification algorithm maps muscle activity to a single grasp at a time. (d) Regression algorithm enables proportional control of several grips or motion classes simultaneously. Figure edited from [67].

By training the machine learning model with physiologically congruent muscle activity for each labelled grasp, biomimetic control can be achieved [68],

[69]. This, in turn, allows the user to produce muscle activity similar to that needed to achieve the same prosthetic hand grasp naturally, thereby enabling more intuitive control and consequently reducing the cognitive load placed on the user during initial use. One of the main advantages of this approach is that functional use of the prosthesis can commence more rapidly [70].

The disadvantages of pattern recognition are that it usually requires the use of more than two EMG sensors, adding computational complexity and cost. Furthermore, this approach tactly assumes that the underlying neural signals are deterministic; in reality, however, changes may occur over time, causing the classifier to become outdated and ill-fitting to new EMG responses. Similar to all control schemes, these changes eventually manifest as misclassifications and require the user to undergo re-calibration of their device [35], [71], [72]. Unfortunately this can be a time-consuming endeavour with pattern recognition devices.

2.2.4 Confounding Factors

Recording muscle activity via surface EMG is an attractive approach for several reasons, the most important of which is that it is non-invasive and requires muscular effort comparable to that of normal movement [43]. It is therefore widely used in myoelectric control systems. This, however, signifies that these control systems also share the shortcomings of the approach. One disadvantage of employing EMG is that it is a non-stationary stochastic signal, meaning its statistical properties are not constant over time [73]. This, in turn, means that EMG signals from repetitions of identical movements can vary substantially from one another; such variability leads to uncertainty in the decoding step of the processing pipeline. (A control scheme must have some tolerance to accommodate this variability.) However, over time, the incoming EMG may become different from the EMG that was initially mapped to the intended grasp. This means that a static control mechanism can quickly become outdated, leading to misclassifications. In reality, this requires the user to recalibrate their device up to several times per day, depending on the control scheme.

Electromyography non-stationarity is caused by a variety of environmental and physiological factors [74]. Environmental factors can be defined as those that manifest from contextual changes acting on the system (such as changes in electrode conductivity), whereas physiological factors include those caused by biological or bio-mechanical reasons (such as muscle fatigue). Intuitively, it is easier to solve environmental factors that cause EMG property changes between its transmission and detection by an electrode with better hardware design. However, factors that directly affect EMG signal generation are typically (but not always) physiological factors, which can be more challenging to solve.

Complicating the problem still further, multiple factors are often coupled and may occur transiently during daily activities. For example, 'prosthesis loading' occurs when the prosthetic hand holds an object of significant weight. This leads to changes in the distribution of pressure on the socket around the residual limb, changing tissue signal filtering effects as well as potentially causing electrode shifts and lifts. Furthermore, additional muscle activity may be detected from surrounding muscles used to support and stabilise the weight. The cumulative impact of these factors can significantly alter the EMG signal and may result in unintentional activation of the prosthesis, increasing the risk of dropping items or forcing users to contract repeatedly until they attain the right grasp, causing fatigue and thus potentially contributing to further EMG changes.

Another factor that has been found to influence EMG variability is limb position [75], which has recieved increased research attention due to its prevalence in activities of daily living. The effect of limb position on prosthesis control is described in more detail in Section 2.4.

2.3 Motor Control and Learning

Many theories attempt to explain the nature of movement execution, each offering unique applications and accompanying limitations [76]. Although there is no consensus as to which model should be predominant, all are useful tools for guiding research and development of motor rehabilitation practices. This section presents a commonly used model of motor control as a basis for exploring key concepts. Subsequently, it introduces a fresh perspective on motor learning that is not typically employed in prosthetic control literature.

2.3.1 Motor Control

The study of motor control can be defined as the exploration of how the central nervous system generates 'purposeful, coordinated movements in its interaction with the rest of the body and with the environment' [77]. One view of motor control assumes that efferent (motor commands) and afferent (sensory) signals are corrupted by noise inherent in the system [78]. Such noise can arise from various sources, such as stochastic bio-chemical events (e.g. synaptic firing or motor unit recruitment during muscle contraction) as well as the environment. Furthermore, signal transduction and processing times cause substantial delays in feedback on the current state of a movement.

Simulations of simple closed-loop systems do not reflect observed motor behaviour, suggesting more complex processing occurs [78]. For example, consider the usefulness of a simple closed-loop control mechanism while tracking a tennis serve with the ball travelling at 60 ms^{-1}. If relying solely on visual feedback of the ball's position, the sensory signals would only arrive after $\approx$ 100 ms [79]. Before movement preparation of the return swing had even begun, the ball would have already moved 6 m - meaning that the central nervous system would lag a quarter of the court's length behind the current state of the game.

Multiple theories have attempted to explain how the central nervous system operates under outdated information and uncertain conditions. One prevalent theory explains motor control in terms of internal models [80], [81]. Internal models are neural representations of the musculoskeletal system and the environment used by the central nervous system to simulate the dynamic behaviour of the motor system [81], [82]. There are two main types of internal models, *inverse* and *forward* models, which are described in further detail below.

- **Inverse models** are responsible for generating the appropriate motor commands to achieve a desired motor outcome given the current state of the motor system. This process is illustrated in Figure 2.5a.
- **Forward models** predict the next state of the motor system by utilising a copy of the issued motor command, known as an 'efference copy', and the current state of the system. In this way, the kinematic and sensory consequences of an action can be estimated and utilised before sensory feedback is available. An example is shown in Figure 2.5b. By

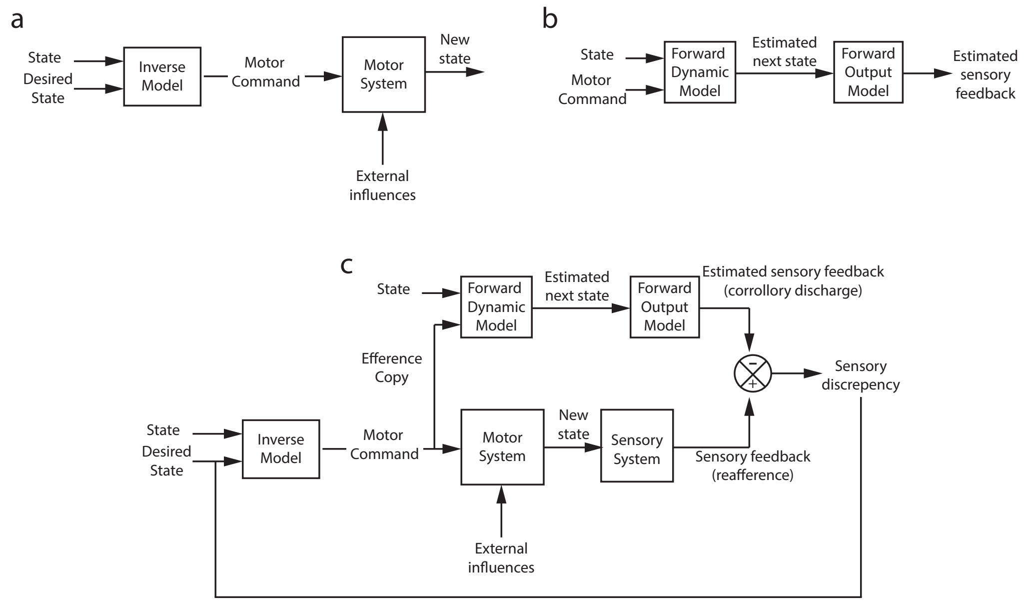

Figure 2.5: Application of forward and inverse models during motor control. (a) Generation and consequence of motor commands via the inverse model. (b) Example of forward model use for kinematic and sensory prediction. Forward dynamic model predicts the kinematics of joints. The forward output model predicts the anticipated sensory consequences of the motor command. (c) An example of the interaction between both models during motor control and learning. Figure edited from [83]

comparing anticipated and actual sensory outcomes, forward models can calculate the error of a motor command, which can then be used to update and refine the internal model, shown in Figure 2.5c. This is referred to as 'motor learning'.

2.3.2 Motor Learning

Motor learning is defined as 'a set of processes associated with practice or experience leading to relatively permanent changes in the capability for skilled movement' [84]. By contrast, motor adaptation describes the iterative modification of movement based on error feedback in order to improve performance [84]. Motor learning generally acts on a slower time scale, requiring prolonged practice in order to observe compound improvement and permanency in skill, whereas motor adaptation reflects a transient response, acting on a faster periods, which enables flexible control that can account for sudden changes in task demands.

To distinguish performance attributable to motor learning from that attributable to motor adaptation, motor learning is often measured with retention tests [84]. Retention tests typically involve performing the same task as done during practice, but without external feedback. During retention tests, the only sources of error signal available to the learner are the internal sense organs, which tend to provide noisy and less reliable source of information, thus stifling the contribution of adaptive processes. Retention tests have been used to assess the effectiveness of the scheduling and type of feedback used during training on motor learning.

The type and timing of feedback given during training has been shown to have different effects on the processes that govern skill learning [23], [85], [86]. Reducing the availability or usefulness of feedback - by either adding noise, delaying its presentation, or omitting it entirely - often slows skill acquisition. Furthermore, it also has been shown to lead to reduced *after-effects* during a washout period [86], [87]. (In our context, 'After-effects' are lingering responses to old task conditions.) This is usually done by removing a perturbation that was present during training. If the participant did not learn during the perturbation trials, there would be no reason to continue attempting to compensate their movements following the perturbation's sudden removal. Therefore, after-effects are often considered a hallmark of motor learning.

Because short-term studies frequently link increased after-effect size to learning, it has been proposed that limiting feedback during training is harmful to learning [86], [88]. Indeed, long-term studies agree that skill acquisition is often slower during reduced feedback conditions. However, when performance is assessed after a longer period of training, in the absence of any external feedback mechanisms, a larger proportion of the performance observed during training is retained [25], [26], [89]–[91].

For example, Armstrong [91] compared different forms of physical guidance for a motor task that involved participants learning to move their elbow in a complex temporal pattern. They found that the participants who were given the most feedback and guidance during the task performed better than those with less guidance. However, when they investigated how well those skills transferred to a different task, the participants who received the least guidance performed the transfer trials most accurately. Subsequent studies found similar results, indicating that feedback often disrupts the retention of motor skill [21], [23], [26], [27]. This phenomenon is explained by the guidance hypothesis.

The guidance hypothesis explains the guiding qualities of feedback and its relationship with performance and learning. It states that although augmented feedback is initially beneficial for motor learning, as it can help to correct errors during performance, it can also be detrimental to motor learning if relied upon [23]. Many explanations have been put forward for this, summarised in [21].

Briefly, it is thought that frequent feedback may overwhelm attention and shift focus away from utilising internal feedback mechanisms for control, such that when augmented feedback is removed, the user has not learned to utilise this sensory information during control. It can also be argued that removing augmented feedback changes the nature of the task in such a way that it can be considered sufficiently distinct, therefore requiring an entirely different set of skills. Another explanation posits that as the learner becomes more skilled, the contribution of sensorimotor noise to their overall error increases. Frequent feedback may encourage maladaptive corrections to counter the noise that is inherently uncorrectable, thereby preventing a stable behaviour from forming.

As such, research has suggested that any form of guidance should be given only when needed [89], [91]. This is especially important in the context of myoelectric training prior to prosthesis use, because the learned skill must be transferred to prosthesis control under conditions of relatively limited external feedback.

2.3.3 Feedback

Feedback is an integral part of the planning and execution of human movement. Feedback can take many forms, which we can classify as originating internally or externally to the body. Internal feedback refers to intrinsic or physiological feedback mechanisms. For example, Golgi tendon organs receive sensory information about the tension of a tendon [92]; this information is used by the nervous system to regulate the force produced by muscles. By contrast, feedback external in origin can be received either from directly carrying out a task, or it can be artificially enhanced. For example, determining whether a goal was scored is often called *inherent feedback* as it is an intrinsic part of the task [84]. When artificially enhanced, it is presented in a way that is not typically available to us, or would be difficult to quantify with our own senses - often referred to as *augmented feedback*. Examples include, one's body weight presented on a bathroom scale or a score given after a dance routine [84]. The timing and type of feedback plays a substantial roll in both motor control and learning.

2.3.4 Motor Learning in Prosthetics

When users interact with a myoelectric system in real time, the accuracy of control often improves. Improvements in myoelectric control accuracy have been documented in single sessions [28], [29], multi-day studies [30]–[34], and multi-week studies [32], [35] using direct control [31], regression [28], [29], and pattern recognition [31], [33]–[35]. However, there was no mention of continuous learning or time-adaptive algorithms in any of these studies. Although multiple factors contribute to the increase in performance, the only variables that change over time in each study are the participants. Therefore, it follows that human learning is the most plausible explanation for the observed gains. If learning occurs during prosthesis use, it would be logical to optimise the process during both prosthesis training and use.

2.3.5 Abstract Decoding

Abstract decoding is a prosthesis control scheme developed at Newcastle University [13], [16], [17], [19], [93] and is one of many learning-based schemes proposed over the last decade [14]–[16], [18], [20], [94]. It relies on users to learn to generate novel patterns of muscle activity. Figure 2.6 shows how abstract decoding compares to other control schemes in terms of their respective task demands. Unlike pattern recognition, which uses machine learning to interpret muscle activity and assign it to a prosthesis output, in abstract decoding the user is tasked with learning this mapping [13], [17], [19]. The resulting muscle activity is physiologically distinct from the muscle activity that would be required to achieve the grasp naturally. Therefore, this is referred to as a 'non-biomimetic approach'. Abstract decoding aims to leverage the plasticity of the human nervous system via user training to teach users to produce distinct signals to control different prosthesis outputs. The end goal is that after enough practice, control over this arbitrary

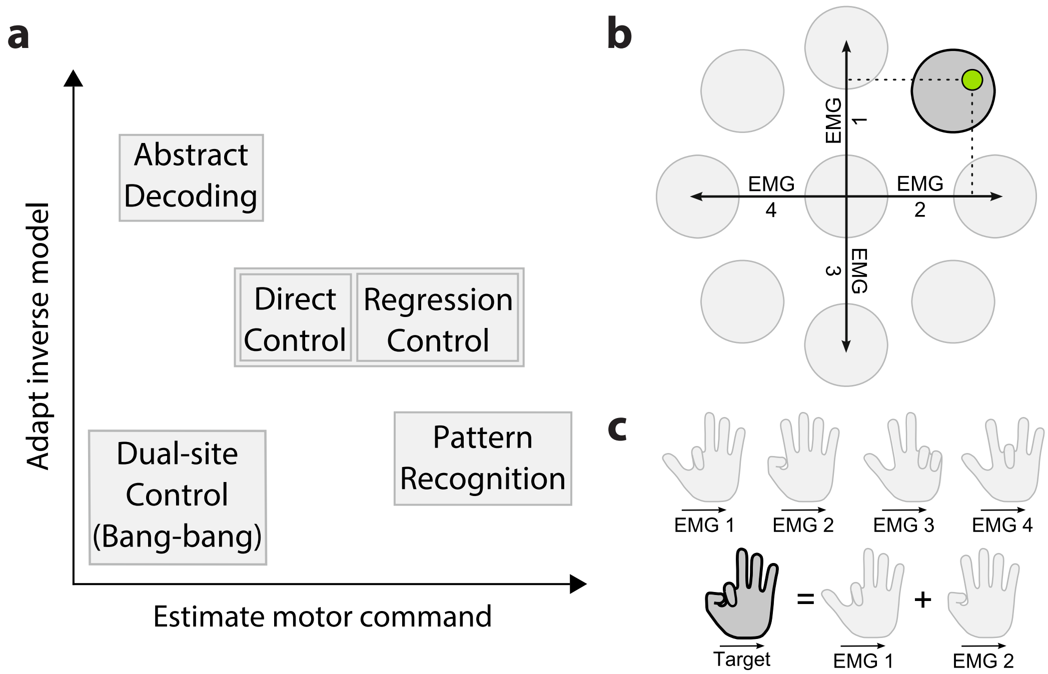

Figure 2.6: (a) Overview of current prosthesis control schemes organised according to how they rely on the motor learning or on the interpretation of feedforward signals that are assumed to be deterministic. (b) An interpretation of abstract decoding cursor control using a four EMG channel interface. Circles represent targets. Green circle represents cursor. Dashed lines correspond to instantaneous EMG activity. (c) Example of mapping the output from a selected target from (b) to a particular posture. Figure from [17]

mapping becomes second nature. This is the same process as learning any other motor task. For example, when writing a word with a pen, we do not consciously think about the individual movements of the wrist or the strokes of the pen. Instead we think of the letter to write and the appropriate motor behaviour follows. Similarly, the idea with learning-based control schemes is to transition users away from consciously thinking about their muscle activity. Handing this processing to the central nervous systems enables abstract decoding to require lower algorithmic complexity and sensor requirements, in comparison to other control schemes [17]. However, because of the arbitrary mapping of muscle activity, this comes at the expense of longer user learning periods. This is in direct contrast to pattern recognition, which takes the converse approach of trading increased algorithmic complexity and hardware requirements for more intuitive control.

The visual representation of the abstract decoding control task space involves presenting muscle activity in a non-representational multidimensional space. In practice, this usually entails learning how to control a cursor with muscle activity displayed over a two-dimensional myoelectric control interface. The normalised and smoothed EMG signals from two sensors are used to control the cursor. The sensors are placed over muscle sites such that each can be activated independently of the other. This is done so that the activity from each sensor can be used to move the cursor along a single axis. Consequently, various levels of co-contraction of both muscle sites move the cursor proportionally towards the centre of the interface.

The position of the cursor on the interface is typically presented concurrently with visual feedback on a computer screen. By providing continuous feedback of muscle activity, the motor system is able to generate an inverse map [95] that connects motor output to arbitrary control variables within the task space [82], [96].

The interface within which the cursor moves can be delineated into multiple segments. Each segment can be assigned to arbitrary prosthesis outputs, such as proportional digit control [13] or grasp selection [15], [20]. By moving the cursor into the corresponding target, a user can select a desired output. In this way, abstract decoding aims to restore multiple hand grasps using two electrodes with no need for cumbersome sequential mode switching. The general approach of abstract decoding was outlined in [17], and subsequent research demonstrated that people with limb differences are capable of learning to generate the novel muscle activities that were required [19].

The ability to learn the necessary muscle activity patterns prior to using a prosthesis is an underlying premise of abstract decoding. However, as discussed previously, visual feedback may not be optimal for user training in the long term. In preparation for real-world use, two conditions must be met: (a) the user must be able to generate the necessary muscle activity patterns in the absence of the precise feedback, and (b) this myoelectric skill must translate to the successful prosthetic operation. These are referred to as *retention* and *transfer* of skill, respectively. Logically, it follows that the learned myoelectric skill must, at the very least, be retained in order for it to transfer to prosthesis control.

2.3.6 Biofeedback vs Motor Learning Prostheses

The ideal prosthesis would be capable of relaying high-fidelity concurrent feedback of the users' control signals to the nervous system in real time. In addition, this prosthetic would mimic natural movement by providing low latency between user intent and completion of the prosthesis grasp. In this theoretical case, the user may not require retention of motor skill at all. Hypothetically, they could operate this prosthesis with real-time biofeedback alone. Their control would be reliant on the tight coupling of input and response, but they would be capable of adapting their muscle activity to counter any perturbation acting upon the system in real time. However, such a system does not yet exist. Currently, users have access only to unreliable proprioceptive signals to infer the state of their muscle activity [97]. In addition, there is a considerable delay between user intent and the onset of prosthetic hand activation [98]. The hand itself also moves relatively slowly. Furthermore, inferring which grasp has been decoded by observing the initial movement of the hand is not typically informative; this means that once a grasp has been decoded, the user is usually committed to it until the grasp has been completed. This emphasises the importance of user control being accurate and consistent in the absence of concurrent feedback. Therefore, the appropriate motor skill must be learned, internalised and retained.

2.4 The Limb Position Effect

The limb position effect refers to a reduction in prosthesis control acuity caused by a change in arm position [75]. Figure 2.7 shows an example of how a change in arm position may lead to decreased classification accuracy in a pattern recognition system. Limb position itself is associated with several physiological and environmental factors that collectively increase signal variability [74]. Muscle excitability, subcutaneous muscle displacement, and motor variability are a few examples of physiological factors that can alter the characteristics of EMG following a change in arm position.

Muscle excitability refers to a muscle fibre's ability to respond to a stimulus (i.e. motor command delivered by a nerve) and initiate a contraction. The more excitable the muscle is, the lower the stimulation threshold needed to generate a contraction. This can result in changes in the level of force production and EMG for muscle contractions that are perceived to be con-

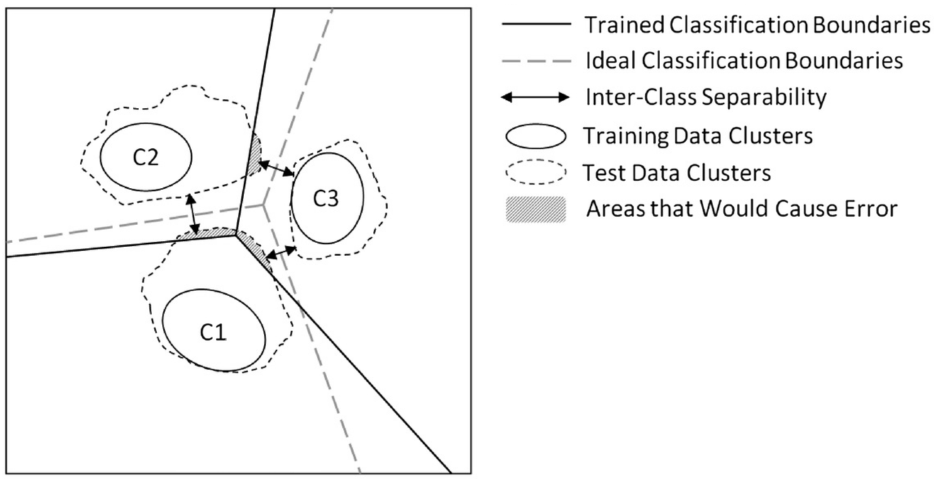

Figure 2.7: Illustration of a classification system trained from data captured in a single arm position, which then tested under multiple arm positions. Figure from [99]

sistent [100], [101], which is problematic for prosthesis users because seemingly consistent muscle contractions can result in an undesired prosthesis response. Muscle excitability is difficult to predict [102] because it is affected by a number of instantaneous factors , such as muscle length during passive movement [103], pre-emptive or tonic contractions [104], [105], and the static positions of up-stream proximal joints [106]–[108]. Therefore, variations in muscle excitability may occur frequently during daily activities.

Furthermore, the spatial relationship between muscle and sensor is not always constant. The relative position between electrode and muscle can change for two reasons. The first case is due to electrode shift: The electrode can slip across the surface of the residual limb and away from its initial recording site. Electrode slippage is usually a secondary consequence of the prosthesis socket moving, which impacts the housed electrodes along with it. Therefore, this type of displacement is considered an environmental or contextual factor, as it is not physiological in origin. The second, biomechanical case is due to subcutaneous muscle displacement relative to the recording site [109]: The surface electrode remains static, but the muscles beneath it move. This may happen during certain postures or contractions that elicit changes in muscle geometry, including length, diameter, degree of superficiality, as well as the relative orientation of muscle fibres [110]. These factors can alter the detected EMG characteristics for a particular muscle [111] or, in extreme cases, record activity from an entirely different muscle [112], [113]. Thus, a sensor could receive different EMG signals for identical underlying muscle activity.

Another physiological factor that directly affects the properties of the detected EMG signal is motor variability. The human body is highly overactuated; we possess an abundance of joints and muscles that enable more degrees of freedom and potential movements than is necessary for most motor tasks [114]. Therefore, for a single coordinated movement, several redundant degrees of freedom may be involved. This *motor abundance* means there are multiple kinematic solutions to achieve the same goal [102], [114]. In mathematics this is called a 'many-to-one' mapping, which describes a function where multiple different inputs produce the same outcome. This can result in seemingly identical movement outcomes having somewhat varied representations in the muscle domain. No matter how many times we attempt a motor task, we can never repeat it perfectly; there will always be some minute differences between repetitions. These differences between repetitions of the same movement can be partly attributed to sensorimotor equivalence. Motor variability is thought to be beneficial in initial task learning and exploration but detrimental to tasks that require consistent and skilled movement, as demanded by tasks like archery [115]. Similarly, motor variability is likely to have a negative impact on the long-term robustness of prosthesis control unless it can be reduced. Fortunately, in contrast to the physiological factors discussed earlier, empirical evidence has shown that motor variability can be reduced through repeated practice. In fact, the reduction of motor variability (and, thus, the increase of motor consistency) is linked to skilled performance [115]. Training a prosthesis user to produce more consistent muscle activity could be a simple and low-cost method of addressing input variability.

2.4.1 Mitigation Attempts

This section focuses on pattern recognition, as the bulk of the corresponding literature has been conducted in the context of this control scheme. Attempts to address confounding factors such as the limb position effect in pattern recognition can be grouped in to three categories: data abundance, feature optimisation, and classifier/algorithm optimisation. A final method - user adaptation - is presented which has been used in regression control literature.

Data abundance

Data abundance refers to the approach of collecting more data to better capture real-world variability, as capturing more variability in the data can provide more tolerant decision boundaries, such that when a perturbation occurs in the classification space, the likelihood of the data lying within the desired decision boundary is higher. The method includes performing calibration routines under multiple conditions, such as multiple arm postures [99], [116]; data from other sensor modalities, such as accelerometers and IMUs or force sensors [99], [117]; and high-density EMG sensors [118].

It has been shown that training a classifier with EMG data recorded from multiple arm positions greatly improves classification accuracy during; static position, activities of daily living, and dynamic position testing, compared to single-position training [99]. However, training in many positions is not practical for users. In order to balance training time and classification accuracy, dynamic training with accelerometry data has been proposed as a good compromise. Including accelerometry data during multiple-position recording can enhance classification accuracy and outperforms the use of EMG alone [116]. However, for a smaller number of training positions, adding more sensor modalities, such as accelerometers, can potentially worsen classification accuracy [99].

In essence, the data-abundance approach can help reduce the impact of the limb position effect, but it has several limitations, namely: diminishing returns, increased hardware cost, and in some cases the performance is not substantially different from that of using EMG alone. Importantly, simply adding more data does not necessarily correspond to improved classification accuracy.

Optimising feature space

It has been shown that EMG features commonly used in pattern recognition are significantly affected by limb position [119]. Another approach for improving classification robustness is to select input features that are less impacted by a change in arm position.

Studies have compared feature robustness for wrist [120] and elbow orientations [121], with similar findings showing that improved classification accuracy can be achieved by selectively choosing a subset of features that exhibit greater robustness across the tested arm positions. However, differences in experimental design, features tested, arm positions used, and chosen classifier parameters make it difficult to draw conclusions about the optimal set of features that maximise classification robustness. However, needlessly adding features can substantially increase computational complexity, which may worsen classification accuracy in certain positions [121].

Optimising classifier

Another approach has focused on optimising the final stage of the processing pipeline, the classifier. This includes the choice of classification algorithm or the structure in which it is implemented.

Literature directly comparing the performance of different classification algorithms, such as Linear Discriminant Analysis (LDA), k-Nearest Neighbours (KNN) and Support Vector Machines (SVMs), with regards to limb position is sparse. In general, for single arm positions, results suggest that most methods yield comparable classification accuracy [122]–[124].

A meta-analysis conducted on three different limb position data-sets found little difference in classification accuracy between LDA and SVM when the same features were used [125]. Furthermore, comparisons of LDA, SVM, and KNN with various numbers of EMG sensors found that all methods performed similarly over several arm positions [118].

Single and multistage classifiers have also been investigated. This entails either incorporating extra sensor data along with EMG data to predict the grasp in a single step, or using cascade classifiers whereby the arm position is classified separately (this position is used to inform a second classifier that estimates the grip, typically with EMG).

An offline study found that a single-stage classifier performed better than a dual-stage classifier when one or two accelerometers were used [75]. However, the effect on classification accuracy was marginal. By contrast, a real-time study found that a dual-stage classifier with EMG-MMG was most effective at reducing arm position variation [126]. One reason for the discrepancy between the two studies may be the effect of dual-stage classification on signal variability. Cascade classifiers discretise the arm position signal to a single data point; therefore, valuable information from this data could be lost, worsening performance. Conversely, if the variability from position data is too high, discretising it reduces the overall signal variability and therefore may benefit classification accuracy.

There appears to be no general consensus on the use of cascade classifiers with regards to limb position; subsequent work has been inconsistent in their use.

User adaptation

At the time of writing, there is limited literature on employing user learning to address the limb position effect. Intentionally leveraging user learning in pattern recognition is not trivial due to its opaque mapping between muscle activity and prosthesis output.

By contrast, user adaptation has been investigated under regression control, which takes a comparable approach to pattern recognition. However, instead of using a classifier that produces discrete outputs, regression control enables proportional and continuous control of multiple degrees of freedom simultaneously. One study found that performance with regression control similarly suffers following limb position changes when evaluated offline [127]. However, they showed in an online experiment that if instantaneous closed-loop feedback is provided, user-adaptation is effective at overcoming the limb position effect in real-time. Furthermore, they found that training the regressor with data from multiple positions was not superior to single position trained models when controlled by the user in real-time. This suggests that instantaneous feedback enables users to generate compensatory muscle activity on the fly, which can alleviate calibration time and complexity.

Importantly, the experiment in [127] used a computer interface to present rich information about the participants' control signals instantaneously. By contrast, a later prosthesis regression control study found that performance was significantly affected by limb position for two out of five participants while carrying out a clothespin relocation test [128]. However, the difference in informativeness of the feedback modalities used in the two studies is relatively large. The computer interface could provide feedback that is more informative and more timely, than feedback from prosthesis movement alone. It is possible that the relatively limited feedback provided by the prosthesis may have stifled the participants' ability to adapt in real time.

2.5 Summary

- Prostheses do not yet provide control-signal feedback in real time, which means that users must be able to control their devices in the absence of real-time feedback.
- Myoelectric control schemes have traditionally provided users with real-time visual feedback about their control signals.
- Motor learning literature suggests users trained with real-time feedback would not be able to produce the same skilled performance in the absence of feedback; therefore, these skills may not transfer to prosthesis control.
- Users can adapt and counter the limb position effect if they are given feedback of their control signals in real time. However, there is no evidence that this can be done in the absence of feedback.

Chapter 3

Methods for Data Collection

3.1 Introduction

This chapter outlines the general methods used across the experiments in this thesis. Where the methods differ substantially, further details will be specified in the corresponding chapters and sections.

3.1.1 Recruitment

Whenever participants were involved, written informed consent was obtained before the commencement of any experiments. Ethical approval was granted by the local committee at Newcastle University (Reference for the iterative biofeedback study: 17-NAZ-056; All other studies: 20-DYS-050).

3.2 Estimation of Muscle Activity

Electromyography is a mature technology that is easy to use, inexpensive and non-invasive. Furthermore, operating a prosthesis with EMG requires similar muscular effort to using an intact hand. Consequently, this has made EMG prevalent in both physiological research and prosthesis control schemes.

A moving window of 750 ms was used to compute the mean absolute value (MAV) of rectified EMG data which was used as an estimate of muscle activity. The size of the smoothing window was set as used in previous experiments, which was found to balance responsive output against stable control during muscle contraction [13]. The resulting control signals output at a consistent rate, similar to the rate at which the display was updated. Therefore, changes in EMG activity were reflected in short time periods, equivalent to either one or two display frames.

3.2.1 EMG Calibration

Before an experiment began, an operator explained how to activate the desired muscle groups by flexing and extending the wrist. A calibration routine was then run, which was intended to normalise the MAV-filtered EMG data, y. During this routine, participants were instructed to relax their muscles so that baseline resting EMG, y_r activity could be recorded. Participants then performed wrist flexion and extension to obtain data representative of a comfortable contraction level, y_c. An operator informed participants that their contractions should be repeatable for long periods of time and, therefore, their contraction intensity should be limited. This corresponded to activity levels ranging from 10% to 20% of the maximum voluntary contraction in previous experiments. After the calibration routine was completed, all experimental activity for controlling the experiment utilised the normalised muscle activation level, $\check{y}$. This was calculated from y according to the following:

$$\check{y} = \frac{y - y_r}{y_c - y_r} \qquad (3.1)$$

The participants' ability to independently activate muscles for each control site was assessed using feedback of the normalised activity.

3.2.2 EMG Recordings

In all studies, the two sensors which were used to control the task targeted the extensor carpi radialis (ECR) and flexor carpi radialis (FCR). The placement of each sensor was determined using muscle palpation. If any additional sensors were used, they were evenly spaced around the forearm. Sensors were placed such that they were aligned laterally with each other. If experiments were conducted over consecutive days, sensor locations were marked on the arm with a pen to ensure consistency of recording sites. If any long-term breaks were included in an experiment physiological landmarks and electrode positions were marked on a Tubigrip. The Tubigrip was used in conjunction with photographs to place the electrodes as close as possible to their original location.

3.3 Estimation of Arm Position

An inertial measurement unit (IMU) is a device that combines data from multiple sensors, such as accelerometers, gyroscopes and magnetometers, to estimate the orientation of an object with reasonable accuracy.

High precision IMUs are relatively affordable, compact and are commonly embedded into EMG acquisition systems used in research, such as the Trigno Quattro Sensors (Delsys Inc. Natick, MA, USA). Therefore, IMUs are an attractive option for tracking the orientation of a limb in real time whilst simultaneously recording EMG activity.

3.3.1 Calibration of Arm Position

The IMU calibration procedure entailed participants positioning their hand to nine different positions while keeping the position of their elbow static. An illustration of these positions is shown in Figure 3.1a. The back of each participant's wrist was aligned to a plumb line to establish vertical and ensure consistency in calibration. The forearm position was represented by 3x3 grid of $\sim 45^{\circ}$ rotations around the elbow. Once a participant had moved in to position, the instantaneous orientations of the IMUs were recorded and used as a reference for the experiment. Participants were shown their current position by highlighting the nearest orientation stored during calibration which corresponded to a location on the grid. This was calculated using the quaternion distance between the orientation of the forearm IMU to all other calibrated positions.

Figure 3.1b shows the IMU graphic. A filled circle denoted the nearest arm position and an 'x' through the circle denoted the target arm position. This acted like an invisible cursor that reflected the arm position relative to the screen. Once the participant was in the correct position the trial would commence. If the participant was not in the correct position during the experiment, the IMU graphic was displayed to assist in repositioning. The calibration procedure could be repeated within a session if signal drift was observed.

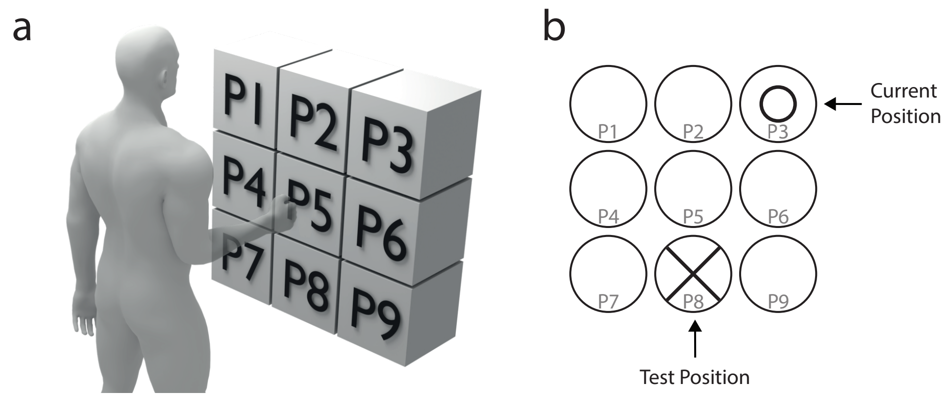

Figure 3.1: Arm position tracking with IMU. (a) Positions used during the calibration procedure. (b) The widget shown to participants to guide them towards the desired arm position for testing. Arm position information was reflected in real-time and gave feedback of the participant's position relative to the screen.

3.3.2 Recording Arm Position

For experiments involving IMU recordings, participants stood in front of a 55-inch screen that displayed the MCI task. Participants were instructed to keep their elbow flexed at 90° and their wrist in a neutral position. They were told to maintain this posture throughout the experiment unless instructed otherwise. An IMU housed inside the base units of two Trigno Quattro Sensors was used to collect position data and to assist in consistent posture. One base unit was placed on the distal end of the forearm. The second base unit was placed on upper arm. The IMU data were acquired at 74 Hz.

3.4 Myoelectric Control Interface Task

In all experiments, participants experienced the myoelectric control interface (MCI) task, which enabled data collection from participants as they gained proficiency in the task. It is represented in two dimensions and consists of a moveable cursor on a segmented grid. An example of the MCI is shown in 3.2. The filtered MAV signal, $\check{y}$, from one of two control sensors, determined the cursor's position along a single axis of the interface. The amplitude of the signal recorded by each control sensor determined the cursor's coordinate value along the axis assigned to that sensor. In this way, by performing

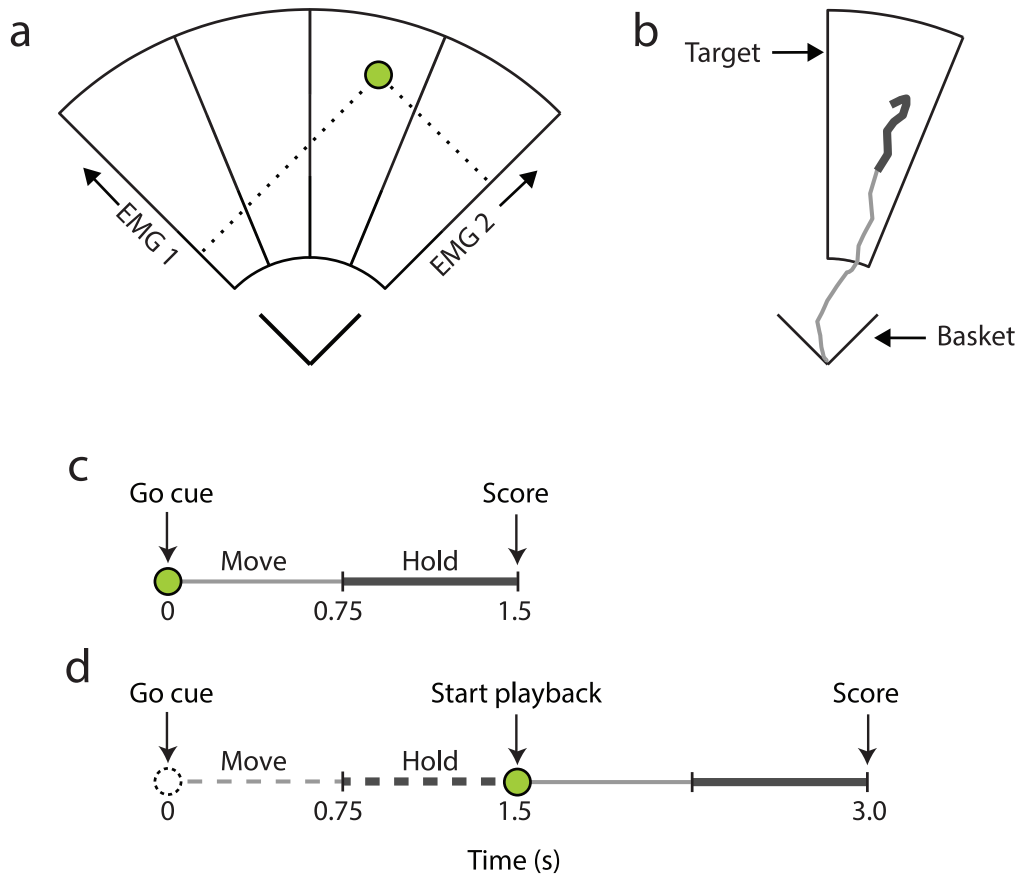

Figure 3.2: The myoelectric control interface (MCI) task. (a) The two dimensional myoelectric controlled interface space. Cursor position is shown in green. (b) A representative cursor trajectory from basket to target. Thick cursor mark denotes the hold period. (c) Task timing structure for the Concurrent condition denoting cues, the move and hold periods. (d) Task timing structure for the Delayed condition denoting cues and the move, hold and playback periods. Dashed traces correspond to the 'blind' control input window. Solid traces refer to the playback of the cursor's recorded path during the move and hold periods.

varying ratios of co-contractions of the two control sites, participants could move the cursor anywhere within the two-dimensional quadrant. The upper boundary of the interface was set to $\check{y} = 1$, (i.e. when the incoming EMG amplitude, y, equalled the contraction value set in calibration, y_c). The lower boundary of the targets was set to $\check{y} = 0.3$. Muscle activity was deemed to be at rest for $\check{y} < 0.2$, corresponding to the cursor being inside the basket. The interface can be divided in to multiple segments called 'targets'. This is typically done along the angular axis to produce four targets, each spanning 27.5°. However, the number of laterally spaced targets can be adjusted depending on the experimental protocol.

A trial starts once the participant has relaxed their muscle activity such that the cursor is positioned within the basket. An audible beep signified the beginning of the trial, followed by the presentation of one of the targets. Trials were typically 1.5 seconds long and consisted of two 750 ms periods known as the 'move' and 'hold' periods. The move period allows the participant to react to the beginning of a trial and begin moving the cursor away from the basket and towards the goal target. The aim of the task was to keep the cursor within the bounds of a target for as long as possible during the hold period. At the end of a typical trial, a score was presented on the screen, corresponding to the proportion of time the cursor dwelled within or contacted the target during the hold period. If the cursor was within or in contact with the target during the entire hold period, a score of 1.0 was given. If the cursor never made contact with the target during the hold period, a score of 0.0 was given. Each target was experienced an equal number of times; therefore, the presentation order of targets was pseudo-random. Python's AxoPy library [129], was used to implement the real-time experimental software.

3.4.1 Feedback Conditions

The scheduling of feedback on a series of trials was often manipulated as part of the experimental design. This included variations on cursor feedback and whether a score was presented at the end of a trial.

An overview of all the trial conditions used across each study are detailed as follows:

- **Concurrent feedback:** During the trial period, the cursor was always visible; its position was displayed in real-time and reflected the normalised muscle activation of the EMG channels used for control. At the end of the trial, a score was also presented.
- **Delayed feedback:** At the start of the trial, the cursor was made invisible to the participant. After the hold period, active control input ceased and the previously recorded movement of the cursor was played back in a continuous way at the same rate it occurred. The score was presented after the playback had finished.

- **Catch trials:** During the trial, the cursor was made invisible, and a score was presented at the end of the trial. No feedback of the cursor's movement was given. These trials were interleaved randomly between a series of either concurrent or delayed feedback trials. The purpose of catch trials was to intermittently probe the state of the internal model during training.
- **Zero feedback:** No augmented feedback whatsoever was given. The cursor was hidden during the trial and no score was presented at the end. A series of zero-feedback trials were used in isolation to test skill permanence.

3.5 Measures and Statistical Analyses

Unless otherwise stated, EMG data from every trial were visually inspected for signal artefacts. Trials with significant artefacts were excluded from analyses.

Data were examined visually and tested for normality using Shapiro-Wilk tests [130]. Even if it was assumed that the data were non-parametric, the mean is presented unless otherwise stated. This choice was made for two reasons. First, the median scores for a collection of trials in various conditions rapidly attenuates to 1.0. Second, presenting the group's median score would reflect the performance of a single participant at a time. As a result, displaying the mean was chosen to better convey overall progression rates.

Chapter 4

Study 1: The Effects of Delayed Feedback Training on Myoelectric Skill Retention

4.1 Introduction

Previous research with motor-learning-based control schemes has traditionally used concurrent visual feedback of the participants' control input [13]–[20]. Some prosthetic adaptation research has used relatively long, 10 second trials, thus risking feedback dependency by encouraging within trial adaptation, as outlined in Chapter 2.3.2. To attempt to mitigate within-trial adaptation, research with abstract decoding has used short, time-constrained, trials of approximately 1.5 seconds to limit exposure to adaptive processes [13]. However, adaptation may still occur at the millisecond level. The degree to which previous results that may have been impacted by adaptation is unknown. The effect of this limited exposure to concurrent visual feedback has not been studied in the context of retention, which is a necessity for prosthesis control operating under motor-learning-based control schemes.

4.2 Description of the Study

This study investigated the retention of motor skills when using concurrent and delayed feedback paradigms during myoelectric training. A delayed feedback protocol was introduced that postponed all visual feedback of the myoelectric interface until after the active control input has ceased, thus preventing any possibility of adaptation occurring within the trial. A multi-day laboratory experiment was performed to compare the use of concurrent and delayed feedback to assess the long-term stability of motor skill retention. Ten participants were trained using either concurrent or delayed feedback over four consecutive days with a follow-up probe that occurred 18 days later. This study compared the real-time feedback and catch trial conditions used in prior studies [17], [19] with new methods intended to periodically probe retention and assess long-term skill acquisition.

Study aim: To investigate the retention of myoelectric skill after concurrent and delayed feedback training.

4.3 Methods

This section details where methods deviate from the general setup detailed in Section 3.1.

4.3.1 Participants

Ten limb-intact participants (2 female, 8 male) were recruited. The participants were either novices or had no experience with the experimental protocol used. None of the participants had a neurological or motor disorder. Ethical approval was granted by the local committee at Newcastle University (Reference: 20-DYS-050). Written informed consent was obtained before the experiment began.

4.3.2 EMG Calibration

Participants were asked to perform dynamic arm movements while data were collected representing either baseline resting EMG, y_r, or contraction, y_c. Prior to each session, the raw and filtered EMG data were visually inspected. Recalibration was strongly discouraged once the normalisation values for y_c

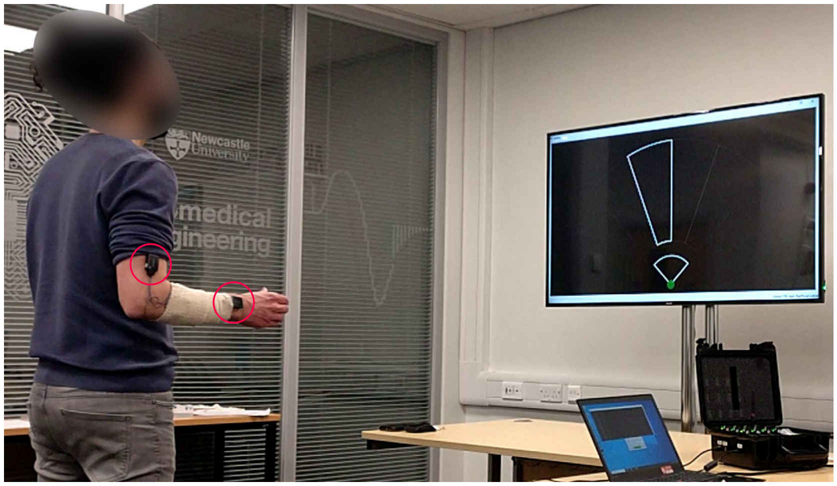

Figure 4.1: Image of a participant carrying out the myoelectric task. Red circles indicate the base unit placement of each Trigno Quattro Sensor (Delsys Inc., Natick, MA, USA), which contains the ground electrode and the IMU.

were finalised. However, baseline EMG activity, y_r, could be recalibrated in subsequent sessions if changes in baseline noise affected control.

4.3.3 Estimation of Muscle Activity

Surface EMG signals were acquired with eight electrodes using two Trigno Quattro Sensors (Delsys Inc. Natick, MA, USA). Signals were sampled at 2000 Hz and band-pass filtered between 20 Hz and 450 Hz.

4.3.4 IMU Calibration

The IMU calibration followed the method described in Section 3.3.1.

4.3.5 Protocol

Data collection on each participant was carried out over a period of four consecutive days, plus an additional follow-up session after an 18 day hiatus. As shown in Figure 4.2a, all participants completed an initial familiarisation period of four blocks, with each block consisting of 80 trials of concurrent feedback.

During the first two blocks of the familiarisation period, participants were

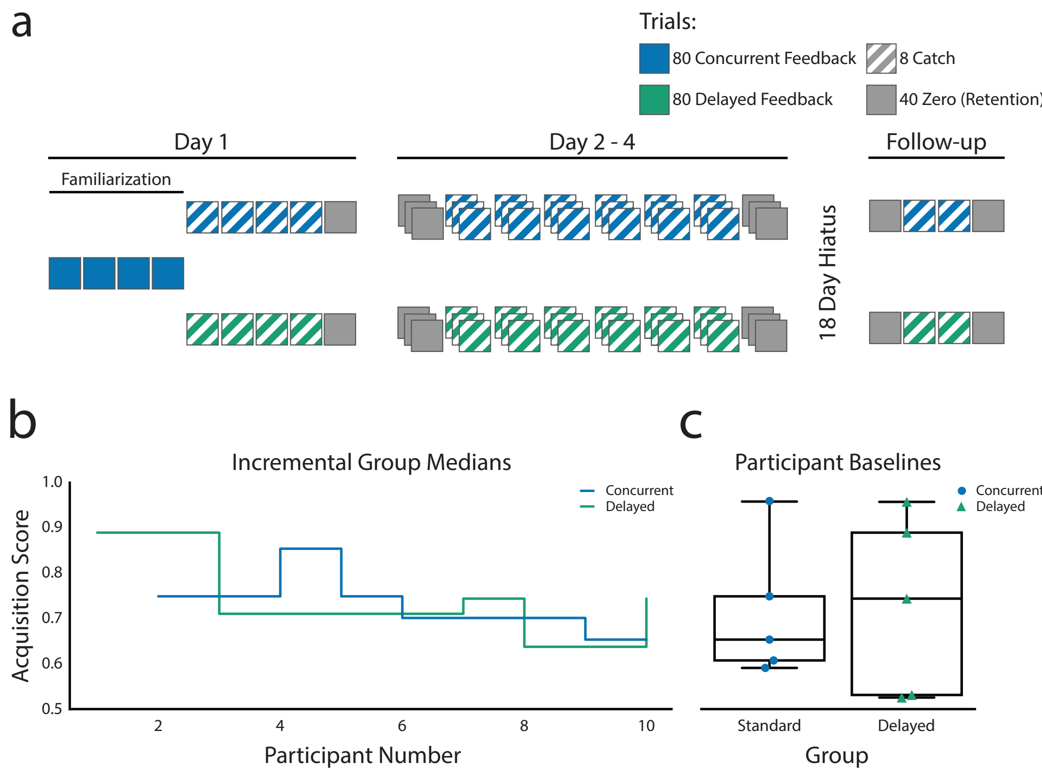

Figure 4.2: Overview of the trial block structure and participant grouping. (a) Trial block structure experienced by participants showing the number and type of trials. Catch trial counts indicate the number of catch trials added to Concurrent or Delayed blocks. (b) Dynamic participant assignment into either the Concurrent or Delayed group based on their performance in the final block of the familiarization period. Traces show the incrementally updated group medians after dynamic participant allocation. Both groups had comparable medians as final participants were assigned. (c) A post hoc distribution of baseline performance between groups upon the final familiarization block, using score axes from Figure (b). Points refer to individual participant mean scores.

permitted to adjust their calibration constants if necessary. Participants were incrementally assigned to one of two groups based on their scores in the final familiarisation block (Figure 4.2b). The allocation aimed to minimise differences in median performance between the two groups; the outcome is shown in Figure 4.2c. Depending on the assigned group, participants experienced either concurrent or delayed feedback trials as the learning condition. Irrespective of group allocation, all participants were subjected to catch and zero-feedback trials.

The experimental protocol consisted of repetitions of two block types. In the first type, participants experienced 80 trials of either concurrent or delayed feedback, depending on the group condition. These blocks are referred to as *acquisition blocks*. Inside each acquisition block, eight catch trials were pseudo-randomly interleaved. These catch trials were intended to periodically probe the state of the participant's internal model throughout training. The second block type consisted of 40 consecutive zero-feedback trials. These blocks are referred to as *retention blocks*. Retention blocks were used to assess the long-term skill permanency and were experienced at the start and end of each day.

To expedite the exploration stage of learning, an explanation of the muscle-cursor relationship was provided prior to beginning the experiment. Before a new block condition was experienced, participants were informed of what to expect. Rest and refreshment breaks were permitted between blocks.

4.3.6 Description of Data Analysis

Data were examined visually and tested for normality using Shapiro-Wilk tests. Distributions did not appear normal when data were aggregated over days for statistical analyses. Furthermore, the data did not tend to be normally distributed at the individual block level. As a result, non-parametric statistical tests were used for comparisons.

All EMG data were visually inspected for signal artefacts. If an artefact significantly impacted a trial, the trial was excluded from the analysis. Mean artefact rejection rate after manual inspection was $0.15\% \pm 0.3\%$.

4.4 Results

Figure 4.3a compares the mean retention scores in the Concurrent and Delayed groups. In total, nine retention tests were carried out: seven over the initial four days of training, and two during the follow-up session. Statistical comparisons were conducted between groups for each retention block using Mann-Whitney U tests. Differences between the mean retention scores on day 1 were not significant (Concurrent: 0.42 ± 0.11; Delayed: 0.40 ± 0.23; $p = 0.68$) which indicated that the groups were well balanced and started at comparable levels. The first significant differences were found on day 4 in the first retention test (Concurrent: 0.32 ± 0.12; Delayed: 0.55 ± 0.15; $p < 0.05$) and the final retention test (Concurrent: 0.28 ± 0.13; Delayed: 0.62 ± 0.15;

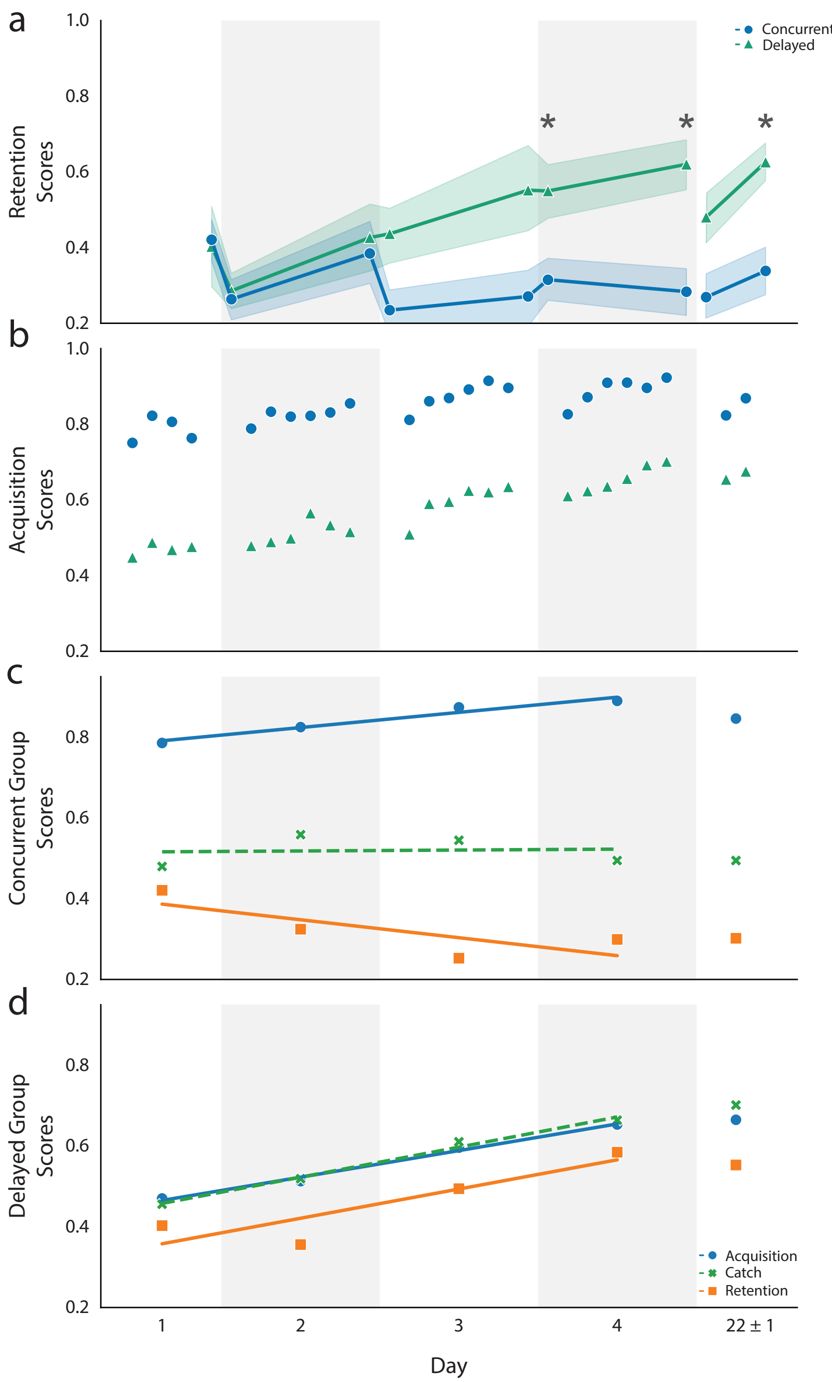

Figure 4.3: Effect of feedback conditions on retention and acquisition. Alternating backgrounds show days. Axes (a) and (b) are aligned such that the points are chronological. (a) Group retention scores over training days and follow-up sessions. Envelopes represent the standard error of mean. (b) Group acquisition scores over training days and follow-up sessions. Points in (a) and (b) are the mean average of the participants' mean block score. (c-d) Concurrent and Delayed group scores over feedback conditions, respectively. Points in (c) and (d) are the collective mean over all corresponding trials completed on a given day. Asterisks indicate significant differences between Concurrent and Delayed training (Mann-Whitney U test, $p < 0.05$).

$p < 0.05$). For the initial retention test during the follow-up session, no significant difference was found (Concurrent: 0.27 ± 0.12; Delayed: 0.48 ± 0.15; $p = 0.1$). However, for the final retention test, the mean score for the Delayed group was significantly higher than the Concurrent group's after two 'refresher' acquisition blocks (Concurrent: 0.34 ± 0.13; Delayed: 0.63 ± 0.12; $p < 0.05$).

Figure 4.3b shows the average acquisition scores for the Concurrent and Delayed groups. The Concurrent group initially had a mean score of 0.75 ± 0.10 and improved to a mean of 0.92 ± 0.03 in the final run on day 4. The Delayed group scored lower (0.45 ± 0.16), as expected, but improved over the four days of training to achieve an average final score of 0.70 ± 0.12. During the follow-up session, both groups were able to rapidly regain acquisition scores similar to those observed prior to the 18-day hiatus (Concurrent: 0.87 ± 0.10; Delayed: 0.68 ± 0.10).

Figures 4.3c and 4.3d show the mean scores obtained over different trial conditions for each day. Over the four days of training, the Concurrent group's (Figure 4.3c) acquisition scores show improvement. However, no corresponding trend of improvement was observed for either catch (day 1: 0.48 ± 0.12, day 4: 0.49 ± 0.16) or retention conditions (day 1: 0.42 ± 0.11, day 4: 0.30 ± 0.13). Whereas, the Delayed group's scores follow a similar trend of improvement for all three trial conditions, catch performance (day 1: 0.46 ± 0.22, day 4: 0.66 ± 0.15) and retention (day 1: 0.40 ± 0.23, day 4: 0.58 ± 0.09), as shown in Figure 4.3d.

The scores achieved over the central and peripheral targets during the final retention test are shown in Figure 4.4b. Comparisons between the two groups yielded no significant difference for peripheral target scores (Concurrent: 0.53 ± 0.23; Delayed: 0.68 ± 0.16; $p = 0.4$). However, the Delayed group scored significantly higher over the central targets than the Concurrent group (Concurrent: 0.15 ± 0.11; Delayed: 0.58 ± 0.11; $p < 0.05$). Visual inspection of cursor trajectories during the retention test showed that the Concurrent group performed poorly over central targets because they tended to drift towards the closest adjacent peripheral target. By contrast, the Delayed group were more able to reach the central targets, suggesting that they were better at producing the necessary muscle co-contraction ratios in the absence of visual feedback.

Figure 4.4c shows a breakdown of the cursor's angle error during the retention

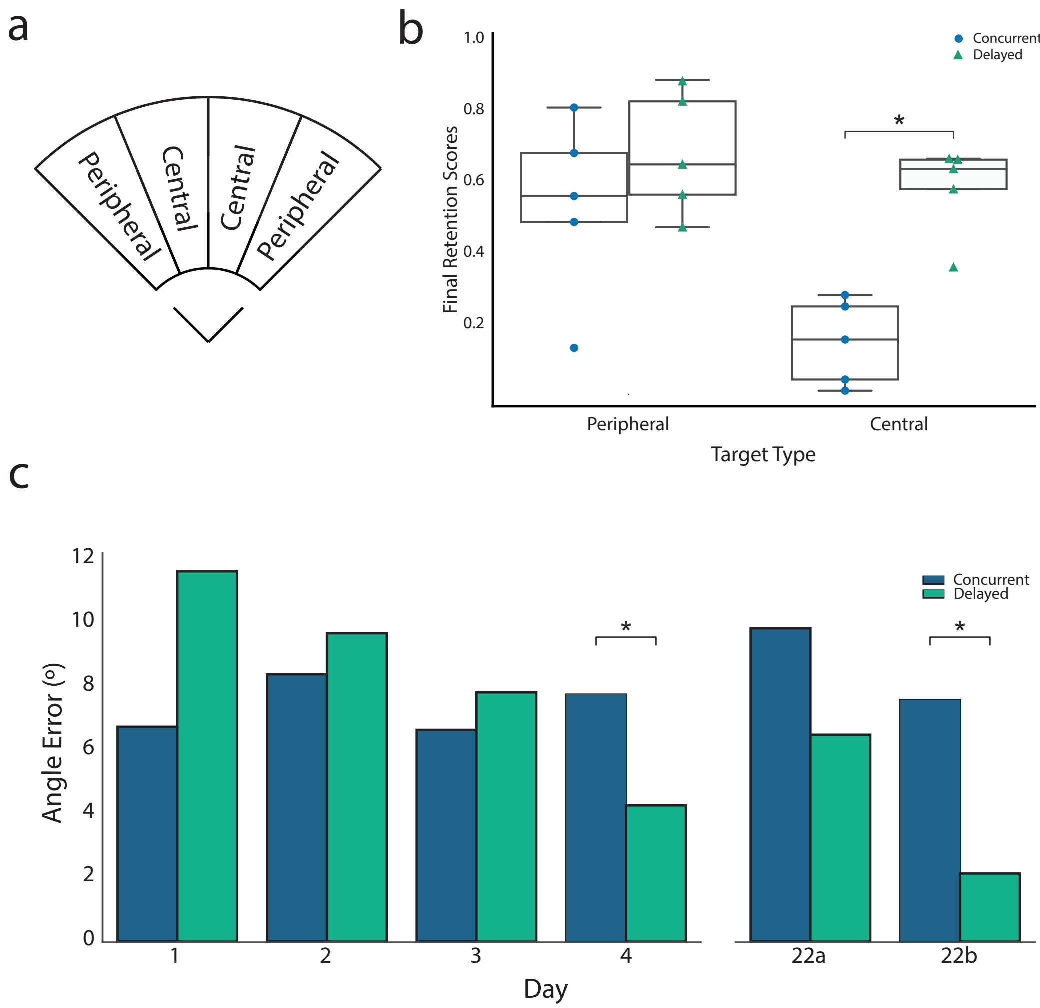

Figure 4.4: Retention differences between groups by target type. (a) Target type labels. (b) Final retention scores for peripheral and central interface targets for the Concurrent and Delayed participant groups. The points show the individual participants' mean scores. (c) Group comparison of muscle activation ratio learning observed in the retention tests. Bars reflect the cursor's mean angular error over the central targets. Initial and closing retention tests during the follow-up session are plotted separately as 22a and 22b, respectively. Asterisks indicate a significant difference between Concurrent and Delayed training (Mann-Whitney U, $p < 0.05$)

tests. The angle error was taken to be the absolute angular distance between the average cursor position during the hold period and the presented target. An angle error of 0 was assigned to a trial if the cursor's average position was within the target boundaries. Days 1-4 show the average score over both initial and closing retention tests for the central targets. Note that, this is plotted for the central targets only, as the peripheral targets do not require the coactivation of two muscle sites. During days 1-4, the Concurrent feedback group showed no trend of improvement towards reducing their angle error. However, the Delayed feedback group showed a consistent reduction in the average angle error over days. A significant difference is observed on day 4 (Concurrent: 7.8°, Delayed: 4.3°, $p < 0.05$), and a similar trend is seen during the follow-up session. Again, improvement can be seen in the Delayed group after two refresher blocks, and a significant difference is found for the closing retention test on day 22 (Concurrent: 7.6°, Delayed: 2.1°, $p < 0.05$).

Figure 4.5 illustrates the differences in learning rate between two participants from the Delayed feedback group. Although both participants generally improved and finished the experiment with comparable scores, participant 8 started with a much lower average - whereas, participant 10 started with a higher average score and showed less improvement over days.

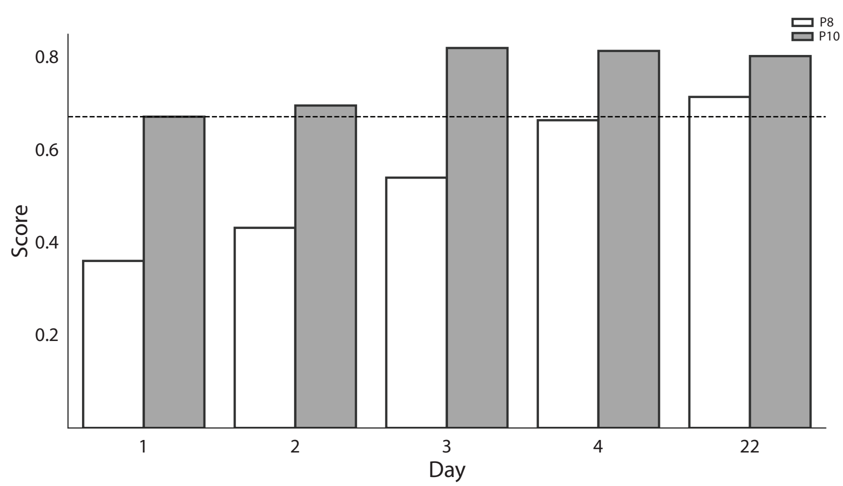

Figure 4.5: Comparison of two delayed feedback participants' average acquisition performance over days demonstrating the unpredictable nature of skill acquisition between individuals. It is observed that Participant 8's daily performance eventually approaches Participant 10's day 1 average (horizontal dashed line) on the fourth day of training

4.5 Discussion

Our findings show that in the absence of concurrent feedback, it is possible to consistently reproduce distinct patterns of abstract muscle activity after appropriate training. Because the intention of abstract decoding is to map each distinct pattern to a prosthesis output, four distinct patterns are equivalent to a four-class prosthesis control with a pattern recognition system, or adding an additional output to dual-site control. Furthermore, the results demonstrate that the retained patterns of activity can be recalled after multiple weeks. This implies two things. First, because delayed feedback isolates adaptive processes, these results stem from motor learning processes rather than adaptive ones. Second, no additional hardware or specialist algorithms beyond the clinical standard are required to restore four grasp classes using existing dual electrode devices.

The presented results are clear and consistent with existing motor learning literature [22], [23]. Figures 4.3a and 4.3b show that, although training with delayed feedback results in lower initial scores, the skills learned are retained three weeks later. The higher performance gains observed with concurrent feedback training, on the other hand, dissipate during retention tests. Figure 4.4b explains why this difference in retention scores exists. Different scores over the central targets can explain the disparity in retention performance. This suggests that the ability to generate the muscle activation ratios required to reach the central targets was retained only by the Delayed feedback group, which is similarly reflected by Figure 4.4c.

In the concurrent feedback condition, performance increased (Figure 4.3b) but learning did not (Figure 4.3a). Figure 4.3c shows that neither catch nor retention performance increased in the concurrent feedback condition. The results clearly replicate the observation that frequent feedback can degrade learning. Multiple theories have attempted to explain this, and many of them have been summarised in [21]. Briefly, one view suggests that feedback not only has beneficial guiding effects on performance but also has a set of negative qualities that can be detrimental to learning. It is thought that feedback could encourage excessive compensation during practice. Therefore, changing the input response too frequently may prevent the formation of a stable behaviour [21]. Additionally, as the user improves, a greater proportion of the learner's total error can be attributed to neuromuscular noise. This noise is, by nature, un-correctable; therefore, any further compensation is maladaptive and continues to prevent consistent behaviour [21]. An alternate hypotheses suggests that frequent feedback may overwhelm attention and interrupt other learning processes (e.g., the development of internal error detection capabilities). Although delayed feedback disrupts implicit learning, explicit learning is minimally affected [131].

This study compared the short-, intermediate-, and long-term stability of skill by probing the internal model at various stages throughout the experiment. In previous research, it was found that catch trial performance correlated with individual acquisition ability [17]. This study compared catch trials with retention tests measured over consecutive zero feedback trials. Figures 4.3c and 4.3d show the different relationships between the acquisition, catch, and retention scores obtained for Concurrent and Delayed feedback groups. Figure 4.3c shows that with concurrent feedback, there is no relationship between concurrent feedback, catch, and retention performance. In contrast, Figure 4.3d shows that delayed feedback, catch, and retention scores all show similar performance increases over the days. This study highlights the important difference between retention and estimates of retention. These data show that delayed feedback performance provides a better estimate of retention than catch trials interleaved during concurrent feedback. Importantly, as seen in Figure 4.3c, estimating retention requires consecutive reduced feedback trials to allow transient memory effects to dissipate.

The peripheral targets of the interface require only independent muscle activation and are therefore easier to reach. This performance pattern matches previous results [17] and is repeated at the start of this experiment (see Figure 4.4c). Figure 4.4 shows that delayed feedback facilitates learning of the ratios of muscle activity necessary to reach the central targets, whereas concurrent feedback does not. This suggests that concurrent feedback encourages iterative ad hoc correction within the trial period; this would be indicative of adaptation during extremely short intervals. Little is understood regarding motor learning without concurrent feedback [131]. The results demonstrate that the ability to produce four distinct muscle patterns, equating to direct access to four prosthesis grasps, can be retained without requiring any algorithmic methods. It is unknown whether additional muscle contraction ratios could be retained from the two control sites. However, additional ratios are likely to be limited by inherent noise in the system rather than by the central nervous system's capability to learn.

One of the most unpredictable aspects of learning-based prosthesis control is individual differences in learning time. The performance curves for two Delayed group participants are shown in Figure 4.5. The plot highlights that it is not possible to predict how long it takes for participants to reach a fixed skill level; for example, participant 8 took four days to reach the performance level that participant 10 achieved on day 1. Laboratory-based training must accommodate all learning rates that are sub-optimal for many other participants and the experimental operators. Sub-optimal training periods increase the risk of two scenarios occurring. In the first case, participants must go through lengthy periods of minimal challenge, which is likely to be detrimental to motivation and engagement. In the second scenario, participants transition to a more difficult condition prematurely, which may stifle performance in the new condition. As such, the fixed-length familiarisation period of concurrent feedback was not optimal for learning across individuals. In applied conditions, participants should transition at bespoke moments. One solution may be to use a score threshold to determine transition moments. This could also be beneficial for maintaining a reasonable level of challenge throughout, and may help with participant engagement or adherence to a rehabilitation regime. For this reason, future research should investigate the effect of tailoring the training protocol to suit the individual.

Literature suggests that the average number of grasps used by prosthesis users is four [132]–[134]. This is likely due to the limitations and reliability of current prosthetic devices, rather than user choice. Consequently, this means that the abstract decoding approach can match how commercially available state-of-the-art prostheses are being used, while requiring only a fraction of the complexity. Therefore, it is theoretically possible to restore four grasps using abstract decoding using currently deployed devices that operate under the clinical standard (i.e. two electrodes). Because the current study uses limb-intact participants, myoelectric skill retention should also be tested with limb-different populations before real-world application. However, it can be inferred that the underlying learning mechanisms in people with limb difference are equivalent and are not impacted by amputation [19], [135]–[137]. Although task acquisition can be slower in people with an amputation, this is likely due to increased sensitivity to fatigue, which leads to reduced training time [19]. Previous work has showed that people with limb difference are capable of generating the muscle activity required in abstract decoding tasks [19].

4.6 Acknowledgements

The findings from this work were published in [36]. Author contributions are detailed as follows:

- Conceived of the experiment - SS, SD, KN, MD
- Experimental design - SD
- Experimental programming - SS
- Collected data - SS, SD, MD
- Data analysis - SS
- Wrote the first draft - SS
- Contributed to the final draft - SS, SD, KN, MD

4.7 Summary

- Myoelectric training with concurrent feedback led to low skill retention, whereas delayed feedback training led to greater skill permanency in the absence of feedback.
- Previously used catch trials, intended to periodically probe learning, may not be a valid estimator of skill retention.
- Differences in learning rate suggests that myoelectric training may benefit from bespoke protocols.

Chapter 5

Study 2: Myoelectric Skill Training in The Home Environment

5.1 Introduction

Previous research has found a weak correlation between offline myoelectric performance and online prosthesis control [138]. One explanation of this discrepancy could be due to the properties of EMG signals changing over time (either from environmental and physiological factors) or to user-directed changes [74].

Furthermore, performance improvements have been observed over time when participants engage with control schemes [28]–[35]. Given that these studies featured control schemes with static parameters, rather than time-adaptive ones, such improvements indicates user learning may play an active role in enhancing prosthesis control. If these improvements, are in fact, due to user learning, research will likely want to observe it and exploit it. In either case, this would require long term experimentation, because motor learning acts on a relatively slow timescale.

However, long-term studies have significant drawbacks. First, multi-day laboratory experiments are logistically challenging, time-consuming and expensive to run. Consequently, long-term studies often suffer from reduced sample sizes. Second, individual differences make the rate of learning difficult to predict; therefore, it is difficult to accommodate all rates of learning in the design of a controlled protocol. This risks subjecting participants to sub-optimal training.

Remote data acquisition systems, and bespoke training structures may offer a solution to both problems. Using multiple low-cost devices outside of the laboratory would enable passive collection of data from many participants in parallel. At the same time, giving participants autonomy over their training structure may improve motivation and engagement with the experimental protocol. Bespoke training protocols also enable participants to learn at their own pace, which may help to manage task difficulty and better stimulate learning.

5.2 Description of the Study

This study introduces a home-based protocol to train myoelectric control outside the laboratory. Four participants underwent five days of bespoke myoelectric training in their homes. The primary purpose of this study was to investigate the upper limits of performance when participants train in an environment more conducive to learning. A network-enabled myoelectric platform, based on common Internet of Things technology, made this research possible. With this platform, new insights were gained on the feasibility of implementing abstract control outside of the laboratory for the first time. The results highlight the importance of personalised, multi-day training during the assessment of motor learning-based control schemes.

Study aim: Assess the feasibility of using bespoke, home-based protocols to train participants within suitable time frames.

5.3 Methods

This section provides methods specific to this study.

5.3.1 Participants

Four limb-intact participants (2 female, 2 male) were recruited. All participants had experienced the concurrent feedback condition prior to testing.

Ethical approval was granted by the local committee at Newcastle University (Reference: 20-DYS-050). Written informed consent was obtained before the experiment began.

5.3.2 EMG Calibration

Participants were asked to perform dynamic arm movements while data were collected representing either baseline resting EMG, y_r, or contraction, y_c. Recalibration was strongly discouraged once the normalisation values for y_c were finalised. As in the previous study, recalibration was allowed if baseline noise affected control.

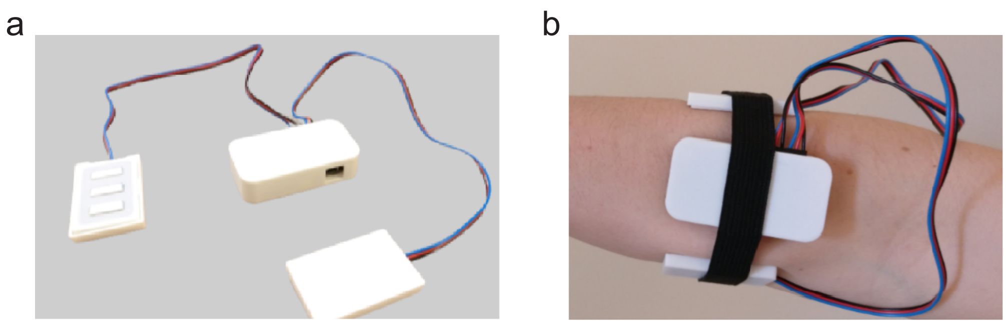

Figure 5.1: Custom Bluetooth EMG sensors used. (a) Myoelectric device in 3D printed housing. (b) Placement of the electrodes on the ECR and FCR muscles on the upper forearm. Image edited from [139].

5.3.3 Estimation of Muscle Activity

Surface EMG signals were recorded with two-channel Gravity analog EMG sensors (OYMotion Technologies Co. Ltd Shanghai, China), shown in Figure 5.1. Signals were sampled at 500Hz and band-pass filtered between 20 Hz and 150 Hz.

5.3.4 IoT Data Acquisition Platform

Figure 5.2 shows an overview of the platform developed for in-home research [139]. It comprises three main components: a wireless myoelectric device, a local machine used to run the experimental protocol, and offsite devices for remote data storage.

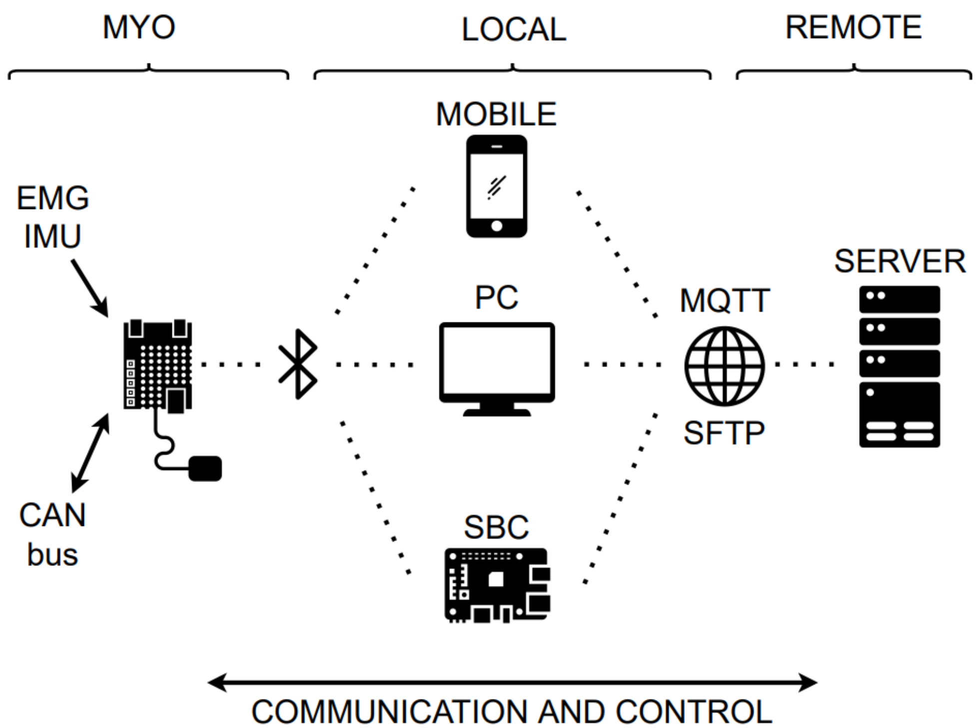

Figure 5.2: Overview of the data acquisition platform and communication between components. Image edited from [139].

Myoelectric

Firstly, a wireless myoelectric device, based on the low cost Adafruit Feather nRF52 Bluefruit LE, is used to acquire and stream EMG data to the local device via Bluetooth. Electromyography signals are acquired by two modified OYMotion Analog EMG sensors [139]. Optionally, an IMU and a CAN bus module can be fitted in order to acquire orientation data or interface with a prosthetic hand, respectively.

Local devices

Various local devices can be used to receive the EMG data over Bluetooth and communicate with an online server. This includes desktop computers, mobile phones, and low-cost single-board computers such as the Raspberry Pi. In the current study, desktop computers were used for the myoelectric computer interface experiment which was written in Python using the AxoPy library.

Remote server

At the end of a set of trials, the data were sent to an online server. Multiple remote services can be stacked; in the current study, two layers were used. First, a web file transfer protocol called Secure File Transfer Protocol (SFTP) was used to upload the experimental data for remote analysis. The SFTP protocol uses public-key cryptography for request authentication. A second service running a standard IoT messaging protocol called Message Queuing Telemetry Transport (MQTT) was used to enhance the myoelectric computer interface with online leaderboard and simple messaging functionality. The MQTT protocol uses a publish/subscribe model for bi-directional communication via a broker that runs on the server. Communication is handled over Websockets and encrypted using Transport Layer Security.

5.3.5 Protocol

The experiment was conducted over five consecutive days. Participants ran the experimental software on their own machines and were given complete freedom in terms of training structure. They could start training at their own convenience, decide how long to train for, and were allowed to flexibly switch between concurrent and delayed feedback blocks. Participants were informed that their only goal was to maximise their average block score in the delayed feedback condition. Participants were given a plot of their progress at the end of each block, as well as an online leaderboard that detailed their ranked performance amongst other participants undergoing home-based training at the same time. This information was provided in an attempt to increase motivation and engagement throughout the training period. An example of the widget is shown in Figure 5.3.

In this particular study, acquisition blocks were redefined as consisting exclusively of 60 trials of either concurrent or delayed feedback trials. Unlike the laboratory experiment, no catch or zero-feedback trials were included in the home-based experiment. Participants 1-4 completed 22, 31, 29, and 30 blocks, respectively, equating to a total of 6,720 trials.

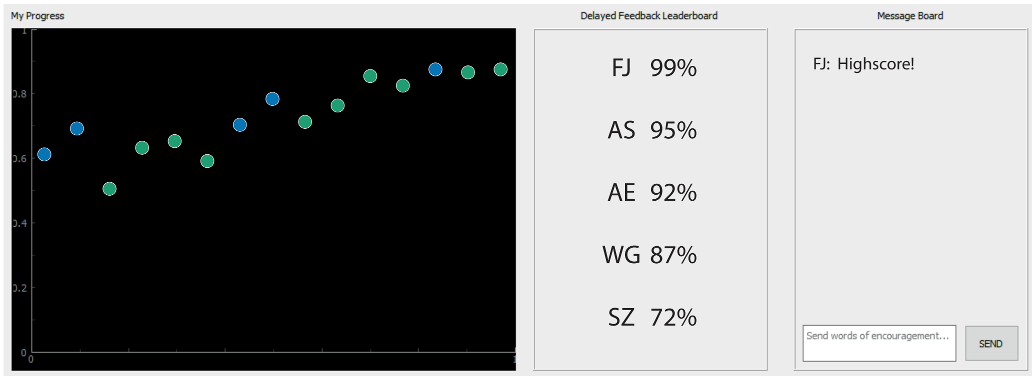

Figure 5.3: The progress and leaderboard widget. Example of what was presented to participants at the end of a block of trials. Blue points corresponded to the mean score over a concurrent feedback block. Green points correspond to delayed feedback blocks.

5.3.6 Description of Data Analysis

Data did not present as being normally distributed when aggregated over days or at the individual block level. Therefore, non-parametric statistical tests were selected for comparisons.

5.4 Results

Figure 5.4a shows the participants' average scores and number of blocks completed during the five days of training. Because each participant completed different amounts of blocks, the values presented are the mean and standard error of the mean. Comparisons were made for each day and the preceding day. A final comparison was made for day 1 and day 5. Therefore, Mann–Whitney U tests with Bonferroni corrections were carried out at a significance level of $p = 0.05$.

For participant 1, no trend of improvement was observed during training (day 1: 0.92 ± 0.002; day 5: 0.89 ± 0.009). Due to the number of blocks completed by participant 1, statistical comparisons including day 1 could not be carried out. For participant 2, no significant improvements were observed between consecutive days of training. However, a comparison between the first and final days of training showed that they significantly improved overall (day 1: 0.54 ± 0.061; day 5: 0.91 ± 0.003). Significant improvements were found for participant 3 after training (day 1: 0.53 ± 0.033; day 5: 0.83 ± 0.017).

Significant differences were also found on days 2, 4 and 5 when compared with the previous day. Finally, for participant 4, scores remained relatively consistent throughout training and did not differ significantly between days (day 1: 0.83 ± 0.020; day 5: 0.91 ± 0.013).

Figures 5.4b and 5.4c show modified confusion matrices corresponding to each participant's first and best-scoring delayed feedback blocks. Predicted targets were calculated offline to better communicate the relationship between the score presented to participants and prosthesis output accuracy. This is because the presented score is a continuous value, whereas the success of a prosthesis output is binary: either 'pass' or 'fail'. For a given trial, the predicted target was determined to be the target the cursor dwelled within for 240 ms consecutively [140]. This length of time is arbitrary but was selected based on previous work so as to not skew results. Because the predicted target values were calculated offline, the confusion matrices have been modified to include a *None* class, in the case where no target was dwelled within for sufficient length during a trial. In the confusion matrices a value of 1.0 corresponds to all predicted targets matching the presented targets.

The highest overall prediction rates for participants 1-4 occurred on blocks 11, 23, 23, and 20, respectively. For these blocks, mean classification accuracy for participants 1-4 was 93.3%, 93.5%, 100%, and 95%, respectively. Figure 5.4b shows that predictions were initially more accurate for the peripheral targets compared to the central targets. However, Figure 5.4c shows that after some training, the overall accuracy of predictions increased. In general, the central targets showed the greatest improvement.

5.5 Discussion

One of the findings from Study 1 highlighted the problem between rigid experimental protocols and differences between individual learning rates. For this reason, participants were allowed greater flexibility in the home-based training. It was anticipated that, given time, most participants would be able to achieve high levels of performance. Therefore, this pilot study was conducted to investigate delayed feedback training at home. Figure 5.4c shows that participants can reach four-class performance suitable for prosthesis control. Although the pilot was carried out over five days, this equates to only approximately five hours of training, with an average of 1680 trials

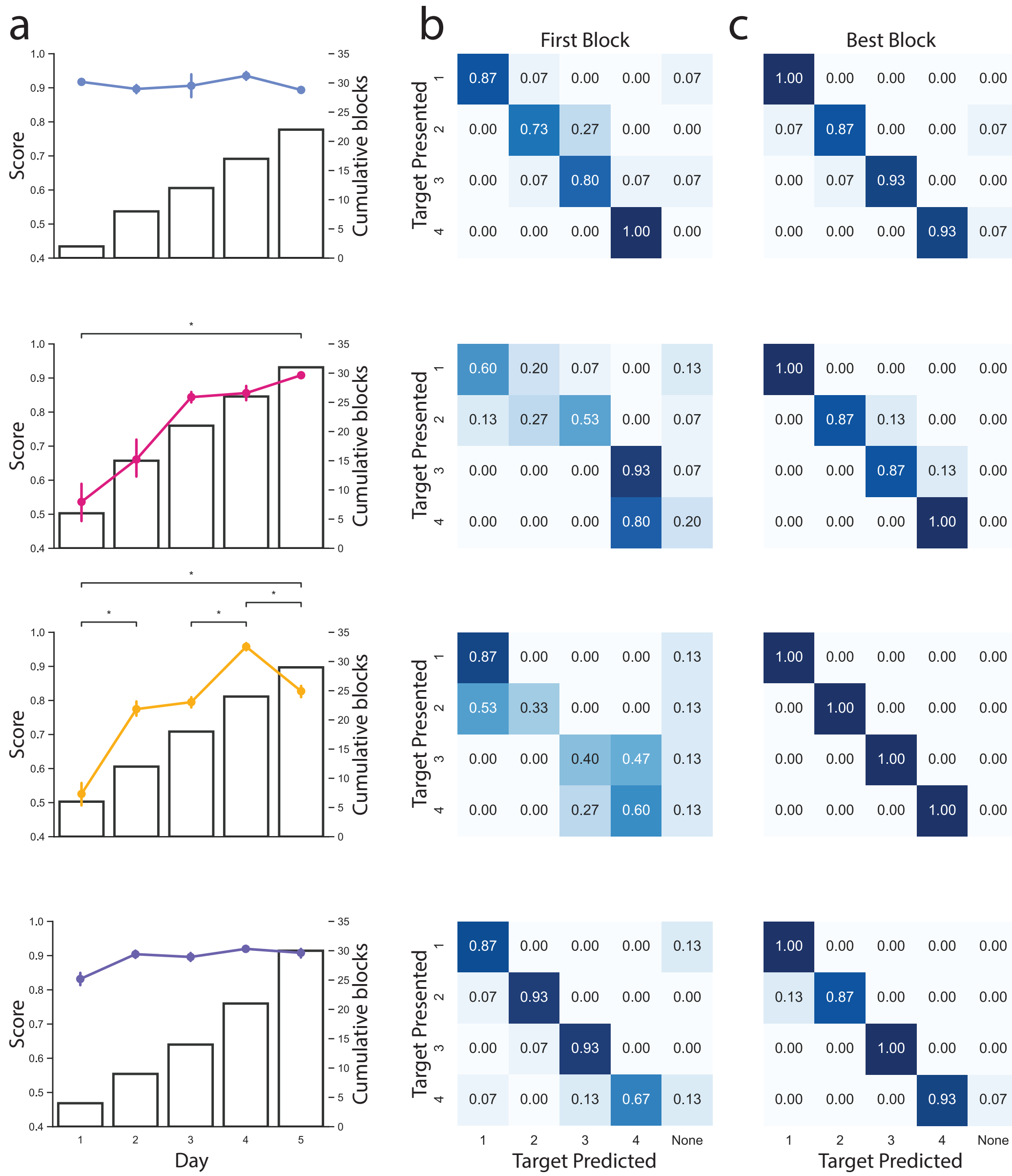

Figure 5.4: Overview of home-based training performance. (a-c) Referring to a column of plots, each row relates to the performance of a single participant. (a) Participants' mean delayed feedback scores and cumulative blocks experienced over five days of training. Error bars correspond to the standard error of the mean. (b-c) Modified confusion matrices derived from the first and best delayed feedback blocks, respectively.

per participant. Future experiments are likely to use a hybrid structure, in which participants train at home and perform rigorous testing in a controlled laboratory environment. The relationship between concurrent and delayed feedback may explain the differences in results obtained in the previous study. Participants in Study 1 either had limited or no prior experience with the task, whereas participants in the current study trained with delayed feedback after significant experience with concurrent feedback. Therefore, it is likely that participants were already prepared to transition to delayed feedback before the experiment started. Furthermore, developing a real-world training protocol should not consider only *when* to transition but also *how* to transition between feedback types. For example, instead of a smooth or faded transition into different feedback mechanisms, this study design compared concurrent and delayed feedback as discrete conditions that were introduced abruptly. This may also be sub-optimal for learning.

Although this was a successful experiment, room for improvement remains for future work. One bottleneck in the training protocol is that the delayed feedback trials take twice as long as the concurrent feedback. There may be alternative forms of feedback that achieve an outcome similar to that of delayed feedback, but do not require the replay of the full trial. For example, a static image of the cursor's path could be displayed after a trial of no feedback. One further inefficiency is the presentation of targets. For example, the peripheral targets of the interface require activation from only a single muscle, and are relatively easy for participants to reach. However, even when the participant has mastered these targets, they are presented equally as often as the more difficult central targets, which require more practice. This unnecessarily lengthens the total training time and may not be challenging. Ideally, the training protocol should change over time and scale its difficulty to the user's ability. During development, I made a version of the training protocol that allowed the participants to tailor the structure of a block to a similar level of granularity. Participants could decide whether the presentation of targets would be randomised or sequential, the total number of trials in a block, and even which targets were to be presented. Although it is likely more suitable for applied settings, this type of training would lead to difficulty in statistical comparisons between participants in academic research, as participants may have experienced vastly different training schemes. Due to said added complexity, this level of customisation was not used in this study.

One surprising anecdotal result was the participants' response to the progress and leaderboard widget. I initially made it as an Easter egg for the pilot testers to enjoy. However, their response to it was so positive that it was left in for the real study. Participants reacted favourably to the leaderboard, which appeared to foster competitiveness and increase motivation in most. Another unexpected result was the leaderboard's effect on the interpretation of the score presented at the end of every trial. When knowing their exact high score over a block of trials, participants sometimes found the trial scores to be de-motivating. For example, at high levels of performance, it would become apparent that a slightly lower score on a single trial would result in the block average being lower than the participant's highscore. This would lead to reduced motivation to do well for the remainder of the block. This may explain the significant decrease in participant 3's score on day 5. Including additional scoring metrics may be beneficial here. Additionally, a more general form of scoring feedback may work equally well. (e.g. 'great' for a trial score above 80%).

To optimise the practical applications of myoelectric training, future research should explore when and how to transition between different types of feedback, as well as how to balance between challenge and motivation. Although the trade-off between the time invested and academic reward may be disproportionate, it is crucial to recognise the importance of refining training approaches to facilitate quicker recovery for individuals undergoing myoelectric rehabilitation. Hopefully, the low-cost remote data collection methods that are introduced also help to lower the costs and barriers associated with performing such research.

5.6 Acknowledgements

The findings from this work were published in [36]. Author contributions are detailed as follows:

- Conceived of the experiment - SS, SD, KN, MD
- Experimental design - SD
- Experimental programming - SS

- Collected data - SS, SD, MD
- Data analysis - SS
- Wrote the first draft - SS
- Contributed to the final draft - SS, SD, KN, MD

5.7 Summary

- Participants were able to achieve the upper limit of delayed feedback performance with home-based training.
- The decoding accuracy suggests that four grasp classes can be restored with abstract decoding without additional feedback mechanisms or hardware above the clinical standard.
- As participants approach the upper limits of simple scoring systems, there is a need for alternative scoring metrics to sustain engagement and challenge.
- Remote data collection methods are likely to scale well for future home-based myoelectric training.

Chapter 6

Study 3: The Effects of Myoelectric Training on Skill Transfer to Prosthesis Control

6.1 Introduction

There can be a significant time lapse between amputation and receiving a wearable prosthesis, due to logistical reasons such as socket manufacturing as well as post-surgery tissue swelling. Long periods of inactivity risks muscle atrophy, which can lead to control difficulties when a patient is first given a myoelectric prosthesis. In the interim, surface EMG can be used to control myoelectric games (*myogames*) which can reduce muscle atrophy and enable learning of a control scheme in advance of prosthesis fitment [141], [142]. One goal of myoelectric rehabilitation is to successfully apply skills from pre-device training to prosthesis control.

In myoelectric prosthetics, the term *transfer* is used to describe successful pre-device training [141]. The 'amount of transfer' refers to the proportion of skilled performance that is preserved from one domain to another. However, there has been a lack of coherence among findings from previous research, which suggests that demonstrating transfer in prosthetics is not trivial [141], [143], [144].

One potential explanation for the lack of coherence is that myogames typically provide visual feedback of the user's control signal in real time, which is distinct from real-world prosthesis use. In addition, van Dijk et al. state the importance of using similar goal-relevant features across tasks for transfer to occur [141]. They devised an experiment to determine whether a myogame, designed to be more similar to actual prosthesis control, led to transfer. They found that: (1) training with myogames that had limited task similarity to prosthesis control subsequently led to limited transfer, and (2) providing augmented feedback during training was important for transfer and was independent of task similarity.

Two later works demonstrated how transfer can vary, even if there is similarity between goals across tasks. Heerschop et al. demonstrated the successful transfer of mode switching skills for dual-site control [143]. However, learning the skill was not affected by the type of feedback used during training. This may be due to the simplicity of the task. The skill needed for mode-switching is relatively coarse; the user needed only to evoke a co-contraction but not necessarily control it with the deftness required by proportional control or abstract decoding. In another study, Kirstoffersen et al. observed no transfer after training users with a more complex machine learning based control scheme [144]. Furthermore, they found that training did not lead to improvements in EMG pattern separability or functional prosthesis use. Although this may have been due to the more complex nature of the task and limited training time, it is important to first assess the validity of the initial training protocol for the specific task prior to testing transfer.

Although retention and transfer tests are often used interchangeably to measure motor learning, most research has not demonstrated retention of skill prior to testing transfer. Therefore, the suitability of a myogame for skill retention is often not evaluated prior to testing. If skills cannot be produced in the absence of the feedback provided during training, transfer tests are likely to suffer. The current research posits that, within the context of pre-device training, motor-skill retention is a necessary prerequisite for transfer to occur.

6.2 Description of Study

Study 1 demonstrated that novel myoelectric skills could be retained with appropriate training. Because retention refers to the persistence of performance [84], it follows that retention of myoelectric ability is necessary for skill transfer to prosthesis control. The focus of this study is to demonstrate the transfer of myoelectric control skills to prosthesis control. Twelve limb-intact participants volunteered to take part in the study. The study was conducted over seven consecutive working days; all participants experienced a weekend break for a portion of the experiment. On the first day, participants carried out several tests that measured their ability to control a prosthesis. This was done to establish their baseline performance. For the five subsequent days, participants underwent myoelectric training in the abstract control task, without a prosthesis. On the final day, participants completed the same prosthesis testing procedure as on day 1. Prosthesis control performance differences pre- and post-myoelectric training were compared.

Study aim: Understand how performance in laboratory settings translates to prosthesis control.

6.3 Methods

This section specifies the particular methods used in this study.

6.3.1 Participants

Twelve limb-intact participants (4 female, 8 male) volunteered for this study. Ethical approval was granted by the local committee at Newcastle University (Reference: 20-DYS-050). Written informed consent was obtained before the experiment began.

6.3.2 Estimation of Muscle Activity

Surface EMG signals were recorded with two-channel Gravity analog EMG sensors (OYMotion Technologies Co. Ltd Shanghai, China). Signals were sampled at 500Hz and band-pass filtered between 20 Hz and 150 Hz.

6.3.3 Protocol

The protocol comprised two main parts: (1) pre- and post-testing with a prosthesis, and (2) myoelectric training without a prosthesis.

Pre- and Post-tests

In both tests, participants wore a transradial bypass socket [145]. The bypass socket is an apparatus that a limb-intact person can wear to simulate prosthetic hand use without the need of a custom prosthesis socket. The bypass socket was fitted with a Touch Bionics robo-limb prosthetic hand and remained attached throughout all tests. The pre- and post-tests consisted of three tasks: grasp matching, box and blocks test, and an object manipulation test.

- **Grasp matching**: Participants first underwent two blocks of 60 concurrent feedback trials of the MCI task. This was done to allow the participants to familiarise themselves with the task and adjust the calibration with the additional weight of the prosthesis. Then participants experience two blocks of 60 zero-feedback trials to assess skill retention. Only once the cursor dwelled inside any target for 750 ms consecutively, would the next trial commence.
- **Box and blocks**: A modified version of the box and blocks test was used. Sixteen wooden cubes were spaced in a 4x4 grid inside one box. The goal was to move as many cubes as possible from one box to another in a given time frame using the prosthesis. Participants were told which grips were most suitable to use and given a practice run of 15 seconds. Each attempt was limited to 60 seconds, and was repeated four times. Only one cube was counted if multiple cubes were deposited with a single grasp.
- **Object manipulation**: This required participants to actuate a series of grasps to move a set of objects in a sequence. The objects were evenly spaced on a table in a 2x4 grid marked by tape. The sequence of grasps and movements were: key grip (move pen), point grip (click a mouse button), tripod grip (move screwdriver), power grip (move wooden cylinder). When placing an object, participants would move it to the empty location in the corresponding column marked on the table. Then the participants repeated the tasks in reverse order, which concluded a single run. Participants were asked to interact with each object with the correct grasp as quickly as possible. If an incorrect grasp was made, the participants had three attempts to repeat the movement. After the third attempt, they were told to move on to

the next object. The number of grasp errors or times an object was dropped due to unintentional activation of the hand were recorded.

Figure 6.1: Intact-limb participant using a bypass socket fitted with a prosthetic hand, completing a box and blocks task. Image source: [145].

Training Period

In between the pre- and post-tests, participants underwent myoelectric training, which was conducted either in their homes or in a laboratory setting. Otherwise, the training phase used the same experimental set-up and protocol developed in Study 2.

6.3.4 Grasp Decoding

To control the prosthesis, each target was mapped to one prosthesis grasp. The grasp was determined by the first target the cursor dwelled within for 750 ms consecutively after leaving the basket. Once an output grasp was selected, the user could relax and the cursor returned to the basket. Entering any target while the prosthesis grasp was closed opened the prosthesis. The only difference relative to the standard protocol is that in the prosthesis control implementation, the user was not penalised for overshooting a target.

6.3.5 Measures and Statistical Analyses

Visual inspection of Q-Q plots suggested that the data were not normally distributed. Therefore, non-parametric statistical tests were used. The two new measures that were used in this study are introduced here.

Path Efficiency describes the optimality of the cursor's path. It is calculated by dividing the cursor's trajectory by the optimal path length. The end of the cursor's trajectory was taken to be where the cursor first intersected the correct target. The optimal path length was the distance between the cursor's starting point and the centroid of the correct target. If the cursor intersected the target below the target centroid, the optimal path end point was taken at the height of the intersection.

Coefficient of Variation is a measure of signal variability and is calculated by normalising the standard deviation of a sample of EMG by its mean absolute value. This calculation was done on EMG activity during the hold period.

6.4 Results

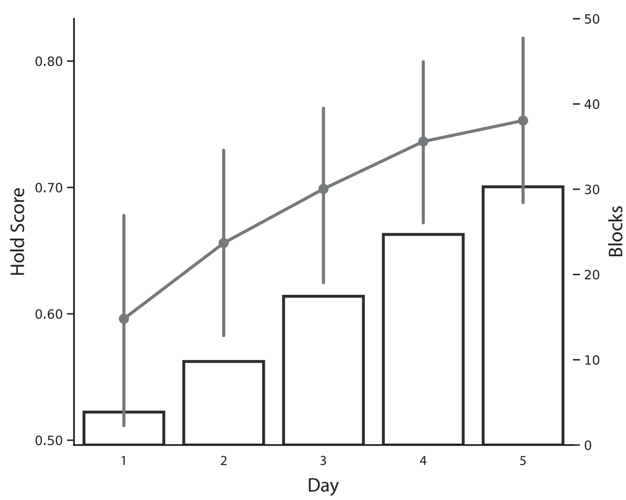

Figure 6.2: MCI performance before, after, and during training. Myoelectric delayed feedback performance during the five day training period. Points, mean scores; error bars, 95% confidence interval; bars, mean number of cumulative blocks completed.

Figure 6.2 shows an overview of the participants' mean performance during the delayed feedback training. On average, participants completed a total of 33 delayed feedback blocks over the five days. A general trend of improvement can be seen between the first and fifth days (day 1: 0.60 ± 0.15; day 5: 0.75 ± 0.12).

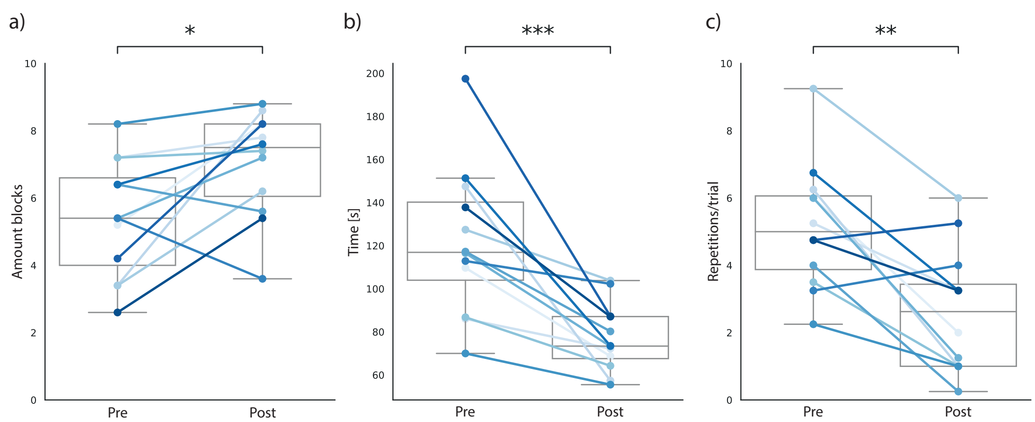

Figure 6.3: Prosthesis control performance before and after training. (a) Box and blocks task performance. (b) Completion time of the object manipulation task. (c) Mean repetitions during the object manipulation task. All points correspond to individual participants. Asterisks denote level of significance. (*, $p < 0.05$; **, $p < 0.01$; *** $p < 0.001$, Wilcoxon signed-rank test)

Figure 6.3 shows that after training, significant gains in performance occurred for tasks that involved prosthesis hand control. The number of blocks moved in the box and blocks task significantly increased (pre: $Mdn = 5.4$; post: $Mdn = 7.5$; $p < 0.05$). Improvements were also found in the object manipulation task: the time taken to complete the task significantly decreased (pre: $Mdn = 116.9$ s; post: $Mdn = 73.4$ s; $p < 0.001$), as did the mean number of errors made on a given trial (pre: $Mdn = 5.0$; post: $Mdn = 2.6$; $p < 0.01$). The rate of unintentional object drops did not change ($Mdn = 0$).

A positive correlation was found between the mean score achieved during the final day of training and the rate of targets successfully hit in the post-test (r: 0.75; $p < 0.01$), shown in Figure 6.4(a). Similarly a moderate negative relationship was found between the final training scores and the mean number of repetitions during the post-test object manipulation task (r: -0.63; $p < 0.05$), shown in Figure 6.4(b).

Figure 6.5 shows the participants' performance on the grasp matching task in the pre- and post-tests. Although median hit scores improved between pre- and post-tests (pre: $Mdn = 0.63$; post: $Mdn = 0.80$), the improvement

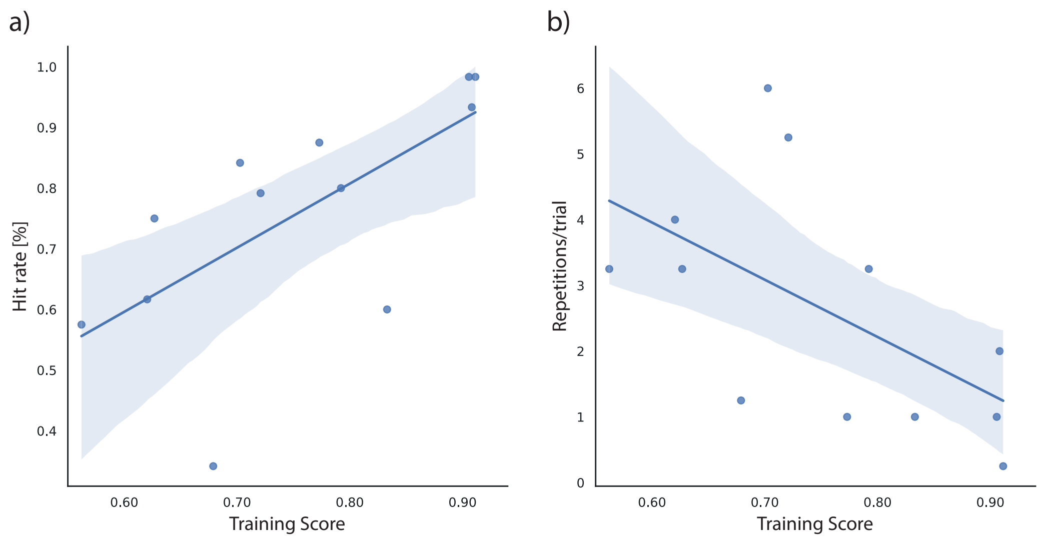

Figure 6.4: Relationship between myoelectric training and prosthesis control. Correlation between the mean delayed feedback scores from the final day of training to prosthesis control in the post test. (a) Positive correlation between training performance and hitting the correct target during the zero-feedback condition ($p < 0.01$). (b) Negative correlation between training performance and the mean number of repetitions during the object manipulation task ($p < 0.05$). Both statistical tests used Spearman's rank correlation coefficient.

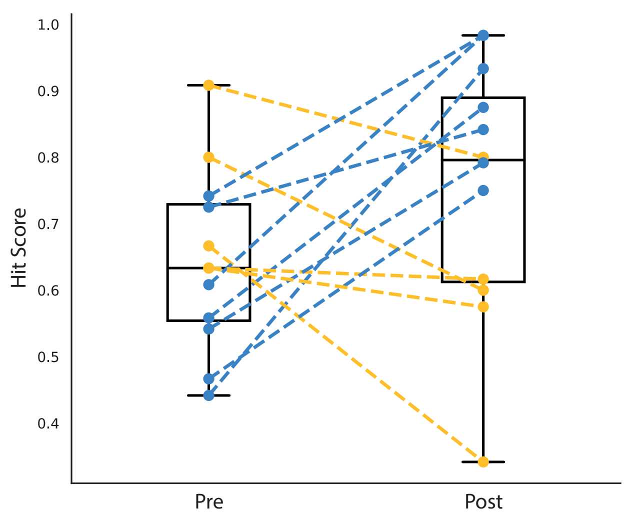

Figure 6.5: Grasp matching performance over zero-feedback trials during the pre- and post-tests, whilst wearing the prosthesis. Points correspond to individual participant scores. A distinction in line colour is made to visually clarify increases and decreases in hit scores across individuals.

failed to reach significance. In addition, no correlations were found between post-test hit scores and any other post-test task measures. No correlations were found between any pre-test metric when compared against itself in the post-test condition.

Figure 6.6 presents evidence that human learning is the driving force behind improvements in task performance, rather than pre-exposure to the tasks, upon repeating them in the post-test. Figure 6.6(a) shows cursor traces for each target from a single participant's first and best delayed feedback blocks. In general, the cursor traces in the participant's highest scoring block are less curved and more directly reach the target with greater path efficiency. Figure 6.6(b) shows that there is a strong negative correlation between hold score and path efficiency. The strength of which is also relatively consistent over days. Figure 6.6(b) shows that the coefficient of variation decreased significantly after delayed feedback training (first: $Mdn = 38\%$, last: $Mdn = 28\%$, $p < 0.01$).

6.5 Discussion

The current study investigated whether the myoelectric skills retained after several days of delayed feedback training would lead to successful control of a prosthetic hand. Our results demonstrate that participants significantly improved in several prosthesis control metrics following five days of training. Also, a significant relationship was found between training performance and prosthesis control metrics. These results strongly suggest that the pre-device training protocols developed in the previously presented studies are effective for training the skills necessary for prosthesis control.

Interestingly, despite significant improvements in prosthesis control speed and accuracy, as shown in Figure 6.3, no corresponding significant improvement was found in post-test grasp matching. Our hypothesis is that the structure of the post-test led to this metric becoming a poor reflection of transfer. Over the five days of training, participants likely became accustomed to completing the task without the additional weight of the bypass socket. Upon commencing the post-test, participants were given two blocks of concurrent feedback trials to check the calibration before completing two blocks of zero-feedback trials. This was a poor experimental choice in retrospect. Participants may have unknowingly reacted to the visual updates of the cursor and adapted their input on the fly to accommodate a slight

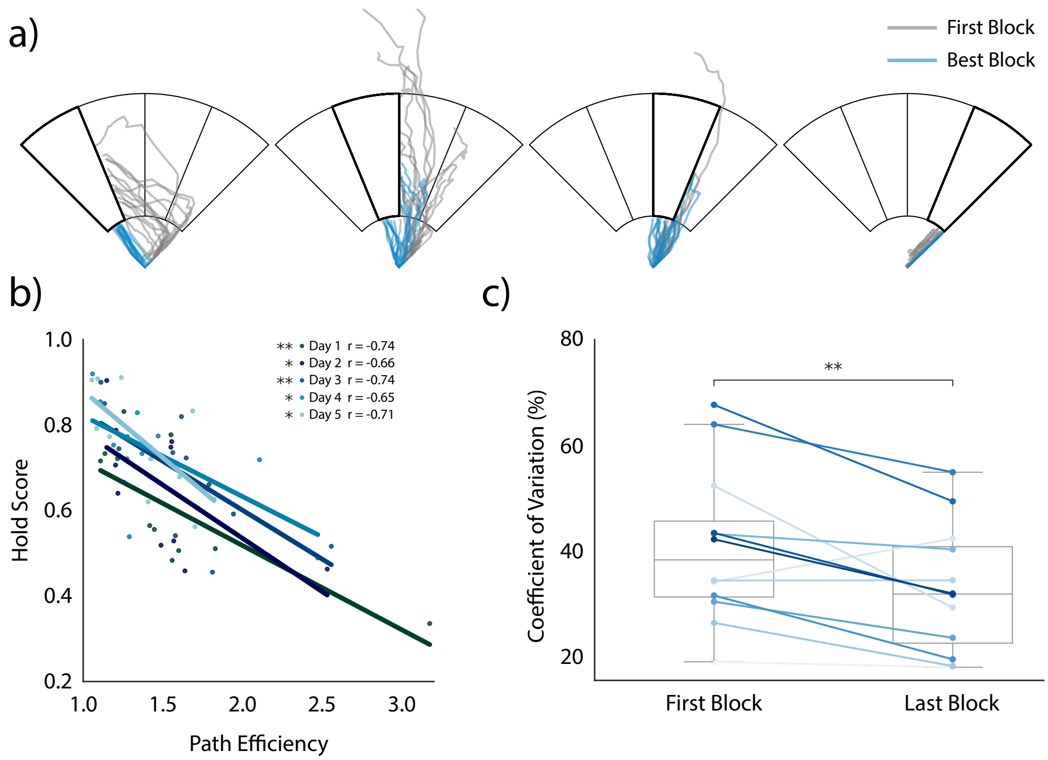

Figure 6.6: Evidence of human learning driving performance changes. (a) Example of cursor path changes over training. Traces correspond to individual trials from a single participant up until the cursor first contacts the correct target. (b) Relationship between hold score and path efficiency over days. Points correspond to participants' mean score over a single day. (c) Coefficient of variation from each participant's first and best scoring blocks. Connected points refer to a single participant. Asterisks denote level of significance ($*, p < 0.05; **, p < 0.01$)

shift in calibration, which was likely caused by the weight of the prosthesis. Therefore, they did not opt to adjust their calibration when asked. Then, when those adaptive processes were no longer active during the zero-feedback trials, hit scores reflected the difference between their internal representation of the interface and the calibration. However, once these individuals received end-point feedback from the prosthesis movement, they could make adjustments to their muscle contraction strategy. Ideally, participants should have experienced delayed feedback blocks, instead of concurrent ones, to assess whether the calibration was optimal. This stresses the importance of recreating the feedback loops during transfer tasks, which are similar to those available during real prosthesis control. Although performance over zero-feedback trials was previously shown to be a good estimate of retention, the feedback loop in these trials is much more limited compared to real prosthesis control. Therefore, this metric may not have been a good indicator of transfer performance.

The main limitation of the current study was the lack of a control group. This makes it challenging to infer with certainty whether performance improvements were due to the training protocol or were simply a result of the participants' previous experience from completing the pre-test. Additional analyses were conducted and presented in Figure 6.6, to investigate this. Three arguments are presented in favour of motor learning.

Firstly, if there was a substantial amount of pre-exposure effects we would expect to find a link between the participant's performance in the pre-test to their performance in the post-test. However, no significant relationships were found between any pre- and post-test measure with itself. Secondly, Figure 6.6(a) shows a typical pattern of cursor traces improving, moving closer toward the optimal route with practice. In addition, the relationship between hold score and path efficiency is strong, significant, and relatively consistent over days. Therefore, suggesting that changes in hold score may also be used as a proxy for motor learning, which increases over days (Figure 6.2). Finally, the coefficient of variation, which is a measure EMG signal variability, significantly decreases after delayed feedback training Figure 6.6(c). Suggesting that after training, participants produce motor outputs that are more consistent. This pattern is also associated with skilled performance. These results indicate that the improvement seen between pre- and post- metrics are unlikely to be entirely due to previous exposure to the task conditions.

Furthermore, in the worst-case scenario that it is, in fact, the prior exposure to the pre-test that leads to significant improvement following a long period of no practice, this would be an exciting result. Although I maintain that this scenario is very unlikely, this would have major implications for abstract decoding! In reality, I predict that some control measures involving simple tasks may improve, such as the box and blocks test. However, I would not expect the speed or accuracy over the object manipulation task to change substantially for the control group. While, the inclusion of a control group is typical for studies that include pre- and post-tests. The results presented in Figure 6.6 suggest that this may be unnecessary.

6.6 Acknowledgements

This study has not yet been published.

- Conceived of the experiment - SS, SD, KN, MD
- Experimental design - SD
- Experimental programming - SS, SD, MD
- Collected data - SS, SD
- Data analysis - SS

6.7 Summary

- The results strongly indicate successful pre-device skill transfer to prosthesis control.
- Participants should not be given concurrent feedback of control signals when calibrating the system during the post-test.

Chapter 7

Study 4: The Impact of Reducing Motor Variability on The Limb Position Effect

7.1 Introduction

The drop in control performance following a change in posture has challenged the robustness of myoelectric prostheses and continues to be the focus of much research [125]. Mitigation attempts in the pattern recognition domain have focused on acquiring high-dimensional data to provide more tolerant decision boundaries [74]. However, these studies did not investigate the influence of user practice prior to addressing the limb position effect. Although previous research in motor learning-based control schemes has leveraged user learning to counter artificial or limb position-induced perturbations [127], [146], [147], there is no evidence that this can be done without real-time feedback.

Before delving into more detail, it is necessary to define certain key terms.

- **The limb position effect** is a confounding factor related to changes in arm posture that negatively affects myoelectric pattern recognition classification accuracy [148]. The effect is quantified by the rate at which intended grasps are decoded incorrectly by the classifier.
- **Input data variability** refers to the statistical properties of the sam-

pled and quantised representation of the signal acquired by a surface EMG sensor, which captures the muscle activity signal but can be impacted by numerous sources of noise, and is typically passed as input to a pattern recognition system.

- **Inter-repetition** or **trial-to-trial variability** is the variability between instances or repetitions of the same intended movement. In motor learning literature, trial-to-trial variability is often used to quantify motor variability. In pattern recognition literature, inter-repetition variability typically defines the within-class statistical properties of a class.

The lab- and home-based retention studies demonstrated that appropriate myoelectric training led to the retention of skilled performance when external feedback was withdrawn. In terms of motor control theory, I hypothesise that this occurs due to increased reliance on the forward (predictive) model, leading to refinement of motor commands and thus skilled performance. Figure 7.1 illustrates the hypothesis of how reducing motor variability through myoelectric training may help reduce the negative effects of limb position changes on prosthesis control performance. Implementing myoelectric training before people receive their prosthesis, as well as optimising the training paradigm for retention, would allow them to produce muscle patterns with reduced trial-to-trial variability the moment they start using their prosthesis, leading to better control acuity.

The goal is to minimise the input data variability by reducing trial-to-trial variability via user practice. In essence, this equates to achieving greater class separability by reducing within-class variability. In this way, more tolerant decision boundaries could be drawn around a tighter cluster of input data, such that a perturbation is less likely to cause the incoming input data to lie outside the desired decision boundary. This approach shares a similar goal with those in the machine learning domain, which have attempted to capture the variability induced by limb position by collecting more exemplar training data to enhance the decision boundaries. I would like to clarify that I do not expect this method to address the full limb position problem. Ideally, user training would work in tandem with existing methods to improve system robustness.

This study compared the impact of limb position between two groups after long-term myoelectric training. The group that trained with delayed feedback

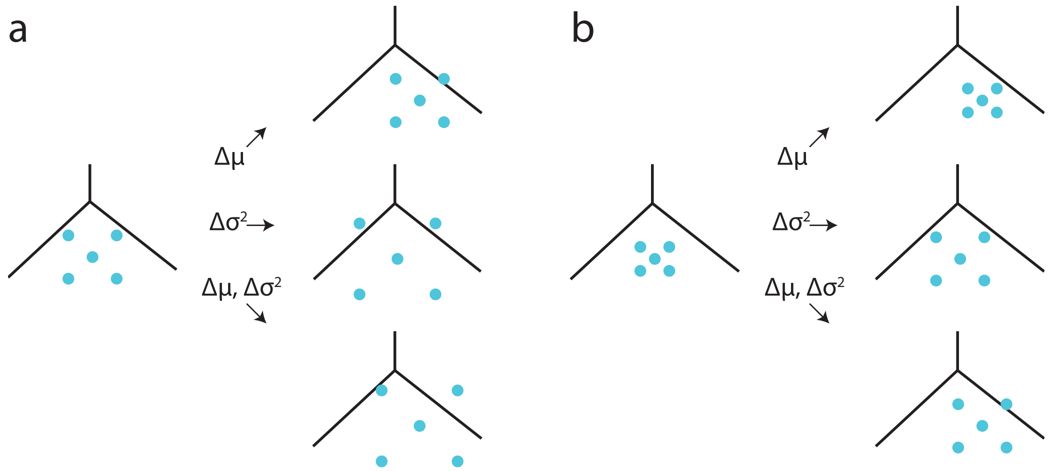

Figure 7.1: Possible impacts of limb position on the parameters of the input data. Points correspond to data from a single movement class. Lines correspond to decision boundaries generated by a classifier trained in a single position. Three possible changes due to differences in limb position, Δ, to the input data are depicted: mean, μ; variance, σ^2; or a combination of both. (a) Data cluster before and after a change in arm position. (b) Less variable data cluster before and after a change in arm position. Note that the size of the perturbations induced by limb position changes are the same in both cases, but the number of misclassifications decreases in (b).

retained less variable muscle activity during the zero-feedback tests. The other group received real-time feedback, which resulted in higher muscle activity variability. How these skills generalised to untrained limb positions was examined.

7.2 Description of the Study

Our previous work demonstrated that appropriate myoelectric training led to the retention of skilled performance when external feedback was withdrawn [36]. This work intended to investigate whether the retention of more consistent motor outputs following practice would lead to subsequent gains in robustness against the limb position effect. Two groups of users were trained: One group retained their myoelectric skill, observed throughout training, during zero-feedback retention tests; the other group was highly accurate with instantaneous feedback, but they did not retain this skill in the absence of feedback. After four days of training in a single arm position, both groups were tested to see how well the retained myoelectric ability, acquired in a single position, generalised to untrained limb positions. Significant differences were found in the limb position effect between the High Retention and Low Retention groups. This research indicates that, if within-class variability can be lowered for a single arm position, the variability across other arm positions is also diminished. This suggests future research should exploit motor learning-based training prior to attempting to address the limb position effect.

Study aim: Investigate whether improved muscle output consistency observed during prolonged training in a single position generalises to untrained arm positions.

7.3 Methods

This study shared methods with Study 1. This section introduces methods that are particularly relevant to this study.

7.3.1 Participants

The same participants from Study 1 were used. In that study, the groups were called 'Concurrent' and 'Delayed'. In the present study, although the groups remain the same, hereinafter they will be referred to as 'Low Retention' and 'High Retention', respectively. Ethical approval was granted by the local committee at Newcastle University (Reference: 20-DYS-050). Written informed consent was obtained before the experiment began.

7.3.2 Estimation of Muscle Activity

Surface EMG signals were acquired with eight electrodes using two Trigno Quattro Sensors (Delsys Inc. Natick, MA, USA). Signals were sampled at 2000 Hz and band-pass filtered between 20 Hz and 450 Hz.

7.3.3 EMG Calibration

Participants were asked to perform dynamic arm movements while data were collected representing either baseline resting EMG, y_r, or contraction, y_c. Prior to each session, the raw and filtered EMG data were visually inspected. Recalibration was strongly discouraged once the normalisation values for y_c

were finalised. However, baseline EMG activity, y_r, could be recalibrated in subsequent sessions if changes in baseline noise affected control.

7.3.4 IMU Calibration

IMU calibration followed the same method described in Section 3.3.1.

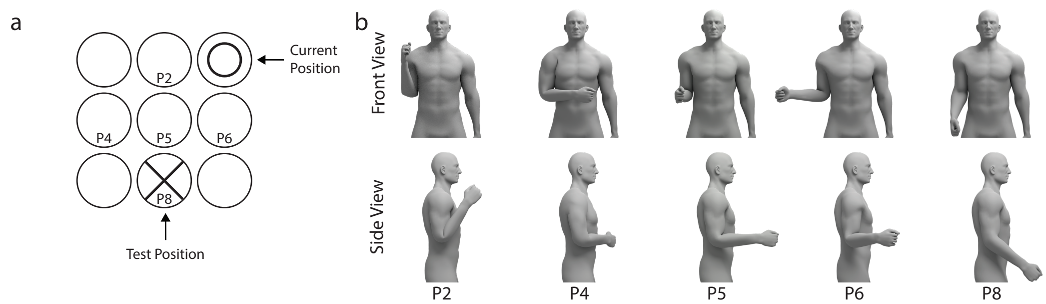

Figure 7.2: The experimental task. (a) Presented arm position widget based on inertial measurement unit (IMU) data. (b) Arm postures corresponding to the IMU widget. Feedback of the forearm direction is relative to the screen, as reflected by the IMU widget.

7.3.5 Recordings

EMG and IMU recordings followed the same methods described in sections 3.2.2 and 3.3.2, respectively. The arm position tested in this study are shown in Figure 7.2.

7.3.6 Protocol

Baseline performance: Before interpreting performance across multiple positions when testing the limb position effect, a baseline measurement is required. This was the purpose of the lab-based retention study where participants learned the control task in position 5. After the final retention block, participants experienced two zero-feedback blocks that tested skill retention over five different arm positions. For each block, a random target was presented for six trials in a row. On the first trial of the series, participants moved into position 5 and were given either concurrent or delayed feedback, depending on the condition. Subsequent trials in the series repeated this target in positions 2, 4, 5, 6, and 8 with zero feedback. The order of each position was shuffled within a run. For each block, this procedure was repeated three times per target. Therefore, each participant completed a total of 120 trials.

Multi-position training: Immediately after the follow-up session of Study 1 had finished, participants continued with the remainder of the this study. This entailed concurrent feedback training over multiple arm positions. This was done for two reasons: (1) to see how long-term exposure to delayed feedback (intended to stifle within-trial adaptation) affected the use of adaptive processes within the same task, and (2) to assess the participants' ability to adapt their control to account multiple positions after extensive training in a single position. Participants completed four blocks, each consisting of 80 trials. Again, a target was randomly selected to be presented in a series of trials. The order of arm positions were randomised within a run.

It is important to note that on day 4 of Study 1, no feedback was provided during untrained arm positions. Furthermore, any feedback that was provided remained congruent to the group condition. This was done to avoid interfering with the results from the follow-up session of Study 1.

7.3.7 Measures and Statistical Analyses

Distributions did not appear normal when data were aggregated over days for statistical analyses. Furthermore, the data did not tend to be normally distributed at the individual block level. As a result, non-parametric statistical tests were used for comparisons. Mean artefact rejection rates after manual inspection were $0.22\% \pm 0.45\%$.

7.4 Results

Once participants had completed single-position testing on day 22 they underwent multi-position testing. Participants from both groups experienced four concurrent feedback blocks in several static arm positions. Each participant's contribution to the group's mean score from the first and last of these blocks is shown in Figure 7.3. After experiencing four blocks of concurrent feedback, participants were able to improve their scores across the new arm positions (First, $Mdn = 0.71$; Last, $Mdn = 0.90$; Wilcoxon signed-rank, $p < 0.01$). Comparisons between groups for the first and last concurrent

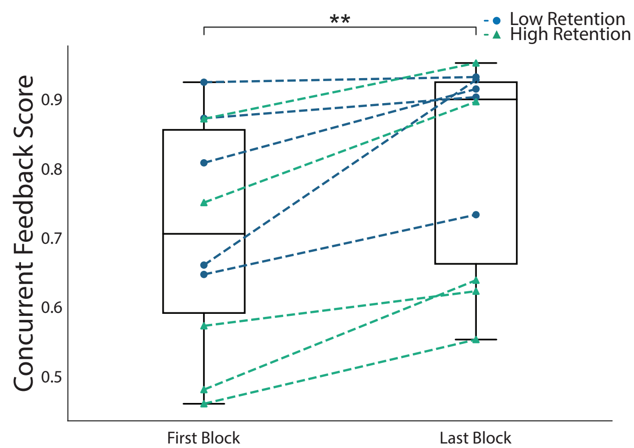

Figure 7.3: Learning to counter the limb position effect with concurrent feedback. Box plots correspond to the mean scores across all participants. Only untrained arm position trials are included. Centroid lines, medians; solid boxes, interquartile ranges; whiskers, overall ranges. Dashed lines correspond to individual participant mean scores. Asterisks denote level of statistical significance (Wilcoxon signed-rank, $p < 0.01$).

feedback blocks yielded no significant difference in score.

After the Study 1 had concluded on day four, participants completed two retention blocks which were conducted under the new arm positions that had not been experienced before. Figure 7.4 shows the mean scores over the zero-feedback trials from both blocks. Between group comparisons only yielded a significant difference for P5 (Low Retention, 0.28 ± 0.12; High Retention, 0.54 ± 0.17; $p < 0.05$). No significant differences were found for all other positions; P2 (Low Retention, 0.31 ± 0.11; High Retention, 0.45 ± 0.16), P4 (Low Retention, 0.29 ± 0.13; High Retention, 0.48 ± 0.15), P6 (Low Retention, 0.25 ± 0.17; High Retention, 0.45 ± 0.22), or P8 (Low Retention, 0.26 ± 0.12; High Retention, 0.51 ± 0.18).

The impact of arm position on the cursor's average location during the retention blocks is illustrated in Figure 7.5. The centre of each ellipse represents The cursor's mean coordinate during the hold period. The major and minor axes of each ellipse corresponding to each control muscle, represent the standard error of the mean of the cursor's location. In general, the High Retention group had less variable muscle activity than the Low Retention group. Furthermore, the variability of muscle activity over arm positions for the same target (i.e. within-class variability) was lower in the High Retention group. The area of the ellipses are shown in Table 7.1 and can be interpreted

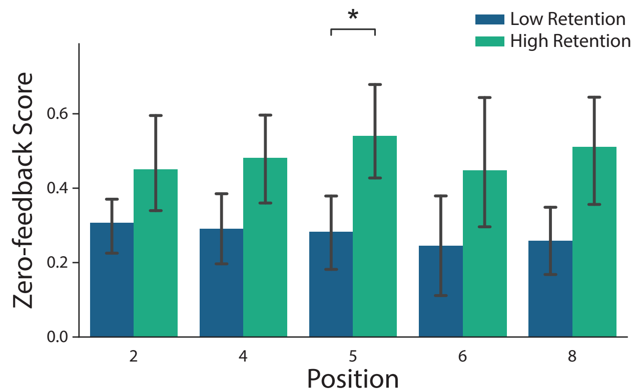

Figure 7.4: Baseline retention between groups. zero feedback scores across limb positions pre-multi-position training. Bars represent the mean. Error bars represent 95% confidence intervals. Asterisk refers to significant differences ($p < 0.05$).

as the product of the standard errors of each control sensor, multiplied by a constant scaling factor. Comparing the area of ellipses over each arm position shows that the total variability in the High Retention group was consistently lower than in the Low Retention group for every target.

A greater misclassification rate is visually represented by ellipses overlapping in to adjacent target boundaries in Figure 7.5. For the Low Retention group, there is a significant amount of overlap into adjacent targets for arm positions in the vertical and horizontal planes, relative to the torso. By contrast, a greater proportion of misclassifications occur for positions on the horizontal plane for the High Retention group.

Because the Low Retention group's data are more variable, any underlying patterns due to the limb position effect are more likely to be obscured. Because the High Retention group has demonstrated lower variability, subsequent analysis will focus on their data.

Figure 7.6a shows mean changes in ECR and FCR muscle activity following a change in arm position relative to position 5 (P5). Muscle activity corresponding to the ECR increased relative to P5 for P2 ($10.8 \pm 14.2\%$) and P6 ($18.7 \pm 9.4\%$), corresponding to elbow flexion and outward shoulder rotation, respectively. In contrast, ECR activity experienced relatively less change for positions P4 ($-2.8 \pm 5.8\%$) and P8 ($-0.9 \pm 8.6\%$). Whereas, the inverse pattern was observed for FCR activity. FCR muscle activity increased relative to P5 for positions P4 ($13.8 \pm 1.6\%$), and P8 ($5.6 \pm 14.4\%$), corresponding

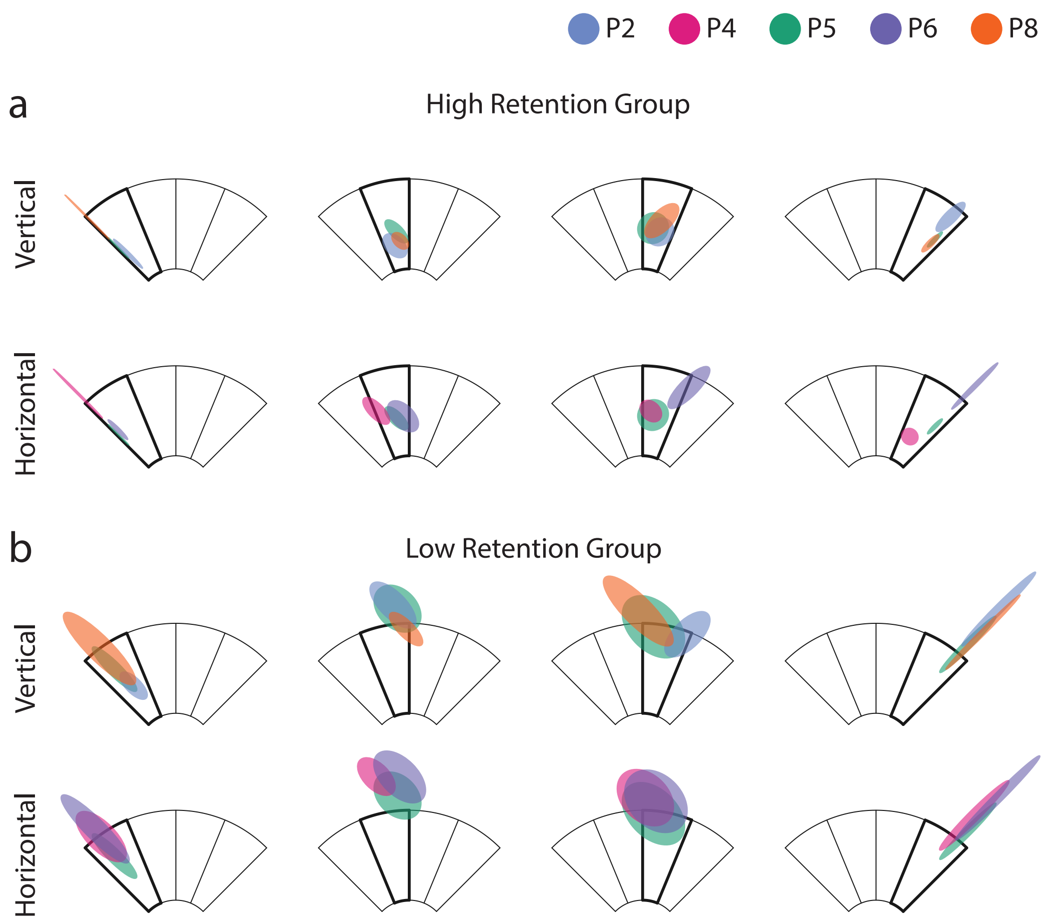

Figure 7.5: Group differences in muscle activity variability during the retention test. (a) and (b) show the cursor's location across limb positions for the High Retention and Low Retention feedback groups, respectively. Plotted activity corresponds to zero feedback trials of the retention blocks. Rows refer to arm positions located in the vertical (P2, P6) and horizontal (P6, P8) planes, relative to the torso. Position P5 is plotted across both planes for comparison. Columns separate the goal target presented during the hold period, shown in bold. Ellipse centre represents the group's mean muscle activation during the hold period. Ellipse semi-major and semi-minor axes represent the standard error in the corresponding control muscle.

Table 7.1: Area of ellipses representing the standard error, presented in Figure 7.5. Values are factored by $4\pi \cdot 10^{-3} units^2$.

		Low Retention Group				High Retention Group			
		Target: 1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Position	**2**	8.2	23.4	24.1	13.9	2.1	8.0	11.7	7.1
	4	27.7	18.1	45.4	16.3	2.0	7.8	6.8	4.1
	5	12.4	31.6	53.6	10.0	0.5	5.7	14.2	1.2
	6	28.8	35.0	56.3	16.7	1.5	12.7	15.4	4.4
	8	36.9	10.8	40.9	8.6	1.1	3.7	13.3	2.2

to inward shoulder rotation and elbow extension, respectively. In addition, smaller changes in FCR activity were found for P2 ($-4.3 \pm 4.6\%$) and P6 ($2.4 \pm 7.8\%$).

Muscle activity changes across all recording sites, relative to P5, are shown in Figure 7.6b In general, a similarity in the profile of changes is shared between P4 and P6 across all recording sites; in both positions, the profile peaks at sensor 1 and has a trough at sensor 4. Similarly, a separate pattern of muscle activity changes appears to be shared between P4 and P8; MAV change peaks for muscles in similar approximate locations, recorded by sensors 4 and 3, respectively. The variability across sensors for P8 is, however, relatively high among participants.

7.5 Discussion

The findings of this study are threefold. First, delayed feedback training in a single-arm position led to the retention of muscle contraction patterns that were more robust against limb position changes. Second, by training participants to produce more consistent muscle activity, it was possible to more confidently attribute observed activation patterns to the limb position effect. Finally, the results stress the importance of providing appropriate feedback mechanisms during both training and real-world use of prosthetic devices.

To counter the limb position effect, pattern recognition solutions have attempted to capture more variability to provide better decision boundaries

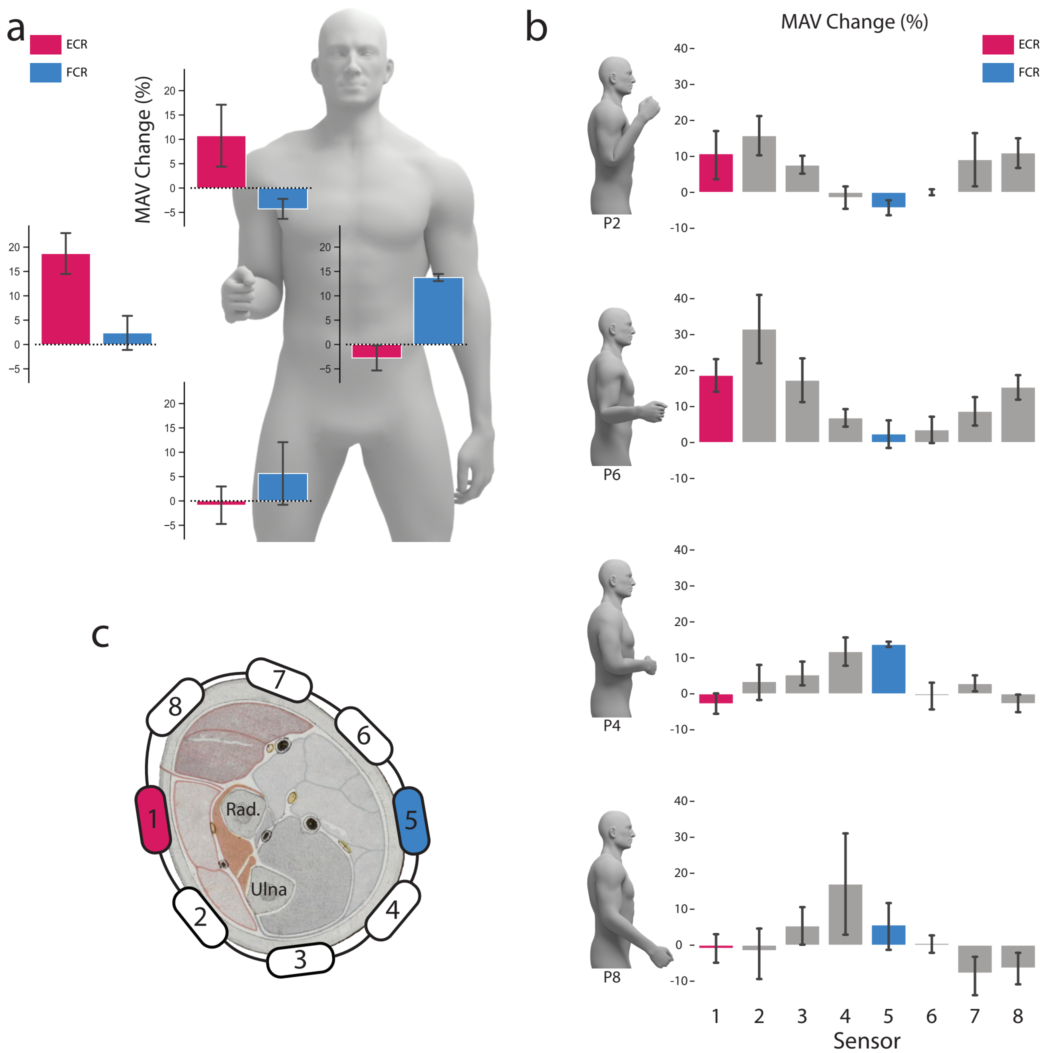

Figure 7.6: The effect of arm position on the High Retention group's muscle activity. (a) ECR and FCR activity changes compared to position P5. The location of each bar plot around the human model reflects results from the corresponding arm position. (b) Activity changes compared to position P5 across all recording sites. (c) Stylistic representation of electrode positions around the forearm. Forearm cross section is adapted from [149] which is in the public domain. Bars represent means. Error bars represent the standard error of the mean.

[74], but have not attempted to reduce the motor variability inherent in the data presented to the classifier. The applicability of the results to pattern recognition are easier to interpret by considering the targets in the myoelectric task as analogous to decision boundaries. For classification to be robust, motor activity must be sufficiently consistent that the EMG signal remains quasi-stationary (i.e. within decision boundaries). In this case, however, rather than adapting the decision boundaries to fit user data (as is done during classifier training) the boundaries are pre-defined and the user must learn to adapt their input accordingly. Following this analogy, Figure 7.5 illustrates the impact of appropriate myoelectric training on within-class variability. When compared to concurrent feedback, it can be seen that delayed feedback training in one limb position reduces within-class variability across all limb positions. Reducing within-class variability can, in turn, increase class separability [44]. This is visually demonstrated in Figure 7.5 by less overlap with other targets. In the context of pattern recognition, the difference between the Low Retention and High Retention groups suggests user training could be beneficial for enhancing the consistency of contraction patterns and hence improve classification robustness. Previous studies have found that increased class separability achieved during pattern recognition training does not necessarily transfer to prosthesis control [144]. However, these studies did not investigate retention. Study 1 showed the importance of demonstrating retention of myoelectric ability prior to demonstrating transfer.

It has been shown that some EMG features are highly reproducible when contraction intensity is controlled [150]–[153]. However, this is distinct from how prosthesis users modulate muscle activity during real-world use, as their production of force typically lacks precise external feedback and is comparatively unconstrained. Removing external feedback can impact the quality of EMG and has been shown to lead to the generation of higher amplitude patterns [34]. The results suggest that delayed feedback training is beneficial for improving the consistency of contraction intensity. Reducing contraction variability, in turn, enabled greater clarity of the underlying structure of the limb position effect. As such, analysis focused on the High Retention group, which was found to have retained more consistent muscle activity than the Low Retention group. Although reduced variability in one position generalised to untrained positions (Figure 7.5), limb positions in the horizontal plane produced results that suggest a more structured change (Figure 7.6).

This was further investigated by analysing changes in the recorded muscle activity.

In general, it can be seen that ECR activity increases when the arm is lifted or moved to the right, whereas positions down or across the body increase activity in FCR. One possible reason for the increase in EMG relative to P5 could be due to shared muscle excitability patterns between certain postures. Equally, similar patterns of subcutaneous muscle displacements may be shared between P2 and, P6 as well as P4 and P8. Furthermore, for each pair of arm positions, a similar pattern appears to hold for the activity profile across all eight sensors (Figure 7.6b). It is important to note that the changes in activity recorded across sensors may not directly correspond to changes in the underlying physiology; for example, activity from a muscle can contaminate the signal recorded by adjacent surface EMG sensors due to crosstalk [112], [154]. Increased activity from a single muscle can lead to a subsequent increase in the contribution of that signal arriving at nearby sensors. It is difficult to ascertain the contribution of muscle-electrode displacement or muscle excitability with surface EMG sensors. In reality, both factors may act simultaneously, and the contribution of each may differ across positions that share seemingly similar EMG responses. Furthermore, due to the spatial resolution limits of surface EMG, one cannot be certain of the underlying pattern of any induced changes. However, irrespective of the exact physiological structure, these results represent the signal changes that would be detected by the electrodes and presented to a prosthesis decoder.

This study intended to investigate muscle activity patterns following changes in limb position. This was possible only because a retention study was conducted first, which enabled greater certainty that any observed patterns were due to limb position and not inconsistent muscle activity. As the participants who trained with delayed feedback reduced their control signal variability, I was able to show that the reduced variability observed in one position also reduced the variability in untrained positions. Finally, I wanted to know how correctable the perturbations induced by the limb positions were, and thus all participants experienced concurrent feedback at the end of the experiment. It was found that, when given concurrent feedback, both groups were able to adapt to limb position changes. In addition, the ability to utilise this information and counter perturbations induced by limb position improved over blocks. This is in agreement with existing literature [146], [147]. Because the main focus of this study was to investigate whether reduced muscle activity variability in one position could generalise to untrained positions, an additional long-term, delayed feedback, retention study was not set up. Future research should investigate the effectiveness of delayed feedback training in multiple limb positions. Previous research has shown that concurrent adaptation may not transfer to real-world control, as users would be dependent on the real-time feedback they were trained with [21]–[27], [36], [89], [90], [155]. One theory of why this occurs is that frequent feedback may overwhelm attention and disrupt learning processes that lead to retention. For example, real-time biofeedback may encourage rapid ad hoc corrections that prevent the formation of a stable skill. By contrast, less frequent or less informative feedback may encourage focus to shift towards proprioceptive signals as a source of guidance, thus leading to skill retention when external feedback mechanisms are removed. This is important to consider when reporting the performance of participants with real-time feedback. Until prostheses widely provide high fidelity, real-time feedback of users' control signals, it is essential for motor skill to be produced in the absence of feedback.

One limitation of this study is its exclusive use of limb-intact participants. Previous work has found that limb different participants' control signals are less affected by limb position. This is thought to be due to anatomical differences. For example, a shorter residual limb enacts a smaller moment of inertia during movement or limb stabilisation [156] and, therefore, less compensatory muscle activity is needed to maintain certain postures. Furthermore, anchoring of the muscle during amputation may also contribute to reduced muscle displacement during movement for some participants [126], [148], [157]. These characteristics diminish the overall variability of muscle activity among arm positions. Therefore, I expect the results with limb-intact participants to reflect a more extreme case of induced physiological perturbations. Furthermore, the findings did not take into account the secondary effects of arm dynamics on the loading and movement of a prosthesis socket. However, this study intended to investigate the impact of reducing the variability introduced by the central nervous system rather than environmental or contextual factors, which have been studied previously. Finally, it is not immediately clear how well user training is likely to scale to machine learning-based systems, which require high dimensional EMG data. Future work will investigate whether user training produces results in machine learning-based systems comparable to those it produces in motor learning-based systems.

7.6 Acknowledgements

The findings from this work were published in [37].

- Conceived of the experiment - SS, SD, KN, MD
- Experimental design - SD
- Experimental programming - SS
- Collected data - SS, SD, MD
- Data analysis - SS
- Wrote the first draft - SS
- Contributed to the final draft - SS, SD, KN, MD

7.7 Summary

From this work we now know:

- Delayed feedback training led to reduced within-class variability of EMG data, which generalised to untrained arm positions.
- Concurrent feedback enabled all participants to counter the limb position effect.

Chapter 8

Discussion

This chapter reflects on the findings from the previous studies and examines the future ramifications of this work. This thesis has posited that, if motor learning appears to be present in any system where the user has feedback and influence over the control system, then by not optimising this aspect of the control loop, unrealised potential performance is inevitably left on the table. This thesis lays the groundwork for further efforts towards merging user and machine learning as the next step for enhancing prosthesis control.

8.1 Introduction

Previous literature on motor-learning based control schemes has boasted impressive performance with online feedback [17], [19]. However, such results are meaningless unless the user is provided with a similar feedback loop during real prosthesis control. In reality, this is often not the case. Although, some research has focused on restoring feedback of sensory afferent signals (i.e. touch), comparatively little research has investigated providing feedback of the user's efferent control signals [84]. Thus, prosthesis users must be able to produce accurate control in the absence of augmented feedback mechanisms.

This thesis sought to apply motor learning principles in a way that would be meaningful beyond laboratory environments.

The initial aim was to explore the possibility of successfully training prosthesis users in a motor learning-based control scheme that did not require, artificial feedback, algorithmic assistance, or additional hardware above the clinical standard. This led to the completion of six studies.

The Study 1 showed that practice with delayed feedback of myoelectric signals leads to skill retention in the absence of feedback. The Study 2 demonstrated that these skills can be trained outside the laboratory within feasible time frames and to a high degree of accuracy. Study 3 showed the efficacy of these methods by successfully demonstrating transfer of myoelectric skills to prosthesis control. Study 4 investigated the application of motor learning principals for assisting in reducing the limb position effect. Finally, potential applications to machine learning-based methods were presented Studies A1 and A2.

8.2 Implications

The results of this thesis have implications for: (1) existing dual-site control devices, (2) enhancing training protocols for current motor learning-based control schemes, and (3) augmenting machine learning control schemes with motor learning principles.

This thesis has shown that it may be possible to restore four grasp classes without mode-switching. Literature suggests that on average, prosthesis users access only four grasp patterns regularly [132]–[134]. The results from Study 2 show that abstract decoding can achieve this functionality with hardware requirements that match the clinical standard. Theoretically, this means that the functionality of existing dual-site control prosthesis could be extended via software rather than hardware upgrades.

This thesis has also shown how to train myoelectric skills such that they can be retained and transferred to prosthesis control, with implications for redefining pre-device training protocols. Previous motor learning-based control schemes have shown high degree of accuracy with online feedback in a lab setting [17], [19]. However, they could not be certain that this performance would translate to prosthesis control with limited feedback. The results shown in this thesis suggest that the high online feedback accuracy may be achievable in the absence of augmented feedback, after appropriate training.

While this research was conducted with a relatively small sample size, its findings have the potential for significant clinical implications if replicated in larger cohorts. One notable example is the widely used "MyoBoy" device [158], which employs myogames to enhance outcomes for myoelectric prosthesis users. These games typically rely on concurrent visual feedback during training, which supports task-space exploration and helps prevent muscle atrophy. However, the findings presented in this thesis suggest that skills acquired through such training protocols are unlikely to transfer to prosthesis control. This raises concerns about the efficacy of current myogame designs, as practitioners and researchers often assume these approaches directly impact prosthesis control performance through improved *online* skill. Which may explain why skill transfer after pre-device training has previously been difficult to achieve in prosthetics. To address this gap, new myogames could be developed for rehabilitation protocols that incorporate delayed feedback during task execution to promote skill retention. By integrating these changes, systems like the MyoBoy could be extended beyond purely physiological rehabilitation tools into comprehensive platforms that also prepare users for proficient prosthesis control prior to receiving their device.

These results also have implications for machine learning-based approaches. The results from the Study 4 showed that it is possible to retain improved trial-to-trial consistency of non-biomimetic contractions, which effectively reduces the likelihood of falling outside the desired decision boundary. The results demonstrate the potential of user learning to improve classification robustness, and offers a new perspective for assisting in mitigating the limb position effect.

Additionally, two pilot studies investigated the incorporation of user learning to machine learning and vice versa. Study A1 provides an initial, but direct insight on the effect of improving contraction consistency on classification accuracy. Early results suggest that machine learning based approaches may benefit from user learning directed at improving biomimetic muscle contractions. Although a full retention study was not done, I predict that its findings would align with the previous results if participants are trained appropriately. Study A2 shows one potential method of tracking changes of the system over time. This could be used to track changes in learning and muscle recruitment strategies, or changes in the environment, such as electrode shift. The results also demonstrated the effect of more consistent muscle activations on the convergence rate of algorithms. I expect that other algorithms that attempt to mitigate the limb position effect would similarly benefit with improved contraction consistency, because they can be more certain that a change is due to a change in the system rather than general EMG variability between trials.

The findings of this thesis have broad applicability across various prosthesis control schemes. The results suggest that tangible improvements in prosthesis control can be realised today with existing devices, the only requirement being appropriate user training.

8.3 Comparison with Existing Literature

The results within this thesis align with long-standing motor learning literature [21], [23]. However, the conclusions are distinct when held against existing prosthesis control literature. This difference may be due to the alternate motor learning frameworks that previous studies have been based on. For example, previous research has claimed that myogames must have task-related goals for transfer to occur [141], [159]. This has been interpreted as a requirement that myogames must be designed to simulate a gripper and provide feedback that is relevant to activities of daily living. Therefore, it was concluded that using feedback of the EMG signals alone is not sufficient for transfer to occur [159]. However, the findings presented in this thesis are in direct contrast with that conclusion. In all experiments, the movement of the cursor was directly related to muscle activity, and yet the results in this thesis indicate successful skill transfer. The difference in findings may be better explained by viewing the problem through the lens of guidance theory.

Guidance theory states that although frequent feedback is beneficial for performance, it can be detrimental if relied upon too heavily [21], [23]. By creating a myogame that more closely simulates prosthesis control, similar feedback conditions are inevitably recreated. Therefore, the guiding properties of feedback that were present during training are also present during the transfer task. As such, both tasks share a similar control loop. By contrast, traditional myogames that typically present EMG signals in real time have a greater guiding effect on performance. Therefore, participants may become dependent on this feedback, which leads to low skill retention. As such, when the feedback during the transfer task becomes sufficiently different or less informative, performance suffers.

Within this perspective, the similarity of the task goals are less important; instead, greater priority is given to the feedback conditions under which the task is performed. Although the level of task similarity is likely key for learning the cognitive mapping between control input and prosthesis response, I posit that feedback similarity (i.e. the type and timing of feedback between training and transfer tasks) is also core to demonstrating transfer. However, this should be considered cautiously because the complexities of motor learning are still not fully understood. Even though promising results were presented in this thesis, the exact processes that produce the observed motor skill remain unknown. This research has only unveiled another dimension to skill transfer for prosthesis control, and I expect that subsequent research will reveal many more facets.

8.4 Limitations

The main limitations of this work are associated with the selection of participants. The research is constrained by a limited sample size, which raises a degree of uncertainty regarding the finding's applicability to a wider population. Although the sample sizes are constrained, it is important to note that the depth of data collected on each participant was large. Over the first four studies, over $60,000$ trials were collected in total, which enabled detailed analyses of long-term changes associated with motor learning. Another aspect of the participant-selection limitation arises from the exclusive use of limb-intact individuals. Due to the anatomical differences in arm structure, it is uncertain to what extent these findings can be extrapolated to people with limb difference. However, previous research has demonstrated that people with an amputation are capable of producing the myoelectric skills necessary for abstract control. Furthermore, since the neural mechanisms required for learning remain intact post-amputation, it is sensible to infer that limb different participants would be able to retain this skill.

A key limitation of the proposed training paradigm is its practicality and affordability, for both academic replication with increased participant groups, as well as for clinicians delivering rehabilitative treatment. Since motor learning is an inherently slow process, it often requires multiple days to observe improvements in skill retention. This may be prohibitively expensive for an experimenter or clinician to carry out in the traditional one-on-one, in-person treatment method, taking place over multiple days, weeks, or months. I addressed the primary costs of clinician time and associated hardware by introducing a low-cost sensing system whereby multiple participants could train in parallel from home, leading to reduced experimenter contact time and more rapid completion of a study. In this research, the hybrid approach of training at home and testing in the lab was logistically successful for a relatively small number of participants over an extended period. However, scaling this approach to larger participant groups or patient populations introduces new challenges. Adherence to training protocols, technical issues, and the need for fault resolution across multiple take-home devices could easily escalate costs. Participants also require proper training to ensure correct system usage, such as the accurate placement of electrodes, which adds an additional layer of complexity and time involvement. In academic settings, these challenges are compounded by the need for consistent training protocols to calculate reliable statistics. Variability introduced by factors such as missed training days can reduce standardisation and complicate data analysis. Despite these challenges, this method is particularly promising in clinical settings, where achieving functional outcomes is more important than strict adherence to a rigid protocol.

This thesis highlights the potential gains of leveraging user learning to enhance the capabilities and robustness of prosthesis control. However, the level of applicability of this work to other control schemes lacks complete clarity. For example, Study 4 showed increased system robustness against the limb position effect after myoelectric training. The underlying premise of this idea is sound (i.e. reducing variability of the input data would, by definition, lead to greater class separability). However, it is not certain how well this will translate to other control schemes in practice. In an early attempt to answer this question, a pilot study was conducted. Study A1 represents one logical progression towards the application of user learning and machine learning. Initial results are promising and suggest that future research should follow a similar trajectory.

8.5 Future Research

Upon reviewing this thesis, the researcher is presented with three options: (1) disregard motor learning and retention, focusing instead on using concurrent biofeedback to enable control based on motor adaptation; (2) apply findings from this thesis to train users to retain myoelectric skills for prosthesis control; or (3) use a hybrid approach by combining motor learning and adaptation principles. All are valid choices with their own outcomes and challenges. This thesis concludes with my thoughts on each approach.

8.5.1 Biofeedback Approach

As previously discussed, motor adaptation is associated with rapid performance gains and flexibility to changing task demands or environment. Therefore, rapid updates of feedback would facilitate motor adaptation. In prosthesis control, this would require providing the user with feedback of their control signals, or their outcome, in real-time.

Outcome: This approach could expect users to be able to adapt on the fly, and counter transient system instabilities. Initial performance gains with this system would be rapid. However, the skills would likely be dependent on this feedback.

Implementation: There are two methods open to the biofeedback approach, and both rely on facilitating motor adaptation by tightening the coupling between user input and response.

One method would focus on providing real-time feedback of the user's control signals. This could be realised in several different ways; for example, a haptic feedback mechanism could be embedded into the prosthetic socket such that concurrent feedback could be provided without interfering with the recording of muscle activity signals. To fully exploit adaptive processes, updates would need to be interpretable, high-fidelity, and rapid.

The other method would focus on reducing the physical delay between user intent and prosthesis movement, whereby users could rapidly adapt their input in response to the current state of the prosthetic hand. This implementation is likely to be more feasible in control schemes that are capable of a continuous estimation of joint positions, like regression control. However, this would require observing the hand during operation, which may be impractical during real-world use.

Disadvantages: One of the disadvantages of this approach is that the control would have a high cognitive load because users must actively pay attention to their control signals at all times. Another drawback is the additional hardware requirements. For example, a haptic implementation would increase device complexity, cost, weight, and power demands.

Research Questions: Future research towards this approach will need to consider the following questions: First, how best to balance the obtrusiveness of concurrent biofeedback as to not become distracting to the user; and second, how to convey feedback in a high-dimensional space that is interpretable by the user. This is particularly important for applications with machine learning-based control schemes.

8.5.2 Retention Approach

This method would share the same goals as the myoelectric training protocols detailed in this thesis, namely, transferring myoelectric skill from pre-device training to prosthesis control. This thesis has focused on retaining the skills for motor learning-based control schemes when users are no longer presented with a rich source of feedback of their control signals. In the context of machine learning, this approach would focus on retaining skills that lead to improved contraction consistency for both biomimetic and non-biomimetic grasps.

Outcome: Although the initial acquisition of skills may be slower, myoelectric training suggests that the resulting skills are likely to be more permanent once feedback is withdrawn. Thus, stable control could be achieved on existing prostheses without any additional hardware. In addition, retaining the skill to produce more consistent muscle contraction patterns may contribute to improved control robustness against some confounding factors, such as the limb position effect. Furthermore, applying user learning principles, in addition to existing approaches that mitigate confounding factors, may act to further improve total system robustness beyond using each method in isolation. For example, algorithms that attempt to detect and counter system instabilities may perform better with input data that is more deterministic.

Implementation: The first three studies outlined how this could be achieved. However, the training protocols used in those studies could be optimised further. Future work going down this route should focus on optimising the training period to expedite learning. This may include investigating other feedback scheduling types.

Disadvantages: One disadvantage is that this approach would likely necessitate a longer training period. This means that, functional use of the prosthesis may occur later. In addition, without real-time feedback, users cannot adapt on the fly and are therefore doomed to make an error when the system is perturbed. However, users would still be able to update their response, albeit on a much slower timescale, because they must wait for the output to be decoded in order to receive end-point feedback.

Research Questions: Future work should expand this approach and investigate the limits of myoelectric skills that could be learned and retained. It is not known whether it is possible to retain even finer myoelectric skills or extend learning to additional degrees of freedom by adding more control channels.

For example, in the abstract control task, this could manifest as splitting the interface into more radial targets, thus extracting more grasp outputs from two control channels. Or, in the machine learning domain this could manifest as learning a myoelectric skill that incorporates the coordinated recruitment of several muscle sites simultaneously. Although it is not known how feasible either situation would be, myoelectric performance is more likely to be limited by the inherent noise in the system than by the central nervous system's capability to learn.

8.5.3 Hybrid Approach

In everyday motor control, fast and slow processes interact in tension with one and other. This enables us to adapt our skills to different environments and allows new skills to be learned. Similarly, using a combination of biofeedback and retention principles could bring together the best of both approaches.

Outcome: A hybrid approach may provide a good balance between skill robustness and adaptability. Users would be able to produce a more robust motor skill in the absence of feedback, but when given feedback, they will be able to readily adapt their input to adjust for new task demands or environmental changes.

Implementation: This could work in the following way: Users first undergo myoelectric training such that they retain the necessary skills. Additional sensors (such as accelerometers) or algorithms (such as CCIPCA) could be used to detect changes in the system or environment. When a circumstance that would lead to decoding uncertainty is detected, instantaneous feedback could be turned on, thus allowing the user to adapt and counter any perturbations in the control space. When the decoding certainty returns to normal, augmented feedback is turned off, and control relies on retention. Therefore, feedback is provided only when it is needed.

Disadvantages: Although the hybrid approach shares the advantages of its components, it also shares their weaknesses. For example, additional hardware will be necessary to convey the biofeedback, and the user training time would remain relatively lengthy.

Research Questions: Future research should explore when and how to transition between control methods during real-world prosthesis operation.

8.6 Conclusion

This thesis investigated three critical aspects of myoelectric control: the effect of feedback on skill retention, the impact of changes in the position of the limb on skilled performance, and the transferability of myoelectric task performance to prosthesis control.

The findings demonstrate that delayed feedback supports superior skill retention compared to commonly used concurrent feedback. With sufficient practice, performance with delayed feedback can match the upper limits achieved with concurrent feedback, offering a pathway to a more robust evaluation of motor learning-based control strategies without requiring additional hardware or augmented feedback mechanisms beyond current clinical standards.

Furthermore, this research shows that retaining skills associated with less variable muscle activity enhances control robustness under limb position perturbations. This underscores the potential performance gains available by optimising user learning within the control loop of modern prosthetic devices, which is often overlooked in contemporary design.

Finally, this work provides the first explicit evidence that myoelectric skills learned without a prosthesis, and without contextual similarity, can be successfully transferred to prosthesis control. This finding validates the assumption underlying pre-device training paradigms and reinforces the relevance of prior research with motor learning-based control schemes.

While these insights may advance our understanding of human learning within myoelectric control, and offer practical implications for rehabilitation protocols, these results are based on a relatively small sample size and replication with larger cohorts is needed to confirm their generalisability.

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Appendix

Chapter 9

Study A1: The Application of User Adaptation on Pattern Recognition

9.1 Introduction

This study applies the principles of motor learning, together with the findings of the previous studies, on a simple pattern recognition system as a proof of concept.

One way of improving classification robustness in machine learning-based control schemes is to increase class separability. The farther apart two clusters are from a decision boundary, the less likely a perturbation is to cause misclassification. Figure 9.1 illustrates two ways of achieving greater class separability in a one-dimensional system.

First, moving the centroid of a class can shift the distribution away such that the overlap with other movement class distributions is decreased. This idea is visually demonstrated in Figure 9.1a. In a myoelectric system, this can easily be achieved by increasing the amplitude of EMG activity at one or more sensor sites [160]. Prosthesis users can use this strategy to better distinguish between muscle activation patterns with relatively little learning [34]. However, a higher level of exertion can lead to early fatigue and is also associated with increased EMG signal variability [34]. Importantly, because the increased signal variability leads to a greater risk of class overlaps, this strategy may become less viable with increased movement classes.

The second method involves reducing the spread of the distribution. Study 4 suggested that reducing within-class variability can be achieved with user training. This effectively shrinks the tails of the distribution, which can lead to reduced overlap with other classes. This is illustrated in Figure 9.1b. In this way, greater class separability can also be achieved with a similar level of muscular effort at the expense of user practice. Unlike the previous strategy, increasing contraction consistency may be applied to several movement classes many times over, whereas increasing EMG amplitude across movement classes is likely to saturate the feature space more rapidly, thereby exhausting the strategy.

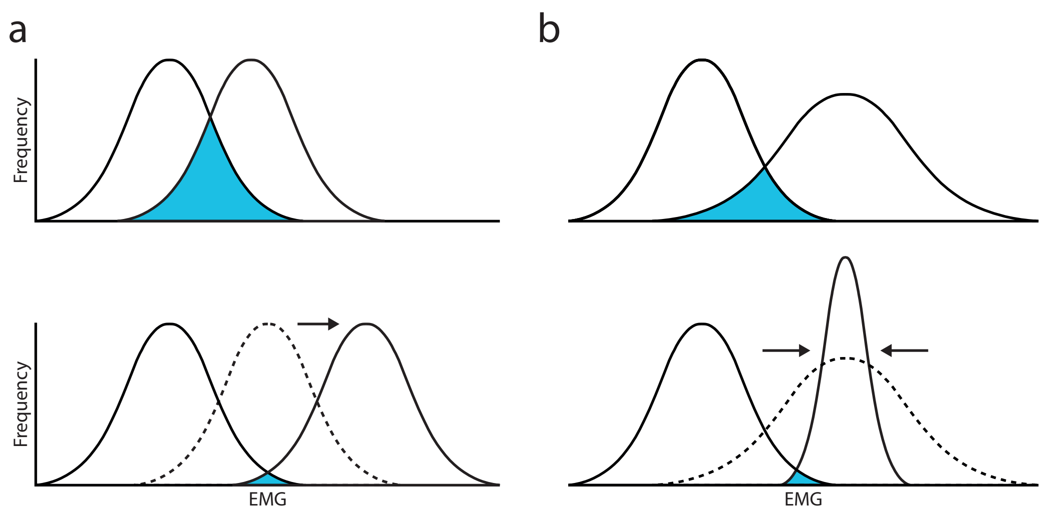

Figure 9.1: Two methods of increasing class separability. (a) Shifting the mean of a distribution. (b) Decreasing the variance of a distribution. Overlaps are highlighted in blue. Figure labels correspond to a single column, which depict the overlap between two motion classes before and after adjustment.

During the processing pipeline in a pattern recognition system, features are selected from the acquired training data. This is typically done sequentially (i.e. features are added until a specific classification accuracy is achieved). Features leading to the greatest classification accuracy are usually prioritised, which means each successive feature contributes less and less to the overall model. One potential application of user learning could offer an alternative approach to feature selection. Theoretically, the feature selection process could be designed to evolve in conjunction with the user's interaction with the system. For example, when one feature is added, the user would first adapt it before additional features are added. This study applied user learning specifically on a single feature to explore whether such a system would be feasible.

9.2 Description of Study

A single-session pilot study is presented. Due to time constraints, a full study was not completed. Two participants operated a pattern recognition system based on linear discriminant analysis (LDA). During the experiment, the participants were provided with concurrent feedback of their muscle activity from eight EMG sensors. The feedback of the EMG from one sensor was manipulated during the experiment, such that adaptive processes would lead to increased contraction consistency without moving the centroid of the class.

Study aim: Investigate the impact of reduced motor output variability on static decision boundaries.

9.3 Methods

The methods used in this study deviated substantially from those of previous studies and the standard methods outlined in Section 3.1.

9.3.1 Participants

Two (male) participants who had no prior experience with the experimental protocol volunteered for the study. Ethical approval was granted by the local committee at Newcastle University (Reference: 20-DYS-050). Written informed consent was obtained before the experiment began.

9.3.2 Estimation of Muscle Activity

Surface EMG signals were acquired with eight electrodes using eight Trigno Sensors (Delsys Inc. Natick, MA, USA). Signals were sampled at 2000 Hz and band-pass filtered between 20 Hz and 450 Hz.

9.3.3 EMG Calibration

Muscle activity data were recorded during a calibration period in order to train a classifier. During the calibration procedure, participants were prompted to complete eight grasps, shown in Figure 9.2. The EMG data were collected while they repeated each grasp three times, separated by a one second rest. Of the eight movement classes, four classes were selected to train the model. The rest class was always included in every subset. The MAV of each sensor was the only feature used to train the model.

Ideally, the first class to improve would be that with the most room for improvement, in terms of classification accuracy and within-class variability. However, brute-forcing the optimal subset of four movement classes out of the eight collected during calibration would require the comparison of 70 models. Instead, I chose a method of approximating a good candidate without recursively training new models.

When thinking in terms of distributions, a movement class that would benefit most from reducing within-class variability would have a mean that is distinct from other classes, but has wide tails that overlap with other distributions. I used a rough method based on the Kruskal-Wallis test [161] and Wasserstein distance [162] as an approximate measure to select such a candidate.

Firstly, the Kruskal-Wallis test was run on all combinations of movements for each feature. Next a subset of classes, corresponding to features with the greatest significant difference, was chosen to train the classifier. Finally, the Wasserstein distance was used on the subset of classes and the identified feature. The class with the greatest distance from the others was selected as the movement to adapt. At the end of the calibration the movement class and feature chosen to adapt were identified and made known to the participant. Because there was only one feature per sensor, from now on this feature will be referred to by its corresponding sensor.

9.3.4 Myoelectric Control Interface Task

Figure 9.3 shows the myoelectric interface, which consisted of a polar plot with eight points that resembled the position of the sensors on the forearm. During the task, participants were presented with MAV feedback of their muscle activity from all eight sensors. The top of the interface was scaled such that it resembled that it represented the 99th percentile of EMG activity

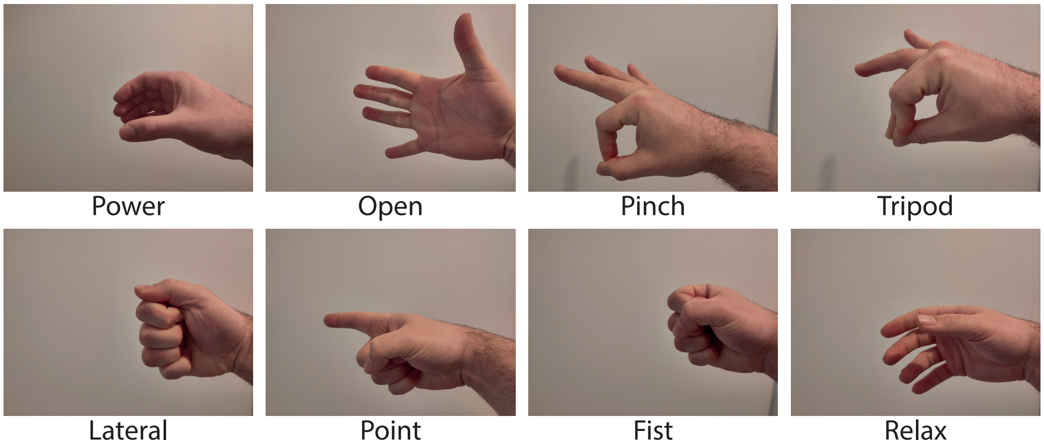

Figure 9.2: The images of the movement classes used to prompt the participants during the calibration period.

acquired during the calibration. During the task, the LDA model was used to predict the current hand grasp. If the predicted grasp was the desired grasp, the interface would turn green. If the predicted grasp was any other grasp, the interface would remain grey.

The goal was to keep the muscle activity within the bounds of the interface, while maintaining a green interface for as long as possible. At the end of the trial, a score was presented that reflected how well the participant kept their muscle activity within the bounds of the interface. If the incorrect grasp was predicted for more than 50% of the trial, 'Fail' was shown on the screen and no score was presented.

9.3.5 Protocol

Before the trial began, participants were made aware of the location of the sensor and the corresponding muscle they would be adapting. Each trial comprised 40 trials of a single movement class, namely, that which had been selected for adaptation. Concurrent feedback of participants' muscle activity was provided during the whole trial.

The experiment started with the participants experiencing the interface scaled to a relatively wide confidence interval bound, using the values acquired from EMG activity during the calibration period. Next, after conducting a block of trials, the experimenter was able to adjust the upper and lower bounds of the

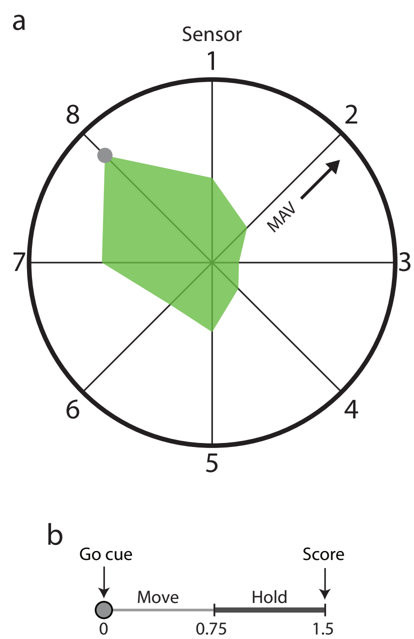

Figure 9.3: The biofeedback interface. (a) Radial axis reflects the level of muscle activity for the corresponding EMG sensor, in real time. Grey cursor depicts the sensor that was selected to be adapted. (b) Feedback scheduling. Trials used the same timing structure as the myoelectric control interface detailed in Chapter 3

interface for the sensor selected for adaptation. This sensor will be referred to as the 'control sensor' from now on. As blocks progressed, the experimental operator could scale the bounds of the interface to reflect a reduced confidence interval. For example, setting the control sensor's confidence interval at 80% would result in the interface's lower threshold reflecting muscle activity that exceeded the 10th percentile of the EMG MAV recorded during calibration. Correspondingly, the upper threshold of the interface would be set at the MAV matching the 90th percentile of activity observed during the calibration period. This meant that the participants had a narrower band of acceptable EMG amplitudes that would correspond to the cursor residing within the bounds of the interface. This had the effect of making the activity of one sensor on the interface much more sensitive than the others.

9.3.6 Measures and Statistical Analyses

The assumption was made that all EMG distributions of movement classes were normally distributed. Because of the limited sample size, no statistical comparisons were made on the results of this data.

Adjusted Hold Score: Scaling the interface to a smaller confidence interval increased the perceived sensitivity of the control sensor. Therefore, the hold score that was presented to the participants would decrease for identical muscle activity patterns as trials became more difficult over time. As such, to better compare the performance over time, an adjusted hold score was calculated offline. This was calculated by artificially scaling the scoring area of the interface to match the strictest confidence interval experienced during the experiment, for all trials.

Classification Score: Because the timing of the trial was based on the sensor updates during the move and hold periods, the classifier may have predicted multiple grasps during a single trial. To better reflect the continuous classification accuracy during the trial, the classification score was calculated as:

$$\text{Classification Score} = \frac{\text{Correct grasps predicted}}{\text{Total grasps predicted}}$$

9.4 Results

The lateral grip was selected for participant 1 to adapt. The open grip was assigned to participant 2. Sensor 1 was selected as the control sensor for both participants.

Figure 9.4 shows the participants' task performance over blocks. Totals of five and eight blocks were completed by participants 1 and 2, respectively. As expected, when the task becomes more challenging by enforcing a stricter tolerance of EMG activity, the hold score that was presented to the participants decreases, as shown in Figure 9.4a. However, when the scores from all blocks are adjusted to reflect the performance in the strictest case, a general improvement can be seen. This is shown in Figure 9.4b. Figure 9.4c shows that initial classification scores were high for both participants; a slight trend of improvement is suggested after experiencing more training blocks.

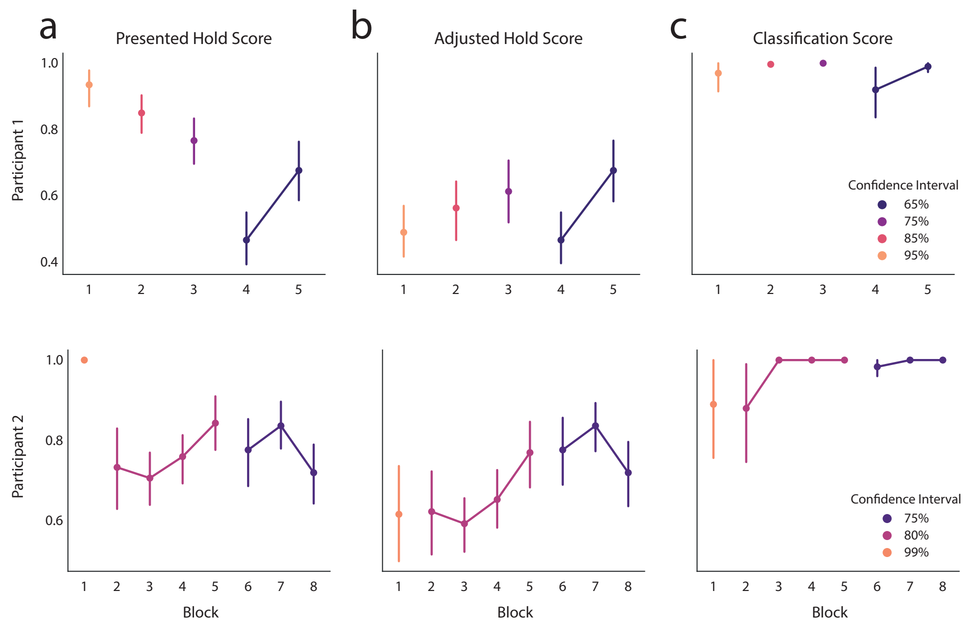

Figure 9.4: Task performance. (a) The mean score that was presented at the end of each trial. (b) The mean score adjusted to match the scoring of the lowest confidence interval experienced by each participant. (c) Mean classification score. Hue corresponds to the confidence interval tolerance experienced at each block.

Figure 9.5 illustrates the changes in the distributions of EMG after training. For both participants, the EMG distributions for the control sensor appear to have a reduced variance while maintaining a similar mean. However, some of the EMG from sensors whose feedback was not constrained, or was not task-relevant, had increased variance and shifted means.

Figure 9.6 shows the data from each participant's best block, projected on to the first two linear discriminants calculated during the calibration period. For participant 1, the cluster of points corresponding to the lateral grasp post-adaptation appears to share a similar centroid with the pre-adaptation cluster, whilst having a reduced spread. By contrast, the post-adaptation cluster for participant 2 appears to have a centroid distinct from that of the pre-adaptation cluster. Furthermore, the spread of the cluster appears to decrease slightly in the first linear discriminant, but increase in the direction of the second linear discriminant.

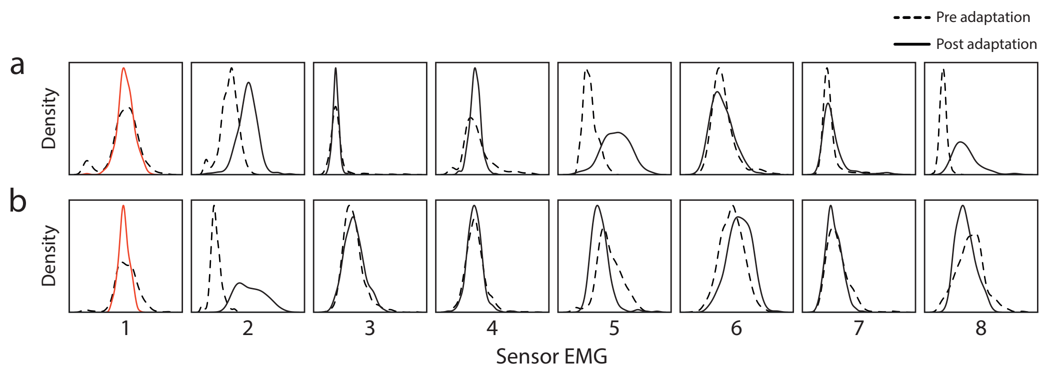

Figure 9.5: Distributions of muscle activity before and after training. (a) Participant 1 data. (b) Participant 2 data. Dashed lines correspond to data collected during the calibration period. Solid lines refer to data collected from each participant's highest adjusted scoring block. Red lines highlight the sensor that was actively adapted in the task.

9.5 Discussion

Although no firm conclusions should be drawn from this proof-of-concept pilot study, the results suggest that it is possible to improve within-class variability within a pattern recognition system by leveraging user adaptation.

The results indicate that users may be able to improve the consistency of muscle contraction patterns of biomimetic grasps. Both participants were able to reduce the variance of their EMG distributions for the control sensor used in this task. Sensors that were not actively adapted also saw changes in their EMG distributions, which may potentially be counterproductive. This was expected, as the activity from these sensors was not strictly relevant to the task. Although the properties of other distributions may appear worse, if the corresponding sensors have a low weighting on the overall classification decision, then more drastic EMG changes may not noticeably affect classification accuracy.

Although the feature selection method used in this study chose to adapt distributions that appeared reasonable, the algorithm itself was not the initial focus. Instead, a greater focus was placed on the extent to which the consistency of biomimetic grasps could be improved. In a real-world implementation of this idea, users should prioritise adapting features that would have the greatest impact on classification accuracy. This is to ensure that the user's efforts are maximised, and that time is not spent learning to improve features that do not contribute significantly to the model. Future work should

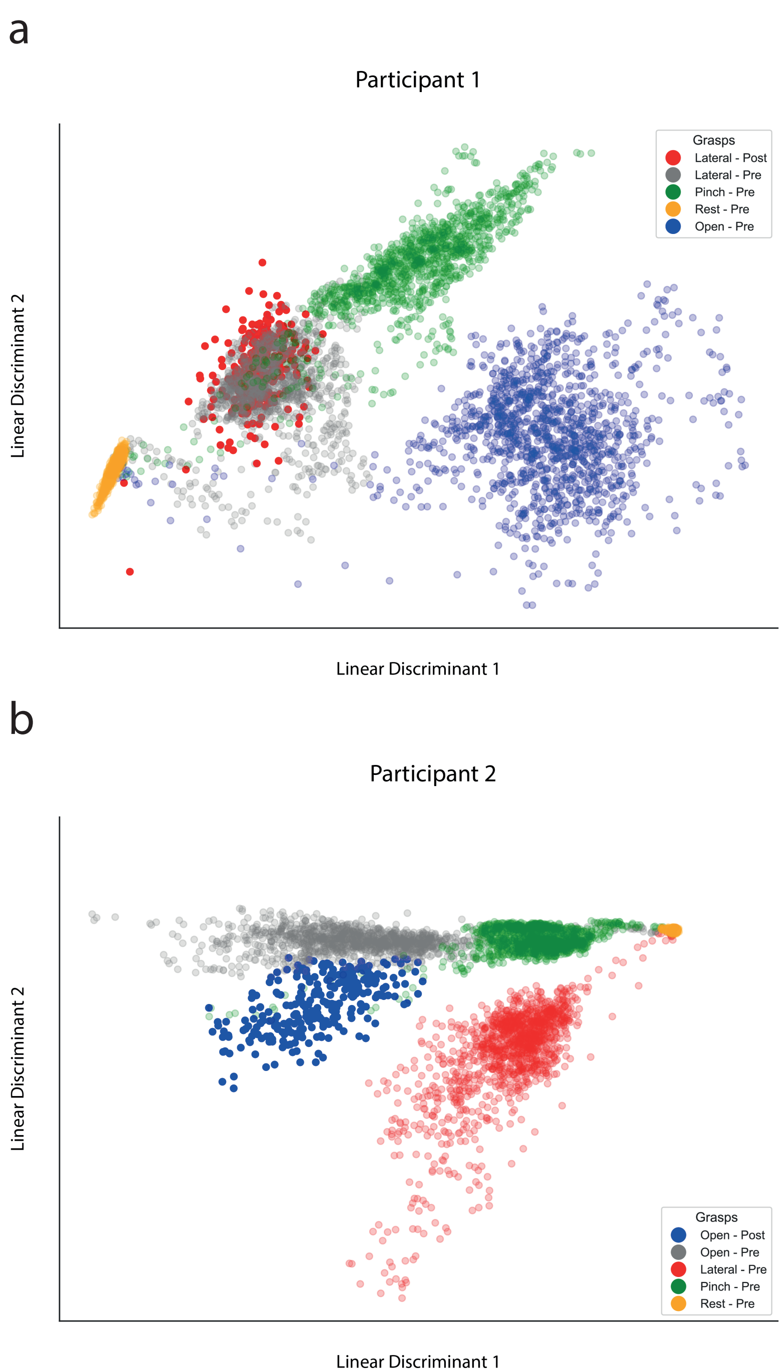

Figure 9.6: Visualisation of the effect of training on the classification space. Points are plotted with respect to pre and post adaptation. 'Pre' refers to the data collected during calibration. 'Post' refers to the data from the block with the highest adjusted hold score.

include the weighting of the features in the selection criteria, and should prevent the distribution of important features from deviating in a way that could lead to decreased classification accuracy. These early results suggest that feedback from multiple sensors may be necessary to optimise the training procedure. However, the more sensors and features used in a system the more challenging feedback communication becomes. Future research should investigate how to communicate high-dimensional feedback in order for user learning to scale with the hardware requirements of pattern recognition.

No retention study was conducted, but if one had been, I predict that the findings would align with the previous studies if participants were trained with the appropriate feedback. If it is possible to retain this skill, two key issues must be considered. First, should the classifier be retrained after the learning process? Second, is it even necessary to use a classifier during the training phase? To elaborate on the second question, the selection criteria for adapting features could work by determining theoretically ideal and separable distributions for each movement class. Then, the training protocol would guide the user to fit their muscle activity to achieve these ideal distributions. Once the skill has been refined, a classifier could then be trained with the optimal muscle activity.

9.6 Acknowledgements

- Conceived of the experiment - SS, SD, MD, KN
- Experimental programming - SS
- Collected data - SS
- Data analysis - SS

9.7 Summary

- The results suggest that it is possible to improve the consistency of biomimetic grasps.
- Muscle activity corresponding to sensors that are not task relevant may lead to counter productive changes, which may lead to decreased classification accuracy.

- Feedback from multiple sensors should be made relevant to the task if the corresponding features have a large contribution to the classifier's prediction. This should be done for two reasons. First, to avoid wasting effort on adapting features that have minimal importance on predictions. Second, to maintain the properties of important features so that they do not drift from ideal values.
- Given the large number of features used in a typical pattern recognition system, future research should investigate how to communicate high-dimensional feedback to the user so that they can adapt their inputs more effectively.

Chapter 10

Study A2: Exploiting Iterative Biofeedback for Automatic Control-site Detection

10.1 Introduction

Unlike limb-intact participants who have the biomechanical advantage of a wrist, people with an amputation often find it challenging to perform isometric contractions. Limb-intact participants can (almost) independently activate forearm muscles by flexing and extending their wrists, and their movements visibly communicate to the experimental operator that the intended muscles are being used. Therefore, there is a need to more easily identify and communicate which muscles can be controlled independently via feedback to both experimental operator and amputee.

Additionally, multiple physiological factors complicate the calibration of myoelectric systems. The composition of muscles surrounding the residual limb is often unknown, making optimal electrode placement difficult. Fat build up around the residual limb insulates and attenuates myoelectric signals [163], and the residual muscles tend to atrophy with lack of use [164]. These factors commonly extend calibration time, which may cause fatigue prior to the research experiment or functional use of the prosthesis. However, if insufficient training data are collected, the system will be sub-optimal and it will be more difficult for the user to achieve the desired output. This again has the effect of early onset fatigue and illustrates the need for participant specific training protocols.

Information extracted from iterative dimensionality reduction techniques can inform optimal sensor locations in real time. The same techniques may also quantitatively infer when sufficient training data has been collected.

10.2 Description of Study

This study had two aims: first, to investigate a data-driven approach for finding suitable control sites without a priori knowledge of the underlying muscle structure. Second, to illustrate the usefulness of an incremental variant of principal component analysis (PCA) in reducing the calibration time period of an upper-limb prosthetic device.

Study aim: Illustrate the usefulness of the biofeedback provided by CCIPCA.

10.3 Methods

This study predominantly used the methods detailed in Section 3.1. Detail is given where methods deviate from the familiar setup.

10.3.1 Participants

Six participants (2 female, 4 male) who had varying levels of experience with the myoelectric task were recruited. Ethical approval was granted by the local committee at Newcastle University (Reference: 17-NAZ-056). Written informed consent was obtained before the experiment began.

10.3.2 Estimation of Muscle Activity

Eight Trigno Wireless EMG sensors (Delsys Inc. Natick, MA, USA) were evenly spaced around the circumference of the forearm. Sensors 1 and 5 were placed on the ECR and FCR muscles, respectively. The signals were recorded at 2000 Hz and band-pass filtered between 20 and 450 Hz.

10.3.3 EMG Calibration

Participants carried out the calibration procedure in a static and seated position. No re-calibrations were necessary due to the relatively short experimental procedure.

10.3.4 Myoelectric Control Interface Task

Because user learning was not the focus of this study, a three-target version of the MCI was used such that each target spanned 30°. This was done to capture three movement types: flexion, extension and, co-contraction of two control sites.

10.3.5 Protocol

The sole purpose of the experimental protocol was to collect example EMG data for offline comparison of two algorithms. The structure of the experiment is therefore straightforward. Data collection required participants to complete 60 trials of the myoelectric task, which corresponded to 20 repetitions of each target. They were provided with concurrent visual feedback throughout the entire experiment.

10.3.6 Measures and Statistical Analyses

In the present work, two varieties of principal component analysis were compared. In an offline analysis, the results from an iterative method proposed by Weng et al. [165] called 'Candid Covariance-free Incremental Principal Component Analysis' (CCIPCA), were measured against a traditional gold-standard method: batch PCA.

PCA

Eigendecomposition is commonly used as a basis for PCA. The eigendecomposition procedure involves factorising a non-zero, diagonalisable matrix, $\mathbf{A}$, into eigenvalues, λ, and eigenvectors, $\mathbf{x}$. This is represented by the following equation,

$$\lambda \mathbf{x} = \mathbf{A}\mathbf{x}. \tag{10.1}$$

In applied scenarios, $\mathbf{A}$ is the covariance matrix of the entire zero centered data set. The data set in the current work is the eight channel EMG data of shape NxM, where N is the total number of samples recorded and M is the total number of EMG channels. Here, the two eigenvectors with the largest associated eigenvalues are selected to become the primary principal components.

This is PCA in it's simplest form, often called 'batch PCA'. Batch PCA is considered to be the gold standard in terms of computational accuracy, but it requires the entire data-set to be present upon calculation. Therefore, it is computationally inefficient to use batch PCA iteratively on new incoming data.

Candid Covariance-free Incremental PCA

Each sample of EMG data can be written sequentially as, $\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_n$ where $\mathbf{u}_n \in \mathbb{R}^d$. In the current work, $d = 8$, the number of electrode channels. For each incoming sample, the mean is calculated and subtracted from the data. In online applications of CCIPCA, it is not possible to know the covariance matrix of the full data-set ahead of time. Therefore, the total covariance matrix, $\mathbf{A}$, from (10.1) is estimated with the sample covariance matrix $\mathbf{u}_n \mathbf{u}_n^T$.

Similarly, for each time step i, the eigenvector $\mathbf{x}$ is replaced with an estimate of the eigenvector, $\mathbf{x}_i$. Substituting these estimates in to (10.1) gives,

$$\mathbf{v}_n = \frac{1}{n} \sum_{i=1}^{n} \mathbf{u}_i \mathbf{u}_i^T \mathbf{x}_i. \tag{10.2}$$

Where $\mathbf{v} = \lambda \mathbf{x}$, therefore, $\mathbf{v}_n$ is the $n-$th estimate of the first eigenvector. The eigenvalues and eigenvectors can be recovered by through utilisation of the vector norm. i.e. $\|\mathbf{v}\| = \lambda$, and $\frac{\mathbf{v}}{\|\mathbf{v}\|} = \mathbf{x}$.

To prevent intensive recalculation of the eigenvector for each time step, the previous eigenvector is used as an estimate. The substitution is written as,

$$\mathbf{x}_i = \mathbf{x}_{i-1} \tag{10.3}$$
$$= \frac{\mathbf{v}_{n-1}}{\|\mathbf{v}_{n-1}\|}. \tag{10.4}$$

For $i = 1$, $\mathbf{v}_0$ is initialised with the first observed sample vector, $\mathbf{u}_1$.

As early samples are assumed to be noisy, an amnesiac parameter, l, is introduced to reduce the weighting of these samples. In most applications, l is commonly set to 2 or 4. The recursive form of CCIPCA can therefore be written as,

$$\mathbf{v}_n = \frac{n-1-l}{n}\mathbf{v}_{n-1} + \frac{1+l}{n}\mathbf{u}_n\mathbf{u}_n^T\frac{\mathbf{v}_{n-1}}{\|\mathbf{v}_{n-1}\|}. \tag{10.5}$$

Cosine Similarity

Cosine similarity is often used to measure the orientational resemblance of two non-zero vectors. It is based on the inner product given by the equation:

$$\frac{a \cdot b}{\|a\|\|b\|} = cos(\theta) \tag{10.6}$$

Therefore, the output is bounded between [-1.0, 1.0]. Outputs of 1.0 and -1.0 correspond to two proportional or opposite vectors, respectively. An output of 0.0 corresponds to two orthogonal vectors.

10.4 Results

An example of CCIPCA's ability to detect and converge towards task-related principal components is depicted in Figure 10.1. Figure 10.1a shows a comparison of snapshots of CCIPCA's convergence at 10 s intervals to the first two principal components calculated by batch PCA. A high degree of visual similarity is achieved at the 20 s mark and is further refined 10 s later. The contribution of the total variance the first two principal components account for is shown in Figure 10.1b. Together they explain approximately 96% of

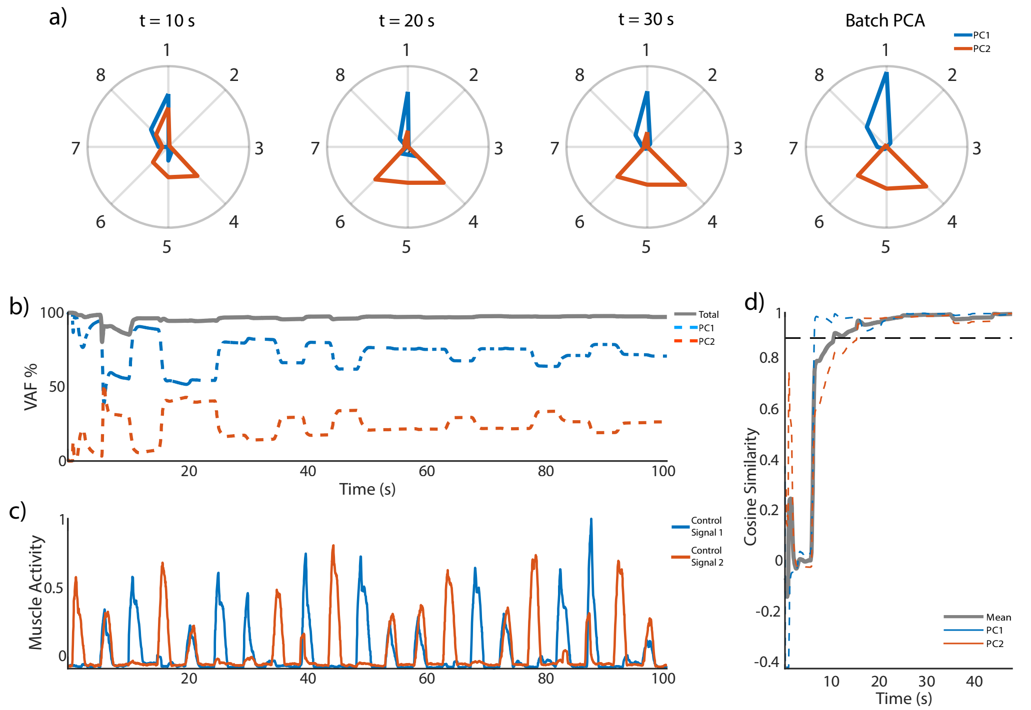

Figure 10.1: Example of CCIPCA's performance on data from one participant. a) Comparison of the PCA vector weights calculated by CCIPCA over time and batch PCA. Radial axes correspond to sensor numbers. b) Percentage of the VAF of the first two PCs. c) Envelopes of EMG activity from control channels. d) Cosine similarity of the incrementally calculated PCs against the corresponding static PCs produced by batch PCA. Dashed line represents cosine similarity of 0.9.

the total variance in the data. The contribution of each principal component to the total variance accounted for (VAF) can be seen to fluctuate with changes in incoming EMG activity, shown in Figure 10.1c. At moments of equal co-contraction, relatively little change of the VAF is attributed to either principal component, whereas updates in the attributions generally occur for isolated flexion and extension movements, suggesting that the first principal component PC1 corresponds to wrist extension activity, while PC2 corresponds to wrist flexion. The cosine similarities between the principal components found by CCIPCA and batch PCA are shown in Figure 10.1d. After 10.3 s, the mean cosine similarity reaches a threshold of 0.9, and continues to increase in an approximate asymptotic trend towards 1.0.

Figure 10.2 shows the rate of convergence of the CCIPCA algorithm across all participants. CCIPCA took medians of 27.6 s and 41.6 s to reach a mean

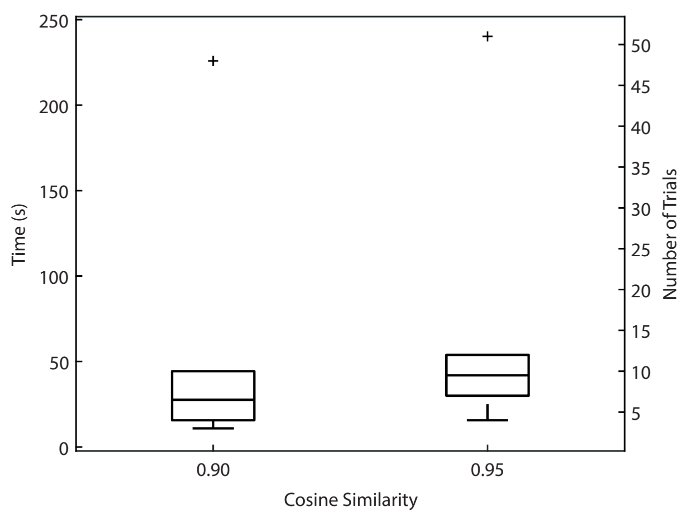

Figure 10.2: Boxplots showing the time and corresponding number of trials required for CCIPCA to reach 0.90 and 0.95 similarity to batch PCA across participants. Red lines, medians; solid boxes, interquartile ranges; whiskers, overall ranges of non-outlier data; red crosses indicate outliers.

cosine similarity of 0.90 and 0.95, respectively. This corresponds to ∼7 and ∼10 trials on average. The most rapid convergence to cosine similarities of 0.90 and 0.95 occurred after 10.3 s and 15.2 s, respectively. This corresponds to ∼3 and ∼4 trials in total. By contrast, the slowest convergence for a non-outlier was achieved after 44.5 s and 53.7 s, corresponding to ∼10 and ∼12 trials, respectively. Figure 10.3 investigates the cause of the outliers performance.

The outliers in Figure 10.2 correspond to one participant. Figure 10.3a shows that it took 225.9 s for CCIPCA to achieve a 0.90 cosine similarity to batch PCA. However, inspection of the participants EMG data suggests an abrupt change in EMG activation strategy may have attributed to this later convergence. Figure 10.3b shows that after 224 s, baseline EMG activity for channel 8 increases where there had historically been relatively little activity. The increased activity on channel 8 coincides with the sudden increase in cosine similarity in Figure 10.3a, as well as changes in the attributed VAF for each principal component in 10.3c. This suggested that CCIPCA had finally encountered a change in the system of which batch PCA had full knowledge upon calculation. This is visually confirmed in Figure 10.3d, where CCIPCA suddenly reorganises the principal components and attributes a greater weighting to sensor 8.

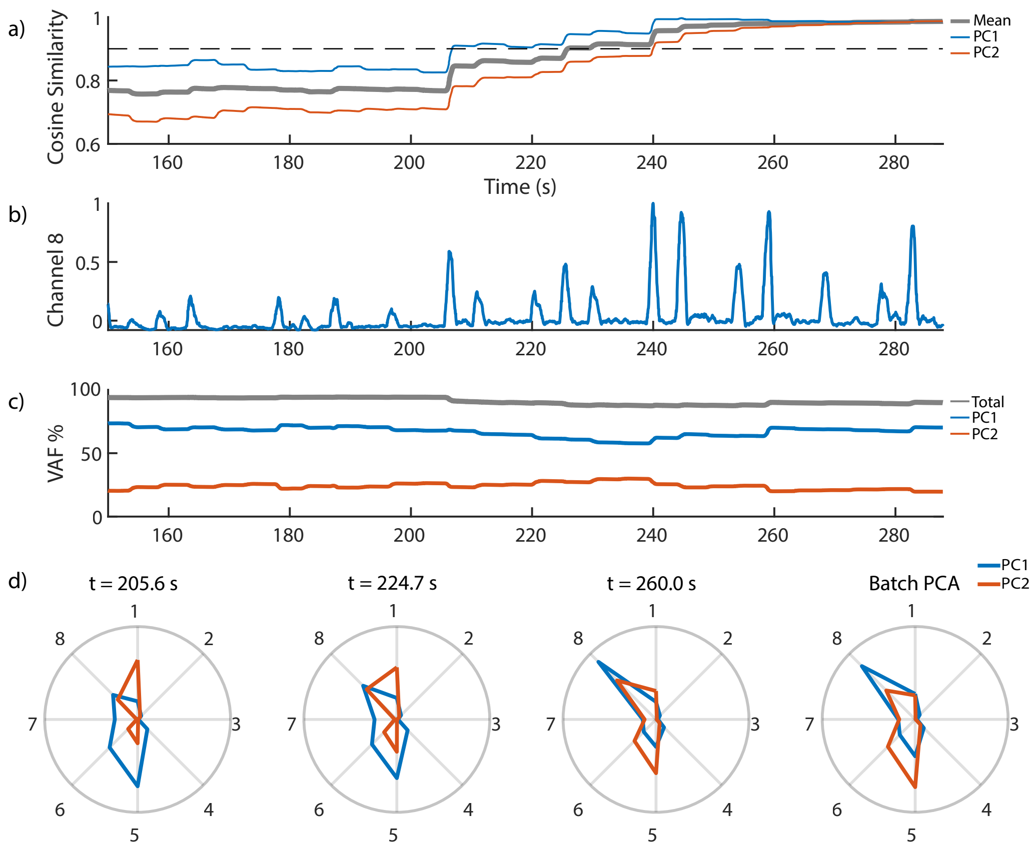

Figure 10.3: Inspection of outlier data. a) Cosine similarity of the incrementally calculated PCs against the corresponding PCs produced by batch PCA. Dashed line represents cosine similarity of 0.9. b) Change of EMG activation strategy, where increased muscle activity on channel 8 can be seen from t = 224 s onwards. c) Percentage of VAF of the first two PCs. d) Weight of the PCA vectors illustrating CCIPCA's response to new data, compared to the batch PCA.

10.5 Discussion

I demonstrated that CCIPCA can successfully detect task-specific muscle synergies and spatially weight an array of electrodes to characterise the sampled muscle activity. This can mitigate the time-consuming nature of locating optimal electrode positions via trial and error.

In theory, this approach could allow abstract decoding to occur without the need for prior channel selection. This process would enable rapid and easy calibrations of a prosthesis, by simply trialling different muscle movements. Iterative algorithms, such as CCIPCA, could initially assist the user in identifying suitable contraction patterns. Subsequently, the most appropriate PCs can be mapped to control the cursor's movement [17].

For the EMG data, the PCs calculated by CCIPCA converged with a cosine similarity of 0.95 to those produced by batch PCA, yet requiring as few as 15 s of data. In addition, feedback derived from the CCIPCA algorithm helped identify a case of inconsistent muscle activity that otherwise would have resulted in a sub-optimal calibration. The inter-trial intervals required by the experimental task increased the time taken for the PCs to converge. More continuous production of EMG activity from two independent movements would accelerate this process.

Visual feedback of the current PCA weights is an interpretable representation of muscle activity, which provides a bespoke output congruent with the participant's physiology. This is likely to be beneficial in discovering independent control sites in amputees by providing an intuitive method to highlight specific muscle activities.

Iterative dimensionality techniques could also bring benefits outside of experimental settings, as they have the potential to minimise costs associated with prolonged clinician contact time. Additionally, convergence towards the PCs extracted in previous sessions could be used to more rapidly calibrate the system between prosthesis doffing and donning in a home environment.

This work demonstrated the advantage of using CCIPCA during short-term calibration periods. However, this algorithm also has potential use-cases for longer-term tracking of changes over time. For example, the changes shown in Figure 10.3 indicated that a shift in the system dynamics occurred after 200 s. Although it cannot be established with certainty, this may in fact have captured the exact moment the participant trialled a new contraction strategy. This is one example of how time-adaptive algorithms could be used to track and observe user learning. Furthermore, CCIPCA could also be used to identify when environmental changes act on the system, such as an electrode shift or subcutaneous muscle displacement. This information could then be used to inform a classifier to counter the change's negative effects.

However, CCIPCA's applicability for use in long-term continuous control faces challenges similar to those affecting other adaptive algorithms, namely managing system changes and controlling adaptivity rates over time. Although PCs can be used for prosthesis control [17], further research is required to confirm whether the PC weights indeed map to optimal electrode sites.

10.6 Acknowledgements

The findings from this work were published in [38].

- Conceived of the experiment - SS, AK, SD, KN, MD
- Experimental design - MD
- Experimental programming - SS
- Collected data - SS, MD
- Data analysis - SS
- Writing of the first draft - SS
- Contributed to the final draft - SS, AK, SD, KN, MD

10.7 Summary

- CCIPCA can calculate principal components with a high degree of similarity to batch PCA in real time, using a fraction of the data.
- This method could be used by clinicians to locate ideal sensor locations or to identify separable contraction patterns for people with limb difference.
- The first two PCs can be used to control the cursor in abstract decoding. Theoretically, CCIPCA could enable control to commence without the need for prior knowledge of optimal electrode placements or suitable muscle contraction patterns.
- CCIPCA can theoretically be used to track long-term changes in a prosthetic system, such as user learning or environmental factors.