The Reality of Myoelectric Prostheses:
How do EMG skill, unpredictability of prosthesis response, and delays impact on user functionality and everyday prosthesis use?

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List of Abbreviations

ADL	Activities of Daily Living
AI	Anatomically Intact
AOI	Area of Interest
ARAT	Action Research Arm Test
BM	Bilateral Magnitude
CNS	Central Nervous System
CRT	Choice Reaction Time
Dom	Dominant
DT	Decision Time
EMG	Electromyography
FDA	US Food and Drug Administration
GCA	Grasp Critical Area
IQR	Interquartile Range
JTHF	Jebsen-Taylor Test of Hand Function
LCA	Location Critical Area
LED	Light Emitting Diode
MR	Magnitude Ratio
NHS	UK National Health Service
NonDom	Non-Dominant
PAULA	Prosthetist's Assistant for Upper Limb Architecture
PCA	Principle Component Analysis
PU	Prosthesis User
RT	Reaction Time
SD	Standard Deviation
SHAP	Southampton Hand Assessment Procedure
SRT	Simple Reaction Time
TAPES-R	Trinity Amputation and Prosthesis Experience Scales - Revised
UK	United Kingdom
UL	Unilateral
US	United States of America
USSR	Union of Soviet Socialist Republics
VM	Vector Magnitude

Abstract

Myoelectric prostheses are designed to provide cosmesis and a degree of upper limb functionality for people with upper limb absence. However, self-reported rejection rates remain stubbornly high, with control of the prosthesis being commonly cited as one of the primary reasons. This observation may indicate that the significant engineering efforts aimed at improving prosthesis control may not have been addressing the most important issues.

Surprisingly, there has been no empirical work outside of lab environments to understand the relative importance of key factors affecting prosthesis control. This thesis explores **the impacts of three factors**: (1) user skill in controlling an EMG signal, (2) unpredictability of prosthesis response introduced at the interface between the electrodes and the skin, and (3) the electromechanical delay in the prosthesis, **on user performance**, quantified in terms of: (1) functionality (kinematic and gaze), and (2), for the first time, everyday prosthesis use.

Chapter 1 introduces the thesis, followed by **Chapter 2**, which contains a review of existing literature relating to the factors affecting control of myoelectric prostheses. **Chapters 3** reports a protocol for the assessment of the impact of skill, unpredictability and delays on user functionality and real world use of a prosthesis. **Chapter 4** introduces the first method for the visualisation of time series data from wrist worn accelerometers and presents the first time series data on everyday prosthesis use. **Chapter 5** presents results of a study, which recruited 20 trans-radial myoelectric prosthesis users from 6 centres across the UK, drawing conclusions as to the relative impacts of each control factor on performance. Results suggest unpredictability introduced at the electrode-skin interface by the socket mounted electrodes may be the key factor affecting control. Additionally, the results show the delay to the onset of hand opening from a fully closed position to be approximately double the delay measured from any other starting hand aperture. **Chapter 6** reports on upper limb activity in the 20 trans-radial prosthesis users and 20 anatomically intact participants. The results show that, by contrast to the anatomically intact participants, upper limb activity of prosthesis users is heavily biased towards the intact limb. Finally **Chapter 7** summarises the main findings of the thesis, addressing limitations and suggesting future work.

1

Introduction

Introducing a thesis which explores the human and engineering factors affecting user performance with a myoelectric prosthesis

Myoelectric upper limb prostheses are controlled using electrical signals naturally generated within the muscles. These devices first became commercially available in the 1960's [1] with a prosthesis developed in the USSR, and over the past 55 years many of the core design features have not fundamentally changed. The Russian hand looked not dissimilar from current commercially available devices provided by the National Health Service (NHS) in the United Kingdom (UK). Two sets of electrodes were placed against the surface of the skin to detect the electrical signals from the residual muscles, which were amplified, analysed and used to control the operation of motors within a single degree of freedom prosthetic hand allowing it to be either opened or closed [2].

In the words of one upper limb amputee:

"In any amputee view, they (myoelectric prostheses) are demonstrably and understandably, repeatedly and repetitively worse than not wearing a prosthetic arm." – Wolf Schweitzer 2013 [3]

Although this is not felt by all amputees, self-reported rejection rates of myoelectric prostheses are high, and many people report preferring to use other styles of prosthesis, or to go without. For those who do use a myoelectric prosthesis, feelings of irritation or annoyance with the functionality and reliability of these devices are common.

Since the 1960's researchers have attempted to improve the functionality of myoelectric prostheses, but so far very few of their efforts have been integrated into clinical devices, and those which have are highly expensive. Hands offering multiple degrees of freedom are now available, yet the pattern recognition systems first conceived in the 1970's [4], which were intended to allow more intuitive control of these movements, are not yet feasible for widespread clinical use [4]; only one system is currently on the market, and only available within North America (Complete Control, Coapt LLC). As such, for many, these more advanced hands offering multiple grip types can only be operated one mode at a time with methods such as co-contraction used to swap between grips. Despite very limited evidence of the user's

ability to exploit the new technologies outside of the lab, recent advances have attracted significant (social) media attention. These include the work of Todd Kuiken [5, 6] in developing Targeted Muscle Re-innervation, the many approaches to sensory feedback [7-11], and most recently 3D-printing technologies and the wave of low-cost hands (e-NABLE [12] and Open Bionics [13]).

Despite the efforts of these researchers and developers to progress the field, there is very little or no evidence as to which aspect of present day myoelectric prostheses is most in need of improvement; hence, in light of the slow progress in the field, it is reasonable to assume that research may be trying to solve the wrong, or at least, a sub-optimal, set of problems.

Research often appears to be driven by the availability of new techniques and technologies, or topics which are able to attract significant public interest. This thesis takes a different approach to most of the technology-driven studies in the area of upper limb prosthetics. The author aims to exploit the potential wealth of data available in the prosthesis user population (a surprisingly poorly explored population) to gain a better understanding of the factors influencing user performance with a prosthesis (termed in this thesis as “control factors”). The thesis was inspired by the work of Saunders and Vijayakumar [14] who noted that although feedback improves prosthesis control, other factors such as the inherent unpredictability in the response of myoelectric prostheses may be just as, if not more important. Additionally the thesis builds on the work of Head [15], who noted that the interface between the skin and the electrodes was a significant source of this unpredictability.

This thesis therefore assesses the major factors affecting the control of myoelectric prostheses in order to understand how they each affect user performance. These control factors are assessed at the highest level rather than breaking each down into its individual components (i.e. we assess whether the hand activates unexpectedly, not why). Once the major factor(s) contributing to poor performance has/have been identified, further work can be undertaken to establish the detailed cause and develop suitable solutions.

In **Chapter 2** a background is provided on the current state of the art for myoelectric prostheses. This chapter addresses the design of the devices, and the possible factors leading to high rates of dissatisfaction and self-reported rejection. This chapter introduces three main factors which may impact on the ability of a user to control their prosthesis, and introduces the research question.

Chapter 3 introduces a novel protocol for the assessment of these three control factors, namely user "*skill*" in controlling muscle signals, "*unpredictability*" introduced at the skin-electrode interface, and the electromechanical "*delay*" of the prosthesis between electrode stimulation and the onset of hand response. This protocol also addresses the methods which will be used to assess "*user performance*". A pilot study was undertaken to assess the feasibility of the protocol and results are presented.

The measurement of "*user performance*" includes objective assessment of "*prosthesis usage*" outside of the clinic using activity monitoring. **Chapter 4** introduces a novel method for the visualisation and quantification of upper limb activity, demonstrated using data from two myoelectric prosthesis users and a healthy anatomically intact adult with no upper limb impairments.

Chapter 5 addresses the primary research question, presenting data collected on 20 upper limb prosthesis users at 6 centres across the UK, to explore the relationships between the three identified control factors and "*user performance*".

To better illustrate the extent to which myoelectric prostheses restore a normal pattern of upper limb activity outside of the clinic, **Chapter 6** presents a comparison of everyday upper limb activity between a group of 20 myoelectric prosthesis users, and a group of 20 healthy anatomically intact adults with no upper limb impairments. Furthermore, measures of "*prosthesis usage*" are compared to clinical measures of "*functionality*".

Finally **Chapter 7** summarises the findings of the thesis, addressing any limitations and providing recommendations of future work.

2

Literature Review

An introduction to limb absence, prostheses and the research gap

2.1. Introduction to limb absence

2.1.1. *Congenital limb deficiencies/absence*

Congenital limb absence or deficiencies are caused by incomplete formation of the upper or lower limbs of the foetus during pregnancy (more commonly the upper limb [16-19]). Infants may be born with part of the limb deformed or missing. For some infants, limb deficiency may necessitate surgery or amputation.

2.1.2. *Amputation*

Amputation is the surgical removal of the limb. The primary reasons for amputation include trauma, vascular disease, cancerous tumours, infection, persistent pain or congenital abnormalities. The large majority of upper limb amputations are undertaken due to trauma, with the next most common cause being congenital abnormalities [19-21].

Upper limb amputations can be classified by location, which will either be through a bone or a joint (**Figure 1**). Classifications include:

a) Partial Hand
b) Wrist Disarticulation (through wrist)
c) Trans-radial (through forearm)
d) Elbow Disarticulation (through elbow)
e) Trans-humeral (through upper arm)
f) Shoulder Disarticulation (through shoulder)
g) Forequarter (including shoulder blade/collarbone)

Upper limb amputations are most commonly undertaken at the trans-radial level [19, 20]. When amputating, a surgeon will usually aim to preserve as much of the limb as possible since a longer residual limb provides a more effective mechanical lever arm, although this must be balanced against the space required for the prosthesis components.

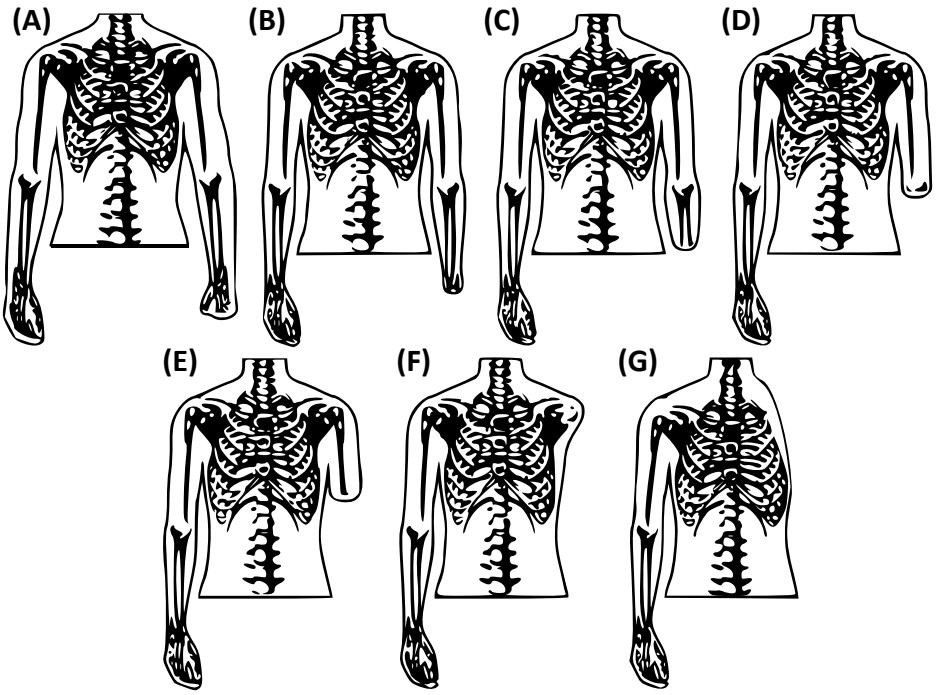


Figure 1. Classification of upper limb amputation locations. **(A)** Partial hand, **(B)** wrist disarticulation, **(C)** trans-radial, **(D)** elbow disarticulation, **(E)** trans-humeral, **(F)** shoulder disarticulation, and **(G)** forequarter. Images adapted from www.ottobockus.com

2.1.3. *Prevalence of upper limb absence*

Statistics relating to the prevalence of limb absence and provision of prostheses are poor. Data from the United States in 2005 suggested that approximately 41,000 people were living there at the time with major upper limb absence (defined as trans-radial and above) [22], which equates to 1 in 10,000 people. Furthermore, according to the UK limbless statistics database [19, 20], each year in the UK approximately 5-6,000 people are referred to NHS limb centres with major limb amputations, of which approximately 1 in 20 (≈280/5600) are undertaken on the upper limb, and most commonly at the trans-radial (forearm) level. In addition, congenital deformities contribute significantly to the number of people living with upper limb absence, although data on prevalence is somewhat inconsistent [15, 20, 23].

It is worth noting that in the period 1981-2013, NHS Scotland reported approximately one fifth of amputations to be undertaken on the upper limb [24]; this figure is also supported by The US National Centre for Health Statistics (according to Chapter 30 of Orthotics and Prosthetics in Rehabilitation [25]). These statistics, which are

significantly different to the 1 in 20 figure presented in the UK Limbless Statistics data [19, 20], or 1 in 16 as reported by Ziegler-Graham relating to the US in 2005 [22], highlight the absence of the availability of exact figures on amputation prevalence.

Both the UK Limbless Statistics data (which reports only the limb centre referrals), and the predictions of prevalence generated by Ziegler-Graham provide, at best, estimates as to amputation prevalence. The US National Centre for Health Statistics data referred to in Orthotics and Prosthetics in Rehabilitation was not referenced, so the specifics of the factors measured cannot be verified.

Due to the small number of sources for limb absence statistics, a small number of references are often widely cited, however, it is not clear whether these figures are representative of the wider population.

2.2. Types of prosthesis

People with upper limb absence can choose to wear a prosthetic device serving an aesthetic and/or functional purpose. These devices are split into three categories: cosmetic, body powered and myoelectric (**Figure 2**).

2.2.1. *Cosmetic*

Cosmetic or passive prostheses may take the form of an anthropomorphic hand, or a tool such as a specialist clamp to hold onto the handlebars of a bike. These devices may be static with no moving parts, or adjustable, for example with a mechanical thumb that is able to be positioned using the sound hand, or the environment [26]. Although cosmetic prostheses are passive, they can serve a minor functional purpose for stabilisation of an object; however, the hand itself is not able to be actively opened and closed. Aesthetically the function of a cosmetic hand is to replicate an anatomical hand as closely as possible (**Figure 2A**) and many advances have been made with high definition silicone gloves allowing for close matching of skin tone and texture and inclusion of artificial hairs and nails. Cosmetic hands can help to disguise the limb absence allowing users to avoid unwanted attention, they can also help with body image and a feeling of symmetry.

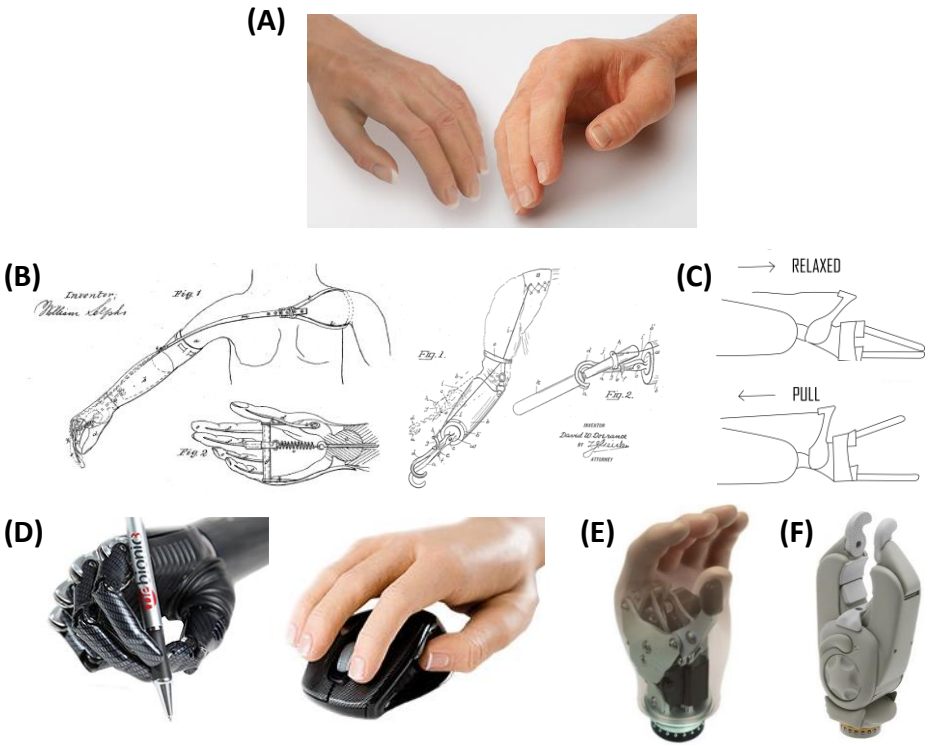


Figure 2. Types of prosthetic hand. **Top (A):** Cosmetic, **Middle (B, C):** Body powered, **Bottom (D, E, and F):** Myoelectric. The cosmetic hand images **(A)** were adapted from www.ottobock.co.uk. The body-powered prosthesis images **(B)** were sourced from the original patents by (Left) William Selpho US 180,21 (1857), and (Right) David Dorrance US 1,042,413 (1912). The image in **(C)** was produced by the author. The images of the myoelectric hands were sourced from **(D)** www.bebionic.com, **(E)** www.rslsteeper.com, and **(F)** www.ottobock.co.uk

2.2.2. *Body powered*

Body powered devices can be actively articulated by the user. A harness is worn around the contralateral shoulder connected to a cable which runs back to the terminal device. Movements of the shoulder generate tension in the cable, which is used to open and close the terminal device (**Figure 2C**). Similarly to cosmetic prostheses, the terminal device can either take the form of an anthropomorphic hand, or a tool. Most commonly a functional split hook is used, primarily for manual work (**Figure 2B**).

2.2.3. *Myoelectric*

Similarly to body-powered devices, myoelectric prostheses can be actively controlled by the user. These devices rely on electrical impulses naturally generated within muscles. Each time a muscle contracts electrical impulses are generated, known as electromyography signals (EMG), which can be measured at the surface of the skin.

Myoelectric prostheses utilise these EMG signals to control the operation of motors within the prosthetic hand generating torque and subsequent movement.

The most advanced myoelectric hands offer multiple degrees of freedom, with life-like movements of the fingers (**Figure 2D**). These hands often offer a rotating thumb and individual movement of the fingers. Consequently a large range of grip patterns are available to the user, however the process of switching between these grip types can be complicated.

The traditional design of myoelectric hand includes a single hinged gripper (**Figure 2E**), allowing for the rigid set of fingers to rotate about the palm, with a range of speeds and grip forces. These hands are available with the option of a rotating wrist unit and are usually covered in a PVC or silicone glove to provide a more aesthetically pleasing appearance.

In some cases, the glove can be an inconvenience becoming damaged and dirty; as with body powered arms the terminal device can therefore take a more practical design, such as the Greifer terminal device shown in **Figure 2F**. The use of a 'tool' is less common with myoelectric devices than with body powered devices. Many prosthesis users find body powered devices to be more functionally effective than myoelectric prostheses, perhaps due to feedback through the tension in the cable. Consequently in situations where cosmesis is seen to be less important, body-powered limbs often become preferable.

2.2.4. *Prevalence of myoelectric prosthesis use*

There is no central database recording the number of devices prescribed each year, however it is well known that the number of users of myoelectric prostheses is small in comparison to body-powered and cosmetic users. Discussions with prosthetists at the Roehampton Disablement Service Centre revealed that almost 20% of their upper limb prescriptions are for myoelectric devices. However, taking a wider view, the reported uptake of myoelectric prostheses as the primary device varies significantly by centre and by study, ranging from 4-44% of populations studied [23, 27, 28]. The widespread use of myoelectric devices is still limited by their usability.

Furthermore, through the NHS in England and Wales multi-articulating hands are not routinely prescribed [29].

Based on discussions with an upper limb prosthetist lecturing at the University of Salford, the best estimate of the number of upper limb myoelectric users in NHS limb centres in the UK is approximately 800-1000 (≈100 of whom are based in the North West). The largest centres are believed to be Roehampton, Birmingham, Manchester, Nottingham, Sheffield and Stanmore.

2.3. Myoelectric prostheses

The following section explains in more detail how a myoelectric prosthesis works. **Figure 3** represents the constituent parts of a myoelectric prosthesis. An electrical signal is generated within the muscles (**Section 2.3.1**), which is acquired by electrodes (**Section 2.3.2**) placed against the surface of the skin (**Section 2.3.3**). This signal is sent to a controller within the hand (**Section 2.3.4**) which determines the state the hand should be in, and operates the motor accordingly (**Section 2.3.5**).

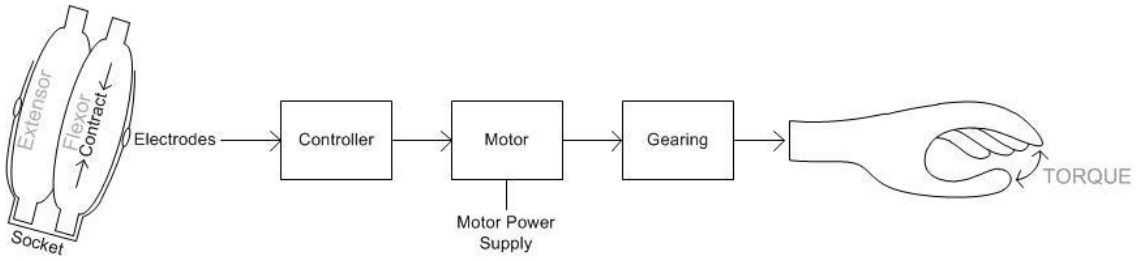


Figure 3. Block diagram detailing the constituent parts of a myoelectric prosthesis.

2.3.1. *The myoelectric signal*

The contraction of muscles is controlled by the Central Nervous System (CNS). Muscles fibres are connected to the CNS via motor neurons; these are elongated cells which originate within the spinal cord and are connected at their distal end to the muscle fibres. Each neuron will innervate a number of muscle fibres and the neuron and associated muscle fibres are known as a motor unit. Activation of a single neuron will contract all the fibres in that motor unit. Each muscle consists of a large number of motor units, and the level of muscle contraction is controlled by the asynchronous activation of a number of motor units. [30, 31]

When a muscle fibre receives an activation signal from the nervous system, the permeability of the fibre membrane to positive Sodium ions is altered and the local transmembrane potential is reduced (depolarisation). With a high enough level of depolarisation, an action potential is generated which propagates over the membrane surface along the length of the fibre, initiating contraction. [30, 31]

As the action potential propagates along the muscle fibre the depolarisation can be measured by a pair of electrodes placed against the surface of the skin in line with the long axis of the fibres. As the depolarisation region travels under the electrodes, a potential difference develops between the two electrodes as shown in **Figure 4**.

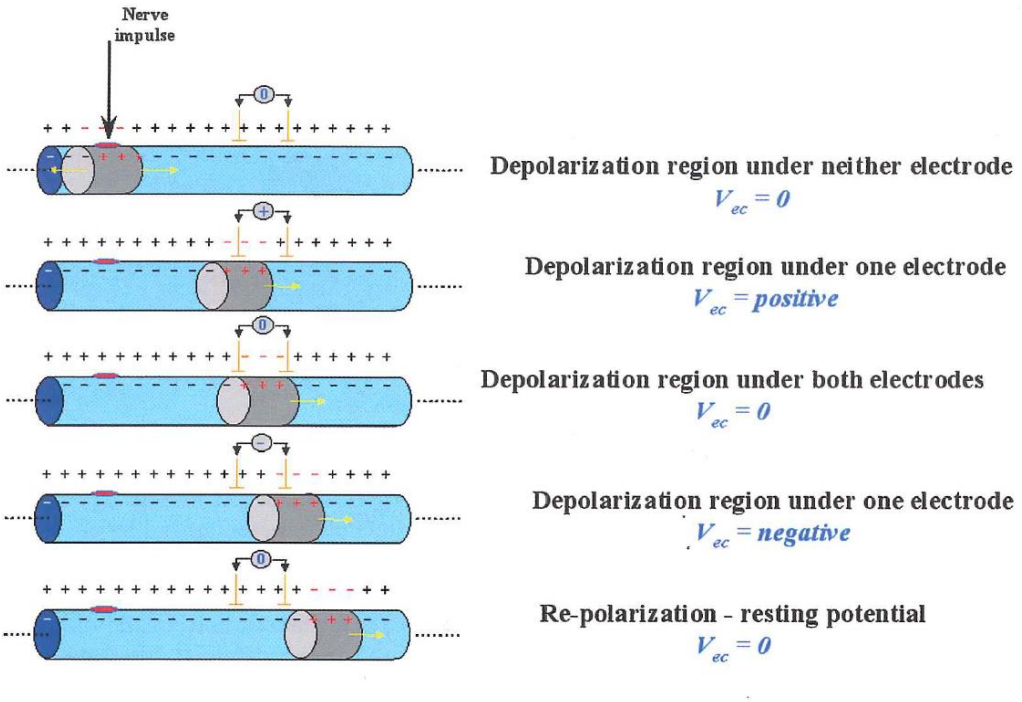


Figure 4. A potential difference is produced across the two electrodes as the depolarisation region generated by the action potential passes beneath them. Image source: Powered Upper Limb Prostheses [31]

The myoelectric signal is a summation of the depolarisations from all of the active motor units local to the sensor. EMG or electromyography is purely the measurement of these myoelectric (or EMG) signals. **Figure 5** demonstrates how the amplitude of the EMG signal increases with the contraction level of the muscle.

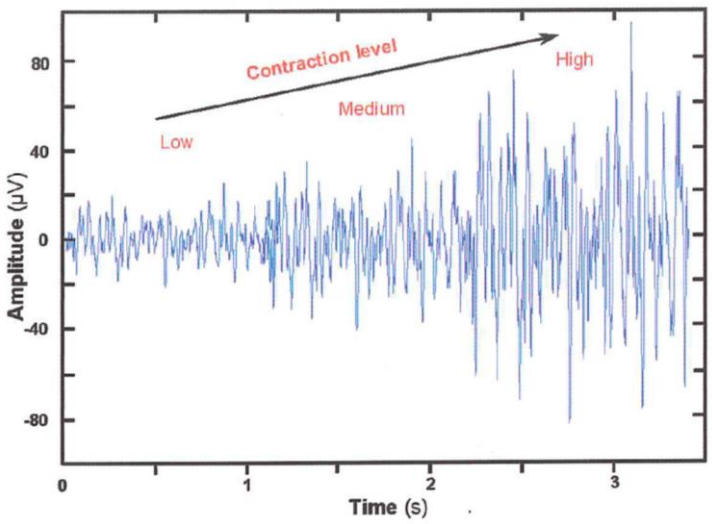


Figure 5. Variation of EMG signal amplitude with contraction level; as contraction increases, amplitude of the signal increases. Image source: Powered Upper Limb Prostheses [31]

2.3.2. *Myoelectrodes*

Standard commercial myoelectric electrodes are an assembly containing a set of three dry metal electrodes and a differential amplifier (**Figure 6**). Two of these three electrodes are used to measure the EMG signal as explained above (**Section 2.3.1**). The third electrode is known as the reference electrode (or ground electrode). Communication devices, power transmission lines and many other aspects of modern day life mean that we are surrounded by electromagnetic fields [32]. These fields induce small currents within the human body, leading to the electrodes detecting an additional voltage which is greater than the EMG signal. The reference electrode is therefore used to subtract this 'common mode' voltage from the measured EMG signal.

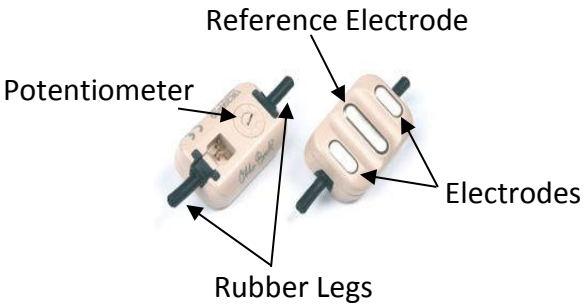


Figure 6. Commercial myoelectrodes. Image source: www.ottobock.com.au

The amplitude of a typical surface EMG measured from the forearm muscles under medium contraction is around 100µV. It is usually desirable to increase this to 1-10V using a differential amplifier [33]. On the rear of the myoelectrode is a dial (potentiometer) which allows the gain of the amplifier to be adjusted in relation to the amplitude of the signal the user is able to generate. If the user has a very weak signal the gain can be increased, however if the gain is set excessively high the electrodes may detect signals from the activation of other muscles, known as crosstalk, or they may become more sensitive to electrical fluctuations from the user's surroundings.

Once amplified, the signal is rectified in order to generate a DC voltage and smoothed (**Figure 7**).

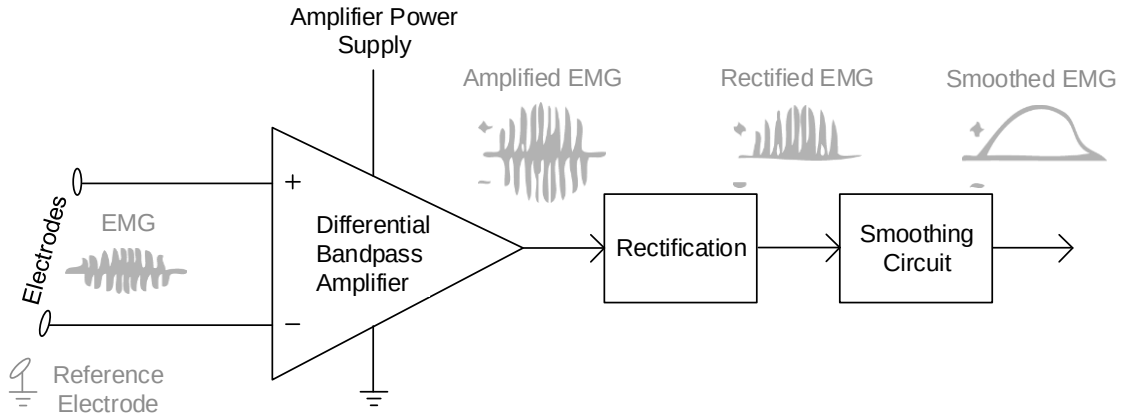


Figure 7. A myoelectrode; adapted from Upper Limb Prosthetics: Control of Limb Prostheses [33]. The EMG signal from the electrodes is amplified, rectified and smoothed. The common mode voltage is also removed.

2.3.3. *Socket design*

The design of a comfortable well-fitting myoelectric socket is vital to the continued use of the device [28, 34, 35]. A loose fitting socket could lead to a poor interface between the electrodes and the skin which will affect the signal acquisition [15]. When casting a myoelectric socket it is important to ensure a tight fit over the electrode locations to reduce movement of the electrodes.

Suspension of the socket from the residual limb can be achieved in a number of ways; the most common methods are suction, self-suspending, liners and harnesses.

Suction sockets are very tightly fitted to the residual limb, using a vacuum system for suspension. A one way valve can be used to allow air to escape but not re-enter the socket-skin interface. These sockets can be donned in one of two manners; either by pushing the limb into the socket, or by pulling it in using a donning sleeve.

A self-suspending socket makes use of bony projections in the arm; for example at the proximal end of the ulna is a bony prominence known as the olecranon and just above the elbow are the epicondyles of the humerus. By tightening the socket proximal to these anatomical markers, the socket can self-suspend.

Another suspension method uses liners with a pin lock, ratchet mechanism. The liners are usually made of gel or silicon. These are rolled onto the residual limb; a pin projecting from the end of the liner locks into a ratcheted hole in the socket to hold the prosthesis in place. A button allows the user to release the ratchet mechanism to allow removal of the prosthesis. This suspension system is not commonly used in the UK for commercial myoelectric prostheses as the liner prevents electrode contact with the skin; holes must therefore be placed in the liner to allow the electrodes to protrude. Furthermore, it is important that the user orientates the socket and liner correctly so that the electrodes are aligned with the correct muscle positions. Recently, CoApt and WillowWood announced the launch of the first liner with integrated electrodes [36].

The final method of suspension is a harness around the shoulder or chest. These are predominantly used for above elbow amputees with limited residual limb length voiding suspension of the socket using the other methods; consequently they are unlikely to be encountered as part of this thesis, which concentrates on trans-radial users.

It is worth noting that people with congenital deficiencies may encounter differences in socket suspension when compared to amputees. For example, incomplete muscle/ligament formation can lead to hyperextension of the elbow which can impact on the suspension of a self-suspending socket.

The most common method of holding the electrodes in place is using holes laminated into the prosthetic socket. As noted in the study by Head et al. [37] the semi-rigid legs on the myoelectrode are slotted into holes left in the socket by the lamination dummy (**Figure 8**). The outer layer of the prosthetic socket prevents the electrode from falling out of the housing and keeps the electrode pushed against the surface of the skin.

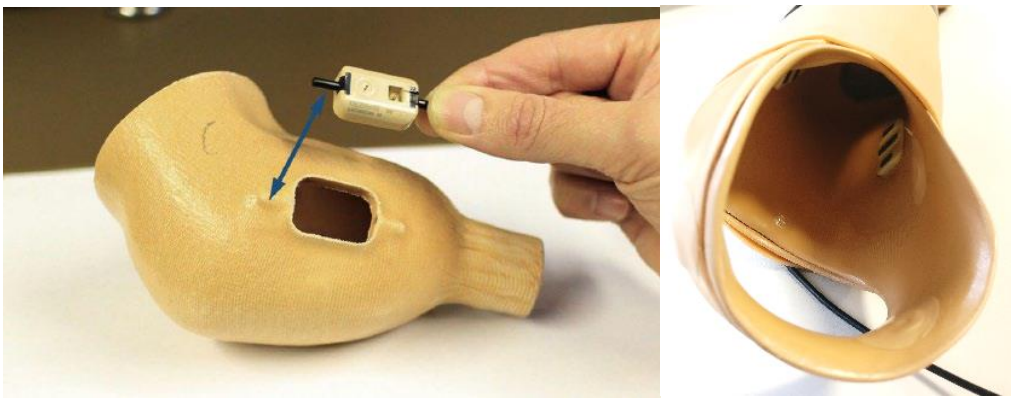


Figure 8. Standard electrode housing; image on left reproduced from Head et al. [37]

2.3.4. *Controllers*

For the past 70 years, the fundamentals of controlling clinical myoelectric prostheses have not changed. Despite over 40 years spent developing signal analysis techniques such as pattern recognition which have the potential to allow more intuitive control over multiple degrees of freedom, the large majority of clinical devices still utilise the threshold and proportional control algorithms first seen in the mid-1900s [4].

Threshold control, also known as on/off control, activates the prosthesis motor at a set speed when the EMG signal crosses a pre-specified threshold. Users with a higher level of control over their EMG signals may prefer to use a proportionally controlled prosthesis. Proportional control systems alter the velocity or torque supplied by the motor proportionally to the amplitude of the input signal.

The majority of users will operate the prosthesis using two-site, three-state control [38]; meaning that signals will be recorded from two muscles, and the controller will be able to distinguish three different states of the signals (corresponding to open, close, and off). For a trans-radial prosthesis, myoelectrodes are normally placed on

the wrist extensors (to open the hand) and flexors (to close the hand) (**Figure 9A**). For more complex devices, co-contraction of the muscles can be used to switch between controlling different degrees of freedom (for example wrist rotation) (**Figure 9B**).

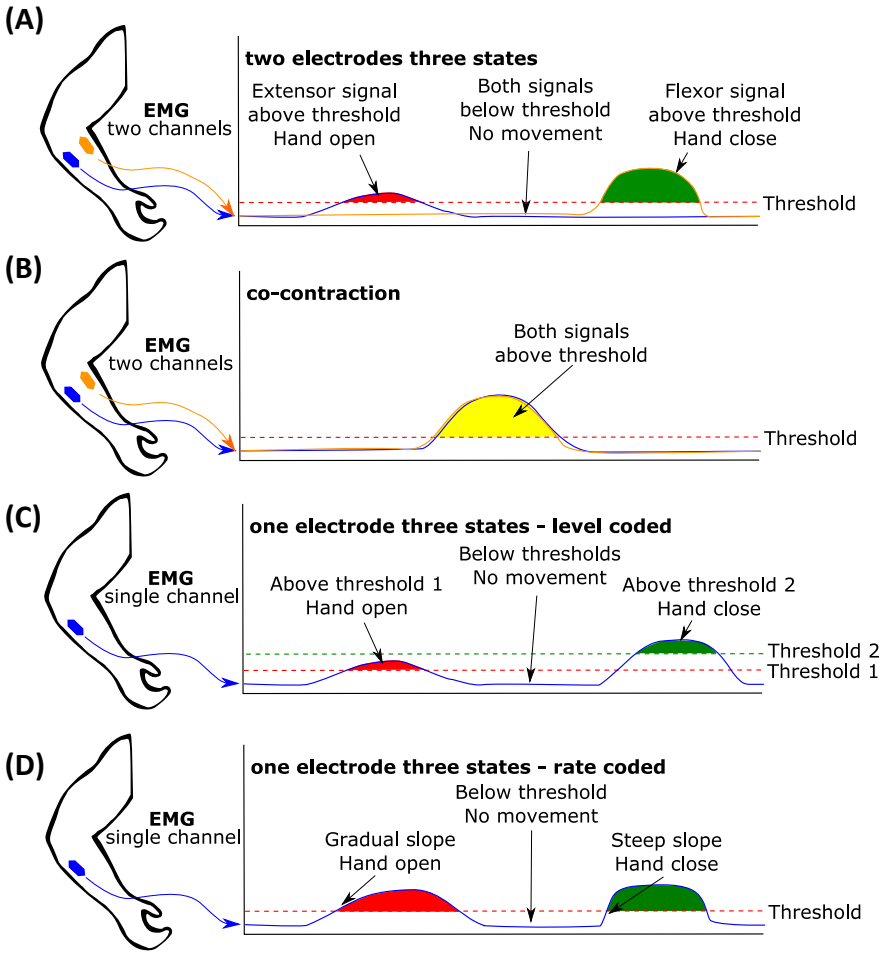


Figure 9. Using thresholds to determine the state the prosthetic hand should be in (opening, closing, off) adapted from Prosthetic Myoelectric Control Strategies - A Clinical Perspective [4]. **(A)** In a two-site, three-state system each electrode controls a single action (open or close), when the threshold is exceeded by either of the signals the hand will activate in the associated direction. **(B)** If both signals exceed the threshold at the same time, this is known as co-contraction. **(C)** In the level coded one-site, three-state system two threshold levels are present, one of which opens the hand and the other closes it. **(D)** In the rate coded system, opening/closing is determined by the gradient of the initial slope.

If a user does not have independent control over two muscles, then a single-site, three-state system is employed. There are two main control strategies for single electrode control: level coded and rate coded. (1) In a level coded system the function of the terminal device is determined by the amplitude of the signal. Two

threshold levels are employed each controlling a different hand movement (**Figure 9C**). This method incorporates an additional delay to ensure the final signal level has been reached before hand movement is initiated. (2) Rate coding (**Figure 9D**) selects the desired movement through the gradient of the initial signal slope. A slow contraction could be used to operate an open signal, whereas a fast contraction may signify a close function. Once a function has been initiated, provided the signal remains above the threshold, the hand will continue to open/close, this can allow for proportional speed control or even multi-function control. [39]

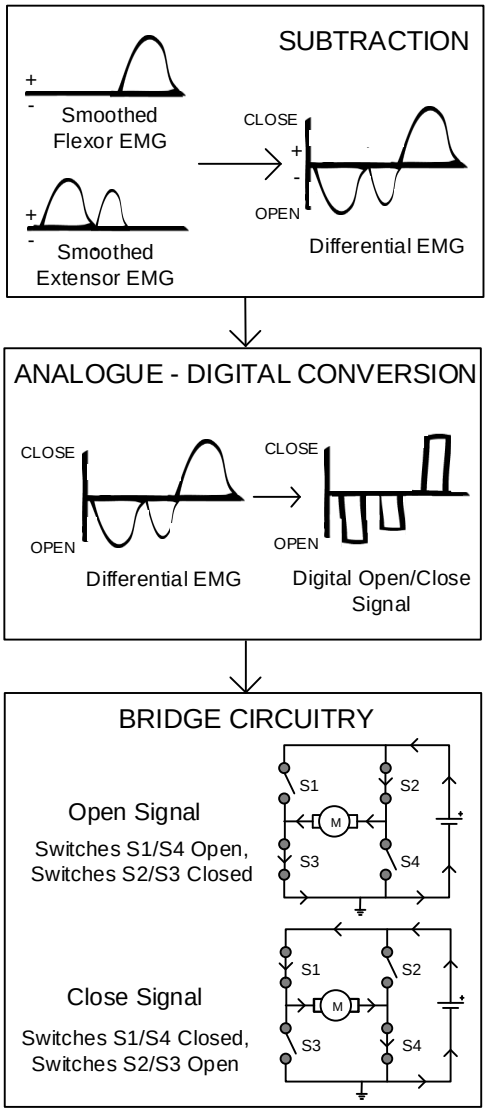


Figure 10. The prosthesis controller combines the signals from the two myoelectrodes. The intended movement is determined based on the control algorithms, and the signal is converted into a digital on/off signal. This signal operates switches within the bridge circuitry which drives the motor in the hand. Figure adapted from Robust, Coordinated and Proportional Control of Upper Limb Prostheses [40] and Powered Upper Limb Prostheses [39].

Based on these control algorithms, the EMG signal is converted into a digital on/off command used to operate the rotation of the motor. The EMG signal itself does not provide the voltage to run the motor, purely control over the circuit; the power for the motor will come directly from the battery. As demonstrated in **Figure 10**, the EMG signal activates switches in the bridge circuitry controlling the direction of flow of the current through the motor. [39]

2.3.5. *Mechanics*

Single degree of freedom myoelectric prostheses are articulated by rotary DC motors; the rotational direction of these motors is determined by the bridge circuitry explained in **Section 2.3.4**. Gears within the hand reduce the shaft speed from the motor, transmitting the required torque to the moving parts within the device (**Figure 11**). When the motors meet the resistance of the object being held, some prosthetic hands continue to run the motor in a stalled condition, which rapidly depletes the battery. Other devices incorporate battery saving mechanisms into the bridge circuitry in order to prolong battery life. Some hands also operate a breakaway clutch allowing for manual opening of the hand in case of power failure.

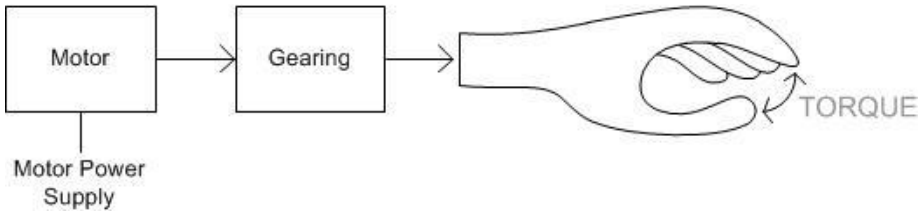


Figure 11. The movement of a prosthetic hand is controlled by a motor, the speed of which is affected by the voltage in the bridge circuitry, and the load presented by the gearing and external factors.

A system seen in devices such as the Ottobock SensorHand Speed is a grip stabilising sensor called the SUVA sensor system. Using a combination of sensors in the thumb and a strain gauge between the thumb and fingers, if the contents of the hand are about to slip, grip force is adjusted without the user providing an EMG signal [41]. Other devices operate similar systems, such as the auto-grasp feature of the i-limb.

Motor speed and consequently hand speed is constrained principally by the supply voltage and the load on the motor. The load introduced by factors such as the stiff

cosmetic glove is fairly consistent, however, as the battery voltage drops a noticeable reduction in operating speed becomes apparent [39].

2.3.6. *Commonly prescribed devices*

The large majority of NHS centres within the UK prescribe hands manufactured by either Steeper or Ottobock. The Steeper Select, threshold controlled hand was previously highly prevalent, however in recent years, a number of users have moved across to faster hands allowing both threshold and proportional control such as the Variplus or Sensor Speed hands manufactured by Ottobock.

2.4. Rejection rates

The terminology used in the literature to characterise device use and/or abandonment is inconsistent and often ill-defined, making comparisons between studies difficult. Furthermore, the reported rates of abandonment of myoelectric prostheses vary significantly. In 2007, Biddiss and Chau [42] undertook a detailed review of the studies published in the previous 25 years. Combining the results suggests that on average roughly 30% of myoelectric prosthesis users subsequently reject their devices; however, individual studies report rejection rates ranging from 0 to 75%. It is important to note that many of these studies do not consider people who use the myoelectric prosthesis as a secondary device, or those who wear and use their device in a passive manner.

Rejection of a myoelectric prosthesis costs the NHS thousands of pounds; for example, the cost of an Ottobock Variplus Speed Hand Kit is £4000-5000, on top of which the cost of the clinician and technician's time must be considered, and the materials and equipment required to fit the socket. Furthermore, rejection or non-use of a prosthesis can lead to longer term overuse injuries affecting the contralateral limb, the neck and the shoulders [43-45].

2.5. Possible explanations for high levels of rejection

2.5.1. *Reasons cited for prosthesis rejection*

To reduce myoelectric prosthesis rejection rates it is important to understand the reasons behind the rejection or non-use of the devices. Kyberd et al. [27] highlighted that every part of the prosthesis would benefit from some level of improvement. Many studies have attempted to determine the key reasons for prosthesis rejection, reporting both functional and non-functional criticisms from users. However, it is important to note that the methodology for these studies often involve self-report questionnaires, which can lead to an inherent ambiguity, with no guarantee that terms such as cosmesis, maintenance or function have been understood in the same way by each participant [27, 35]. Furthermore the majority of the studies provide participants with a list of possible reasons and ask them to rank or rate them, with limited numbers of open ended questions.

Many of these studies relating to prosthesis use involve fairly small participant numbers, **Table 1** therefore lists some of the comments and explanations given for high rates of rejection by studies involving over 100 participants [27, 46-51].

Table 1. Possible reasons for prosthesis rejection cited by studies involving >100 participants.

Area under consideration	Comments related to:	References
Functionality	Increased degrees of freedom, improved grip force control, stronger grip	Atkins [46], Millstein [50], Østlie [51], Biddiss [47], Engdahl [49], Kyberd [27]
Control	Co-ordinated movement of multiple joints, ease of control, intuitiveness, electrode sensitivity to sweating	Atkins [46], Østlie [51], Biddiss [47], Engdahl [49]
Feedback	Less reliance on visual feedback, absence of proprioception	Atkins [46], Biddiss [47] , Burger [48]
Maintenance	Reliability and durability of glove, battery, electrodes, hand, fewer repairs required	Atkins [46], Millstein [50], Biddiss [47], Engdahl [49], Kyberd [27] , Burger [48]
Aesthetics	Looked more like a hand	Atkins [46], Biddiss [47], Kyberd [27]
Comfort	Weight, heat, fit	Millstein [50], Østlie [51], Biddiss [47], Engdahl [49], Kyberd [27], Burger [48]
Usefulness and perceived need	Suitability for purpose, suitable for vigorous activities, waterproof, perceived lack of need, more functional without	Atkins [46], Østlie [51], Biddiss [47], Engdahl [49] , Burger [48]
Cost	Too expensive, fear of breaking	Millstein [50], Biddiss [47] , Burger [48]

2.5.2. *Non-functional complaints*

One of the primary complaints about myoelectric prostheses relates to comfort, specifically the weight of the terminal device [47-49, 51]. Myoelectric prostheses require heavy gears and motors for their operation, which due to the modular design are located at the distal end of the prosthesis within the hand. For users with a fairly short residual limb, the moment generated around the elbow by this distal load can have a significant impact on the effort required to support the prosthesis. Furthermore, in the case of a poorly fitted socket, this moment can exacerbate problems that may be encountered with electrode-skin contact; these are addressed in more detail in **Section 2.5.4**.

Research has shown that prosthesis users struggle to regulate the temperature of the skin within a prosthetic socket [52]. Myoelectric prostheses depend for control on a reliable connection between the electrode(s) and the surface of the skin, which is often achieved through a tight fitted socket. Furthermore, a tight fitting socket assists prosthesis suspension. This can, however, lead to a hot and sweaty environment for the residual limb adding to the discomfort experienced by the user [47, 48, 51].

Further issues relate to the aesthetics of the arm, and the fact that the skin cover (glove) is easy to damage or get dirty [27, 50]. The cost [47, 49, 50] of the device is also a limitation for some, although this complaint is less common in studies undertaken within the UK, where the cost of the prosthesis is met by the NHS. There is, however, a common concern about damaging the device [47-50].

2.5.3. *Functional complaints - Absence of feedback*

Due to the nature of the control method (feed-forward EMG control), myoelectric prostheses offer no tactile feedback to the user. This encourages reliance on visual feedback to inform on hand position and state. In recent years there has been a large amount of research into the development of prosthetic hands offering biofeedback to the user [7-11]. Feedback methods include vibrotactile, electrotactile, auditory sensory substitution, mechanotactile, temperature sensors, and direct neural stimulation.

It is interesting to note that in an anonymous online survey undertaken in 2015 [49] aiming to establish opinions on novel control techniques, the majority of participants did not put touch sensation as a high design priority, preferring instead to improve the intuitiveness, durability and functionality of the device.

2.5.4. *Functional complaints - Poor control*

Poor functionality or a lack of control are often highlighted as reasons for prosthesis rejection [27, 46, 47, 49, 51]. However, aside from the study by Atkins [46], qualitative studies often fail to explain what is meant by these terms. It is possible therefore, that this lack of clarification can lead to participants in the study ranking control highly for a variety of different reasons. The following section explores control challenges faced by users in more detail.

2.6. Factors affecting user control

Researchers and developers have proposed numerous solutions to improve the control of myoelectric prostheses, including virtual reality training tools [53-55], more technically advanced hands with multiple grip patterns, or the provision of tactile feedback to the user [7]. Alternative control methods have been proposed such as the use of inertial measurement units [56], or measurements of the muscle movements through Opticalmyography [57], Sonomyography [58], Mechanomyography [59], or the Myokinematic signal [60]. Additionally research into pattern recognition of EMG signals [61], Targeted Muscle Re-innervation [5, 6], implantable electrodes, neural interfaces and brain control [62] are all pushing the boundaries of the prosthetics field to attempt to more intuitively integrate the prosthesis with the person.

Nevertheless, of these developments, only the multi-grip hands are widely clinically available; furthermore, due to the high cost of these advanced hands, and a lack of evidence as to their impact, insurance companies and the NHS in the UK struggle to justify the provision of these devices [29]. In recent years, Coapt have developed an FDA Class 2 certified pattern recognition system, however this is only currently available in North America.

Many of the proposed improvements to the control of myoelectric prostheses to date have revolved around improving either the intuitiveness or the acquisition of the signal of movement intent from the user, or around providing the user with a hand which is more like the anatomical hand, both in its movements, and in the way it can 'feel'. One of the few papers that has explored the underlying problems affecting prosthesis control is the paper published by Saunders and Vijayakumar in 2011 [14].

2.6.1. *Unpredictability of prosthesis response*

Work by Saunders and Vijayakumar [14] demonstrated that in an ideal situation with a perfect, fast responding terminal device, feedback (visual or tactile) is of minimal benefit to the user. Instead, the user is able to rely on internal feed-forward models generated by the CNS. However, in an inevitably unpredictable system, which we know most clinically available prostheses to be, the feed-forward models are disrupted and feedback becomes vital to accurate control of the prosthesis. This does not mean that the removal of unpredictability removes the necessity for feedback, but rather the two processes are co-dependant.

Researchers within Kording's group in Chicago have noted that when provided with sensory feedback, the level of adaptation depends upon the perceived predictability of the feedback [63, 64]. Johnson et al. suggest that users who continually experience large errors may be so unsure over their feed-forward signals that they may not adapt at all [63]. Consequently it is visible that both feed-forward and feedback unpredictability have a negative impact on controllability of the device.

When faced by unpredictable feedback there are three methods to increase accuracy [65]: (1) the acceleration/speed of the hand can be reduced, (2) the CNS can generate a more detailed internal model or learn the behaviour, or (3) the feedback can be improved. Subsequently, it is unsurprising that unskilled prosthesis users with no tactile feedback have slow uncertain movements, and are heavily reliant on visual feedback.

2.6.2. *Breaking down the control chain*

As noted above, any deviation in performance from a perfectly predictable and fast responding device will cause challenges to the user [14]. To understand the relative importance of the factors which might be impacting on control, the prosthesis control chain can be broken down into 3 key areas: signal generation, signal acquisition, and device response.

2.6.2.1. EMG SIGNAL GENERATION

If a participant is unable to generate the required EMG signal then they will struggle to gain fine control over the prosthetic hand; in this thesis this will be referred to as "*EMG skill*".

Control of clinically available myoelectric prostheses requires the use of muscles (with their associated neural pathways) which were anatomically intended to serve a different purpose. Nevertheless, recent research suggests that humans can adapt to this through practice.

A study by Radhakrishnan et al.[66] in which participants were required to use their EMG signals to move a cursor to a position on the screen and maintain that position for 1s, found that subjects could not only learn to control the level of activation of their EMG signals, but that they could even learn non-intuitive muscle arrangements to a high level of speed and accuracy, given practice (**Figure 12**). Similarly, researchers at the University of Michigan concluded that the location and intended function of the muscle was less important to control of the signal than practice and training [67, 68].

It is important to note that recent work has queried whether improvements in EMG control assessed using abstract on screen tasks, transfers to improved control over the prosthetic hand itself [69-72]. Further exploration is required to determine the relationship between *EMG skill* as assessed using standard EMG training tools, and measures of prosthesis *user performance* (see **Section 2.7**).

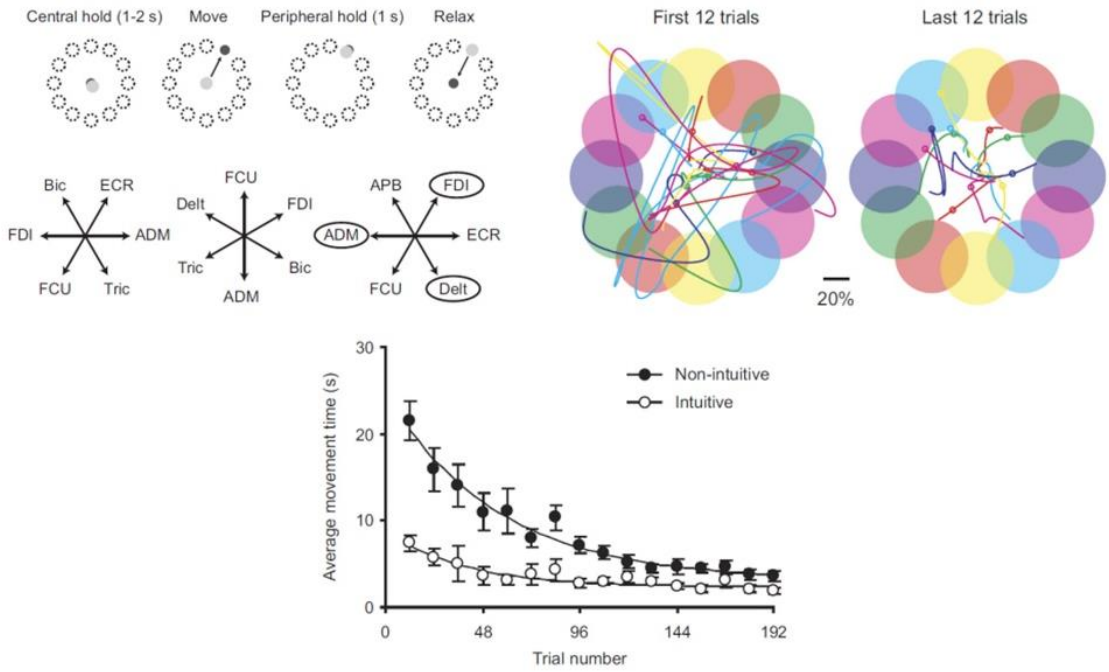


Figure 12. In a multi-control channel task [66], participants were required to use a combination of EMG signals from different muscles to control the movement of a cursor. Each muscle controlled movement of the cursor in a set direction, and when the muscles relaxed the cursor naturally relocated to the centre of the screen. This study was undertaken with both intuitive and non-intuitive muscle-direction combinations **(Top Left)**, and in both cases participants learnt to achieve a good level of control by the final trial **(Bottom)**. The image **(Top Right)** shows the improvement in the cursor trajectories over the testing period for a non-intuitive muscle-direction combination.

2.6.2.2. EMG SIGNAL AQUISITION

Regardless of the level of *EMG skill*, if the interface between the electrodes and the skin does not allow for accurate and reliable signal transduction, then the user will experience difficulty in controlling the device. If the socket is too loose, the arm will move around within the socket and the electrodes may lose contact with the skin. In a study by Head [15], some upper limb prosthesis users used their electrodes more like switches, physically moving the limb within the socket to activate the prosthetic hand. This finding was corroborated by Sims [73] who questioned children on their experiences with prostheses. One participant referred to the electrode as a button and explained how she had to hold the socket in her hand and move her arm into the right place to activate it. Head's work [15] also found a clear relationship between the tightness of the electrodes and unwanted prehensor activation; whilst Sims

identified a number of occasions where devices had activated unexpectedly, become stuck in a closed position or had simply broken down [73].

When the electrodes are able move against the surface of the skin, signals known as motion artefacts can be generated which are mistaken by the controller for activation signals. Motion artefacts can occur for one of two reasons, either the electrode moves relative to the skin, or the skin itself stretches producing artefacts which can be up to 5mV in amplitude [39]. In a laboratory setting reliable EMG transduction can be achieved through abrasion of the top layer of the epidermis, combined with the use of ionic rich gels; however, this is not practical for everyday prostheses. Myoelectrodes are referred to as dry electrodes, however, perspiration from the skin forms a slightly conductive layer; this acts similarly to the gels, but to a much lesser extent. Fluctuations in the level of sweat may affect the performance of the electrodes adding a further source of unpredictability. The large majority of users experience motion artefacts to differing extents whilst undertaking daily activities. When an additional mass is added at the distal end of the prosthesis (for example when an object is being carried), the movement of the socket, and subsequent artefacts, can be exacerbated [15].

In cases of extreme motion artefact it is possible for an electrode to completely lose contact with the skin (electrode lift). In these cases the common mode voltage discussed in **Section 2.3.2** is present on only one of the electrodes, meaning that it cannot be filtered out of the signal. As a result the 50Hz interference (60Hz in the Americas and parts of Asia) causes a large spike in the signal, activating the hand [39]. **Figure 13** demonstrates motion artefact and electrode lift.

All of these factors contribute to what will be referred to in this thesis as the "*unpredictability*" introduced by the interface between the skin and the electrodes.

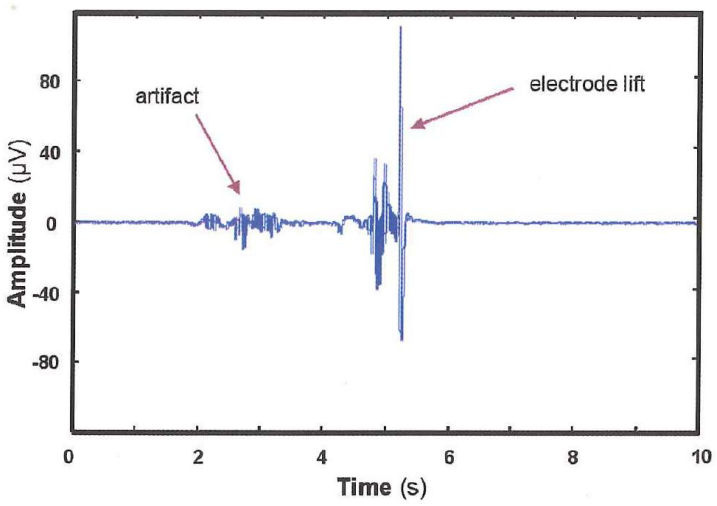


Figure 13. Signals generated by motion artefact and electrode lift. Electrode lift generates a much larger signal due to the introduction of the common mode voltage into the system. Image source: Powered Upper Limb Prostheses [39].

2.6.2.3. DEVICE RESPONSE

Delays introduced to the control chain resemble the effects of reducing the sampling frequency of the feedback process. The CNS must work with old information and consequently it is more difficult to control the prosthesis and adapt to perturbations. If the time taken for the hand to respond to the input signals is excessive, control becomes less intuitive and users may discard their devices [74].

Delays are introduced at every stage of the prosthesis control chain (**Figure 14**), and although it is possible to minimise these delays through good design, it is not possible to completely remove them. Within the prosthesis, delays are introduced through the processing of the EMG signal, the controller determining how to respond, and the backlash and stiction introduced by the mechanical components.

Paciga et al. [75] found that the addition of a 200ms delay between EMG signal generation and visual feedback of movement increased error rates in signal tracking tasks from 1.1% to 6.6%, and in the majority of cases subjects were overestimating their movements. To date no research has been published detailing the total length of the electromechanical delay encountered within clinical myoelectric prostheses. However, Farrell [76] determined that the maximum controller delay that would allow for maximised classification accuracy without impacting on controllability (for 90% of users) is 100-125ms.

In this thesis, "*delay*" will refer to the complete electromechanical delay from the instant of signal generation to the onset of movement of the terminal device.

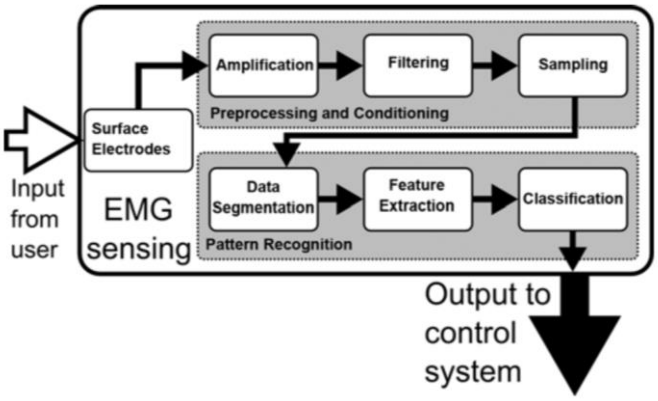


Figure 14. Peerdeman et al. defined the delay in the prosthesis as the time from user input to initiation of the intended motion. Each aspect of the control chain added an additional time to this delay as depicted here. Image source: Myoelectric forearm prostheses: state of the art from a user-centred perspective [74].

If the delay introduced within the prosthesis is unpredictable in length, this can cause further uncertainty as to how the hand will respond. Consequently, Saunders [14] found that introducing unpredictable delays into the response time of a prosthesis significantly reduced grip force control. To date, the predictability of delays within clinical myoelectric prostheses has not been explored.

2.7. Methods for evaluating user performance

This thesis considers two key aspects of "*user performance*"; these are the user's "*functionality*" assessed within the clinical/lab based environment, and their actual "*usage*" of the prosthesis outside of the clinic.

2.7.1. *Assessment of clinical functionality*

There are many existing tests of clinical "*functionality*", which can be categorised as: (1) Questionnaires, (2) Abstract tasks, (3) Activities of Daily Living (ADL).

ADL based assessments such as the Southampton Hand Assessment Procedure (SHAP) [77] and the Jebsen-Taylor Test of Hand Function (JTHF) [78] provide an insight into the user's ability to perform different tasks using a range of hand grips. However, these assessments often take a long time to perform. Abstract tasks such as the box

and blocks or peg tests can be faster to undertake, however, these tasks measure specific dexterity, thus the potential for providing valid information on overall hand function is limited [79]. Furthermore, validation of tasks such as the box and blocks has often only been performed on an anatomically intact cohort [79]. Recently the box and blocks test has been modified to allow for quantification of quality of motion and compensatory movements of prosthesis users, however further validation is required [80, 81].

The majority of tests assessing upper limb *functionality* evaluate the time taken to successfully complete specific tasks, with faster completion times corresponding to higher *functionality* scores. Although the duration of task performance is one measure of *functionality*, it provides no information on how tasks are completed. A number of studies have shown that combining several outcome measures provides a more complete picture of the functional abilities of prosthesis users [82-86]. Kinematic outcome measures [86, 87] and gaze behaviour [85, 88, 89] can be recorded during the performance of multistage tasks to provide information which complements speed of performance measures. It has previously been shown that *functionality* characterised using these measures clearly differentiates amputees from anatomically intact controls [85, 86, 90].

2.7.2. *Assessment of everyday prosthesis usage*

The assessments introduced in **Section 2.7.1** provide an overview of *functionality*, however, another arguably more important measure is real world *"usage*" of the prosthesis. Daily usage is only covered in questionnaire and interview based techniques, such as the Trinity Amputation and Prosthesis Experience Scales (TAPES-R) [91, 92]. Questionnaires are reliant on accurate and unbiased recall, and provide at best an approximation of the real usage data [50, 93, 94]. Activity monitoring allows for objective assessment of an individual's activity over a longer period than that of the clinical assessments introduced in the previous section.

Despite the benefits activity monitoring has been shown to have for the assessment of upper limb activity in the field of stroke rehabilitation [95], no one has published any data using activity monitors to assess the use of upper limb prostheses. Only

Makin [96] has combined the use of activity monitoring with upper limb amputees, however, this was for the purpose of validating a questionnaire and did not specifically assess *prosthesis usage*. Multi-articulating hands such as the i-limb contain built in activity monitoring [97], however this data has not yet been published.

2.8. **Research gap**

To date, many of the high profile improvements to myoelectric prostheses have concentrated on cosmetic and functional aspects, avoiding issues surrounding fit and reliability which research shows to be just as important to users [15, 27]. Furthermore, few of these developments have translated into clinically available prostheses; and those which have, such as the multi-articulating hands, high-definition silicone gloves, or pattern recognition systems are highly expensive or unavailable within the NHS/UK. For this reason, this thesis will take a different approach, focussing on understanding issues with the control of standard clinically prescribed myoelectric prostheses.

Although some of the human and engineering factors affecting the control of a prosthesis have been addressed previously (**Section 2.6**), their relative impact on *user performance* has not. If the relative impact of each control factor can be established, then we can ensure that the future efforts of researchers, designers and clinicians can be concentrated on areas which will have the greatest contribution to improving user *functionality* and *prosthesis usage* outside of the clinic.

This thesis aims to address this gap by assessing current myoelectric prosthesis users with their own clinically prescribed prostheses. The level of *skill* in controlling the EMG signal will be established, the *unpredictability* introduced at the interface between the electrodes and the skin will be assessed, and the electromechanical *delay* of the prosthesis will be measured. These three control factors will be assessed within the clinic against a range of kinematic and visuomotor measures of *functionality*. Furthermore, this will be the first study to use activity monitoring to objectively assess everyday *prosthesis usage*; the relationship between clinical *functionality* and everyday *prosthesis usage* will therefore also be addressed.

3

Methodology

Protocol for the assessment of the impact of skill, unpredictability and delays on user performance

In the previous chapter three key factors affecting control were identified: (1) "*skill*" in controlling the EMG signals, (2) "*unpredictability*" introduced at the interface between the skin and the electrodes, and (3) the electromechanical "*delay*" within the prosthesis. This chapter introduces the protocol for the assessment of each of these factors, alongside the measures of user "*functionality*" and everyday "*prosthesis usage*". This methodology chapter has been published in Frontiers in Neurorobotics, however, for completeness, sections have since been added relating to the measurement of the electromechanical "*delay*" which was still under development at the time of publishing. Additionally, having inspected the data from the larger dataset which has since been collected, changes have been made to the proposed data analysis for the main study. These changes are detailed in the chapter.

Chadwell A, Kenney L, Thies S, Galpin A, Head J; ***(2016);*** *The reality of myoelectric prostheses: Understanding what makes these devices difficult for some users to control;*
Frontiers in Neurorobotics; *DOI: 10.3389/fnbot.2016.00007*

Abstract

Users of myoelectric prostheses can often find them difficult to control. This can lead to passive-use of the device or total rejection, which can have detrimental effects on the contralateral limb due to overuse. Current clinically available prostheses are "open loop" systems, and although considerable effort has been focused on developing bio-feedback to "close the loop", there is evidence from laboratory-based studies that other factors, notably improving predictability of response, may be as, if not more, important. Interestingly, despite a large volume of research aimed at improving myoelectric prostheses, it is not currently known which aspect of clinically available systems has the greatest impact on overall functionality and everyday prosthesis usage. A protocol has, therefore, been designed to assess EMG skill of the user, predictability of the prosthesis response, and electromechanical delay as significant parts of the control chain, and to relate these to functionality and everyday usage. Here, we present the protocol and results from early pilot work. A set of experiments has been developed. First, to characterise user "*skill*" in generating the required level of EMG signal, as well as the speed with which users are able to make the decision to activate the appropriate muscles. Second, to measure "*unpredictability*" introduced at the skin–electrode interface, in order to understand the effects of the socket-mounted electrode fit under different loads on the variability of time taken for the prosthetic hand to respond. And finally, to measure the electromechanical "*delay*" introduced by the prosthesis. To evaluate prosthesis user "*functionality*", four different outcome measures are assessed. Using a simple upper limb functional task prosthesis users are assessed for (1) success of task completion, (2) task duration, (3) quality of movement including patterns in the hand aperture and temporal variability in the acceleration of the forearm, and (4) gaze behaviour. To evaluate everyday "*prosthesis usage*" away from the clinic, the symmetry of their real-world arm usage is assessed using activity monitoring. These methods will later be used to assess a prosthesis user cohort to establish the relative contribution of each control factor to the individual measures of *functionality* and everyday *prosthesis usage*. The results will support future researchers, designers,

and clinicians in concentrating their efforts on the area that will have the greatest impact on improving prosthesis use.

3.1. Introduction

Chapter 2 introduced the reader to upper limb absence, explaining the types of prosthesis available, and providing an insight into myoelectric prostheses. Despite the potential offered by myoelectric hands, prosthesis users report these devices to be challenging to control [15, 47, 49, 74] and to still be limited in function [47, 74]. These user reports are supported by the results of clinical assessment tests in which upper limb prosthesis users generally perform at less than 50% of the level of their anatomically intact counterparts [88, 98-103]. Unsurprisingly, passive-use and rejection of myoelectric prostheses have been reported as problems [42], leading to over-use injuries of the intact limb [43-45].

In response to user feedback, attempts have been made to improve the control of myoelectric prostheses. Since current clinically available devices are "open loop" with respect to the user, promoting reliance on visual feedback, recent advances have frequently focused on providing users with tactile feedback [7, 104-107]. However, Saunders and Vijayakumar [14] demonstrated that, although the introduction of feedback can improve control of myoelectric prostheses, other characteristics of the prosthesis may be equally, or even more important in determining the ability of the user to control their prosthesis. In their study, participants demonstrated that when using a "perfect" fast-responding prosthesis they were able to demonstrate good levels of control over grip force even in the absence of any feedback; however, in the presence of uncertainty as to how the hand would react (presented in the form of random delays in prosthesis response time), their control of the prosthetic hand decreased. Saunders concluded that if the central nervous system (CNS) is able to produce accurate predictions of anticipated prosthesis behaviour (forward models), then reliance on feedback from the hand is reduced. Saunders and Vijayakumar [14] also noted that a degree of uncertainty was an inherent part of myoelectric prosthesis use. This observation was further investigated by Head [15] who identified that the standard method for housing electrodes in prosthetic sockets can result in

EMG signal artefacts, or loss of electrode contact with the skin, leading to unpredictability in the response of the prosthesis to muscle contractions. Moreover, the delay introduced by the prosthesis itself can impact on functionality [76], and when combined with unpredictability, could exacerbate the difficulty in responding to external perturbations whilst undertaking everyday tasks. Finally, despite recent findings in anatomically intact subjects challenging the assumption [69], there is a widely held belief that there is a relationship between the level of skill in producing the required EMG signals and prosthesis control.

In summary, despite technological advances, control of myoelectric prostheses remains challenging, leading to device rejection and associated overuse injuries of the intact limb. Introducing feedback into the system is one possible solution to enhance prosthesis control for improved functionality and everyday prosthesis usage, however, research into the different aspects of the prosthesis control chain (e.g., *EMG skill* of the user, *unpredictability* in the system, and electromechanical *delay*) may be equally important. Here, a novel protocol is introduced, including purpose-built, portable instrumentation that has been designed for the assessment of these individual factors contributing to feed-forward prosthesis control in relation to aspects of overall upper limb performance. Specifically, the protocol assesses how well a myoelectric user can control their EMG signals (*EMG skill*), how reliably the electrodes pick up the signals (*unpredictability*), and how long it takes for the hand to respond (*delay*). These outcomes are then related to measures reflecting how close the kinematic and gaze patterns of the user are to healthy norms (*functionality*) during performance of a structured multistage manual task, and how often the myoelectric prosthesis is used in everyday life (*prosthesis usage*). It is important to note the separation of these two performance measures. Literature has shown that an increase in upper limb functionality as assessed using clinical tests may not necessarily correspond to an equivalent improvement in everyday arm use [108]. By comparing the control factors against *functionality* and *prosthesis usage*, it should be possible to identify which control factor(s) has/have the greatest impact on overall *user performance*. Longer-term, researchers, designers, and clinicians can then

ensure that their efforts are concentrated on the area(s) that will be of greatest benefit to prosthesis users.

In this chapter, the experimental procedures to characterise key factors contributing to the feed-forward prosthesis control chain are introduced, namely skill in controlling the EMG signals (*EMG skill*), *unpredictability* in transduction of the EMG signal (between the skin and the electrode), and the electromechanical *delay* introduced by the prosthesis itself. The measures designed to capture the user's overall upper limb performance (*functionality* and *prosthesis usage*) are also described. Initial results of pilot work and their discussion are included to demonstrate the feasibility of the protocol. Furthermore, a data analysis method is proposed for use in the main study, which attributes variance in measures of *user performance* to one or more elements of the control chain.

As the protocol is complex and involves the description of several experimental setups, the detail in this chapter has been kept to a minimum and, where appropriate, further information is provided in the appendices. **Appendix 1** provides an overview of the experimental setups.

3.1.1. *Changes made to this chapter since publication*

Since the initial publication of this chapter in Frontiers in Neurorobotics [109], some changes have been made to the protocol. These changes will be briefly introduced here, and are described in more detail throughout the chapter.

The most significant change was the extension of the protocol to include the measurement of the electromechanical *delay*, which was still under development at the time of publishing.

In the pilot study presented in this chapter, onset and completion of the functional task were found using a button to timestamp the data. Subsequently automated methods of segmentation were developed to be used in the main study (see **Appendix 5** for full details). These include the detection of: (1) task onset, (2) the end of reach-to-grasp, and (3) task completion. The definition of task completion was also changed for data analysis purposes. The methodology has been updated accordingly.

Many of the measures introduced in this chapter were developed specifically for this study, and consequently no previous data existed upon which to base decisions relating to the data analysis. After initial inspection of the larger dataset which was collected for the main study (see **Chapter 5**), the methods of data analysis proposed in this chapter have been simplified. These include: (1) the simplification of task success into a simple measure of whole task completion, rather than the published dissection of the task into five movement components, and (2) reduction of the number of Areas of Interest (AOIs) for the analysis of gaze behaviour.

3.2. Methods and analysis

3.2.1. *EMG skill*

The muscle groups used to control the opening and closing of myoelectric hands and their associated neural pathways differ from those used in the anatomical hand [110]. It is, therefore, reasonable to assume that opening/closing the hand with this "new" set of muscles in response to a relevant prompt may be less intuitive and require an increase in mental processing time as reflected in an increased reaction time [5, 6]. It is also reasonable to assume that practice using this "new" set of muscles to open/close the hand may decrease the reaction time [66, 111].

To establish the mental processing time to activate the "new" set of muscles, the subtractive method developed in the 1860s by Donders [112] can be used. Donders proposed the use of different types of reaction time tasks to establish the time spent undertaking cognitive and motor processes. Such reaction time tasks include the simple reaction time (SRT) task in which participants are aware of the required response before stimulus presentation, and the choice reaction time (CRT) task where the stimulus dictates the required response. Donders segmented the reaction time into the time taken to perceive the stimulus (signal perception), time taken to decide how to respond (decision time), and time taken to activate the neurons (motor response) (**Figure 15**). For the SRT task, there is no decision time as the required response is already known and the person is primed to react. Donders also declared that the time for signal perception and motor response does not vary between conditions. Consequently, he suggested that subtracting the SRT from the

CRT provides information as to the decision time to undertake the CRT task, or in this case, how long it takes the person to decide which muscles to activate to operate the prosthesis ("Decision Time"). Accordingly, this study uses reaction times measured under these two different conditions to characterise the "Decision Time", and the associated task is termed **Intuition Task** (see **Section 3.2.1.2**).

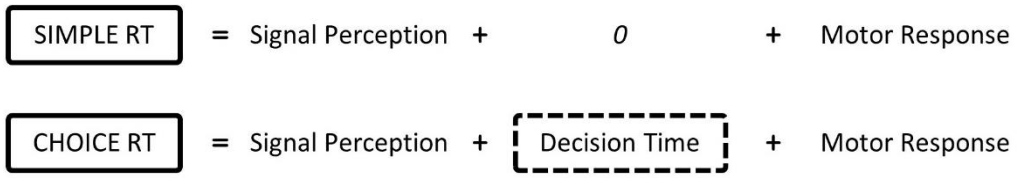


Figure 15. Donders proposed that reaction times are made up of a series of cognitive and motor processes. According to Donders' subtraction method, the choice reaction time minus simple reaction time provides the time taken to decide which muscle to activate based on the stimulus [112].

Furthermore, the ability to control the amplitude of the EMG signal using the musculature of the residual limb can be measured through the performance of a series of continuous signal tracking tasks. There are two main types of tracking tasks: static and dynamic. For a static tracking task the subject is required to match their EMG signal to a target amplitude [68], while a dynamic tracking task involves modulating the amplitude of the EMG signal to match a moving target [68, 113-115]. Most clinically prescribed myoelectric prostheses are equipped with proportional control, meaning that it is not only important that a user is able to generate a signal strong enough to activate the hand but that they can also modulate the level of the signal to allow for control of the hand speed and the grip force. Dynamic tracking tasks take different forms: some contain a repetitive signal modulation, such as a sinusoidal wave of a set amplitude [113], while others vary the amplitude at random [114, 115]. For this study, we use a commercially available software package originally designed for the clinical training of myoelectric prosthesis users, which provides us with a means to test user performance in tracking both static and random amplitude modulated targets, using their EMG signal. The approach also allows us to use clinical EMG electrodes (rather than laboratory-standard EMG gel electrodes), thereby reflecting the transduction, signal processing, and amplification used in practice. We

term the set of static and dynamic tracking tasks to be **Signal Tracking Tasks** (**Section 3.2.1.3**).

Details of the number of repeats for each task are provided in **Table 2**.

Table 2. Protocol summary – tasks for the assessment of *EMG skill*. Tasks include the intuition task (**Section 3.2.1.2**) consisting of the simple and choice reaction time tasks, and the signal tracking tasks (**Section 3.2.1.3**). For the simple reaction time task, participants knew in advance which response to make to the stimulus (hand opening or hand closing). For the choice reaction time task, the stimulus informed on the required response; the required response was randomly assigned and the participant was not aware of the required response in advance. The static tracking task involved matching the amplitude of the EMG signal to a pre-specified level. The dynamic tracking task involved fluctuating the amplitude of the EMG signal to avoid on-screen obstacles.

Description	Task	Number of trials
Tasks for the assessment of *EMG skill*. All undertaken with an "ideal" electrode interface condition (see **Section 3.2.1.1**)	Simple reaction time (SRT) – hand opening	2 × practice, 10 × assessed
	Simple reaction time (SRT) – hand closing	2 × practice, 10 × assessed
	Choice reaction time (CRT)	4 × practice (2 × open, 2 × close – random order) 20 × assessed (10 × open, 10 × close – random order)
	Static tracking task – open signal	3 × assessed
	Static tracking task – close signal	3 × assessed
	Dynamic tracking task – open signal	2 × assessed
	Dynamic tracking task – close signal	2 × assessed
	Dynamic tracking task – both signals simultaneously	2 × assessed

3.2.1.1. ELECTRODE PLACEMENT

The *EMG skill* analysis tests require an "ideal" electrode placement on the residual limb to ensure that the participant is able to perform to their best ability. This "ideal" placement requires the electrode to be placed in the optimal location, with the optimal gain and good contact with the skin.

Slight variations exist in the methods used to find the optimal location for the electrodes; for this protocol, we use the methods taught to student prosthetists at the University of Salford. Rather than use the participant's own electrodes, which would necessitate dismantling the prosthetic socket, we use standard electrodes, (Ottobock 13E200 = 50). Optimal settings for the selected electrode are found using the clinical assessment tool Myoboy® (Ottobock Gmbh). Initially, the gain for each electrode is set at a mid-level of 3–4. Participants are then asked to repeatedly and

consistently contract the muscle to a comfortable level. The electrode is initially placed in the centre of the muscle bulk and the signal level is noted. The electrode is then moved in each of four directions (up, down, left, and right) from the starting location, by half an electrodes width. If the amplitude of the signal is greater in any of these new locations, the process is repeated using the new location as the central starting point. This is continued until the position with maximum signal amplitude is found, and the location marked using an indelible pencil.

The gain settings are adjusted until the participant is able to comfortably achieve a post-processed signal amplitude (recorded by Myoboy®) between 30 and 60, and separation between the two signals greater than 5.[1] To achieve consistent good contact of the electrodes with the skin, they are bandaged in place using elasticated bandages. The difference between the optimal location and gains, and the location and gains for the participant's own prosthesis, is noted.

3.2.1.2. INTUITION TASK

To assess how intuitive participants find the activation of the muscles used to open and close the prosthetic hand, the "ideal" electrode placement (**Section 3.2.1.1**) is used to control a MyoHand VariPlus Speed (Ottobock Gmbh).

A schematic of the experimental setup for the measurement of reaction times is shown in **Figure 16A**. The participant begins each trial with the prosthetic hand in a neutral position (neither fully open nor fully closed). In front of the participant is a custom-made reaction time box (see **Appendix 3**) with two 10 mm red LEDs serving as stimuli for hand opening (top) and closing (bottom), and one 5 mm red LED in their middle to focus the subject's attention at the start of each trial. The anatomical hand is placed on a large blue button situated on the bottom portion of the box. Each trial begins when the participant indicates that they are ready by pressing the blue button. The 5 mm LED illuminates for 1 s to attract the participant's attention. At a randomly generated time between 2 and 3.5 s [116] after the subject pushes the

[1] The manufacturers do not disclose the details of the scale used to represent signal amplitude, hence, the units are not reported.

button, one of the 10 mm LEDs illuminates for 1 s. Once the 10 mm LED turns on, the participant should either open (if top LED) or close (if bottom LED) their prosthetic hand in response. For the SRT task, the subject is aware which LED will illuminate, i.e., which response is required. For the CRT task, the subject needs to respond with either hand opening or closing, dependent on whether the top or bottom LED is illuminated. An electronic goniometer (Biometrics Ltd) is attached across the proximal knuckle of the index finger to measure the movement of the prosthetic hand, thereby allowing for identification of the onset of hand opening or closing.

Details of the instrumentation used in SRT and CRT tasks is shown in **Figure 16B** (more detail is provided in **Appendix 3**). The reaction time box and goniometer are controlled via Arduino Leonardo boards (www.arduino.cc) communicating over serial with Matlab (The Mathworks Inc.). The wait time and LED number are sent from Matlab to "*Arduino 1*" to start the test. "*Arduino 1*" waits for acknowledgment that the participant is ready, based on their button press. "*Arduino 1*" then initiates recording of the goniometer data on "*Arduino 2*" (see **Appendix 2**) and controls the LEDs on the reaction time box. Matlab then analyses the goniometer data establishing the reaction time (see **Appendix 3**), which is sent back to "*Arduino 1*" and displayed to the participant. A T9545 goniometer adaptor (Thought Technology Ltd.) and TT Sensor Isolator ST9405AM (Thought Technology Ltd.) are used to interface between the goniometer and "*Arduino 2*" (see **Appendix 2**).

3.2.1.3. SIGNAL TRACKING TASKS

These tasks use commercially available assessment tools from Ottobock Gmbh that are routinely used in clinical care. The Myoboy® hardware is designed to measure the signal from the clinical electrodes and send it to a computer. Using the PAULA (Prosthetist's Assistant for Upper Limb Architecture) software, the signal can be viewed and the participant can then undertake activities to train and improve signal control. The "ideal" electrode placement (**Section 3.2.1.1**) is used with the electrodes connected to the Myoboy® hardware. Two different aspects of the PAULA software are used, one for the **static tracking task** and one for the **dynamic tracking task**.

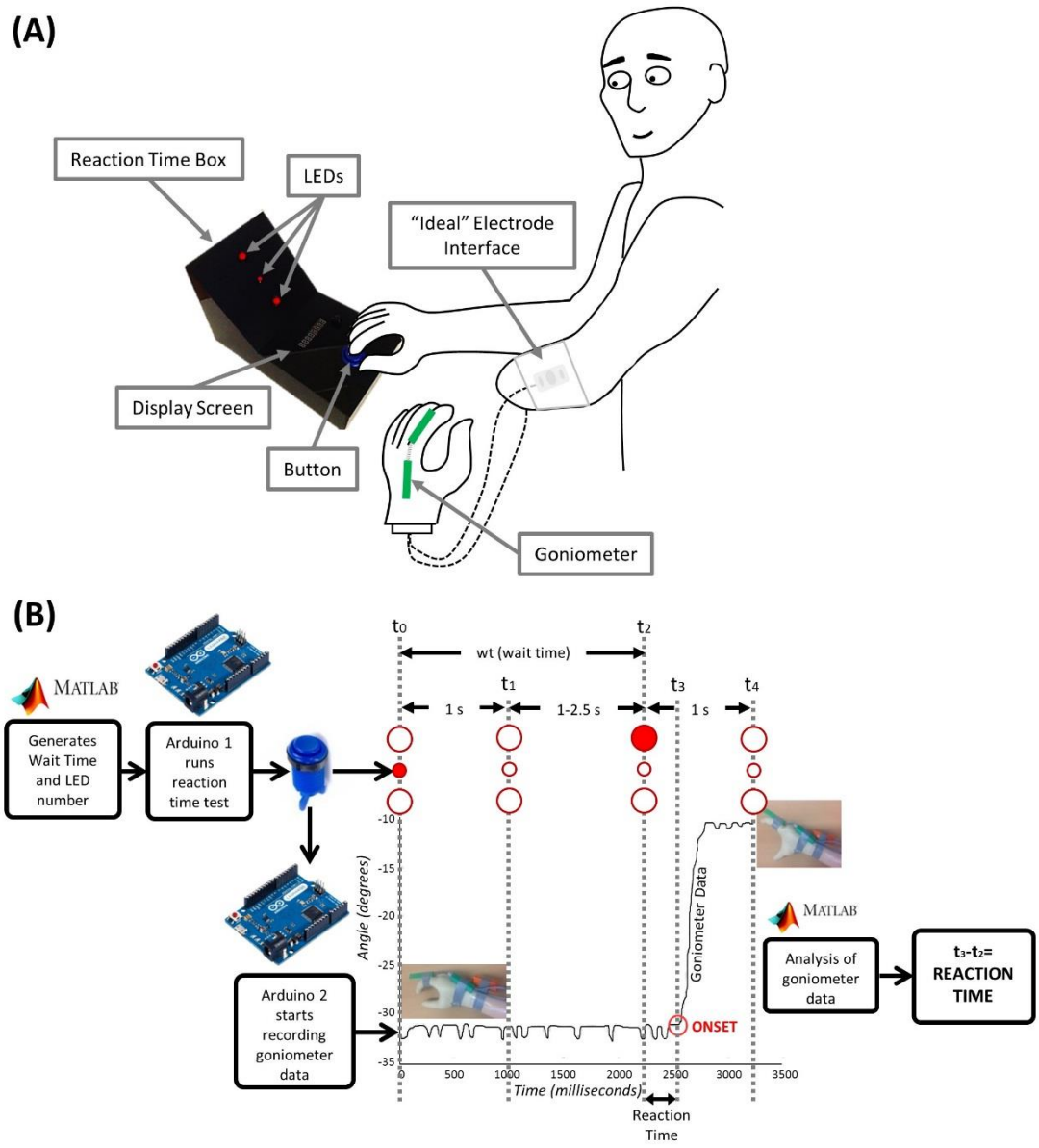


Figure 16. Reaction time task: **(A)** Experimental setup and **(B)** underlying instrumentation. Matlab generates the wait time and LED number and sends them to "*Arduino 1*" which starts the task. The participant acknowledges that they are ready by pressing the button. The goniometer begins recording and the central LED lights up for 1 s. After a period of 2–3.5 s, one of the larger LED's lights up and the participant opens or closes their hand. "*Arduino 2*" connected to the goniometer sends the movement data to Matlab where it is analysed and a reaction time is sent back to the participant.

The **static tracking task** uses the myo-testing signal visualisation screen (**Figure 17A**). The boundary lines within this screen are adjustable and in this protocol are set to 39 and 51; these values were determined through pilot work as a level that is sufficiently challenging for the more skilled participant, yet somewhat achievable for the least able. The participant is given three contraction attempts to keep their signal

amplitude within the boundaries for each muscle. Each contraction is 3 s long from the moment the signal first crosses the lower boundary line. Participants are scored on the percentage of time the signal remains within the boundaries.

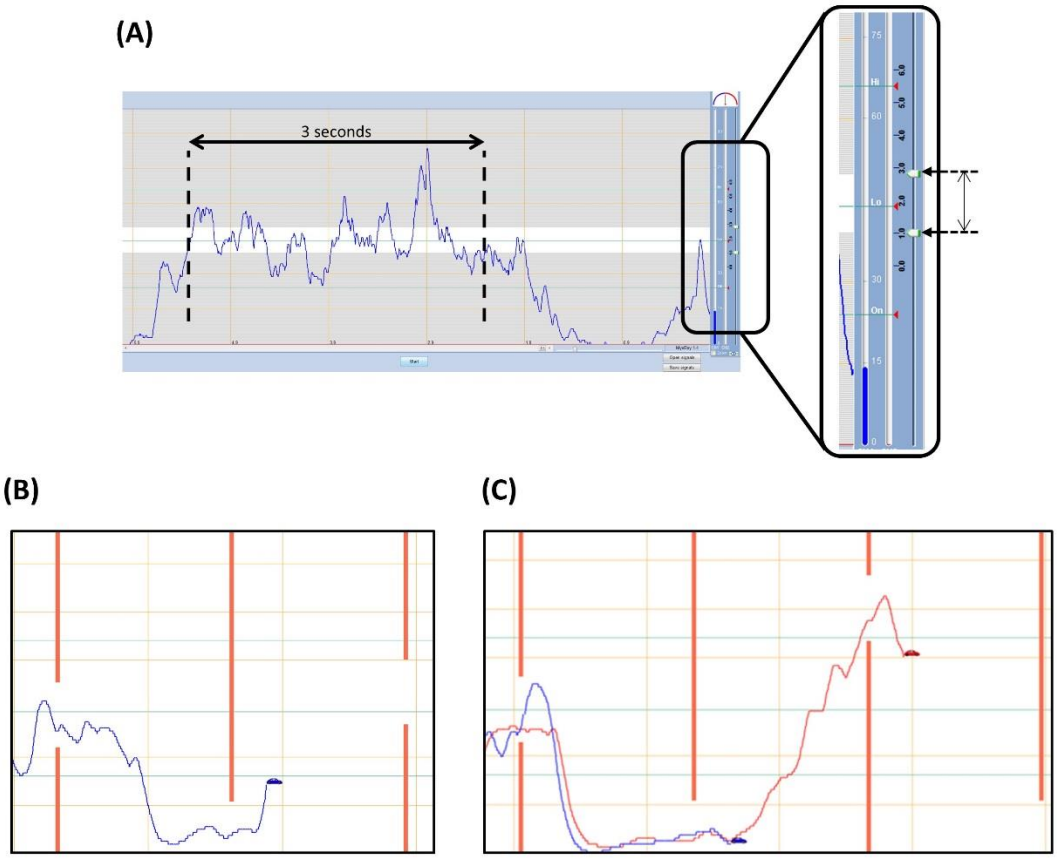


Figure 17. (A) Static tracking task – participants must aim to keep their signal within the boundaries for a 3 s period. **(B)** Dynamic tracking task (Part 1) – participants must navigate a single car through gaps in approaching walls using muscle contraction and relaxation from a single muscle. **(C)** Dynamic tracking task (Part 2) – participants must navigate two cars through gaps in approaching walls using muscle contraction and relaxation. One muscle is used to control each car. The cars travel at a set distance from each other passing through gaps at the same time (one car passing through a high gap requiring muscle contraction, whilst the other passes through a low gap requiring muscle relaxation, and then alternating).

The **dynamic tracking task**, on the other hand, uses the training "car game" within PAULA. The task involves steering a car through gaps in approaching walls that fluctuate in height (**Figure 17B**). The game level is set in the middle of the available options at 5, and the training time is 1 min which during pilot work proved to be long enough that no one achieved a perfect score, without being too long that people who were struggling stopped trying. The height of the car is controlled using the EMG signal; muscle contraction elevates the car on the screen and muscle relaxation drops

the car to the bottom of the screen. Beginning with the hand-open signal the participant must steer the car through the approaching gaps that cycle between being high and low (contraction and relaxation). Participants are given two attempts to get the best score they can achieve, defined as the percentage of gaps successfully passed through without crashing (Part 1a). The test is then repeated for the hand-close signal (Part 1b). Finally, the participant must control two cars at once using one muscle signal for each (Part 2); similarly to part 1, muscle contraction elevates the car on the screen and muscle relaxation allows the car to drop back to the bottom of the screen. During part 2, the cars are set up with one in front of the other a set distance apart (see **Figure 17C**) so that when one muscle is contracted the other one should be relaxed, assessing the ability of the participant to separate their signals, while cycling the contractions between a hand opening signal and a hand closing signal. For part 2 the participant will receive 2 scores from the one test, one for the percentage of gaps successfully passed through using the muscle signal for hand opening, and one for the percentage of gaps successfully passed through using the muscle signal for hand closing. Both scores (open and close) will be taken from the same trial, so the 'best' score for each muscle would be taken from the trial in which the participant avoided the highest percentage of obstacles overall (across both cars).

Details of the number of repeats for each task are provided in **Table 2**.

3.2.2. *Unpredictability*

Good electrode contact with the skin is required for reliable transduction of the EMG signal. Prosthesis electrodes (known as myoelectrodes) are "dry" metal electrodes housed in a plastic case; a small gap in the prosthesis socket is designed to house the myoelectrode; two rubber projections extend from each end of the casing, which locate within pre-manufactured slots in the socket walls. Although a surprisingly neglected area, it is established that the design of prosthetic sockets and associated electrode housings can lead to problems in the transduction of the EMG signal. For example, applied load may cause the socket to move relative to the residual limb and, hence, produce signal artefacts, or electrode contact may be lost altogether [15].

Furthermore, it is possible that re-donning of the socket may lead to the electrodes moving from the optimal location (see **Section 3.2.1.1**), leading to crosstalk from other muscles. These factors constitute *unpredictability* in the transduction of the EMG signal, leading to uncertainty as to the response of the prosthetic hand to neural commands.

Our protocol builds on previous work in this area [15] to assess two key aspects of *unpredictability*: (1) whether the hand responds when the user desires it (termed **desired activation**) and (2) whether the hand activates unexpectedly (termed **undesired activation**). Specifically, to assess the impact of the socket-housed electrode fit on these two *unpredictability* measures, participants complete a set of tasks with the forearm held at two different angles, under three electrode interface conditions (**Figure 18**): (1) "*Ideal*" – the electrodes are placed in the optimal position on the residual limb and held in place using elastic bandage as in **Section 3.2.1.1** (**Figure 18A**). The electrodes are connected to the MyoHand VariPlus Speed (Ottobock Gmbh) as in **Section 3.2.1.2**, which is sat on the table top; using this method, there should be minimal or no movement of the electrodes in relation to the skin. (2) "*Normal*" – the prosthesis is worn as normal, and the electrodes are housed in the prosthetic socket (**Figure 18B**). From this part of the study onward, the participant uses their own prosthesis with the electrode location and gain settings which they would use in everyday life. (3) "*Additional load*" – the prosthesis is worn as normal; however, an additional 500 g load is strapped to the hand to simulate the weight of an object, such as a full jar (**Figure 18C**).

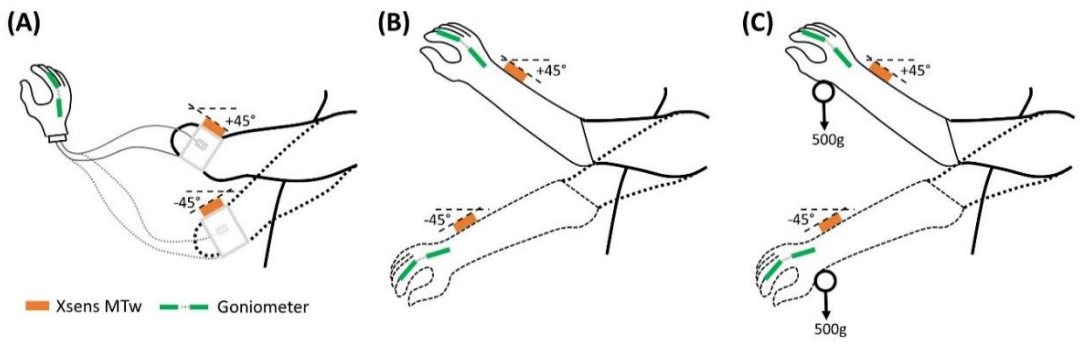


Figure 18. Three electrode interface conditions will be assessed. **(A)** "Ideal": no socket, electrodes bandaged to residual limb, **(B)** "Normal": prosthetic socket-housed electrodes, and **(C)** "Additional load": prosthetic socket + 500 g load.

Tasks are undertaken with the arm in postures that are representative of those encountered during daily activities, such as reaching to a shelf, or down into a drawer, corresponding to ≈45° above and below the horizontal. Forearm angles from the horizontal are measured using an inertial measurement unit (IMU). For this study, an Xsens MTw sensor (Xsens Technologies B.V.) is used. The IMU is placed on the back of the wrist (for the "*Ideal*" condition, the IMU is placed on the residual limb). The *x*-axis is aligned along the forearm axis pointing toward the hand. For our pilot work, a proprietary algorithm was used, which output orientation components based on Euler angles (XYZ earth fixed); however, for the main study, this will be replaced with an algorithm that calculates the orientation of the *x*-axis relative to gravity [117].

The set of tasks performed at each of the two arm orientations, for each of the three electrode interface conditions are described in the following two sections.

3.2.2.1. DESIRED ACTIVATION OF THE PROSTHETIC HAND

The impact of the electrode interface conditions on variability in reaction times is assessed using the equipment described in **Section 3.2.1.2** above. Participants begin with the "*ideal*" electrode interface condition; the simple reaction time (SRT) task is undertaken at each of the two arm postures. The number of trials is detailed in **Table 3**. The task is then repeated for the other two interface conditions ("*Normal*," "*Additional Load*") at each of the two arm postures. The spread in reaction times is compared across the electrode interface conditions, between the "*ideal*" interface and the two socket-housed electrode conditions ("*Normal*", "*Additional Load*").

3.2.2.2. UNDESIRED ACTIVATION OF THE PROSTHETIC HAND

Transitions from one posture to another may, in the case of a poor fitting socket, cause an EMG artefact and, hence, cause the prosthetic hand to open or close when the user does not desire it [15]. Such an event could lead to the user dropping or squashing an object. Therefore, between each set of reaction time tasks (see **Section 3.2.2.1**), prosthetic hand posture is recorded as the arm moves between the two arm postures. The hand begins each "transition" either completely open or completely closed, and prosthetic hand posture is recorded throughout the "transition" using

the goniometer (see **Section 3.2.1.2**); any undesired activation, i.e., opening or closing of the hand is recorded. See **Table 3** for the number of trials.

Table 3. Protocol summary – tasks for the assessment of unpredictability. The simple reaction time tasks detailed in **Section 3.2.2.1** are undertaken for both hand opening and hand closing, with the arm held at a +45° and -45° angle from the horizontal. Undesired activations of the hand (see **Section 3.2.2.2**) are assessed as the arm 'transitions' between the two arm positions. All tests are undertaken using (1) the "ideal" electrode-skin interface (see **Section 3.2.1.1**), (2) the prosthetic socket, and (3) the addition of a 500g load at the hand (see **Section 3.2.2**).

Description	Task	Arm position	Number of trials
Tasks for the assessment of unpredictability introduced by the electrode interface condition. All tasks are repeated for each interface condition ("Ideal," "Normal," and "Additional Load")	Simple reaction time (SRT) – open signal	45° above horizontal	10 × assessed using "ideal" interface, 5 × assessed using "normal" 5 × assessed using "additional load"
	Simple reaction time (SRT) – close signal	45° above horizontal	10 × assessed using "ideal" interface, 5 × assessed using "normal" 5 × assessed using "additional load"
	Simple reaction time (SRT) – open signal	45° below horizontal	10 × assessed using "ideal" interface, 5 × assessed using "normal" 5 × assessed using "additional load"
	Simple reaction time (SRT) – close signal	45° below horizontal	10 × assessed using "ideal" interface, 5 × assessed using "normal" 5 × assessed using "additional load"
	Transition between arm postures – hand open	from 45° above horizontal to 45° below	6 × assessed using "ideal" interface, 3 × assessed using "normal" 3 x assessed using "additional load"
	Transition between arm postures – hand closed	from 45° above horizontal to 45° below	6 × assessed using "ideal" interface, 3 × assessed using "normal" 3 x assessed using "additional load"
	Transition between arm postures – hand open	from 45° below horizontal to 45° above	6 × assessed using "ideal" interface, 3 × assessed using "normal" 3 x assessed using "additional load"
	Transition between arm postures – hand closed	from 45° below horizontal to 45° above	6 × assessed using "ideal" interface, 3 × assessed using "normal" 3 x assessed using "additional load"

3.2.3. *Electromechanical delay*

The addition of a *delay* to a perfectly predictable system can make control difficult, hence, delays in a system in which there is already inherent *unpredictability*, are likely to make control very challenging indeed. Farrell [76] indicated that the optimal controller delay for 90% of the population, allowing sufficient time for signal analysis, is 100-125 ms, whilst the actual *delay* in clinically prescribed prostheses is currently unpublished. Here we use a simple bench-top method for measuring the electromechanical *delay* between an activation signal applied at the electrode and initial movement of the prosthetic hand. Specifically, the electrodes will be artificially stimulated synchronously with recording of hand movement from a goniometer placed across the proximal knuckle of the index finger as in earlier tests.

Myoelectrodes are prosthesis-specific electrodes with two measurement electrodes, a reference electrode and amplification. These differential electrodes are designed to measure microvolt signals at the skin's surface as the action potential travels along the muscle fibres. A difference in voltage between the two outer electrodes which exceeds a pre-set threshold causes the hand to activate. Communication devices, power transmission lines and many other aspects of modern day life mean that we are surrounded by electromagnetic fields [32]. These fields induce small currents within the human body of a significant enough level to cause a prosthesis to activate if one of the electrodes loses contact with the skin. We can similarly use the electromagnetic fields in the environment and resultant induced voltage to artificially stimulate the electrodes.

Here we developed a system where the two outer electrodes are connected by short wires through a fast acting relay switch. When the circuit is complete, the voltage across the two electrodes is the same; disconnecting the switch causes an imbalance in the voltage on each wire, activating the prosthesis. The switch is controlled via an Arduino ("*Arduino 1*") which also controls the collection of goniometer data as in **Section 3.2.1.2**. By measuring the time between the start of goniometer recording (synchronised with the switch) and the onset of hand movement it is possible to quantify the delay (**Figure 19**).

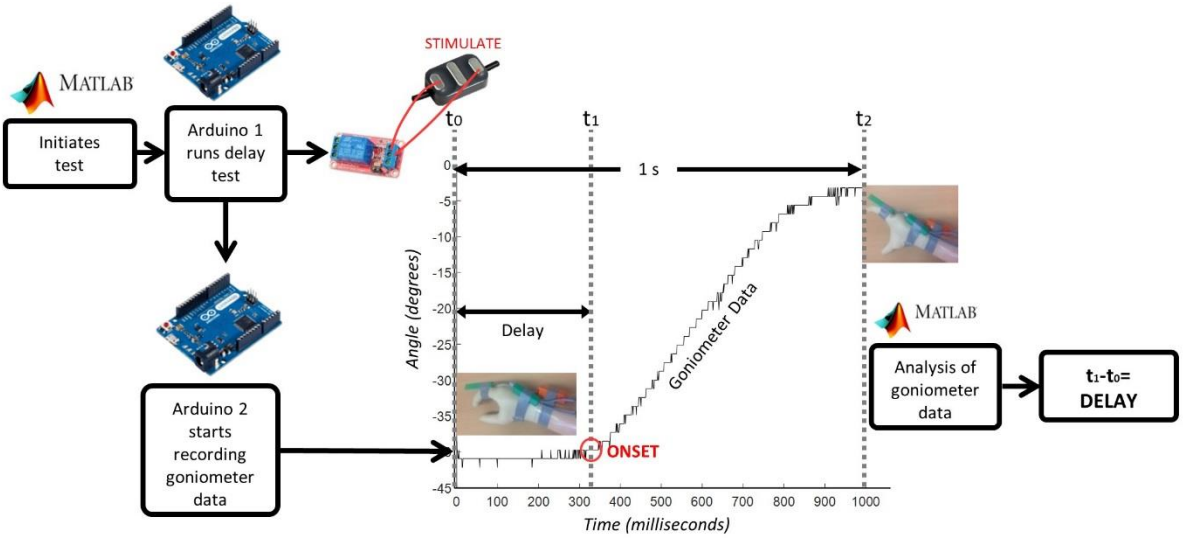


Figure 19. Instrumentation for the calculation of the delay introduced by the prosthesis. The delay is measured as the time difference between electrode stimulation and prosthesis movement recorded using the goniometer attached across the proximal knuckle of the index finger. "*Arduino 1*" ensures synchronisation between the electrode stimulation and goniometer recording.

3.2.3.1. DELAY TASKS

Table 4 details the tasks undertaken for the measurement of electromechanical *delay*. The delay to onset of hand movement is measured both from the extremes (hand fully open or fully closed) and from a neutral aperture. Initial pilot work suggested that the *delay* to movement onset when the hand begins fully closed, is significantly longer than the *delay* from any other hand aperture. It is believed that the difference is due to stiction between parts designed to move relative to one another, backlash in the gears, and some give in the metal of the finger and thumb when the hand is fully closed. For more information see **Appendix 4**, where a short study is presented to evaluate the *delay* to movement onset from different starting hand apertures. In this thesis the following terms will be used to differentiate between the delay measures for clarity:

- "$delay_{O\_C}$" = delay to onset of hand opening from fully closed starting aperture
- "$delay_{O\_N}$" = delay to onset of hand opening from neutral starting aperture
- "$delay_{C\_O}$" = delay to onset of hand closing from fully open starting aperture
- "$delay_{C\_N}$" = delay to onset of hand closing from neutral starting aperture

Table 4. Protocol summary – tasks for the assessment of delay. The delay to the onset of hand movement is measured from the extremes (hand fully open/closed) and from a neutral hand aperture (hand neither fully open nor closed). The delay is measured 5 times from each starting aperture.

Description	Task	Number of trials
Tasks for the assessment of delay. Tasks are undertaken on the prosthesis, the participant need not be present.	Delay for hand to open from fully closed	5 × assessed
	Delay for hand to open from neutral	5 × assessed
	Delay for hand to close from fully open	5 × assessed
	Delay for hand to close from neutral	5 × assessed

3.2.4. *Functionality*

As discussed in **Chapter 2**, upper limb prosthesis user *functionality* is typically appraised using an appropriate, validated assessment tool, such as the Southampton Hand Assessment Procedure (SHAP) [77]. In common with a number of other clinical tests, *functionality* is evaluated on the time taken to successfully complete specific tasks. Faster completion times are assumed to correspond to higher levels of *functionality*. In order to evaluate how a task is completed, previous studies have shown that it is beneficial to combine several different kinematic and gaze based outcome measures (**Section 2.7.1**).

When faced with a novel task, young children are known to try a number of different movement trajectories, allowing the CNS to build a representation of the optimum trajectory [118]. When faced with structured multistage manual upper limb tasks, novice prosthesis users have been shown to demonstrate similar trends [119]. During the first few task attempts, variability in the linear acceleration patterns of the forearm is high; however, after practice with the prosthesis, variability has been shown to decrease [90]. Moreover, Bouwsema et al. [86] demonstrated that prosthesis users demonstrate a later onset of hand opening during "reach-to-grasp" movements than anatomically intact subjects, and a plateau in the hand aperture between opening and closing around the object.

Furthermore, previous studies undertaken by Bouwsema et al. [85] and Sobuh et al. [88] have shown that the gaze behaviour of inexperienced prosthesis users differs from that of anatomically intact controls, however, with practice gaze patterns

approach those of controls. A more functional user would be expected to demonstrate a larger number of "look-ahead-fixations" and spend less time concentrating on the prosthetic hand. In a multistage task, "look-ahead-fixations" involve gaze fixation on an area of the task critical to a future task component (such as looking at the object to be grasped, or the location it will be moved to while completing the reach, rather than concentrating on the hand). Fewer transitions between areas of interest (AOIs, e.g., hand, grasp area of the target) would also be expected. Interestingly, participants who self-report rarely using their devices in everyday life have been shown to demonstrate more gaze transitions, irrespective of their *functionality* with the device [85]. Prosthesis users are reliant on visual feedback, as such it would be expected that patterns in gaze behaviour may be related to a person's knowledge as to how their hand will respond. If a participant cannot accurately predict the response of their prosthesis, it is possible that this will be reflected in the number of gaze transitions or the time spent looking at the hand.

We, therefore, assess *functionality* using a structured multistage manual task, which involves the reaching for, grasping, then placing and releasing of a cylinder in a tube. Three levels of task difficulty are available to the participants (as described below). *Functionality* is then characterised based on number of successfully completed trials, time to complete the task, the delay in the onset of hand opening, the length of the plateau in aperture between opening and closing the prosthetic hand, the temporal variability in the accelerations of the forearm, and gaze behaviour over successive trials.

3.2.4.1. TASK DESIGN

Previous work has suggested that certain movements are prone to cause users with poor fitting sockets particular difficulties in prosthesis control, possibly as a result of artefacts caused by electrode movement in relation to the skin or separation from the skin [15]. These include movements that would be achieved through pronation or supination in anatomically intact participants. A set of three multistage unilateral tasks (**cylinder tasks**) have been developed (termed "tasks A–C"), the harder of which ("tasks B and C") encompass these movements and, hence, present a

significant challenge to some participants. Each participant attempts 10 trials (**Table 5**) of 2 of the 3 tasks, as follows. All participants begin with the medium difficulty level ("task B"). Using the prosthesis, participants reach to grasp a cylinder (dia. 52 mm, length 200 mm, weight ≈350 g), lift and rotate it through 90° to the horizontal, place it into a horizontally orientated tube (inner dia. 64 mm, length 100 mm), and then release it returning their hand to the starting position. Participants who have a prosthesis with a wrist rotator are asked not to use this function during completion of any of the **cylinder tasks**. If the participant is successful in completing over 80% of the trials without dropping the cylinder, they move to "task C" in which the tolerance between the cylinder (dia. 52 mm, length 200 mm, weight ~350 g) and the tube (inner dia. 58 mm, length 100 mm) is reduced. If they are unsuccessful in completing 80% of the medium difficulty trials ("task B") they perform the easier task ("task A"), in which the cylinder is placed vertically into a vertically orientated target tube with the same dimensions as "task B" (inner dia. 64 mm, length 100 mm).

Table 5. Protocol summary – tasks for the assessment of *functionality* and *prosthesis usage*. For the assessment of *functionality* three difficulty levels are available of which participants undertake two. Task A involves the placement of a cylinder into a vertically orientated tube. Tasks B and C both involve the placement of a cylinder into a horizontally orientated tube of different internal diameters. For all tasks the cylinder starts in a vertical orientation. In the 2nd part of the assessment, participants are asked to wear activity monitoring sensors on each of their wrists over a 7 day period. All tasks are undertaken using a "normal" electrode interface condition, meaning the participant wears their prosthetic socket.

Description	Task	Number of trials
Tasks for the assessment of *functionality* and *prosthesis usage*. All undertaken with a "normal" electrode interface condition	Cylinder task – Task B	10 × assessed
	Cylinder task – Task A or Task C	10 × assessed
	Activity monitoring	1 week (7 days)

As before, participants wear sensors allowing kinematics to be assessed and an eye tracker to record gaze behaviour. IMUs (Xsens MTw) are worn on the wrist of the prosthesis and on the chest,[2] an electronic Goniometer (Biometrics Ltd.) is worn across the proximal knuckle of the index finger, and participants wear a Dikablis

[2] The trunk sensor is used for setting up the cylinder tasks; the distance of the cylinder from the resting hand position should allow the participant to reach the cylinder without leaning forwards. The trunk sensor will also record trunk compensatory movements during task performance.

Professional Wireless Eye Tracker system (Ergoneers). The IMUs and goniometer are both sampled at 50Hz, the field of view (scene) camera for the eye tracker records video with a frame rate of 30Hz, whilst the eye cameras are sampled at 60Hz. The three systems are synchronised using an arcade style button.

3.2.4.2. TASK SEGMENTATION

Participants were instructed to start the task with their hand closed and placed on a board on the table in front of them. An arcade style button was mounted into the board, and participants were seated in a position which allowed for the hand to rest comfortably on the button. An LED was also mounted in the board informing the participant as to whether their hand was successfully in contact with the button. A change in state of the button (e.g. pressed to not pressed) turned the LED on/off and placed a timestamp in the IMU data.

For the pilot work presented in this chapter, task onset and task completion were calculated based on these timestamps when the hand left and returned to the starting position. In the main study (**Chapters 5 & 6**), task onset will be taken as the onset of movement (either lifting the arm or opening the hand, calculated using the IMU and goniometer, respectively), whilst task completion will be taken as the moment the fingers begin to open to release the cylinder after the "transport plateau" (see **Appendix 5** for full details).

The change in definition for the task completion was made after looking at the data recorded from the participants recruited for the main study. Some prosthesis users were unable to successfully and smoothly complete the return phase, repeatedly missing the button. This was considered to not be a measure of their ability to use their prosthesis and was consequently skewing the results; therefore, this phase of the movement was excluded from the analysis.

3.2.4.3. EVALUATION OF TASK PERFORMANCE

Performance of the **cylinder task** is measured according to two factors, **task success** and **task duration**.

Task success is evaluated according to the number of trials completed without dropping or knocking over the cylinder. Points are awarded for successful (smooth) completion of the task first time. Half points are allocated if the task was not completed in one smooth movement (i.e. the hand opened and closed more than once during reach to grasp). No points were allocated if the cylinder was dropped or knocked over.

As noted above, the method of detecting task onset and task completion were altered between the pilot study and the main study. For both studies, **task duration** was calculated as the difference between these two times.

3.2.4.4. QUALITY OF MOVEMENT

Quality of movement encompasses both the pattern of hand aperture during "reach-to-grasp" and the temporal movement variability throughout the task. It is possible to determine the end of the "reach-to-grasp" phase by analysing the goniometer data. When the task begins, the hand is completely closed; the hand then opens, before closing again around the cylinder to generate a "transport plateau" as the object is transported. It has been shown that prosthesis users demonstrate a delay in opening the hand at the start of "reach-to-grasp", demonstrated by a "delay plateau," and decoupling between opening and closing the hand, termed the "reach plateau" [86]. The start of the "transport plateau" is taken as the end of the "reach-to-grasp" phase of the task. By segmenting the "reach-to-grasp" phase of the task (see **Appendix 5**), the delay in onset of hand movement (the length of the "delay plateau") is calculated as a percentage of the "reach-to-grasp" phase, and the length of the "reach plateau" is calculated as a percentage of the "reach-to-grasp" phase. Furthermore, using the wrist-mounted IMU, the temporal variability in the linear acceleration of the forearm between trials is assessed using the methods developed by Thies et al. [120].

3.2.4.5. GAZE BEHAVIOUR

For the purpose of analysing the eye tracking videos, the task area is split into AOIs. During the pilot work six AOIs were identified: (1) start point (button), (2) prosthetic hand, (3) "grasp critical" area (GCA) (bottom half of the cylinder for "tasks A and B",

top half for "task C"), (4) other "location critical" half of the cylinder (LCA) that is required to be placed into the tube, (5) tube, and (6) LED. Further inspection of the data for these participants and the participants in the main study led to a slight change in the proposed analysis for the main study. During the "reach-to-grasp" phase AOIs will include: (1) the prosthetic hand, (2) the GCA, (3) the LCA / the tube, (4) other, and (5) missing data. At the completion of "reach-to-grasp" the hand and GCA will be combined into a single AOI leaving 4. The full coding scheme is presented in **Appendix 6**. The combination of the hand and GCA during the second part of the task is similar to the methodologies proposed by researchers from the BLINC lab in Alberta at the Myoelectric Controls Symposium 2017 [121]. In their paper on 3D-gaze and movement, Hebert et al. reported analysing the eye fixations according to the 'current' location being acted on by the hand, the 'future' location relevant to the subsequent portion of the task, and the 'hand' itself. Due to the nature of the task used in our study, whilst the cylinder is being inserted into the tube it is almost impossible to differentiate between fixations on the transparent tube and fixations on the cylinder within the tube. Based on the results of the pilot work the tube and LCA were therefore combined into a single AOI to be compared against the time spent looking at the GCA and the hand itself. These two AOIs were also combined during the reach-to-grasp phase in order to reduce the complexity of the coding scheme as they both constituted a look-ahead-fixation.

The percentage of time spent looking at each AOI is calculated, alongside the number of times that the gaze location transitions between each of these areas. Finally, the percentage of time spent looking at areas of the task relevant to subsequent components of the task ("look-ahead-fixations") is calculated for each point in the task (e.g., the cylinder and tube during "reach-to-grasp," or the tube during manipulation and transport).

3.2.5. *Everyday prosthesis usage*

Current methods of quantifying everyday *prosthesis usage* involve self-report [122-125], which is known to be prone to recall and bias errors [126, 127]. Accelerometer-based activity monitoring [95] provides an opportunity to observe actual prosthesis use

outside of the clinical environment; however, to date no studies have been published on a cohort of upper limb prosthesis users. We have adapted a protocol developed for stroke patients [108]. This research involved participants wearing an activity monitor (Actigraph GT3X+) on each of their wrists while they went about their normal daily activities. The Actigraph monitors provided continuous logging of raw accelerometer data (sampled at 30 Hz). The data were downloaded using proprietary software, filtered and collated into 1 sec epochs. The processed data were expressed as activity counts (0.001664 g/count) (Actigraph Corp, 2015), which were converted into Vector Magnitudes (sum of the counts along each axis $\sqrt{x^2 + y^2 + z^2}$). For each second of data, Bailey et al.[108] combined the Vector Magnitudes from the two wrist worn monitors (dominant and non-dominant arm) to inform on the magnitude of activity across both arms, expressed as the "bilateral magnitude" ($VM_{Dominant} + VM_{NonDominant}$), and the contribution of each arm to the activity, expressed as the "magnitude ratio" $[\ln(VM_{NonDominant}/VM_{Dominant})]$.

Bailey found that in healthy, anatomically intact controls, the median "magnitude ratio" was around zero (symmetrical bilateral arm use); however, in the stroke cohort, the "magnitude ratio" was skewed toward unilateral non-paretic (unaffected) arm use. In general, participants in the stroke cohort who demonstrated higher levels of functionality (according to the Action Research Arm Test [128]) also demonstrated "magnitude ratios" closer to those of the healthy control subjects; nevertheless, a third of participants demonstrated a median "magnitude ratio" representing unilateral non-paretic arm use, regardless of their functionality with the paretic arm.

For our study, the activity monitors are placed on the anatomical wrist and the wrist of the myoelectric prosthesis. The monitor is not transferred to other prostheses the participant may wear (e.g., body-powered), as only the times when the myoelectric prosthesis is in use are of interest to this study. Participants are invited to wear the monitors for 1 week.

3.2.6. *Pilot study*

3.2.6.1. RECRUITMENT

The purpose of this pilot study was to assess the robustness and feasibility of the protocol before undertaking the main study with a cohort of myoelectric prosthesis users. Ethical approval was granted by the University of Salford School of Health Sciences Research Ethics committee (*REF: HSCR 15-130*) to pilot the above protocol with anatomically intact subjects using a prosthesis simulator designed to fit over their intact arm (**Figure 20**), and myoelectric prosthesis users recruited from the University of Salford Prosthetics and Orthotics Professional Patient Database. Inclusion criteria for the latter were (1) an amputation or congenital limb loss at the trans-radial level, (2) owning a myoelectric prosthesis, and (3) over 18 years of age. Exclusion criteria were (1) bilateral upper limb absence, (2) injury to the residual limb at the time of testing, and (3) using single site muscle control.

Figure 20. Prosthesis simulator for use with anatomically intact subjects. The socket is designed to fit over the forearm and fist. Straps allow the socket to be tightened to the persons arm. It is not possible to tailor electrode placement to each person.

3.2.6.2. DATA ANALYSIS

Factors Affecting Prosthesis Control

As described above (see **Sections 3.2.1**, **3.2.2**, and **3.2.3**), *EMG skill*, *unpredictability*, and *delay* all affect control of the prosthesis. Multiple variables are generated as part of this protocol that characterise these factors, and which would ideally be combined into overall scores for *skill* in controlling the EMG signals, *unpredictability* introduced by the electrode interface, and a measure of *delay*. For this reason, the pilot study data were reduced to ordinal data.

Specifically, the *EMG Skill* score would be devised of the reaction time difference (**Intuition Task**) between the choice and simple reaction times (termed "Decision Time", see **Section 3.2.1**), and the scores from the **Signal Tracking Tasks**. To ensure that the reaction times reported were not biased by early or late reactions, any responses faster than 100 ms or slower than 1000 ms were excluded from the analysis [129].

A combined score for the *unpredictability* introduced by the electrode interface would be an ordinal score based on the reaction time spread across the conditions highlighted in **Section 3.2.2.1** and the number of **undesired activations** during the "transitions" (see **Section 3.2.2.2**).

Finally participants will be provided with a ranked score based on the average *delay* measured in the prosthesis for opening and closing.

Prosthesis functionality and everyday usage

Of the three possible **cylinder tasks** (easy "A," medium "B," and hard "C"), all participants attempted two that were analysed independently.

Initially, a basic performance evaluation was undertaken. A score relating to task success was generated (see **Section 3.2.4.2**) and the task duration (in seconds) was calculated.

For all trials where the participant completed the "reach-to-grasp" component of the task, the hand aperture profile was analysed to establish the percentage of "reach-to-grasp" consumed by the "reach plateau" period and the "delay plateau". Further, using the methods developed by Thies et al. [120], temporal variability in the linear acceleration of the forearm throughout the full task was calculated.

Analysis of the eye tracking data used a coding scheme to record the AOIs on which the gaze was concentrated for every frame, allowing for the time spent in each AOI and the number of transitions between AOIs to be calculated. Furthermore, the time spent looking ahead to the next component of the task was calculated.

Finally, analysis of the activity counts recorded by the Actigraph activity monitors allowed for the calculation of the "bilateral magnitude" and "magnitude ratio" using the methods described in **Section 3.2.5**. By combining the raw data with the activity diary, it was also possible to establish the wear time of the prosthesis. In this pilot work, the results are reported based on the data recorded throughout the week, irrespective of whether the prosthesis was worn. However, to allow fair comparison of the "magnitude ratio" between prosthesis users and stroke patients [108], analysis was also undertaken based only on the periods when the prosthesis was worn. For this secondary analysis, overnight removal of the prosthesis was excluded based on visual assessment of the raw accelerometer data and activity counts from the monitor worn on the prosthesis. Data were excluded from the last activity count on one day until the first count on the next day (activity count spikes during these non-wear periods, lasting less than 1 min with at least 10 min of non-use either side, were also excluded). If visual analysis of the raw data showed long periods (>1 h) of no prosthesis activity during the day, these periods were also excluded based on the activity counts, with the assumption that the prosthesis was removed. For more information on the visual analysis, please see **Appendix 7a**. Similarly to Bailey's data, the median "magnitude ratio" was reported to avoid the effects of skewness.[3]

Relationships between control factors and functionality/usage

The early pilot work was not intended to draw conclusions on the relationship between the different control factors. However, the main study will aim to establish how measures of *functionality* and everyday *prosthesis usage*, can be explained by the factors affecting myoelectric prosthesis control. Principle Component Analysis (PCA) will be used to establish whether the data collected can be combined into single values for each control factor (*EMG Skill* score, *unpredictability* score, and *delay* score). Using multiple regression techniques, factors affecting prosthesis

[3] For the main study, a new method of analysis has been developed for the activity monitoring data. This method is introduced in **Chapter 4**; the detection of prosthesis non-wear was also improved as will be highlighted in **Chapter 5**.

control will be related to measures of *functionality* and everyday *prosthesis usage*, specifically:

- task success,
- task duration,
- the hand aperture profile during the reaching phase,
- the temporal movement variability during the performance of the full task,
- the percentage of time spent looking at each AOI, and
- the "magnitude ratio" between the two hands during everyday activity [4]

To further characterise upper limb performance, measures of everyday *prosthesis usage* will be correlated against measures of *functionality* collected within the clinic. These may include association of the "magnitude ratio" and "prosthesis wear time" with:

- the percentage of time spent looking at each AOI,
- the movement variability during the performance of the full task.

Based on the findings of these analyses, it should be possible to establish the relative contribution of the factors affecting prosthesis control to each measure of *functionality* and everyday *prosthesis usage*.

3.3. Initial pilot study results and discussion

In this section, we use early results from initial pilot work with anatomically intact subjects using a prosthesis simulator and prosthesis users to demonstrate the feasibility of this protocol. Data collected from two prosthesis users (both male, age 44–45, with congenital limb absence, and 1.5–35 years using a myoelectric prosthesis) and one anatomically intact subject using a prosthesis simulator (male, age 21, no experience) are presented.

[4] This measure will be replaced by new measures of upper limb symmetry introduced in **Chapter 4**.

3.3.1. *Data collection*

The data collection period lasted between 4 and 5h, including breaks, which was longer than desired, however, the protocol included tasks that have since been removed. In the format presented above, the protocol would, therefore, be expected to last less than 4 h. For our study in this reduced format, the first 40 min consisted of finding the "ideal" electrode placement (see **Section 3.2.1.1**) and undertaking the **signal tracking tasks** (see **Section 3.2.1.3**). The **intuition task** for *EMG skill* analysis (see **Section 3.2.1.2**) took 20–30 min while the tasks to measure *unpredictability* (see **Sections 3.2.2.1** and **3.2.2.2**) lasted a further 50–60 min. Finally, 40–50 min were spent setting up the **cylinder task** and undertaking the assessment of *functionality* (see **Section 3.2.4**). Breaks were provided at set points in the protocol to ensure participants' attention was maintained. During the longest of these breaks (15 min) the *delay* in the prosthesis was measured (see **Section 3.2.3**).

3.3.2. *Initial analysis*

3.3.2.1. EMG SKILL (INTUITION TASK)

During the **intuition task** (see **Section 3.2.1.2**), data were recorded from the goniometer both before and after the stimulus (LED) was presented. **Figure 21** shows example data recorded during the second of stimulus presentation. The red circle indicates the time point identified as the moment of hand movement onset in response to stimulus presentation. More detail on the algorithms employed to identify movement onset are presented in **Appendix 3**.

It is widely accepted that the mean reaction time for college-aged individuals undertaking simple reaction time (SRT) tasks with light-based stimuli is around 190ms (0.19s) [130]. During tasks where the stimulus determines the reaction (CRT tasks), times are often slower; exact speeds depend on the task. The inherent *"delay"* introduced within the prosthesis would be expected to produce prosthesis reaction times that are longer than the anatomical reaction times. Initial results demonstrated measured SRT of 270–290ms (**Figure 22**); furthermore, an increase in reaction time was seen between the Simple and Choice Reaction Times of 45–100ms ("Decision Time"). It is worth noting that reaction times and consistency improve

after first introduction to a new task [130]; this may show as a learning effect in the "decision time" over the small number of repeats. However, we decided not to randomise the order of the tasks so that all participants underwent the same sequence of testing: the SRT first, then the CRT (see **Section 3.4**). The "decision times" presented in **Figure 22** suggest that Prosthesis User 2 was less skilled at deciding which muscles to activate than the other two participants.

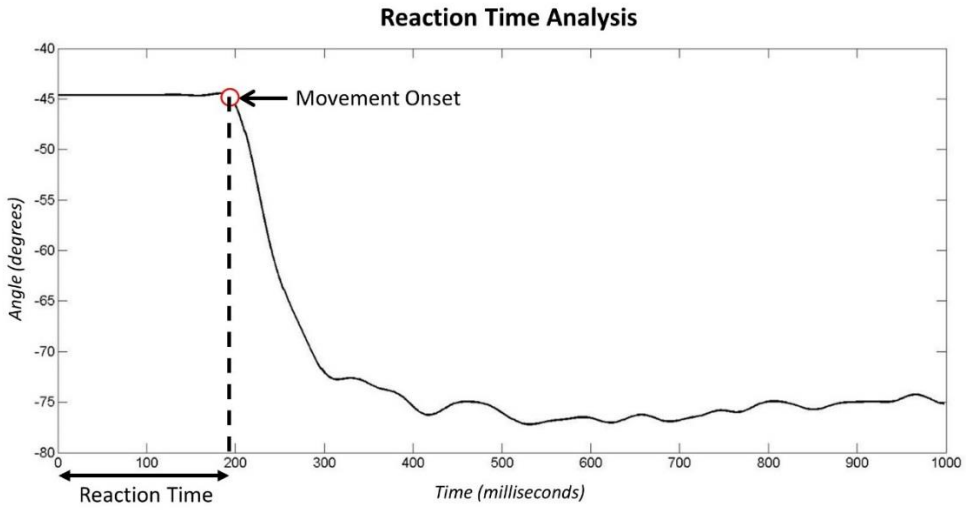


Figure 21. Reaction time to close the hand. Goniometer data recorded during the LED stimulus presentation is shown. The red marker signifies the point identified as the onset of movement.

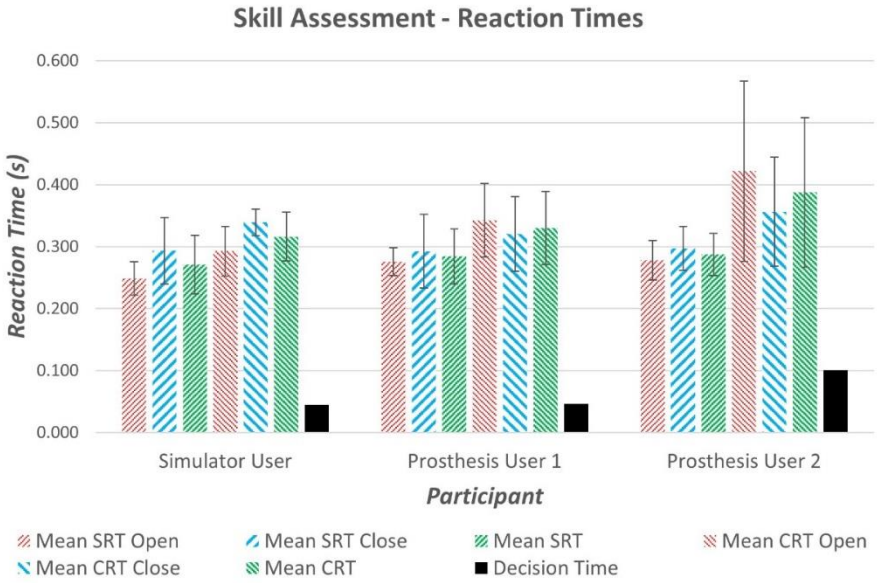


Figure 22. Average simple (SRT) and choice (CRT) reaction times for the anatomically intact participant and prosthesis users. The decision time was calculated as the difference between the mean CRT and the mean SRT.

3.3.2.2. EMG SKILL (SIGNAL TRACKING TASKS)

The **static tracking task** (see **Section 3.2.1.3**) assessed the participant's ability to maintain a specified signal level. This task demonstrated that different levels of *EMG skill* can be measured and did not show a ceiling effect; i.e., no participant achieved 100% (**Figure 23A**). The simulator user appeared to perform better than either of the prosthesis users. It is interesting to note that during a sustained contraction, both prosthesis users demonstrated co-contraction and/or encountered crosstalk for one of the two muscle groups (**Figure 23B**).

All participants were able to complete the **dynamic tracking task** (see **Section 3.2.1.3**). Two participants performed better when only one car (muscle signal) was under assessment (Part 1), with a 20–40% higher success rate than when presented with 2 cars (Part 2). Prosthesis User 2, who demonstrated large amounts of co-contraction or crosstalk when activating the close signal (**Figure 23B**), did not fit this trend, instead a 10% improvement was seen in the success rate for the close signal for Part 2, and a 60% reduction in success with the open signal. During this second part of the dynamic task when two cars were being controlled, the participant was unable to relax the open signal while contracting the close muscle. This meant that the "open car" was guaranteed to "crash" for at least 50% of the gaps. It is possible that this participant, therefore, changed strategy to concentrate on the easier to control close signal. Alternatively, it is possible that this participant was unable to visually track the two cars and struggled with focusing equally on controlling each signal. One further suggestion is that this links with the reaction time results, which showed that this participant found deciding which muscle to activate harder than the other participants.

At this stage, it is not possible to draw any firm conclusions based on these results. However, we have demonstrated that both **signal tracking tasks** offer the possibility of differentiating between different levels of *skill* in controlling the EMG signal. Based on these tracking tasks, the simulator user demonstrated a higher level of skill than the two prosthesis users.

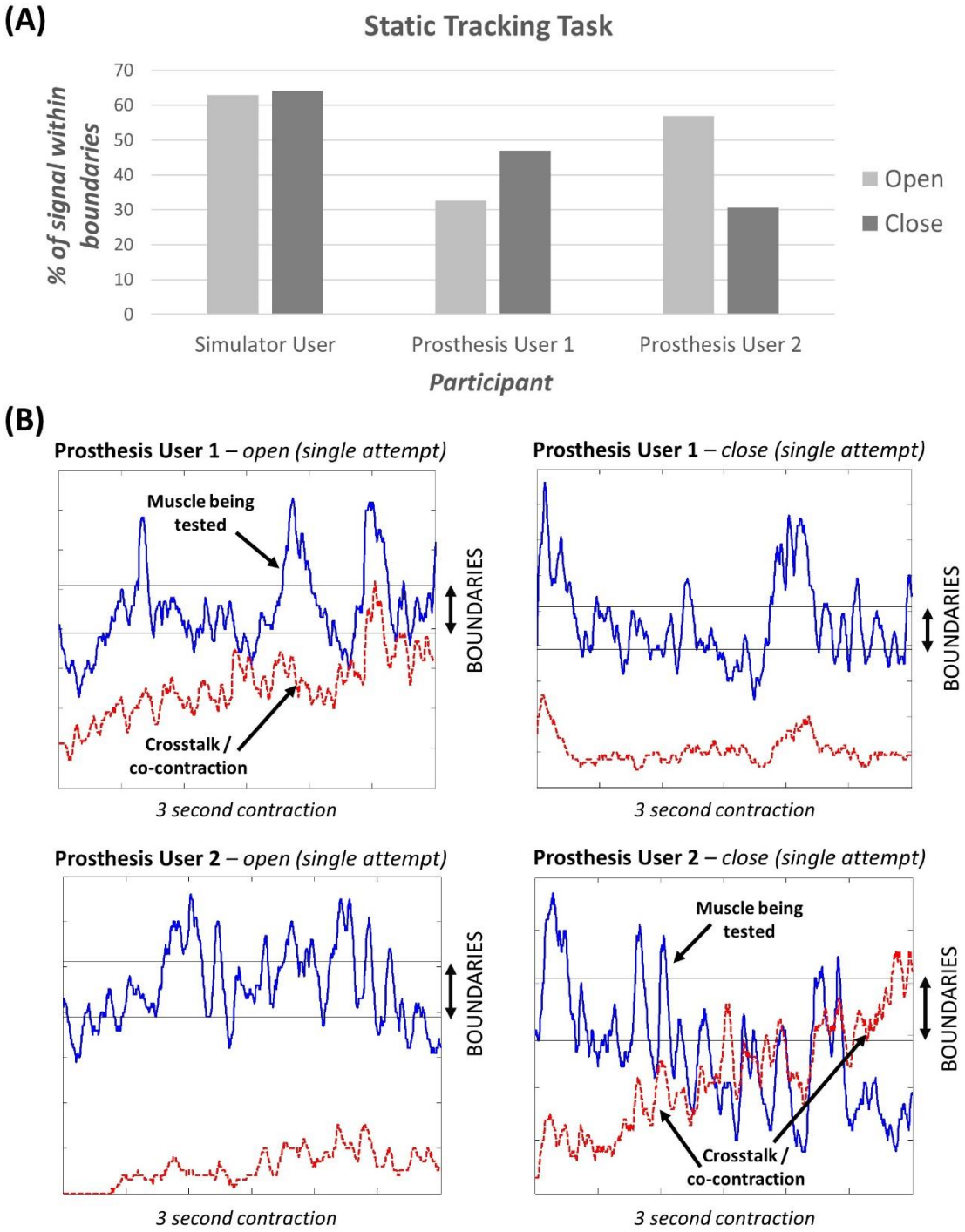


Figure 23. (A) Results of the static tracking task. Participants were provided with three opportunities to achieve their best signal (signal remains within the boundaries). Here, we present the percentage of time the signal was within the boundaries over the 3-second period. **(B)** Signals from the two prosthesis users – the blue line is the signal being tested, the red dashed line shows the signal from the muscle that should remain relaxed.

3.3.2.3. UNPREDICTABILITY

Both prosthesis users experienced some difficulty in completing the tasks designed to measure the extent of *unpredictability* in transduction of the EMG signal (see **Section 3.2.2**). User 1 had a good level of control over the prosthesis, and was able to operate it as desired, however, the residual limb was very short. Consequently the participant found the addition of the 500 g mass fairly difficult to hold, reporting discomfort at the elbow. User 2 had a longer residual limb and reported feeling the additional load in his shoulder muscles. Both participants were happy to undertake the task with a 500 g load attached to the hand but would have struggled to support the prosthesis if the mass was much heavier.

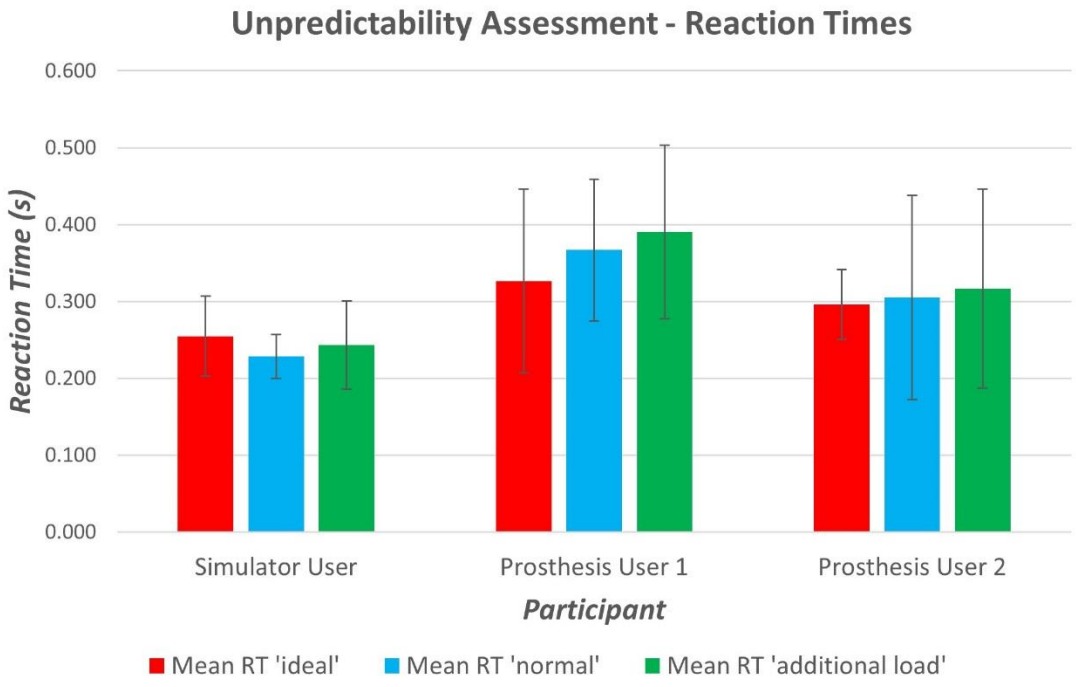


Figure 24. Result of reaction time tasks to assess *unpredictability* of the desired activation of the prosthetic hand. Prosthesis User 2 demonstrates a larger amount of variability in reaction times with the prosthetic socket than when using the "ideal" electrode contact setup with the electrodes bandaged to the limb.

The anatomically intact participant using the simulator did not exhibit any clear difficulty with completing the reaction time portion of the task (**Section 3.2.2.1**), however, when "transitioning" between the arm postures (see **Section 3.2.2.2**), four undesired activations occurred (two with the "*Ideal*" interface condition and two with the "*Additional load*"). The reaction time data from Prosthesis User 1 showed a large amount of variation in reaction times for all three interface conditions (**Figure 24**); however, this user did not experience any undesired activations of the hand. Finally, Prosthesis User 2 only experienced a small amount of variability in reaction times (**Figure 24**) when undertaking the tests with the "*Ideal*" electrode interface condition (electrodes bandaged to the limb). However, when the socket was introduced ("*Normal*" interface condition and "A*dditional load*"), the participant encountered a large amount of difficulty in getting the prosthesis to react as desired. For 13 of the 20 open trials, the hand closed when the participant attempted to open it; and for those repeats where the participant did manage to open the hand, the movement trajectory was not smooth. **Figure 25** shows a comparison of the goniometer data between Prosthesis User 2 and the other two participants. It is worth noting that each participant used a different prosthetic hand for this assessment and that the total aperture for the hand used by Prosthesis User 2 was much smaller than for the other two participants, hence the difference in range. Prosthesis User 2 had a much looser socket fit than User 1. Consequently, as the "open muscle" contracted, the limb seemed to push against the socket moving the "close electrode" away from the skin and activating the close movement instead. This *unpredictability* introduced by the socket fit was also highlighted by the seven undesired activations when transitioning between the different arm positions.

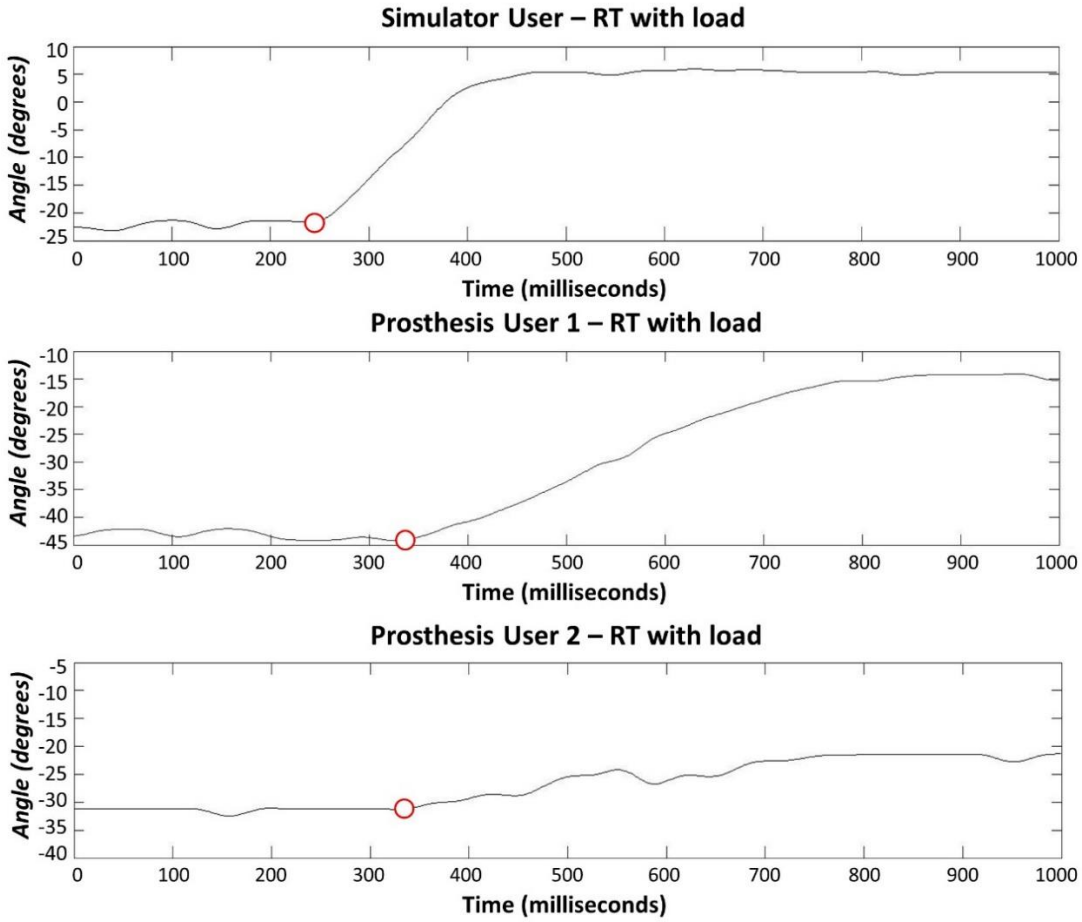


Figure 25. Reaction times (hand opening) using the socket-housed electrodes with additional load added to the hand. The angle recorded by the goniometer attached across the proximal knuckle of the index finger is presented over the 1s period. Prosthesis User 1 noticed slower movement of the hand with the addition of the load, whereas Prosthesis User 2 experienced a large amount of difficulty in overcoming the close function while trying to open the hand. The red circles represent the time identified as movement onset.

3.3.2.4. ELECTROMECHANICAL DELAY

The early pilot work measured the electromechanical *delay* in the onset of hand movement only from the aperture extremes (hand fully open/closed), this differs from the methodology introduced in **Section 3.2.3.1**. For more information on the *delay* from different apertures see **Appendix 4**.

For all prostheses, onset of hand opening ($delay_{O\_C}$) took significantly longer than hand closing ($delay_{C\_O}$) (**Figure 26**). Each *delay* was measured three times [5]. Although

[5] This has since been increased to 5 for the main study.

the standard deviation across each set of three measurements was small, the overall $delay_{O\_C}$ measured for Prosthesis User 2 was notably high; the measured value of 399ms was longer than the reaction times achieved using the same hand. This was further investigated (see **Appendix 4**) and it was found that the onset of hand opening from a fully closed position ($delay_{O\_C}$) was significantly slower than from a neutral aperture (as was used for the reaction time tests) for almost all prosthetic hands. This has led to subsequent changes in the protocol with the delay being measured under four conditions as detailed in **Section 3.2.3.1**.

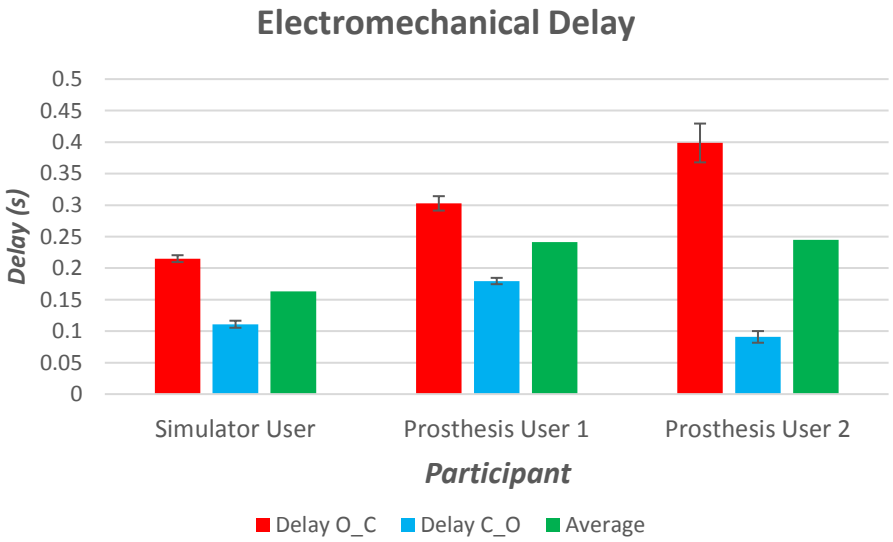


Figure 26. Measurement of the electromechanical delay in the three different prostheses. In all cases, the $delay_{O\_C}$ to the onset of hand opening from a fully closed starting aperture is longer than the $delay_{C\_O}$ to the onset of hand closing from a fully open starting aperture.

3.3.2.5. FUNCTIONALITY

All participants began with the medium difficulty task ("task B"); completion of the task ranged from 100% (Prosthesis User 1) to less than 50% (Prosthesis User 2) of trials. Both Prosthesis User 1 and the simulator user completed over 80% of trials of "task B" and, therefore, moved on to the harder task ("task C"). Prosthesis User 2 experienced difficulty grasping the cylinder, and often dropped it as he rotated it to the horizontal. When attempting the easier task ("task A"), he completed 90% of the trials; however, during two of these trials, he missed the cylinder on the first attempt of "reach-to-grasp."

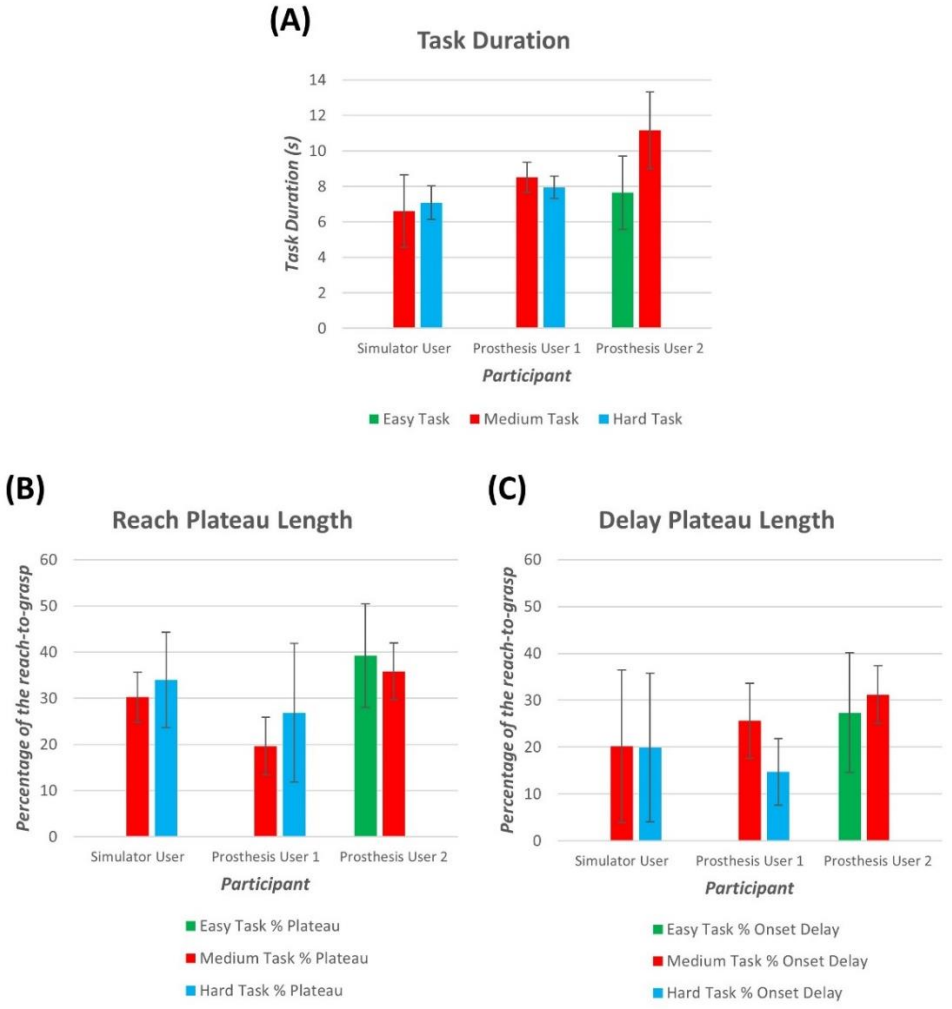


Figure 27. (A) Mean "cylinder task" duration for each of the difficulty levels (Easy "A," Medium "B," and Hard "C"), **(B)** mean length of the plateau in the hand aperture between hand opening and hand closing ("reach plateau") as a percentage of the reach phase, **(C)** mean delay to the onset of hand opening ("delay plateau") as a percentage of the reach phase. Participants undertook the task at two difficulty levels; all participants attempted the medium difficulty level.

As introduced in **Section 3.2.4.1**, data were collected using wrist and chest-mounted IMUs, an electronic goniometer and an eye tracker. The systems were synchronised using the button press (see **Appendix 5**); pilot data demonstrated that synchronisation was successful. The task durations, based on the button timestamps, illustrate that Prosthesis User 2 performed the medium difficulty task ("task B") at a slower rate than the other two participants (**Figure 27A**). Prosthesis User 1 was the most consistent regarding the time taken to perform the task, and as noted above, the most successful. Furthermore, Prosthesis User 1 demonstrated aperture patterns more similar to the healthy norms with a shorter "reach plateau" in the

"reach-to-grasp" phase (**Figure 27B**); the length of the "delay plateau" was similar across the three participants (**Figure 27C**).

As highlighted above, Prosthesis User 2 struggled to complete "task B", dropping the cylinder during rotation of the arm; the screenshots in **Figure 28** summarise the technique employed by the participant to overcome this *unpredictability*. Unlike Prosthesis User 1 and the simulator user, Prosthesis User 2 waited until the last minute, when the cylinder was in contact with the tube, before rotating the cylinder to the horizontal. The participant's uncertainty as to how the hand would respond is highlighted in the results of the eye tracking. The eye tracking videos (**Figure 28**) were individually coded frame by frame to establish where the participant was looking. As can be seen in the images at the top of **Figure 28**, both prosthesis users looked at their hand during "reach-to-grasp," however as can be seen in **Figure 29**, there were noticeable differences in the gaze patterns of these two users. Prosthesis User 2 spent the majority of the time looking at the hand and the cylinder, tracking its movement, while Prosthesis User 1 showed a higher level of confidence in the hand, looking ahead to the cylinder and the tube. During the "reach-to-grasp" phase of the task, Prosthesis User 1 looked ahead of the hand for 76% of the time, while Prosthesis User 2 relied on looking at the hand for over 50% of the time.

Figure 28. Example eye tracking video – the crosshair shows the point of gaze fixation. **Top:** both Prosthesis Users looked at the hand at a point in the reach to check their hand aperture. **Bottom:** the different strategies employed to complete "task B" can be seen – **left:** simulator user, **middle:** Prosthesis User 1, and **right:** Prosthesis User 2 – Prosthesis User 2 struggled

to complete this task and would drop the cylinder when the arm was brought to the horizontal, therefore, he delayed this movement until the last possible moment.

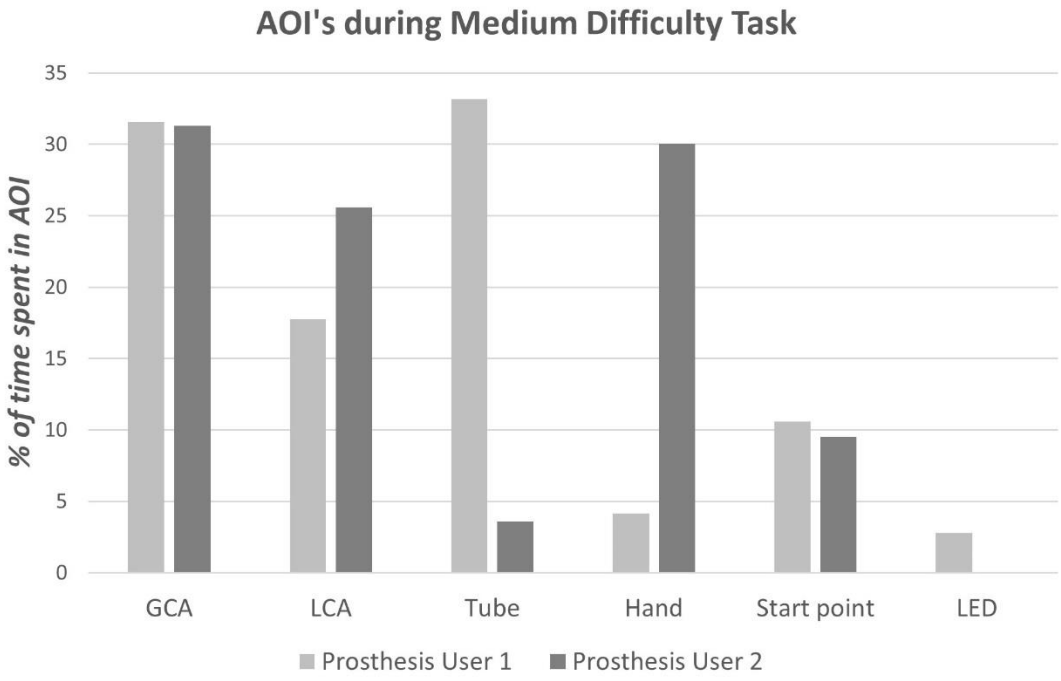


Figure 29. Results of the gaze analysis for the first successful trial of the medium difficulty task ("task B") for each of the prosthesis users. GCA = grasp critical area of the cylinder (the half to be grasped), LCA = location critical area of the cylinder (the half to be placed into the tube).

3.3.2.6. EVERYDAY PROSTHESIS USAGE

As explained in **Section 3.2.5** participants were asked to undertake activity monitoring over the period of 1 week. For the purposes of this pilot study, data were only collected for the two prosthesis users; however, to check the methods against Bailey's data [108] (see **Section 3.2.5**), one separate anatomically intact participant underwent activity monitoring using their anatomical arms. The anatomical results echoed Bailey's findings with symmetrical use across the two arms represented by a median "magnitude ratio" of 0.11 (IQR = 3.28) (**Figure 30A**).

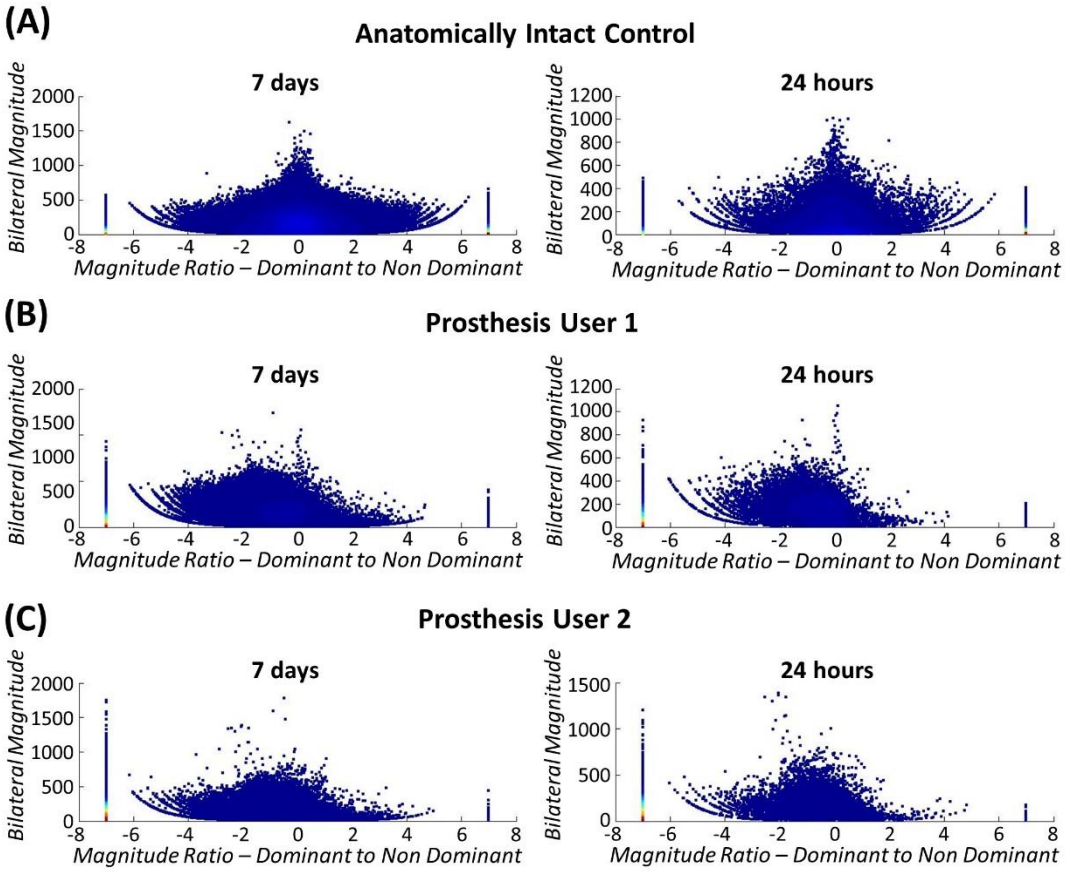


Figure 30. Bilateral arm use (left: 7 days, right: 24 h). The column at −7 signifies unilateral dominant arm use (anatomical arm), +7 signifies unilateral non-dominant arm use (prosthesis), and 0 signifies both limbs contributing to activity at the same level. Each marker represents 1 s of data and the colour density is a count of the number of data points. **(A) Top:** bilateral arm use for anatomically intact control subject. Arm use is symmetrical across both arms, regardless of limb dominance. **(B) Middle:** bilateral arm use for Prosthesis User 1. **(C) Bottom:** bilateral arm use for Prosthesis User 2.

At present, no algorithm exists allowing for differentiation between non-wear and passive-use of the prosthesis using the wrist worn Actigraph monitors. Consequently, participants were asked to complete activity diaries, which subsequently showed that Prosthesis User 2 only wore his device for 3 of the 7 days, while User 1 wore his all week. This non-wear is reflected in the activity monitor data with purely unilateral use of the anatomical arm on these days and no activity counts for the prosthesis. From the activity diaries, we know that both participants generally wore their prosthesis for 10h or more on the days when they were worn. It is, therefore,

important that the data are collected over the week long period to ensure that representative data for each user is collected.

Figure 30B/C illustrate that both prosthesis users rely on their anatomically intact arm to a greater extent than the stroke patients participating in Bailey's study [108]. Both prosthesis users demonstrated median "magnitude ratios" of −7 [IQR = 5.40 (Participant 1) IQR = 0 (Participant 2)] (unilateral use of the intact arm) similar to the group of Bailey's stroke participants who rely most on their non-paretic arm. However, when only the data collected while the prosthesis was worn is included in the comparison, the median "magnitude ratios" reduce to −2.55 (IQR = 6.42) for Prosthesis User 1, and −2.42 (IQR = 6.76) for Prosthesis User 2. It is interesting to note that although Prosthesis User 1 wore the device for more hours during the week, both participants demonstrated similar median "magnitude ratios." Furthermore, it is notable that the "bilateral magnitude" of User 1's activity was of a level much closer to the stroke patients, while User 2 demonstrated activity to the same magnitude as Bailey's healthy controls.

3.4. Limitations and summary of changes

3.4.1. *Limitations*

Assumptions have been made with respect to the **Intuition Task** (**Section 3.2.1.2**). Reaction time experiments involving simple and choice reaction times would normally be randomised, and undertaken in large numbers, to overcome learning or attentional effects. This study involves the comparison of performance in these tasks between participants, therefore, it is important that all participants experience the same tasks in the same order. Furthermore, time constraints limit the number of repeats that can be undertaken. Although different participants may learn at different rates, it is assumed that as the task is novel to all participants the results will be comparable.

The tube used in the **cylinder task** is transparent, meaning that when the cylinder is within the tube it can be difficult to identify whether the participant is looking at the cylinder or the tube (likely both). Similarly when the gaze is on the GCA of the

cylinder, as the hand approaches and blocks the view, it is not clear whether the AOI should be coded as the hand or the GCA. In the main study a slight simplification of the coding scheme will be used combining the tube and LCA; however, as gaze fixations on the GCA and hand differentiate performance between prosthesis users and anatomically intact controls, these AOIs will be kept separate during "reach-to-grasp". A robust set of rules for coding the data have been developed (**Appendix 6**). Furthermore **Appendix 6** shows the results from an inter-rater reliability study to assess the proposed approach to coding the gaze data.

As discussed in **Section 3.2.5**, the analysis methods for the assessment of everyday upper limb *usage* were borrowed from the study by Bailey et al. [108]. A limitation of this method is that it does not inform on actual hand use. Therefore, it is not possible to confirm whether the activity counts recorded relate to the prosthetic hand being used in an active or passive manner. For future studies, it would, therefore, be worth including a system to also monitor hand movements. This approach was advocated by Sobuh et al. [131] and a recent paper by Rowe et al. [132] demonstrated the potential for a similar approach in the monitoring of anatomically intact upper limb movements. This is outside of the scope for this thesis and will be further addressed in **Chapter 7** as proposed future work.

Finally, reliability and validity of the experimental setups and corresponding outcome measures need yet to be explored. Reliability can be established through a test–retest study in a subset of our planned cohort. Validity of measures, where possible, may be investigated via comparison to related, established measures, for example, by comparing functional measures during the **cylinder task** to SHAP and/or Box and Blocks test scores. For validation of measures characteristic of prosthesis control, we may utilise a known-groups assessment to investigate their sensitivity to distinguish between novice and experienced myoelectric prosthesis users, and we could further conduct a responsiveness study in novice myoelectric prosthesis users to identify whether an individual measure of prosthesis control responds to effects of training to perform the corresponding experimental set up of the protocol.

3.4.2. *Changes to the published protocol*

As noted throughout this chapter, a couple of changes were made to the protocol after its publication in Frontiers in Neurorobotics [109]. In the published work, the prosthesis control chain was only characterised up to the point of EMG signal transduction. As demonstrated in **Section 3.3.2.4**, the *delay* test produced some unexpected results during the pilot study, and further work was therefore required. Since publication, this additional analysis has been undertaken (see **Appendix 4**), and the protocol was adapted.

Another significant change made since publication is the new definition of task completion for the **cylinder task**. As noted, this change was made after inspection of the data from the main study, which will be presented in **Chapter 5**. Full details of the automated approaches to task segmentation for use in the main study are presented in **Appendix 5**.

Finally in the published work, proposals were made relating to the data analysis approaches for the main study. After further inspection of the pilot data alongside the data collected for the main study, these methods have been simplified. This is covered in more detail in **Chapter 5**.

3.5. Conclusion

In this chapter, a protocol was presented for the assessment of user *skill* in controlling EMG signals, *unpredictability* in the acquisition of these signals, and the electromechanical *delay* to hand aperture movement onset. These are to be assessed against overall user *functionality* and everyday *prosthesis usage*. To demonstrate the protocol, results of initial pilot work were presented.

Pilot work and initial analysis of the results suggest that this protocol will be able to successfully identify differences in the *EMG skill* level of participants and characterise the *unpredictability* introduced at the electrode interface, although additional work (see **Appendix 4**) was required to finalise the measurement of *delay*. Data have been successfully collected for each aspect of the functional task that will allow analysis of

how each control factor affects *functionality*. Furthermore, analysis of the activity monitoring data will allow assessment of control factors against *prosthesis usage*.

Although the results presented are not sufficient to draw firm conclusions, Prosthesis User 2 appeared to demonstrate a lower level of *functionality* than User 1, which could be attributed to any of the control factors at this stage. By collecting data across a larger cohort of prosthesis users, it should be possible to identify the relative contributions of these factors.

Finally, although the protocol is relatively long, pilot participants were provided with regular breaks and were happy with the distribution of the tasks; the length of the study was not felt to be excessive. Performing all tasks in a single test session (including breaks to avoid fatigue) has the advantage that it facilitates protocol completion in myoelectric prosthesis users, who are largely part of the working population and, hence, could prove difficult to schedule on multiple occasions within a reasonable time frame. Nevertheless, each experimental setup has been designed in such a way that it could be performed in isolation of other parts of the protocol, providing useful insights on the isolated factor the experiment is concerned with. Hence, while the complete protocol may be predominantly used by researchers due to its complexity, individual parts could be adopted by clinicians to support their decision making.

4

Methodology

Introducing a new method for the visualisation and analysis of everyday upper limb activity

In **Chapter 3**, the protocols developed for the assessment of each of the control factors and the outcome measures were introduced. An improved novel method for the visualisation and assessment of the upper limb activity monitoring data has since been developed. This chapter introduces this technique, illustrated with the user data which was presented in the previous chapter from the two prosthesis users involved in the pilot study. The content of this chapter has been published in Prosthetics and Orthotics International.

*Chadwell A, Kenney L, Granat M, Thies S, Head J, Galpin A; (2017); Visualisation of upper limb activity using spirals: A new approach to the assessment of daily prosthesis usage; Prosthetics and Orthotics International; **42**(1): p. 37-44; DOI: 10.1177/0309364617706751*

4.1. **Introduction**

Upper limb myoelectric prostheses are designed to replace the anatomical arm and restore a level of functionality in people with partial limb loss/absence. To date, clinical studies evaluating myoelectric prostheses have been limited to assessing the ability of the user to perform tasks under controlled conditions. The assessment tools used in these studies have well-known limitations [133] and, at best, provide a 'snapshot' of performance on a small set of tasks, on a given day, typically under 'ideal' conditions. In recent years, research in the field of stroke rehabilitation has questioned the assumption that upper limb capacity, as measured using one-off clinical assessment tools, relates to upper limb usage outside of the clinic [108] and that improvements in clinical *functionality* translate to real-world improvements in upper limb *usage* [134, 135]. These studies raise serious questions with regard to the way in which upper limb prostheses are currently evaluated.

The use or otherwise of upper limb prostheses is currently determined through self-report questionnaires, which rely on accurate and unbiased recall and provide information only on average characteristics [50, 93, 94]. For example, the Trinity Amputation and Prosthesis Experience Scales (TAPES-R) [91] asks participants "On average how many hours a day do you wear your prosthesis". It is also clear that the terminology in the literature used to characterise device use and/or abandonment is inconsistent and often ill-defined, making comparisons between studies difficult. For example, the continuum between active frequent users of a prosthesis and total rejecters encompasses a range of terms including "active users" [94], "passive wearers … who do not use the active capabilities of their device" [42], "partially active users" [94], "occasional users" [28], and "primary and secondary prosthesis rejecters" [51]. The importance of being able to properly understand real-world use of a prosthesis is emphasised by reports of high rates of myoelectric prosthesis rejection [42] and overuse injuries of joints and muscles [44].

Activity monitors offer the potential to objectively characterise upper limb activity outside of the clinic. These monitors typically comprise tri-axial accelerometers, a battery, signal processing and data storage and are worn on the wrist(s). Activity

monitoring has been used successfully in numerous studies to characterise upper limb usage for people recovering from a stroke [108, 136-139]. Despite the clear benefit of obtaining objective data on upper limb motion outside of the clinical environment, we have identified only two previous papers relating to the use of activity monitors for the assessment of people with upper limb absence [96, 109]. In the previous chapter (published as [109]) activity monitoring data were presented from two congenital prosthesis users (PUs), one reporting to be a satisfied and one a dissatisfied user of a myoelectric prosthesis. Participants were asked to wear the monitors on both wrists (anatomical and prosthesis) and, to allow comparison with previously published data, the activity monitoring data were analysed using the methods of Bailey et al. [108].

In Bailey's study, activity monitors (Actigraph GT3X+) were worn on both wrists (monitors were only removed during bathing/showering). Using proprietary algorithms within the Actilife6 software, the data were filtered, grouped into 1s epochs and converted into activity counts [140]. For each second, activity counts across the three axes were summed to generate a vector magnitude ($VM = \sqrt{x^2 + y^2 + z^2}$). Bailey used these vector magnitudes to derive two variables, a "bilateral magnitude" (BM) representing the overall intensity of activity per second across the upper limbs ($BM = VM_{Paretic} + VM_{NonParetic}$) and a "magnitude ratio" (MR) representing the relative contribution of each arm to the activity [$MR = ln(VM_{Paretic}/VM_{NonParetic})$]. Bailey's methods meant that unilateral activity, where the vector magnitude on one of the arms was equal to 0, generated a non-finite MR; consequently, arbitrary values were introduced for unilateral activity (MR = 7 and −7 for unilateral use of the paretic and non-paretic arms, respectively). The data were represented visually by plotting a scatter of the MR (x-axis) versus BM (y-axis) with a colour map used to represent the number of occurrences (seconds) of each point; furthermore, the median MR and BM were reported to provide summary measures of symmetry and intensity of use.

Bailey's methods provided a good initial insight into the upper limb data; however, the somewhat abstracted approach to presentation of the data made interpretation difficult. A simple summary of the amount of activity across the upper limbs over the

monitoring period can be displayed using histograms. The measure of contribution to activity used in Bailey's study (MR) is based off a natural log and is therefore not intuitive; additionally, due to the arbitrary value introduced for unilateral activity, the scale of MR is not continuous. In this chapter, we therefore propose assessing the relative contribution of each arm to the activity as a percentage. In addition, Bailey's methods do not consider temporal patterns in prosthesis usage throughout the day. Temporal patterns may be of particular relevance in this context as users have previously reported problems of discomfort [27, 47, 49-51] and battery life [39, 46, 49, 50], both of which may lead to an increased likelihood of prosthesis non-wear and/or non-use later in the day.

Visualisation of time series whole body activity data has been addressed in a previous study by Loudon and Granat [141]. In this approach, the authors collected data from a thigh worn activity monitor (activPAL3) over a 7-day period. Data were sampled at 20 Hz and proprietary algorithms were used to allocate event markers (upright, lying or sitting) to each sample. Different visualisation methods were used to display the data, including an Archimedean spiral plot, first introduced by Carlis and Konstan [142]. This approach is of particular interest as patterns in activity over time/between days are clearly visible. The properties of an Archimedean spiral are such that a straight line drawn from the origin will intersect each ring of the spiral at the same time point in the data.

This chapter introduces the use of simple histograms of activity counts, together with Archimedean spiral plots to visualise upper limb activity data. The new approaches are illustrated with example data from anatomically intact (AI) subjects and PUs. In brief, we first demonstrate how histograms of activity counts, together with simple descriptive statistics, may be used to illustrate the distribution of activity between limbs over the monitoring period. Second, we show how spiral plots offer the potential to visualise in detail the use of the participant's upper limbs over time. Through the use of graduated colour, there is a potential to quickly see the relative dependence on a particular arm. Finally, we propose that by adapting the spiral plot it would be possible to overlay relevant events such as non-wear or hand activations

to further understand patterns in usage throughout the day. This approach is illustrated by overlaying data from a wear diary onto the spiral plots.

4.2. Methods

4.2.1. *Participants*

Four participants were recruited: two healthy AI participants (female, age: 27 and 28 years, one left and one right-handed) recruited from the University of Salford, and two myoelectric PUs with congenital trans-radial limb absence (male, age: 44 and 45 years, one with left and one with right limb absence) recruited from the University of Salford Prosthetics and Orthotics Professional Patient Database. Both PUs were prescribed with single degree of freedom myoelectric hands. PU1 who reported to be satisfied with his prosthesis had 1.5 years of experience with a myoelectric prosthesis; his prosthesis included a wrist rotator. PU2 had 35 years of experience with myoelectric prostheses; he reported to be dissatisfied with his prosthesis. All participants were recruited as part of a larger pilot study for which activity monitoring was a key outcome measure [109]. Ethical approval for the study was granted by the University of Salford School of Health Sciences Research Ethics committee (REF: HSCR 15-130) and informed consent was gained from all participants.

4.2.2. *Equipment*

Each participant was provided with two Actigraph GT3X+ activity monitors which provide continuous logging of acceleration across three axes at 30 Hz. For PUs, one monitor was worn on the wrist of the anatomical arm and the other on the wrist of the myoelectric prosthesis; for AI participants, one monitor was worn on each wrist. Both monitors were placed on elasticated wristbands labelled as to which wrist they should be worn on and in what orientation they should be worn.

4.2.3. *Protocol*

Participants were asked to wear the monitors for a 7-day period, only removing them when bathing. For the PUs, the monitor worn on the wrist of the myoelectric prosthesis was to remain on the myoelectric prosthesis throughout the week and not

be swapped onto other prostheses the person may use. Participants were asked not to alter their behaviour during the data collection period. Each participant was also supplied with a wear diary to assist interpretation of the activity monitoring data, in which they were asked to record times when they were asleep, and when they removed the monitors or the prosthesis.

Data were downloaded, filtered (employing the low-frequency extension filter [143]) and collated into 1-min epochs (for ease of visualisation) using proprietary Actilife5 software. Furthermore, the processed data were converted into activity counts [140] which were summed across the axes generating vector magnitudes $\left(VM = \sqrt{x^2 + y^2 + z^2}\right)$. The precise algorithm for calculating counts from accelerometer signals is not provided by the manufacturer, however, some attempts have been made to replicate the activity counts from Actigraph sensors using raw acceleration data recorded from sensors produced by alternative manufacturers [144]. Activity counts reflect change in accelerometer readings; hence, no movement would correspond to zero counts. The raw acceleration data, which included both true acceleration and gravity components, were also exported. Data were transferred into MATLAB (v. 2016a) for further analysis.

4.2.4. *Data analysis*

4.2.4.1. HISTOGRAMS

By displaying the data in the form of a histogram, it is possible to visualise the contribution of each arm to all activities undertaken throughout the recording period. The ratio of contribution to activity between the upper limbs is provided as a percentage. The percentage contribution of each arm for each epoch (minute of use) was calculated by dividing the vector magnitude on the dominant/anatomical arm by the total vector magnitude across both arms $[round(VM_{Dom}/(VM_{Dom} + VM_{NonDom}) \times 100)]$; any time points where the vector magnitude across both arms was equal to 0 (no activity) were removed from the dataset. For each percentage band (0–100% in 1% increments), the time in minutes was summed; for ease of visualisation, the time was displayed on a $\log_{10}$ scale to mitigate for large amounts of unilateral activity.

4.2.4.2. SPIRAL PLOTS

A script was written using MATLAB (The Mathworks, Inc.) to produce spiral plots from the CSV data tables exported from the Actilife software. Each epoch was marked with an event marker. Where no activity counts were recorded on either monitor (VM = 0), the epoch was marked as 'both arms at rest', where activity counts were only recorded on one of the arms the epoch was marked as 'unilateral' use of the corresponding limb, and where counts were recorded on both arms, a percentage contribution was calculated (see **Section 4.2.4.1**) and the data were split into 10% bands (**Figure 32**). Colours were allocated to each of these bands, complementary colours were chosen to ensure that patterns of usage would be clearly visible. The periods when there was activity recorded on either/both upper limbs, were given a gradient of colour between unilateral use of the prosthesis and unilateral use of the anatomically intact arm. A spiral was plotted in the form of a 24h clock with midnight at the top. Data were built up day by day working out from the centre.

4.3. Results

4.3.1. *Raw data*

Monitors and completed wear diaries were returned by all four participants. The raw accelerations along all three axes were visually inspected and there were no cases of missing data. Comparison of the raw data with the wear diary showed some disagreement. For one PU (user 2), accelerations were recorded on the monitor worn on the wrist of the prosthesis on days when it was reported in the diary not to be worn by the user; this transpired to be due to the prosthesis being carried. Furthermore, for the same user, self-report showed the prosthesis to be worn for a full 12h when no accelerations were recorded on the monitor. It was assumed that the user had incorrectly used the 24h clock, reporting to don the prosthesis at 05:30 when he should have put 17:30.

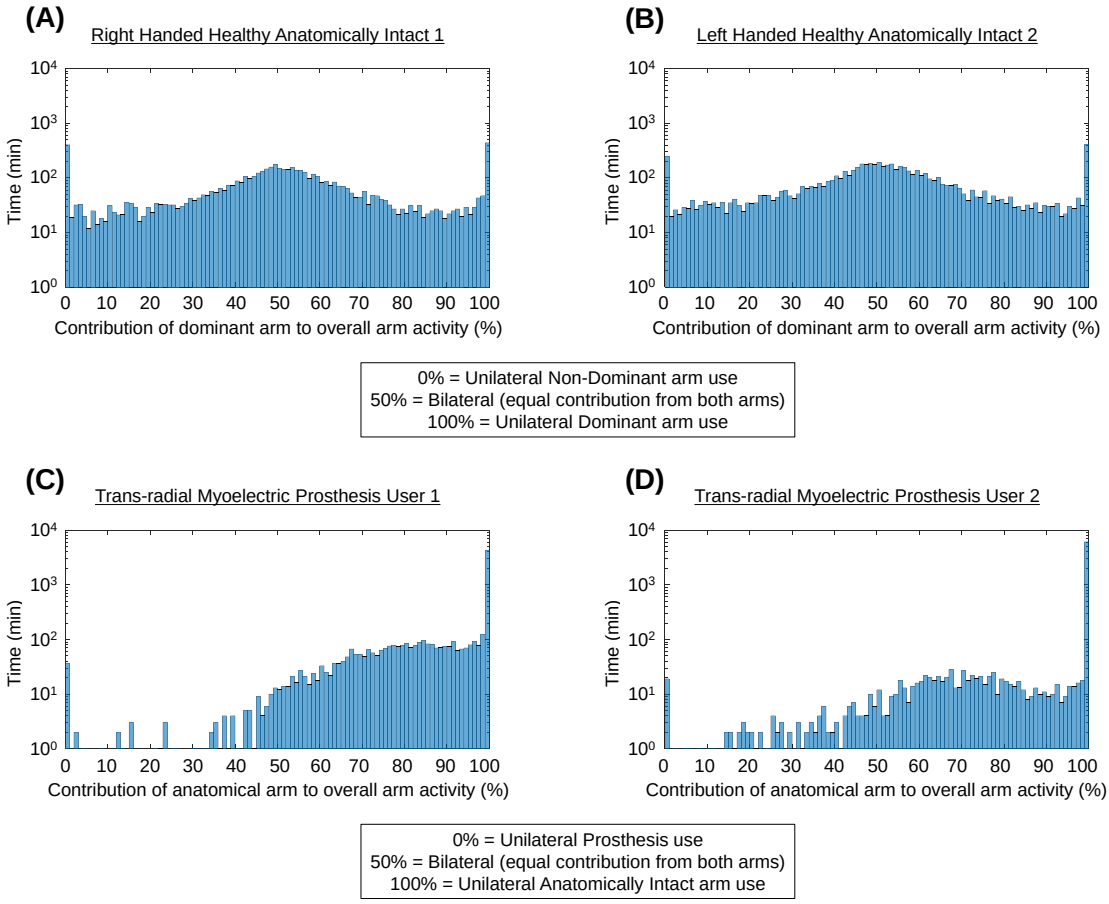


Figure 31. Histograms representing the balance of activity across the upper limbs. **(A, B)** Data recorded for the two anatomically intact participants (1 and 2, respectively) and **(C, D)** data for the two prosthesis users. On the x-axis, the ratio of contribution to activity between the upper limbs is shown as a percentage. 100% indicates unilateral use of the dominant/anatomical limb, 50% indicates equal use of both arms and 0% indicates unilateral use of the non-dominant arm/prosthesis. The data have been grouped into 1% bins, and the y-axis shows the total time in minutes, plotted using a $\log_{10}$ scale. A $\log_{10}$ scale is used for ease of visualisation of the prosthesis user data considering the large amount of unilateral activity on the anatomical arm.

4.3.2. *Histograms*

For the two AI participants (**Figure 31A/B**), the peak in the data is centred around 50% usage of each arm. The median contribution of the dominant arm to the overall activity was 51.20% and 51.27% for participants 1 and 2, respectively. The activity for the two PUs (**Figure 31C/D**), however was, as expected, heavily skewed towards the anatomical arm. For both PUs, the median percentage contribution of the anatomical arm to overall upper limb activity was 100% (unilateral use of the anatomical arm). This value is biased by times when the prosthesis was removed which would also show as unilateral use of the anatomical arm; therefore, the median was re-

calculated only for the times the prosthesis was worn (based on self-report). The median values were 87.64% (wear time: 69.37h) and 87.06% (wear time: 22.05h) for user 1 and user 2, respectively.

All participants demonstrate columns representing unilateral activity (0% = unilateral activity on the non-dominant/prosthesis side, 100% = unilateral activity on the dominant/anatomically intact side). The ratio of unilateral activity between the two arms (dominant ÷ non-dominant or anatomical ÷ prosthesis) allows clear differentiation between healthy AI participants and PUs. Both AI participants demonstrated almost equal unilateral activity on each arm (ratio = 1.03:1 and 1.68:1). The ratio for the PUs was once again skewed by the prosthesis non-wear times (ratio = 115.42:1 and 230.21:1); however, when only the wear time was considered, both users demonstrated similar ratios to each other (ratio = 29.61:1 and 24.11:1).

4.3.3. *Spiral plots*

In **Figure 32**, data are presented from the two AI participants and two PUs. Immediately, a colour difference can be seen between the two pairs of participants due to the reliance on the anatomical hand for the PUs. Furthermore, the period when the participants were asleep can also be clearly seen. **Figure 32E/F** shows magnified sections for AI participant 1 and PU1 (during a period when the prosthesis was worn) highlighting differences in upper limb usage between the two. The upper limb activity for the AI participant (**Figure 32E**) is predominantly bilateral (blue), interspersed with bursts of unilateral activity on both the dominant and non-dominant sides. In comparison, the PU (**Figure 32F**) demonstrates very little unilateral prosthesis use (green) and large amounts of unilateral use of the anatomical arm (magenta); on occasions where the PU is performing bilaterally, there is a preference towards the anatomical arm as demonstrated by the purple colouring.

To demonstrate the capacity of these plots for inclusion of additional data, **Figure 33** shows data from PU1 in which self-reported removal of the prosthesis (black) has been included. If the self-report is accurate, it would be expected that during the

black periods all data points would be orange or magenta (no activity on the prosthesis).

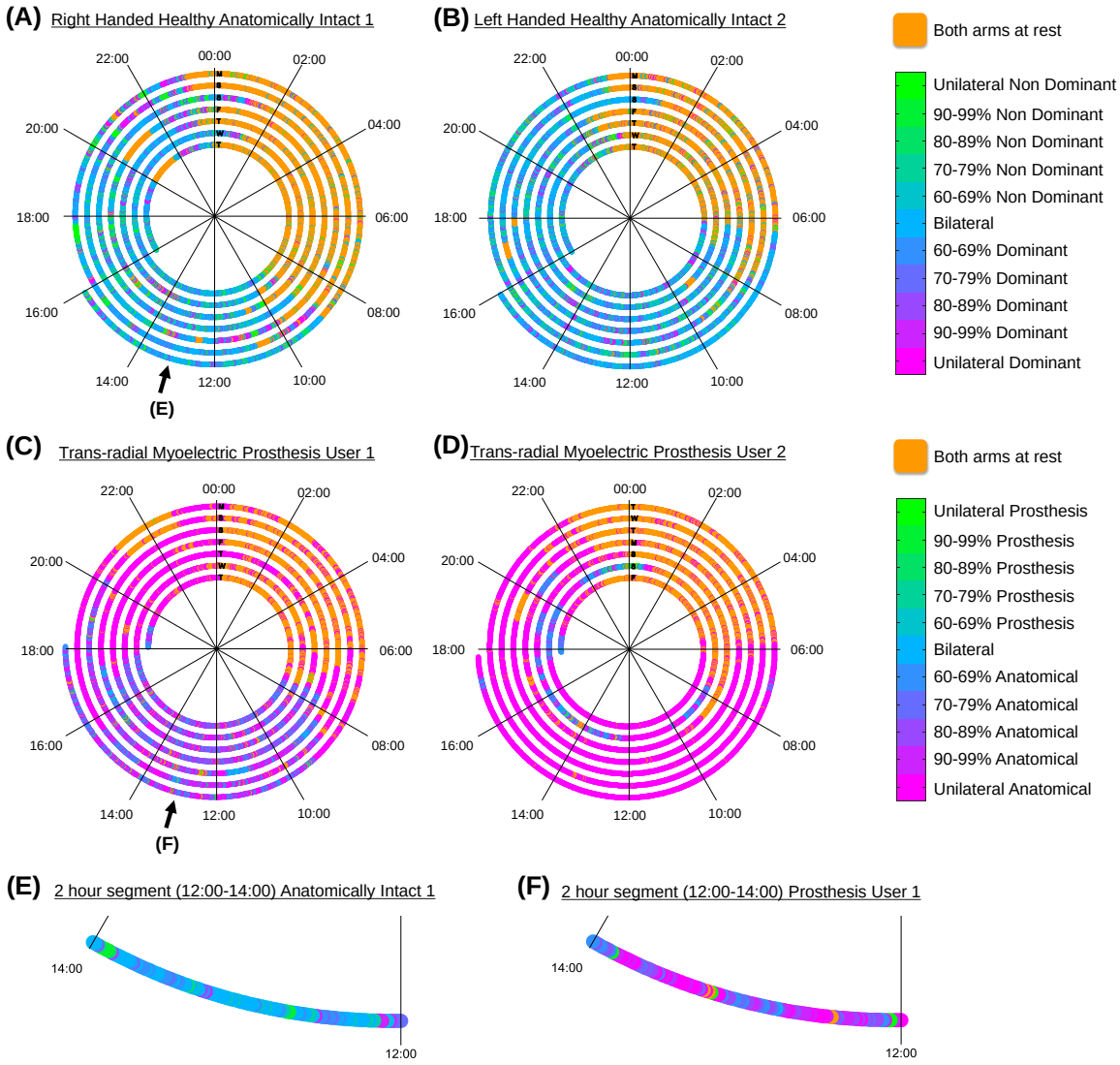


Figure 32. Upper limb activity recorded from two wrist worn activity monitors. Each graph **(A–D)** represents data recorded over a 7-day period, with each ring representing 24 h. Progression of time is from the centre outwards. Each ring is labelled with a letter signifying the day of the week corresponding to the subsequent 24 h of data. The scale in the legend displays colours relating to the ratio of activity counts recorded on each monitor. **(A)** Right-handed healthy anatomically intact participant, **(B)** left-handed healthy anatomically intact participant, **(C)** myoelectric prosthesis user with congenital trans-radial limb absence on the right-hand side – Prosthesis User 1 (self-reports to be satisfied with prosthesis), **(D)** myoelectric prosthesis user with congenital trans-radial limb absence on the left-hand side – Prosthesis User 2 (self-reports to be dissatisfied with prosthesis). **(E, F)** Expanded views of the 2 h segment between 12:00 and 14:00 on the final day (Monday) for **(E)** anatomically intact participant 1 and **(F)** Prosthesis User 1.

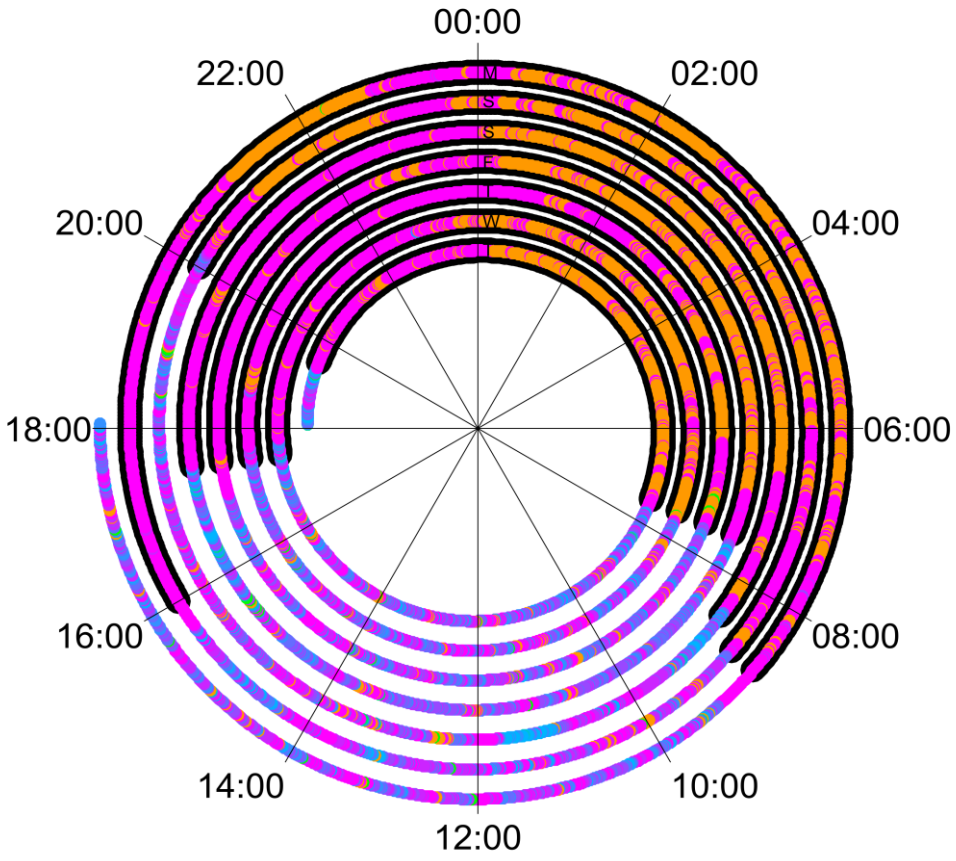


Figure 33. Data for Prosthesis User 1 with an underlay of information from the wear diary. The black markers represent times when the user reported removing the prosthesis, approximately from 18:00 to 08:00. It would be expected that these would align with times when only the anatomical arm showed to be active or when there was no activity on either arm. The participant slept from approximately midnight to 7am as can be seen by the increase in periods where both arms were at rest (orange).

4.4. Discussion

Research in the field of stroke rehabilitation has highlighted both the limitations with self-report as a tool for assessment of real-world upper limb use and, perhaps more importantly, that clinically assessed upper limb functionality correlates weakly with real-world arm usage. These findings raise questions with regard to current upper limb prosthetics research. Previously, we reported the first real-world data on upper limb prosthesis use [109], but the data visualisation tools used were limited in scope; they did not provide a clear summary of upper limb activity over the recording period, nor did they illustrate the temporal patterns in the data.

Archimedean spirals, combined with histograms, offer a promising approach for the display of upper limb activity. Using these plots, very clear differences in upper limb

usage behaviours between PUs and AI participants were observed, as well as patterns in behaviour in relation to time-of-day. The benefit of these plots over the methods used previously is that changes in the patterns of behaviour can be easily identified. For example, PU1 (**Figure 32C**) reported to be fairly satisfied with his prosthesis; however, it is clear that he regularly removed his prosthesis around 17:00–19:00 for the remainder of the evening, shown by the large portion of magenta representing unilateral activity of the anatomical arm during the evening period (validated by comparison with the wear diary - **Figure 33**). The spiral plots also offer the potential for the display of additional data by under-laying thicker lines around the existing spiral. In future, if further data could be logged regarding the way the prosthesis is used, such as hand activations, then this could be plotted over the activity monitor data to help explain potential patterns in prosthesis use/non-use or highlight passive prosthesis use.

The use of accelerometers to characterise upper limb activity is not without its limitations [145]. For example, the analysis of wrist-worn accelerometer data presented here does not discriminate between the swinging of the arm during walking and active functional use of the upper limb. Furthermore, the choice of epoch length can impact on the amount of unilateral activity recorded. Nevertheless, wrist-worn accelerometry has gained acceptance as an objective measure of upper limb activity outside of the clinic [146].

The data displayed in this chapter are part of a larger study designed to improve our understanding of factors contributing to user performance with upper limb myoelectric prostheses. The PUs involved in the study, therefore, only wore the activity monitors on their myoelectric prostheses, despite one of them wearing an alternative prosthesis during some of the days of testing. It is therefore not possible to differentiate unilateral use of the anatomical arm from bilateral activity with either the residual limb or a secondary prosthesis. In future, studies addressing the more general question about upper limb activity should place activity monitors on the wrist of all prostheses the participant may wear (e.g. a cosmetic, or body-powered secondary prostheses). Furthermore, it may also be useful to assess the usage of the residual limb; by placing monitors on the upper part of both arms, it

may be possible to gain an insight into times when the prosthesis was removed, times it may have been carried, and information about bilateral activity at times when no prosthesis was worn. These approaches, however, do raise significant questions about practicality, and until such time as prosthesis non-wear can be accurately identified, data should be considered in parallel to a wear diary.

A further limitation raised in the previous chapter regarded the lack of ability of the activity monitors to inform on active prosthesis use; from this data, we can only determine that there was movement of the upper limb, we cannot infer that the user was opening or closing the hand. These limitations should be considered during the analysis of the data we have presented, however, as has been highlighted in this chapter, there is a capacity within the spiral plot design to reflect more advanced information if it were to be available.

Finally, the spirals have been designed to display data derived from pre-processed activity counts, generated by the Actilife software. In future, it would be more beneficial to derive the percentage contribution of each arm from the raw accelerations, this would enable compatibility with activity monitors from different manufacturers.

5

Results

Investigating the impact of skill, unpredictability and delays on user performance

5.1. Introduction

This thesis aims to establish the relative impact of the *EMG skill* of a user, *unpredictability* introduced at the interface between the electrodes and the skin, and the electromechanical *delay* in the prosthesis itself, on measures of *user performance*.

In **Chapter 3** the protocol for the assessment of each of these factors was introduced. Here, data collected from a multi-site study of twenty trans-radial myoelectric prosthesis users are presented.

5.2. Methods

5.2.1. *Ethical approval*

Ethical approval for this study was granted by the School of Health Sciences Research Ethics committee (REF: HSCR 16-25), by the University of Strathclyde Department of Biomedical Engineering Ethics Committee (DEC.BioMed.2017.220) and through the NHS IRAS system (IRAS Project ID: 193794). Informed consent was gained from all participants.

5.2.2. *Recruitment centres*

Four NHS mobility centres were involved in this study. Seven participants were recruited from Manchester Specialised Ability Centre, four from the Douglas Bader Rehabilitation Centre in Roehampton, three from Sheffield Mobility and Specialised Rehabilitation Centre, and two from the Nottingham Mobility Centre. An additional two participants were recruited through their links with the University of Salford, and two through their links with the University of Strathclyde.

5.2.3. *Participants*

Participants with unilateral upper limb absence at a trans-radial level were recruited. All participants had been prescribed a single degree of freedom myoelectric prostheses (e.g. Steeper Select or Ottobock DMC Plus/VariPlus/Sensor Speed). Regular use of the prosthesis was not a requirement.

5.2.3.1. DEMOGRAPHICS

Twenty participants (14 male, 6 female), age range 18-75 (mean age 53) were recruited. Time since prescription of a myoelectric prosthesis ranged from 1.5-39 years (mean 20). Eleven people were recruited with congenital limb absence (6 Right/5 Left), and nine with an amputation (6 Right/3 Left); six of the amputations had occurred on the dominant side. Time since amputation ranged from 8-47 years (mean 25).

5.2.4. *Protocol*

Each participant attended a 3-4 hour testing session. Here the protocol will be briefly summarised, for full details see **Chapter 3**.

5.2.4.1. ASSESSMENT OF EMG SKILL

Three separate tasks were used to assess the *EMG skill* of the user, these will be referred to as: (1) **intuition task**, (2) **static tracking task**, and (3) **dynamic tracking task**. For all of these tasks, the "ideal" electrode placement introduced in **Chapter 3** (**Section 3.2.1.1**) was used, this involved bandaging the electrodes to the optimal positions on the residual limb and setting the gains appropriately.

The **intuition task** aimed to measure the time taken for the user to decide which muscles to contract in order to open or close the prosthetic hand. This task consisted of the simple and choice reaction time tasks (SRT & CRT tasks) introduced in **Chapter 3** (**Section 3.2.1.2**). Participants completed 10 trials of the SRT hand opening task, followed by 10 trials of the SRT hand closing task. 20 CRT trials were then undertaken. A "decision time" was calculated based on the difference between the mean CRT and mean SRT.

The tracking tasks (**Section 3.2.1.3**) aimed to establish the level of control the user had over the amplitude of the EMG signals. Both of the tracking tasks used the Myoboy® with the PAULA software developed by Ottobock Gmbh.

The **static tracking task** involved the participant sustaining their myoelectric signal between on screen boundaries of 39 and 51 for a period of 3 s. Participants were scored based on the percentage of time the signal stayed within the boundaries.

Three trials were given for each muscle (open then close) for the participant to get the best scores they could.

The **dynamic tracking task** used a "car game" integrated into the PAULA software. The game involved the participant steering a car past on screen obstacles; the height of the car on the screen was controlled using the amplitude of the EMG signals from each of the muscles. Participants were scored based on the percentage of obstacles successfully avoided (best of 2 trials). Initially participants were given one car to control, first using their open signal (2 trials) and then using their close signal (2 trials). Finally participants were given two cars to control simultaneously (one car for each muscle); again two trials were given for the participants to get the highest score they were able.

5.2.4.2. ASSESSMENT OF UNPREDICTABILITY

To assess the *unpredictability* introduced at the interface between the electrodes and the skin three different conditions were evaluated. Task performance was compared between the "ideal" interface used in the previous section, and between two conditions where the user's own socket was worn ("Normal" and "Additional load" where an 500g weight was added at the hand).

Two metrics of *unpredictability* were assessed: the **desired activation** of the hand when the participant attempted to activate it, and the **undesired activation** of the hand when the participant did not attempt to activate it.

The **desired activation** was evaluated using simple reaction time (SRT) tasks. To exacerbate the problems with *unpredictability* experienced by some users, two arm positions were evaluated (45° above and below the horizontal) (see **Chapter 3 Section 3.2.2** for more details). Participants completed 20 open trials and 20 close trials for the "ideal" interface. For each of the socket conditions 10 open and 10 close trials were undertaken; for analysis the results for the two socket conditions were combined. The standard deviation of the reaction times was calculated for both the "ideal" interface and the combined socket conditions. The "*unpredictability*" of the **desired activation** introduced by the socket interface was calculated according to $Difference\ in\ Spread = SD_{Socket} - SD_{Ideal\ Interface}$.

To assess the number of **undesired activations**, participants were asked to move their arm between the two positions (±45°). The number of undesired activations of the hand were recorded (24 'transitions' were undertaken for the "ideal" interface and 12 for each of the socket conditions).

5.2.4.3. ASSESSMENT OF DELAYS IN THE MYOELECTRIC CONTROL SYSTEM

The *delay* was calculated as the time from stimulation of electrodes until the onset of hand movement. The *delay* to the onset of hand opening was measured from a fully closed position ($delay_{O\_C}$) and from a neutral position ($delay_{O\_N}$) (5 times each), the *delay* to the onset of hand closing was measured from a fully open position ($delay_{C\_O}$) and from a neutral position ($delay_{C\_N}$) (5 times each).

5.2.4.4. ASSESSMENT OF CLINICAL FUNCTIONALITY

As noted in **Chapter 3, Section 3.2.4** participants were asked to perform a multi-stage functional task where they were asked to reach to grasp a cylinder, lift and rotate it, and place it into a horizontal tube. Three difficulty levels were available to the participant; in this chapter, data will only be presented on the medium difficulty task which was undertaken by all twenty participants to allow a direct comparison of performance.

User *functionality* was evaluated based on:

- **Task success** – the number of trials successfully completed (out of 10)[6],
- **Task duration** – the mean duration across the 10 trials,
- **"Delay plateau" length** – the delay in the onset of hand opening as a percentage of the "reach-to-grasp" phase (mean of 10 trials),
- **"Reach plateau" length** – the length of the plateau between hand opening and the hand closing around the cylinder as a percentage of the "reach-to-grasp" phase (mean of 10 trials),

[6] Half points were given if the task was not completed in one smooth movement e.g. the hand opened and closed more than once during "reach-to-grasp".

- **Movement variability** – the temporal variability [120] in the tri-axial acceleration of the forearm (measured at the wrist) across the 10 trials,
- **Gaze patterns**[7] – the percentage of time spent looking at the hand during the "reach-to-grasp" phase (mean of 10 trials), the percentage of time spent looking at the grasp critical area (GCA) of the cylinder during the "reach-to-grasp" phase (mean of 10 trials), the percentage of time spent looking at the hand or the GCA during the "transport" phase (mean of 10 trials), and the percentage of time spent looking at the location critical area (LCA) of the cylinder or at the tube during the "reach-to-grasp" phase and during the "transport" phase (mean of 10 trials).

5.2.4.5. ASSESSMENT OF EVERYDAY PROSTHESIS USE

To evaluate actual *usage* of the prosthesis outside of the clinic, participants wore an activity monitoring sensor (tri-axial accelerometer), on each wrist over the period of 7 days. As described in **Chapter 4**, the percentage reliance on the anatomically intact arm can be calculated for each epoch of activity data using the following equation:

$$[\%Reliance_{Anat} = round(VM_{Anat}/(VM_{Anat} + VM_{Pros}) \times 100)]$$

The activity monitors allowed the measurement of:

- "***Prosthesis wear time***" (calculated using the non-wear algorithm introduced in **Appendix 7b**),
- The median of the percentage reliance values over the 7-day period (termed "***Median %Anatomical***"),
- The time spent using the anatomical and prosthetic arms unilaterally (termed "UL_{Anat}" and "UL_{Pros}"), and

[7] As noted in **Chapter 3**, the gaze coding scheme was adjusted between the pilot study and the main study presented here. This included separation of the "reach-to-grasp" phase from the "transport" phase, and reduction of the number of AOIs. For full details, see **Section 3.2.4.5** and **Appendix 6**.

- The ratio between the unilateral use of each arm (termed "***Unilateral ratio***" = "UL_{Anat}" : "UL_{Pros}"). [8]

5.2.5. *Statistical analysis*

5.2.5.1. DESCRIPTIVE STATISTICS

In the first part of the results section (**Section 5.3.1**), data are presented from the twenty participants. Each participant was provided a score for each measure (the calculation of which is summarised in **Table 6**); in **Section 5.3.1** the central tendency and spread of these scores between participants are reported. The scores for some participants were detected as outliers, therefore for the majority of measures the median and interquartile range (IQR) values are reported; where the data was suitable the grand mean and standard deviation (SD) are reported (see **Table 6** for more details). For all measures where the tasks were undertaken both for hand opening and for hand closing, the results are presented separately (e.g. the static task opening score and the static task closing score are presented rather than a mean static task score combining the two).

5.2.5.2. CONTROL FACTOR REDUCTION

A number of aspects of each control factor were measured. To establish whether these measures were suitable for reduction into the single factors of *EMG skill*, *unpredictability*, and *delay*, Kendall's Tau-b correlations were explored using the IBM SPSS Statistics software (**Section 5.3.2.2**). Kendall's Tau-b was chosen as the most appropriate non-parametric test due to some measures containing a large number of tied ranks. Kendall's Tau-b is also reported to work well for small sample sizes. Where the measures appeared to correlate, Principle Component Analysis (PCA) was used to investigate whether a single factor might be used to represent the data (see **Appendix 8**).

[8] These measures were first introduced in **Chapter 4**. The calculation of each of these measures, including the methods used to determine wear time are explained in more detail in **Chapter 6.**

Table 6. Summary explanation of the descriptive statistics presented in **Chapter 5**. The "ideal" electrode-skin interface involves bandaging the electrodes to the skin.

Task	Interface condition	Muscle/ Movement direction under assessment	Calculation of score for each participant	Descriptive statistics across participants
EMG SKILL ASSESSMENT				
Static tracking task	"Ideal"	Opening	Best score (out of 3 trials)	Median (IQR)
Static tracking task		Closing		
Dynamic tracking task (1 signal at a time)	"Ideal"	Opening	Best score (out of 2 trials)	
		Closing		
Dynamic tracking task (2 signals at once)		Opening		
		Closing		
Simple Reaction Time (SRT) task	"Ideal"	Opening	Descriptive statistics are presented (median and IQR) describing the full dataset rather than between participant differences	
		Closing		
Choice Reaction Time (CRT) task		Opening		
		Closing		
Decision Time		Opening	Mean CRT (10 trials) - Mean SRT (10 trials)	Median (IQR)
		Closing		
UNPREDICTABILITY ASSESSMENT				
No. of completed Reaction Time task responses	"Ideal"	Opening	Out of 20 trials	Median (IQR)
		Closing		
	Socket	Opening		
		Closing		
Spread of Reaction Times	"Ideal"	Opening	SD across 20 trials	
		Closing		
	Socket	Opening		
		Closing		
Difference in RT spread between the interfaces	N/A	Opening	SD Socket - SD "ideal"	
		Closing		
No of undesired hand activations	"Ideal"	Opening	Out of 24 trials	Median (IQR)
		Closing		
	Socket	Opening		
		Closing		
DELAY ASSESSMENT				
Delay from closed	N/A	Opening	Mean of 5 trials	Grand mean (SD)
Delay from neutral		Closing		
Delay from open				
OUTCOME MEASURES				
Success rate	Socket	N/A	Out of 10 trials	Median (IQR)
Task duration			Mean of 10 trials	Grand mean (SD)
Delay plateau				
Delay plateau				
Variability			Warp cost across 10 trials	Median (IQR)
Gaze measures			Mean of 10 trials	
Activity measures			Single value per person	Median (IQR)

5.2.5.3. FUNCTIONALITY MEASURE COMPARISON

To provide confidence in the measures of *functionality*, building on the analysis of Bouwsema [85], Thies [87], and Sobuh [88] who showed correlations between measures such as variability, the time spent looking at the hand, and the length of the "reach plateau" with task success and speed of performance measures, the strength of the correlations between the different measures of functionality were tested. Kendall's Tau-b correlations were performed using the IBM SPSS Statistics software (**Section 5.3.2.3**).

5.2.5.4. EVALUATING RELATIONSHIPS BETWEEN CONTROL FACTORS AND USER PERFORMANCE

Based on initial analysis of the data the multiple regression analysis proposed in **Chapter 3** was found to be inappropriate; the sample size (number of participants) was too small, and as will be presented in **Section 5.3.2.2**, the data was not suitable for reduction (using Principle Component Analysis) into single variables representing the three control factors. An alternative analysis was therefore carried out to identify the strength of correlations between the various measures of *EMG skill*, *unpredictability* and *delay* and the measures of *user performance*. The analysis, which is based on Kendall's Tau-b correlations is presented in **Section 5.3.2.4**.

5.2.5.5. STATISTICAL POWER AND SAMPLE SIZES

As the original study design was exploratory a power calculation was not performed. To aid the interpretation of the findings and to guide future researchers in this field, statistical powers and sample sizes were calculated using the G*Power 3.1.9.2 software.

G*Power was used to calculate the statistical power achieved within this study based on the effect and sample sizes (α=0.05). The software was also used to establish the sample size that would be needed in future repeats of this work to provide a power of 0.8 (80% chance of detecting a statistically significant effect where there is one) for an effect size ≥0.3.

G*Power does not have an in-built function to calculate sample size for Kendall's Tau-b correlations. Therefore, the sample size for the equivalent Pearson's-r correlation was calculated, and multiplied by 1.1 [147]; similarly to calculate the achieved power the sample size was divided by 1.1.

In this chapter, all correlations with coefficient (τ_b) greater than 0.3, and less than a 5% chance of incorrectly detecting an effect where none exists ($p<0.05$) are reported regardless of the sample size. The sample size is also presented.

5.3. Results

5.3.1. *Data summary*

5.3.1.1. EMG SKILL

Intuition Task

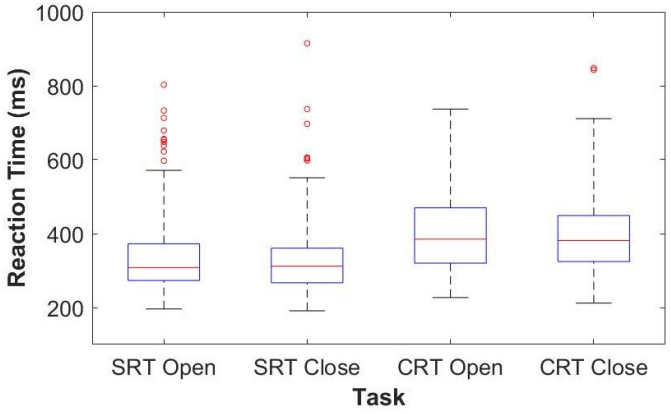
Trials where the participant reacted early (before 100ms [129]), reacted late (after 1000ms [129]), or responded with the incorrect response (e.g. opened the hand instead of closing) were excluded from the analysis. For the SRT task 11 of the 400 trials (20 participants, 20 trials each) were excluded; for the CRT task 36 of the 400 trials were excluded.

The remaining reaction time data showed a group median[9] SRT of 308ms for opening the hand and 312ms for closing the hand. The group median CRT was slightly higher at 385ms for opening the hand, and 381ms for closing the hand (**Figure 34**).

For each participant a mean of each set of responses (SRT opening, SRT closing, CRT opening, and CRT closing) were used to calculate the "decision times".

$$\boldsymbol{Decision\ Time = Choice\ Reaction\ Time - Simple\ Reaction\ Time}$$

[9] The group median is the median of all values recorded from all participants

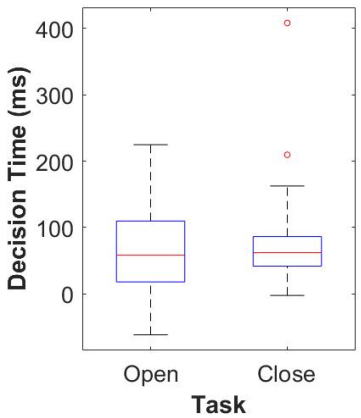


	SRT (ms)		CRT (ms)	
	Open	Close	Open	Close
Min	196	191	227	212
Q1	273	267	320	324
Q2	308	312	385	381
Q3	373	361	471	451
Max	803	915	737	848

Figure 34. Box plots comparing the Simple Reaction Time (SRT) and Choice Reaction Time (CRT) values recorded across the twenty participants for hand opening and hand closing. NB. Values greater than 2.2*IQR above Q3 are marked as outliers [148]. No outliers were detected in the region below Q1.

For three of the participants the "decision time $_{OPEN}$" was negative (meaning the mean SRT was longer than the mean CRT), and for one of these three participants the "decision time $_{CLOSE}$" was also negative.

The median "decision time $_{OPEN}$" across participants was 58ms, whilst the median "decision time $_{CLOSE}$" was 62ms (**Figure 35**). The participant with the maximum "decision time" of 408ms struggled to respond correctly to the CRT task and only managed to correctly complete 1 CRT closing trial out of 10. All other participants successfully completed at least 7 of the 10 trials for each group of responses (median = 10/10).

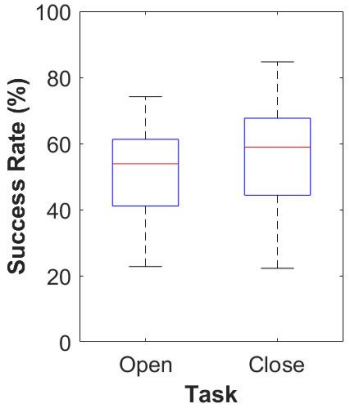


	DT (ms)	
	Open	Close
Min	-62	-3
Q1	12	41
Q2	58	62
Q3	112	90
Max	225	408

Figure 35. Box plot describing the "Decision Times" calculated for the twenty participants for hand opening and hand closing. NB. Values greater than 2.2*IQR above Q3 are marked as outliers [148].

Static Tracking Task

The **static tracking task** was designed to be sufficiently difficult so that no participant was likely to achieve a perfect score where the signal was kept within the boundaries for the full 3 s. As demonstrated in **Figure 36**, the results showed clear differences between participants. For the muscle used to open the hand (wrist flexor), the median score was 54%, and for the muscle used to close the hand (wrist extensor), the median score was 59%. **Figure 37** shows an example of **(A)** the minimum (22%) and **(B)** the maximum (85%) wrist flexor (hand closing) attempts.



	Success Rate	
	Open	Close
Min	23 %	22 %
Q1	40 %	44 %
Q2	54 %	59 %
Q3	61 %	69 %
Max	74 %	85 %

Figure 36. Box plot describing the scores on the static task using the muscle signal for hand opening and the muscle signal for hand closing for the twenty participants.

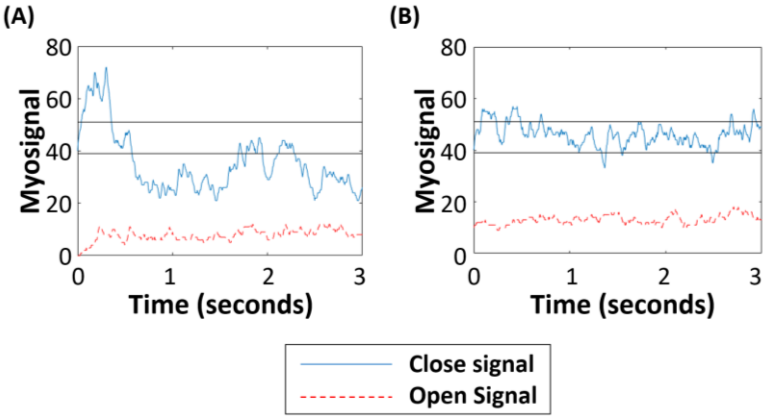
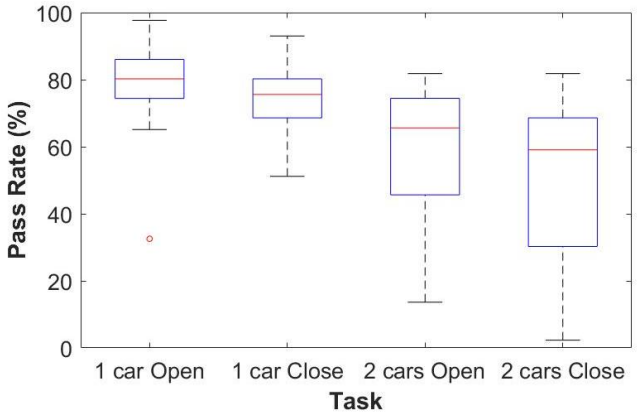


Figure 37. Static Tracking Task closing trial example for the **(A)** worst (22%) and **(B)** best (85%) performers. Participants were instructed to keep the blue signal (controlled using the muscle for hand closing) inside the boundary lines, whilst keeping the other muscle (red) relaxed. The trial lasted 3 seconds.

Dynamic Tracking Task

The **dynamic tracking task** allows the assessment of a participant's ability to adjust the amplitude of their EMG signals in response to time-varying targets. The first part of the task involved controlling a single car; the second part of the task involved controlling two cars simultaneously (one with each muscle). Participants were scored based on the percentage of obstacles successfully passed by each car. Data describing scores for the twenty participants on both parts of the task are presented in **Figure 38**.



	1 car		2 cars	
	Open	Close	Open	Close
Min	33 %	51 %	14 %	2 %
Q1	73 %	68 %	43 %	29 %
Q2	80 %	76 %	66 %	59 %
Q3	86 %	81 %	75 %	69 %
Max	98 %	93 %	82 %	82 %

Figure 38. Box plots describing the dynamic task scores for the twenty participants. Participants generally performed better when asked to control the movement of 1 car at a time (steered through the obstacles using a single muscle signal) than when asked to control the movement of 2 cars at the same time (using one muscle signal to control the amplitude on the screen of each car). For each task participants were provided with a score for the percentage of gaps (both high/contraction and low/relaxation) successfully passed through without crashing for each of the two muscle signals over the 1 minute testing period. During the one car task the muscles were assessed independently of each other; during the two car task, the participant was required to pay attention to both signals controlling them simultaneously. Results for the muscle signal for hand opening and the muscle signal for hand closing are presented separately.

For the first part of the task, controlling one car using the wrist extensor (open) signal the median pass rate was 80%, and for the wrist flexor (close) signal the median pass rate was 76%.

For the second part of the task, controlling two cars simultaneously (one with each muscle), on average the pass rates were lower. For the wrist extensor (open) signal the median pass rate was 66%, and for the wrist flexor (close) signal the median pass rate was 59%.

It is worth noting that some participants struggled to complete the two car task. **Figure 39** provides some example screenshots to help to illustrate some of the scenarios described here. For comparison, **Figure 39A** shows the successful completion of the two car task.

Two participants only passed 1 of the 43 obstacles using their close signal, these participants self-reported struggling to visually track both cars on the screen at once (**Figure 39B**). For both participants a significant decrease in the score for the close muscle was seen, but an improvement was seen in the pass rate for the open signal compared to the single car task (shown by the orange lines in **Figure 40** [10]).

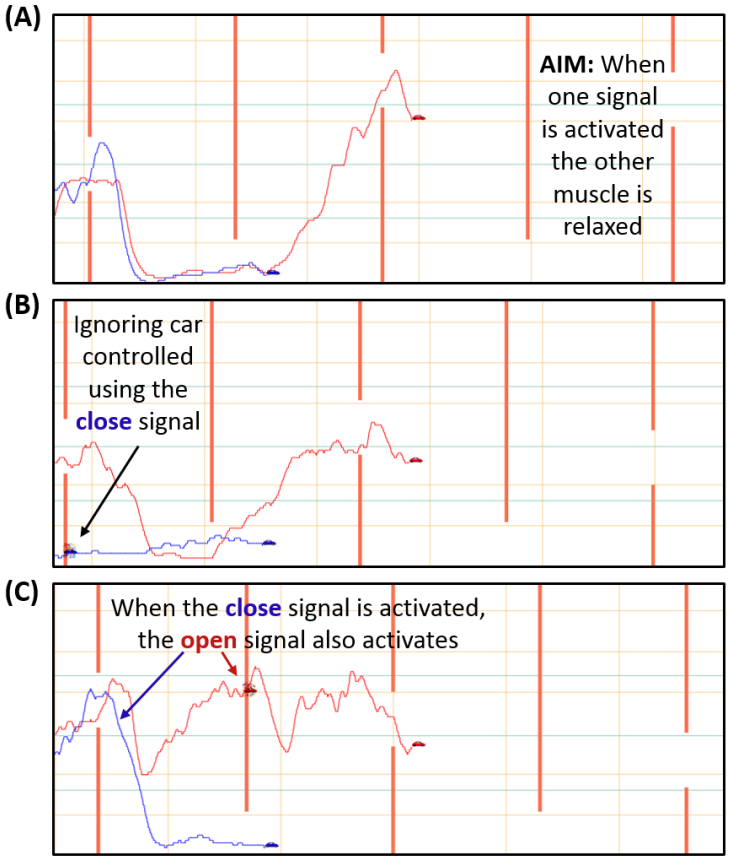


Figure 39. Example images of dynamic tracking task with two cars to be controlled. **(A)** the aim of the task is to keep one muscle relaxed whilst the other is contracted, **(B)** if the rear car is ignored, the car will crash and the score for the 'close' signal will reduce, and **(C)** if the 'open' signal activates each time the 'close' signal is activated then the car will crash. NB. These are just two examples of poor control.

[10] Both participants scored the same for both parts of the task using the open signal so the two orange lines are over the top of each other in the first plot.

Similarly two participants performed poorly in the two car task using their hand opening signal (**Figure 40** highlighted in purple), but managed to improve their scores using the close signal. For these two participants, this could potentially be explained by an inability to activate the close signal without also contracting the antagonistic muscle (**Figure 39C**).

All other participants performed better when only given one car to control than when attempting to control both cars simultaneously (shown by the green lines in **Figure 40**).

One participant performed particularly poorly on all of the **dynamic tracking tasks** (shown by the blue line in **Figure 40**); this participant struggled to contract either muscle group without also contracting the antagonistic group.

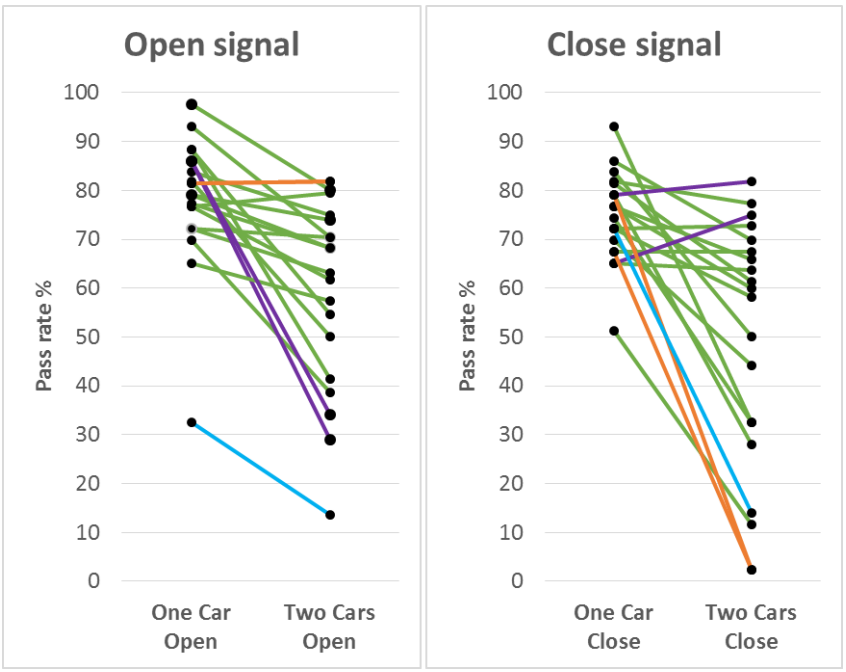


Figure 40. Dynamic tracking task results for each of the 20 participants. The majority of participants performed better in the single car task (controlling the amplitude of one muscle signal at a time) than in the two car task (controlling the amplitude of both muscle signals simultaneously).

5.3.1.2. UNPREDICTABILITY

Desired activation

Across the twenty participants, 800 reaction trials were undertaken using the "ideal" interface (769 successful), and a further 800 trials were undertaken using one or other of the two socket conditions (693 successful) (see **Figure 41** for a breakdown of the failed trials by participant). Unsuccessful trials were identified as those where the participant responded early (<100ms) or late (>1000ms) [129] and those trials where the participants moved the hand in the wrong direction (i.e. opening during a closing trial). A note was kept if the participant believed that they were attempting to make the correct response. As shown in **Figure 42** the median reaction times were similar between the "ideal" interface condition and the socket conditions.

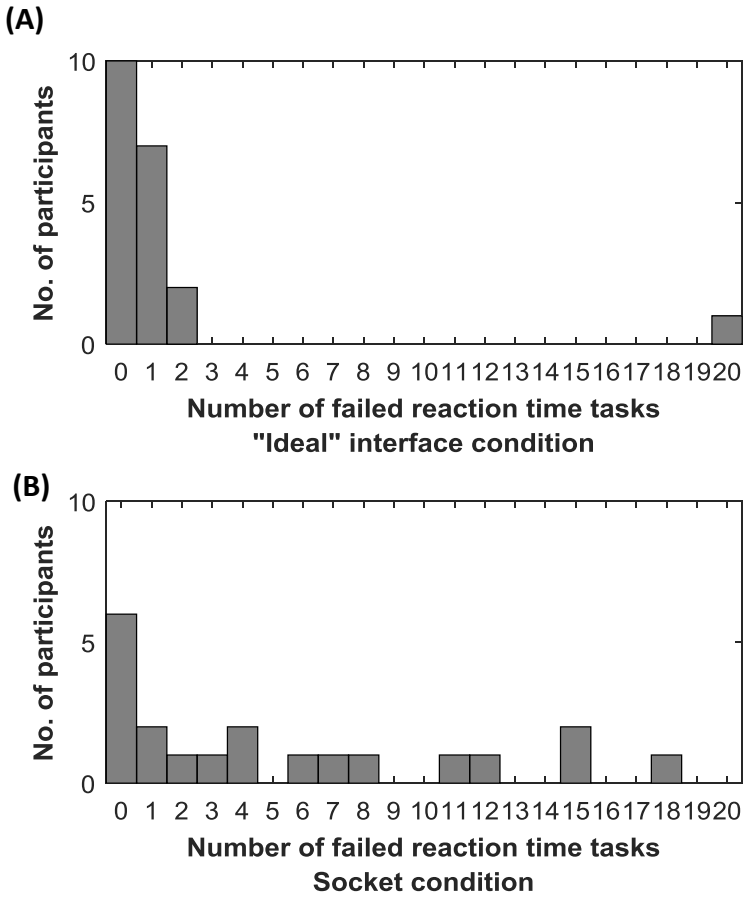
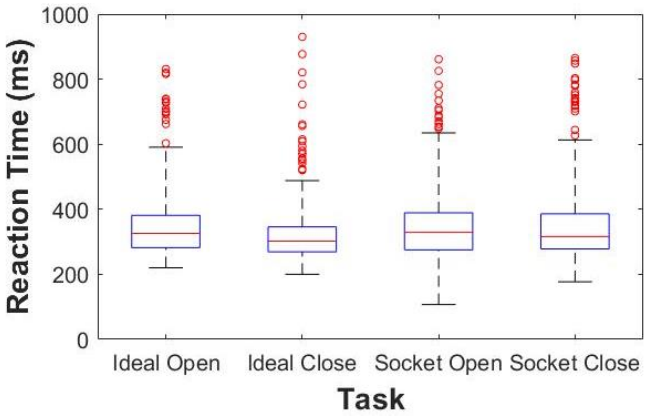


Figure 41. Number of failed reaction time task responses during the assessment of unpredictability for each participant using **(A)** the "ideal" interface and **(B)** the prosthetic socket (both with and without the additional 500g load attached to the hand).

In the socket conditions some participants were unable to operate the hand at all with their arm in the +/- 45° positions, this is reflected in a low number of successful responses e.g. one participant completed none of the 10 closing SRT trials with the arm held at a -45° angle as they were unable to close the hand without pressing the socket (and electrodes) against the arm with their anatomical hand.

As shown in **Figure 41A** one participant struggled to operate the hand using the "ideal" interface (correct responses = 13/20 for hand opening and 7/20 for hand closing); from discussions with the participant it is possible that the lack of a prosthetic socket was causing them confusion as to how to operate the hand ('overthinking'), and they therefore regularly responded too slowly or with the incorrect muscle activation. When undertaking the same task using their own prosthesis, they successfully completed 14 open and 11 closing trials.



	"Ideal" (ms)		Socket (ms)	
	Open	Close	Open	Close
Min	220	200	107	177
Q1	282	269	275	278
Q2	326	302	329	316
Q3	382	346	389	387
Max	831	930	861	865

Figure 42. Box plots comparing the reaction times recorded for the "ideal" interface and the two combined socket conditions across the twenty participants. NB. Values greater than 2.2*IQR above Q3 are marked as outliers [148]. No outliers were detected in the region below Q1.

For the other 19 participants, all participants completed over 38/40 responses correctly for the "ideal" interface condition. Eight participants successfully completed 39 or 40 responses (out of 40) for both conditions ("ideal" and socket), and the other eleven participants completed a lower number of trials successfully during the socket conditions than with the "ideal" interface (min = 2 fewer successful trials, Q1 = 2, median = 7, Q3 = 10, max = 17).

The maximum spread in reaction times (SD) was 210ms, whilst the median spread was 79ms. The spread alone does not provide a measure of *unpredictability* as each person will inherently have a different SD in their reaction times. We therefore measure the difference in the spread between the socket conditions and the ideal interface condition. A positive "**difference in spread**" would suggest that the response of the prosthetic hand was less predictable with the socket then when using an "ideal" interface. For 14/20 participants the "**difference in spread**" was negative for one or both of opening/closing. For twelve of the participants, the spread when closing the hand in the socket conditions was greater than the spread for the "ideal" interface (max difference = 158ms); only eight participants showed an increased spread for the open movement (max difference = 138ms).

Undesired activation

Using the "ideal" interface to perform the task, ten undesired activations of the hand occurred (out of 480 transitions), eight of these were undesired hand closing, and seven were recorded from only two of the participants. For the socket conditions, 56 undesired activations occurred (out of 480 transitions); 36 of these undesired activations were undesired opening of the hand, the remaining 20 were undesired closing. Fifteen of the participants experienced at least 1 undesired activation of the hand (out of 24) in one of the conditions (min = 0, Q1 = 0.25, median = 2.5, Q3 = 4.75, max = 16) (**Figure 43**).

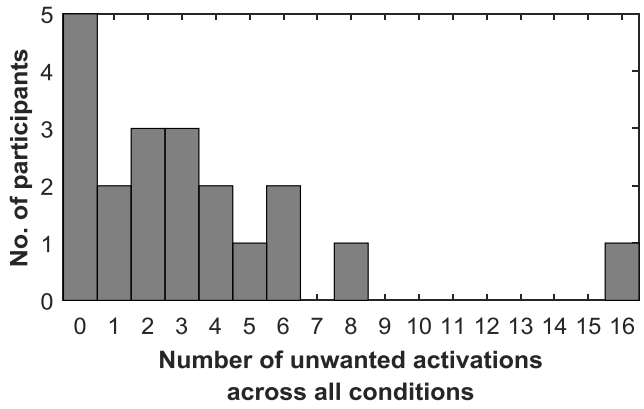


Figure 43. Histogram showing the number of undesired activations of the hand experienced by each participant across all conditions ("ideal" interface and the two conditions where the electrodes are housed in the prosthetic socket, with and without the additional load attached to the hand).

5.3.1.3. DELAYS

We were unable to record any of the measures of *delay* for 6 of the prostheses tested; for one further prosthesis we were unable to set the hand in a neutral position whilst the equipment was set up to activate the open electrode; the $delay_{O\_N}$ measure was not taken for this prosthesis (Prosthesis 1). Among the reasons for missing *delay* data were an older style of electrodes which were a different shape and hence not compatible with the measurement approach, a wrist rotator which the participant was unable to turn off, and material on the inside of the socket which prevented good contact with the electrodes.

Across all of the prostheses, the grand mean[11] $delay_{O\_C}$ was 240 ms, the grand mean $delay_{O\_N}$ was 116 ms, the grand mean $delay_{C\_O}$ was 109 ms, and the grand mean $delay_{C\_N}$ was 116 ms (**Table 7**).

Table 7. Statistical description of the delays recorded from 14 different clinically prescribed prosthetic hands (N.B. only 13 hands are included in the delay to onset of opening from a neutral position $delay_{O\_N}$).

	Min (ms)	Max (ms)	Mean (ms)	SD (ms)
Delay to onset of opening from closed "$delay_{O\_C}$"	98	375	240	69
Delay to onset of opening from neutral "$delay_{O\_N}$"	97	155	116	17
Delay to onset of closing from open "$delay_{C\_O}$"	91	135	109	15
Delay to onset of closing from neutral "$delay_{C\_N}$"	93	149	116	18

For 13 of the 14 assessed prostheses, the $delay_{O\_C}$ was significantly longer than the $delay_{O\_N}$ (**Figure 44**). A different pattern of delays was recorded for Prosthesis 9; for this device the $delay_{O\_C}$ was equivalent to the $delay_{O\_N}$.

[11] To calculate the grand mean, first the mean for each participant is calculated; the grand mean is then the mean of these mean values.

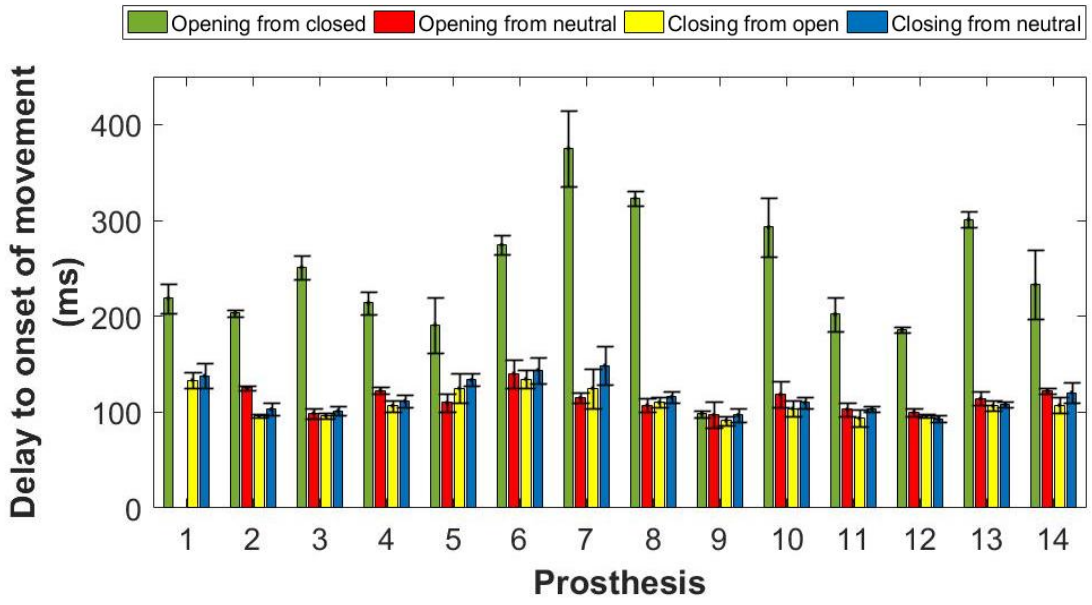


Figure 44. Mean delay (out of 5 trials) to the onset of hand movement for each of the 14 user owned prostheses. For all hands except hand 9, the delay to the onset of hand opening from a fully closed position was significantly longer than all other measures of delay. For hand 1, it was not possible to record the delay to the onset of hand opening from a neutral aperture.

5.3.1.4. CLINICAL FUNCTIONALITY

All participants attempted the medium difficulty task; nine participants successfully completed all 10 trials, a further nine participants completed 7.5-9.5 trials (half points were given if the task was not completed in one smooth movement e.g. the hand opened and closed more than once during "reach-to-grasp"[12]). Only two participants showed significant difficulty in completing the task (≤35% "**success rate**"). Both of these participants struggled with unexpected hand opening while attempting to rotate the grasped cylinder to the horizontal prior to placing it into the tube. One of these participants never managed to get the cylinder all the way into the tube before the hand unexpectedly released the cylinder. Where the cylinder was placed far enough into the tube that it remained there after release, the task was counted as successful but only half points were awarded (the same rule was used for all participants). This way we were still able to compare the task duration, reach profile, kinematic variability, and gaze characteristics from this participant with

[12] NB. Trials where half points were awarded were still included in the calculation of the other measures such as task duration and kinematic variability.

other participants. The grand mean task **duration** for the successful trials[13] was 5.87 s (min = 2.7 s, max = 9.3 s, SD = 1.98 s).

Two measures relating to the patterns in the hand aperture during the "reach-to-grasp" phase were evaluated. The grand mean length of the "**delay plateau**" for the successful trials was 24% of "reach-to-grasp" (min = 5%, max = 41%, SD = 10%). On occasions, some participants struggled to open the hand. The grand mean length of the "**reach plateau**" between opening and closing the hand for the successful trials was 29% of the "reach-to-grasp" phase (min = 13%, max = 43%, SD = 9%).

The measures developed by Thies et al. [120] were used to evaluate the temporal **variability** in the patterns of acceleration measured at the wrist of the prosthesis across all of the successful trials. These methods use dynamic time warping as an alternative to linear time normalisation. This involves warping one signal onto another through a combination of non-uniform compression and stretching of the signal along the time axis. The aim of the time-warping is to achieve the best possible temporal match between the two signals; the amount of time-warping required is reflected in the warp cost (a measure of temporal variability) [120]. Here the warp cost ranged from 7.59 to 55.69 (median=18.90, Q1=13.84, Q3=27.31).

The final measures were taken from the eye tracking data for the successful trials (**gaze** data was only available for 19 participants). Larger between subject differences were noted for the "reach-to-grasp" phase than the "transport" phase (**Figure 45** shows the mean time spent looking at each AOI). During "reach-to-grasp", only five participants did not look at the hand at all; the maximum time spent looking at the hand was 50% of the "reach-to-grasp" phase (median=3%, Q1=0%, Q3=14%). All participants spent some time looking at the cylinder and/or tube whilst performing "reach-to-grasp"; the time spent looking at the GCA ranged from 1% to 84% of the "reach-to-grasp" phase (median=50%, Q1=30%, Q3=62%), and the time spent

[13] Successful trials included all trials where the cylinder was not knocked over or dropped, and those trials where the cylinder remained inside the tube after release. This includes trials where only half a point was awarded for the success rate.

looking at the LCA and/or tube ranged from 1% to 58% of the "reach-to-grasp" phase (median=21%, Q1=30%, Q3=34%).

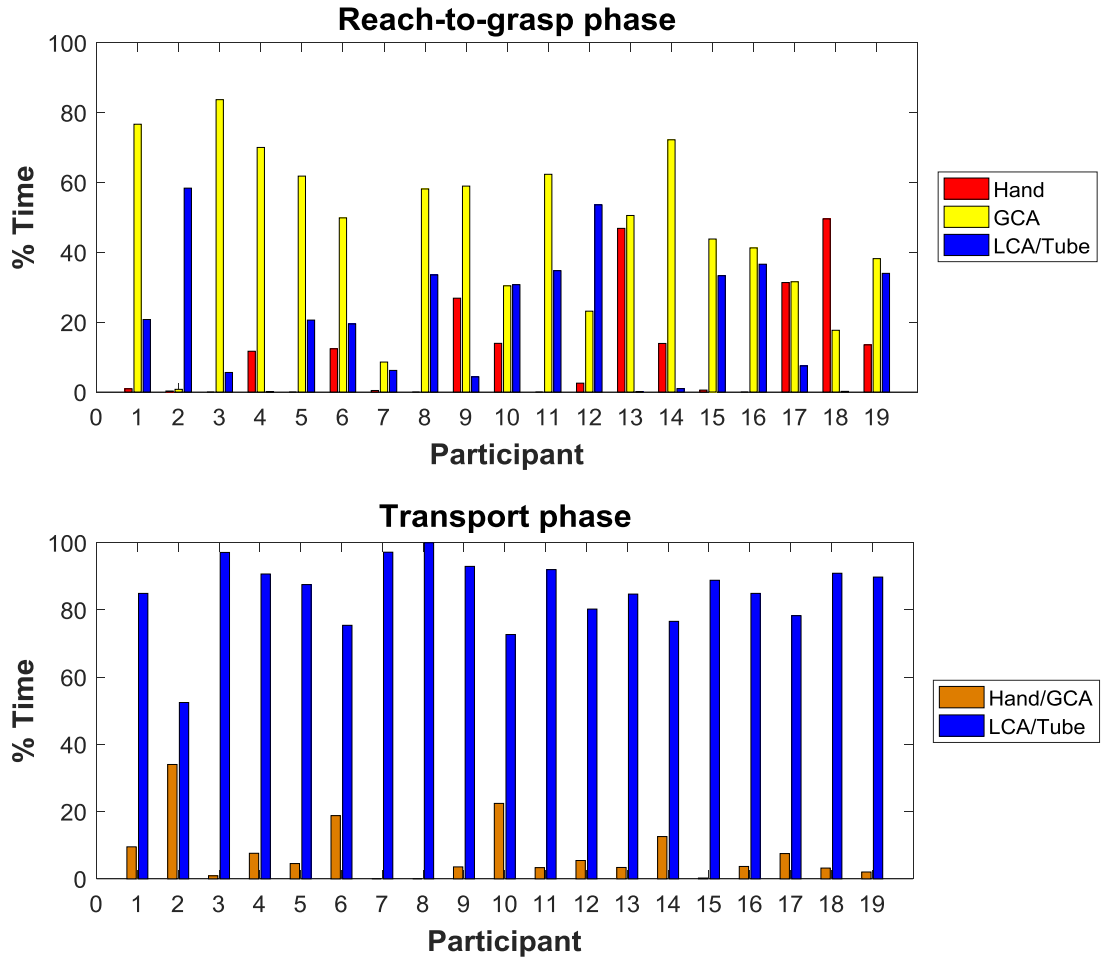


Figure 45. Mean time spent looking at each Area of Interest (AOI) as a percentage of the "reach-to-grasp" and "transport" phases. Missing data and time spent looking at parts of the task other than the hand, cylinder and tube are not plotted. Gaze data was only recorded for 19 participants.

During the "transport" phase, only two of the participants did not look at the hand at all (only one of these two participants did not look at the hand at all throughout both parts of the task). All participants spent more time looking at the LCA and/or tube, than at the hand and/or GCA. The time spent looking at the hand and/or GCA ranged from 0% to 34% of the "transport" phase (median=4%, Q1=2%, Q3=10%), whilst the time spent looking at the LCA and/or tube ranged from 52% to 100% of the "transport" phase (median=87%, Q1=78%, Q3=92%).

5.3.1.5. EVERYDAY PROSTHESIS USAGE

"***Prosthesis wear time***" over the 7 days ranged from 2.8h to 106.9h (median=45.6h, Q1=25.4h, Q3=88.7h). Usage of the prosthesis during the times the prosthesis was worn was evaluated based on the median percentage reliance on the anatomical arm ("***Median %Anatomical***"), this ranged from 67% to 87% (median=80%, Q1=74%, Q3=85%). The secondary measure of usage compared the time spent using the anatomical arm unilaterally over the 7-day period ("**UL_{Anat}**" min=23min, max=732min, median=189min), to the time spent using the prosthetic arm unilaterally over the 7-day period ("**UL_{Pros}**" min=0min, max=82min, median=15min). Two participants did not use the prosthesis unilaterally at all throughout the recording period resulting in infinite ratios. For the remaining 18 participants the "***unilateral ratio***" ("**UL_{Anat}**":"**UL_{Pros}**") ranged from 4.3:1 to 73:1 (median=11.5:1). [14]

5.3.2. *Statistical analysis*

5.3.2.1. IMPACT OF PARTICIPANT DEMOGRAPHICS

We found that the older a participant was, the worse they performed on the **dynamic tracking task** "car game". When faced with two cars, older participants tended to score lower for the car controlled using the muscle signal for hand closing; NB. This was the rear of the two cars. The Kendall's Tau-b correlation between age and the 2 car closing score was -.334, with a significance of .041 (n=20). We also found age to be weakly correlated with the total number of undesired activations of the hand during the *unpredictability* tasks (τ_b=.334, p=.048, n=20).

Significant correlations were found between the side with limb absence (right or left), and: (1) the "decision time" to open the hand (right limb absence was correlated with shorter DT: τ_b=-.429, p=.025, n=20), (2) the number of completed RT when undertaking the *unpredictability* assessment with the "ideal" interface (right limb absence correlated with more completed trials: τ_b=.479, p=.028, n=20), and (3)

[14] This activity data is explored in more detail in **Chapter 6**

the time spent looking at the GCA during "reach-to-grasp" (right limb absence correlated with more time spent looking at the GCA: τ_b=.501, p=.011, n=19).

Participants who had been prescribed a prosthesis for longer demonstrated a smaller spread of reaction times for hand closing using the "ideal" interface (τ_b=-.347, p=.034, n=20).

Finally, participants with amputation on the dominant side were generally less successful with the **cylinder task** (τ_b=-.645, p=.043, n=9).

Relationships between the demographic data and the measures of everyday *prosthesis usage* are presented in **Chapter 6**. No other significant correlations were found.

5.3.2.2. WITHIN FACTOR CORRELATIONS

The factor *EMG skill* consisted of the results from the two **tracking tasks** and the "decision time" from the **intuition task**. No significant correlations were found between the "decision time" and the results of the **tracking tasks**. Within the **tracking tasks**, the only significant correlation was that a higher level of performance on the **static tracking task** using the signal for hand closing correlated with a higher score on the single car **dynamic tracking task** using the same signal (τ_b = .351, p = .034, n=20). No other significant correlations were found. Therefore, the measures were not considered suitable for collapsing into a single factor.

The factor *unpredictability* consisted of the difference in the spread of reaction times between the "ideal" interface and the conditions where the participant wore their own prosthetic socket, the number of successful responses to the reaction time task, and the number of undesired activations of the hand when transitioning between the two arm positions. As shown in **Table 8**, the number of reaction time tasks successfully completed was significantly positively correlated between the "ideal" interface and the socket conditions; for example, if a person was unable to complete all of the opening reaction time tasks with the ideal interface, they would tend to have similar problems whilst wearing the socket. It is interesting to note that there was no significant correlation between the number of open responses completed

and the number of close responses completed. There were no significant correlations between the measures of spread (*not shown in table*) and the number of successful responses or the number of undesired hand activations. However, for the "ideal" interface there was a significant correlation between the number of reaction time tasks successfully completed and the number of undesired activations (more undesired activations, fewer successful responses). This was not the case for the socket conditions. Similarly to the measures constituting *EMG skill*, these measures were not considered to be suitable for consolidation into a single factor.

The factor *delay* consisted of the delays to both open and close the hand measured from a neutral starting aperture and from the extremes. As shown in **Table 9**, aside from the delay to open the hand from a fully closed position ($delay_{O\_C}$), all measures of delay were significantly positively correlated suggesting they may be suitable for reduction into a single factor. Principle Component Analysis (PCA) was undertaken on the measures of *delay* (**Appendix 8**); the results suggested that the data would not be recommended for reduction into a single factor.

Table 8. Kendall's Tau-b 2-tailed correlation matrix for the number of successful responses to the reaction time task and the number of undesired activations of the hand as the arm was moved between 45° above and below the horizontal. The correlation matrix between these measures and the difference in the spread of the reaction times between the interface conditions is not shown. ** Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

			"Ideal" interface						Socket					
			Open		Close		Overall		Open		Close		Overall	
			No. RTs complete	No. undesired activations	No. RTs complete	No. undesired activations	No. RTs complete	No. undesired activations	No. RTs complete	No. undesired activations	No. RTs complete	No. undesired activations	No. RTs complete	No. undesired activations
"Ideal"	Open	No. RTs complete	τ = 1 n = 20	τ = -0.437* p = 0.048 n = 20	τ = 0.169 p = 0.437 n = 20	τ = -0.643** p = 0.003 n = 20	τ = 0.836** p = 0.001 n = 20	τ = -0.703** p = 0.001 n = 20	τ = 0.409* p = 0.039 n = 20	τ = 0.051 p = 0.803 n = 20	τ = 0.367 p = 0.070 n = 20	τ = -0.025 p = 0.903 n = 20	τ = 0.357 p = 0.062 n = 20	τ = 0.081 p = 0.678 n = 20
		No. undesired activations	τ = -0.437* p = 0.048 n = 20	τ = 1 n = 20	τ = -0.466* p = 0.040 n = 20	τ = 0.261 p = 0.241 n = 20	τ = -0.391 p = 0.073 n = 20	τ = 0.552* p = 0.013 n = 20	τ = -0.418* p = 0.043 n = 20	τ = 0.030 p = 0.887 n = 20	τ = -0.087 p = 0.679 n = 20	τ = 0.030 p = 0.889 n = 20	τ = -0.343 p = 0.084 n = 20	τ = -0.013 p = 0.948 n = 20
	Close	No. RTs complete	τ = 0.169 p = 0.437 n = 20	τ = -0.466* p = 0.040 n = 20	τ = 1 n = 20	τ = -0.277 p = 0.207 n = 20	τ = 0.534* p = 0.013 n = 20	τ = -0.236 p = 0.281 n = 20	τ = 0.027 p = 0.896 n = 20	τ = 0.238 p = 0.256 n = 20	τ = 0.472* p = 0.023 n = 20	τ = -0.015 p = 0.945 n = 20	τ = 0.376 p = 0.056 n = 20	τ = 0.181 p = 0.366 n = 20
		No. undesired activations	τ = -0.643** p = 0.003 n = 20	τ = 0.261 p = 0.241 n = 20	τ = -0.277 p = 0.207 n = 20	τ = 1 n = 20	τ = -0.564** p = 0.008 n = 20	τ = 0.891** p = 0.001 n = 20	τ = -0.185 p = 0.355 n = 20	τ = -0.153 p = 0.458 n = 20	τ = -0.220 p = 0.280 n = 20	τ = 0.151 p = 0.468 n = 20	τ = -0.129 p = 0.506 n = 20	τ = -0.047 p = 0.810 n = 20
	Overall	No. RTs complete	τ = 0.836** p = 0.001 n = 20	τ = -0.391 p = 0.073 n = 20	τ = 0.534* p = 0.013 n = 20	τ = -0.564** p = 0.008 n = 20	τ = 1 n = 20	τ = -0.607** p = 0.004 n = 20	τ = 0.270 p = 0.168 n = 20	τ = 0.139 p = 0.491 n = 20	τ = 0.549** p = 0.006 n = 20	τ = -0.146 p = 0.475 n = 20	τ = 0.461* p = 0.015 n = 20	τ = 0.078 p = 0.686 n = 20
		No. undesired activations	τ = -0.703** p = 0.001 n = 20	τ = 0.552* p = 0.013 n = 20	τ = -0.236 p = 0.281 n = 20	τ = 0.891** p = 0.001 n = 20	τ = -0.607** p = 0.004 n = 20	τ = 1 n = 20	τ = -0.312 p = 0.117 n = 20	τ = -0.060 p = 0.770 n = 20	τ = -0.135 p = 0.508 n = 20	τ = 0.248 p = 0.233 n = 20	τ = -0.211 p = 0.274 n = 20	τ = 0.061 p = 0.757 n = 20
Socket	Open	No. RTs complete	τ = 0.409* p = 0.039 n = 20	τ = -0.418* p = 0.043 n = 20	τ = 0.027 p = 0.896 n = 20	τ = -0.185 p = 0.355 n = 20	τ = 0.270 p = 0.168 n = 20	τ = -0.312 p = 0.117 n = 20	τ = 1 n = 20	τ = -0.212 p = 0.266 n = 20	τ = 0.197 p = 0.297 n = 20	τ = -0.109 p = 0.573 n = 20	τ = 0.641** p = 0.001 n = 20	τ = -0.127 p = 0.486 n = 20
		No. undesired activations	τ = 0.051 p = 0.803 n = 20	τ = 0.030 p = 0.887 n = 20	τ = 0.238 p = 0.256 n = 20	τ = -0.153 p = 0.458 n = 20	τ = 0.139 p = 0.491 n = 20	τ = -0.060 p = 0.770 n = 20	τ = -0.212 p = 0.266 n = 20	τ = 1 n = 20	τ = -0.047 p = 0.808 n = 20	τ = 0.016 p = 0.935 n = 20	τ = -0.228 p = 0.217 n = 20	τ = 0.706** p = 0.001 n = 20
	Close	No. RTs complete	τ = 0.367 p = 0.070 n = 20	τ = -0.087 p = 0.679 n = 20	τ = 0.472* p = 0.023 n = 20	τ = -0.220 p = 0.280 n = 20	τ = 0.549** p = 0.006 n = 20	τ = -0.135 p = 0.508 n = 20	τ = 0.197 p = 0.297 n = 20	τ = -0.047 p = 0.808 n = 20	τ = 1 n = 20	τ = -0.086 p = 0.663 n = 20	τ = 0.644** p = 0.001 n = 20	τ = -0.082 p = 0.659 n = 20
		No. undesired activations	τ = -0.025 p = 0.903 n = 20	τ = 0.030 p = 0.889 n = 20	τ = -0.015 p = 0.945 n = 20	τ = 0.151 p = 0.468 n = 20	τ = -0.146 p = 0.475 n = 20	τ = 0.248 p = 0.233 n = 20	τ = -0.109 p = 0.573 n = 20	τ = 0.016 p = 0.935 n = 20	τ = -0.086 p = 0.663 n = 20	τ = 1 n = 20	τ = -0.082 p = 0.660 n = 20	τ = 0.488* p = 0.010 n = 20
	Overall	No. RTs complete	τ = 0.357 p = 0.062 n = 20	τ = -0.343 p = 0.084 n = 20	τ = 0.376 p = 0.056 n = 20	τ = -0.129 p = 0.506 n = 20	τ = 0.461* p = 0.015 n = 20	τ = -0.211 p = 0.274 n = 20	τ = 0.641** p = 0.001 n = 20	τ = -0.228 p = 0.217 n = 20	τ = 0.644** p = 0.001 n = 20	τ = -0.082 p = 0.660 n = 20	τ = 1 n = 20	τ = -0.162 p = 0.359 n = 20
		No. undesired activations	τ = 0.081 p = 0.678 n = 20	τ = -0.013 p = 0.948 n = 20	τ = 0.181 p = 0.366 n = 20	τ = -0.047 p = 0.810 n = 20	τ = 0.078 p = 0.686 n = 20	τ = 0.061 p = 0.757 n = 20	τ = -0.127 p = 0.486 n = 20	τ = 0.706** p = 0.001 n = 20	τ = -0.082 p = 0.659 n = 20	τ = 0.488* p = 0.010 n = 20	τ = -0.162 p = 0.359 n = 20	τ = 1 n = 20

Table 9. Kendall's Tau-b 2-tailed correlation matrix between measures of delay. ** Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

	Delay to open from closed	**Delay to open from neutral**	**Delay to close from open**	**Delay to close from neutral**
$Delay_{O\_C}$	τ = 1 n = 14	τ = 0.333 p = 0.113 n = 13	τ = 0.456* p = 0.024 n = 14	τ = 0.385 p = 0.055 n = 14
$Delay_{O\_N}$	τ = 0.333 p = 0.113 n = 13	τ = 1 n = 13	τ = 0.442* p = 0.037 n = 13	τ = 0.564** p = 0.007 n = 13
$Delay_{C\_O}$	τ = 0.456* p = 0.024 n = 14	τ = 0.442* p = 0.037 n = 13	τ = 1 n = 14	τ = 0.789** p = 0.001 n = 14
$Delay_{C\_N}$	τ = 0.385 p = 0.055 n = 14	τ = 0.564** p = 0.007 n = 13	τ = 0.789** p = 0.001 n = 14	τ = 1 n = 14

5.3.2.3. CORRELATIONS BETWEEN FUNCTIONALITY MEASURES

Success rate (τ_b=-.557, p=.001, n=20), the length of the "**delay plateau**" (τ_b=.379, p=.019, n=20), and **variability** (τ_b=.653, p<0.001, n=20) all correlated with task **duration**. No significant correlation was found between the length of the "**reach plateau**" and the **duration**. Task **duration** was also significantly correlated with the time spent looking at the hand during the "reach-to-grasp" phase (τ_b=.464, p=0.006, n=19). **Duration** was not significantly correlated with any other **gaze** measures.

Success rate was shown to correlate significantly with temporal **variability** (τ_b=-.486, p=0.005, n=20); similarly, the time spent looking at the GCA during "reach-to-grasp" was also shown to correlate significantly with temporal **variability** (τ_b=-.404, p=0.016, n=19).

Within the **gaze** measures, the time spent looking at the hand during "reach-to-grasp" was significantly negatively correlated with the time spent looking ahead to the LCA and/or tube (τ=-.380, p=0.026, n=19). Similarly in the "transport" phase, there was a significant negative correlation between the time spent looking at the hand and/or GCA, and the time spent looking ahead to the LCA and/or tube (τ=-.692, p<0.001, n=19).

The relationships between the measures of *functionality* and the measures of everyday *usage* will be covered in **Chapter 6**.

No other significant correlations were found.

5.3.2.4. CONTROL FACTORS VS USER PERFORMANCE

The measures reflecting the *EMG skill* of the user, and the measures of user *functionality* and everyday *prosthesis usage* were very poorly correlated. Participants who performed better on the single car dynamic tracking task using the muscle signal for hand opening demonstrated longer task durations (τ_b=.332, p=.044, n=20), and the participants who performed better on the two car dynamic tracking task using the muscle signal for hand closing demonstrated more symmetrical arm everyday arm use ("***Median %Anatomical***") (τ_b=-.339, p=.038, n=20). No other significant correlations were found.

No significant correlations were found between the measures of everyday *prosthesis usage* and the measures reflecting the *unpredictability* introduced at the interface between the skin and the electrodes. **Table 10** shows the correlation matrix between the *unpredictability* measures and the performance measures. A limited number of significant correlations were seen between the *functionality* measures and the measures relating to the desired activation of the prosthesis. The difference in the spread of reaction times to open the hand was correlated with the two measures reflecting the patterns in the hand aperture during "reach-to-grasp" (**Table 10**), however, no significant correlations were found for closing the hand.

The undesired activations of the hand showed a stronger relationship with *functionality* (see **Table 10**). Less time spent looking at the LCA and/or tube during "transport" correlated with fewer responses to the reaction time tasks. Similarly, higher temporal **variability** in the acceleration of the forearm was significantly correlated with fewer responses to the reaction time tasks. Finally higher numbers of undesired activations of the hand were significantly correlated with a lower **success rate**, longer task **duration**, and higher temporal kinematic **variability**.

Table 10. Kendall's Tau-b 2-tailed correlation matrix, comparing the measures of *unpredictability* to the measures of performance. ** Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed). † Correlation is significant at the 0.10 level (2-tailed).

	Difference in spread open	Difference in spread close	Total no. RTs completed	Total no. undesired activations
Success Rate	τ = -0.059 p = 0.732 n = 20	τ = -0.142 p = 0.411 n = 20	τ = 0.061 p = 0.730 n = 20	τ = -0.402* p = 0.037 n = 20
Duration	τ = 0.189 p = 0.243 n = 20	τ = 0.011 p = 0.948 n = 20	τ = -0.104 p = 0.533 n = 20	τ = 0.649** p = 0.001 n = 20
"Delay plateau" length	τ = 0.474** p = 0.004 n = 20	τ = 0.189 p = 0.243 n = 20	τ = -0.147 p = 0.376 n = 20	τ = 0.128 p = 0.449 n = 20
"Reach plateau" length	τ = -0.368* p = 0.023 n = 20	τ = -0.021 p = 0.897 n = 20	τ = -0.071 p = 0.670 n = 20	τ = 0.105 p = 0.532 n = 20
Kinematic variability	τ = 0.221 p = 0.173 n = 20	τ = 0.000 p = 1.000 n = 20	τ = -0.333* p = 0.046 n = 20	τ = 0.583** p = 0.001 n = 20
Gaze Time Hand (Reach)	τ = 0.127 p = 0.458 n = 19	τ = -0.090 p = 0.596 n = 19	τ = -0.074 p = 0.669 n = 19	τ = 0.338† p = 0.057 n = 19
Gaze Time GCA (Reach)	τ = -0.135 p = 0.421 n = 19	τ = 0.123 p = 0.463 n = 19	τ = 0.144 p = 0.398 n = 19	τ = -0.315† p = 0.070 n = 19
Gaze Time LCA/Tube (Reach)	τ = 0.053 p = 0.753 n = 19	τ = 0.193 p = 0.248 n = 19	τ = -0.192 p = 0.259 n = 19	τ = 0.093 p = 0.594 n = 19
Gaze Time Hand/GCA (Transport)	τ = -0.270 p = 0.107 n = 19	τ = 0.082 p = 0.624 n = 19	τ = -0.277 p = 0.105 n = 19	τ = 0.254 p = 0.145 n = 19
Gaze Time LCA/Tube (Transport)	τ = 0.053 p = 0.753 n = 19	τ = -0.135 p = 0.421 n = 19	τ = 0.457** p = 0.007 n = 19	τ = -0.328† p = 0.060 n = 19
Median % Anatomical	τ = -0.032 p = 0.846 n = 20	τ = -0.105 p = 0.516 n = 20	τ = 0.115 p = 0.491 n = 20	τ = -0.006 p = 0.974 n = 20
Unilateral ratio	τ = -0.098 p = 0.570 n = 18	τ = 0.020 p = 0.910 n = 18	τ = 0.205 p = 0.249 n = 18	τ = -0.191 p = 0.283 n = 18
Prosthesis wear time	τ = 0.095 p = 0.559 n = 20	τ = 0.063 p = 0.697 n = 20	τ = 0.038 p = 0.818 n = 20	τ = 0.050 p = 0.767 n = 20

It is worth noting that if the threshold for the avoidance of a Type I error was raised to $p<0.10$ (less than a 10% probability that the recorded effect occurred by chance), then 3 further weak correlations exist suggesting that participants who experienced

more undesired activations of the hand, spent more time looking at the hand during reach-to-grasp, and less time looking at the GCA; they also spent less time looking at the LCA/Tube during the "transport" phase.

The correlation matrix between the measures constituting the *delay* and the measures of *functionality* and everyday *prosthesis usage*, showed some significant correlations. A longer $delay_{C\_O}$ related to a longer task **duration** (τ_b=-.411, p=0.042). The $delay_{O\_C}$ and the $delay_{C\_N}$ both showed significant negative correlations with the length of the "**reach plateau**" (τ_b=-.495, p=.014 & τ_b=.451, p=.025). The greatest correlations were seen between the measures of *delay* and the **gaze** during the "transport" phase as shown in **Table 11**.

No other significant correlations were found.

Table 11. Kendall's Tau-b 2-tailed correlation matrix, comparing the electromechanical *delay* in the prosthesis to measures of **gaze** during the "transport" phase. ** Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

	$Delay_{O\_C}$	**$Delay_{O\_N}$**	**$Delay_{C\_O}$**	**$Delay_{C\_N}$**
Gaze Time Hand/GCA (Transport)	τ = -0.245 p = 0.246 n = 13	τ = -0.260 p = 0.243 n = 12	τ = -0.562** p = 0.008 n = 13	τ = -0.555** p = 0.09 n = 13
Gaze Time LCA/Tube (Transport)	τ = 0.436* p = 0.038 n = 13	τ = 0.455* p = 0.040 n = 12	τ = 0.805** p = 0.000 n = 13	τ = 0.641** p = 0.002 n = 13

5.3.2.5. STATISTICAL POWER

Twenty participants were involved in this study, and for some of the correlations the sample size was as low as 12. With a sample size of 20 participants, the desired power of 0.8 (80% chance of detecting a statistically significant effect where one exists), was only achieved when the correlation coefficient was greater than 0.6 (α=0.05). For weaker correlations, the achieved power dropped significantly (**Table 12**). If this study were to be repeated, **Table 13** shows the required sample sizes to achieve a power of 0.8 for these lower values of τ_b. It is worth noting that if correlations with p<0.10 were to be included in the analysis, then the required sample size would be smaller.

Table 12. Achieved powers for Kendall's Tau-b correlation coefficients 0.3-0.8 with sample sizes of 12-20 (α=0.05).

Correlation Coefficient	Achieved Power								
	n=20	n=19	n=18	n=17	n=16	n=15	n=14	n=13	n=12
0.3	0.23	0.22	0.21	0.19	0.19	0.18	0.17	0.16	0.15
0.4	0.39	0.37	0.35	0.32	0.32	0.30	0.28	0.26	0.23
0.5	0.59	0.56	0.53	0.50	0.50	0.47	0.44	0.40	0.36
0.6	0.79	0.76	0.73	0.70	0.70	0.67	0.63	0.58	0.54
0.7	0.93	10.92	0.90	0.88	0.88	0.85	0.82	0.78	0.73
0.8	0.99	0.99	0.98	0.98	0.98	0.97	0.95	0.93	0.91

Table 13. Required sample sizes to achieve a statistical power of 0.8 (α=0.05 and α=0.10) for Kendall's Tau-b correlation coefficients of 0.3-0.6.

Correlation Coefficient	Required Sample Size α=0.05	Required Sample Size α=0.10
0.3	93	73
0.4	51	40
0.5	31	24
0.6	20	17

5.4. Discussion

In this study each control factor was characterised using a large number of different variables. Performance using the 'open muscle' often differed from performance using the 'close muscle', therefore the two measures were reported separately. Furthermore, correlation analysis showed that the individual measures (such as the time taken to decide which muscle to activate and the ability to dynamically control the amplitude of the EMG signal) measure separate unrelated aspects of each control factor; therefore it was not possible to reduce the data into single variables characterising each control factor.

5.4.1. *Measures representing EMG skill*

As noted in **Chapter 3**, it is widely accepted that college-aged individuals take around 190 ms to respond to light based stimuli [130]. In this study the group median SRT was just over 300 ms. Accounting for the measured delay of approximately 100 ms in the response of the prosthetic hand, these SRT values are in line with previous published research. Three participants demonstrated faster responses on the CRT task than the

SRT task (resulting in a negative "decision time"). This may be explained by the effects of practice due to the small number of repeats. However, for the majority of participants, the CRT was, as expected, longer than the SRT resulting in a positive "decision time". One participant struggled to correctly complete the CRT task, opening the hand each time rather than responding as prompted by the LEDs; no other participants struggled with the instructions for this task.

All participants were able to complete the **static tracking task** successfully, and the results demonstrated a good range of skill levels. All participants were able to generate a signal which could be used to operate a prosthetic hand, however, some participants struggled to sustain the signal, whilst for others the signal was fairly noisy due to a high gain setting on the electrodes. As the task was designed specifically for this study, no data is available to compare the results to.

Similarly no published data exists upon which to compare the performance on the **dynamic tracking task**, however on average, participants performed better in the single car task than when asked to simultaneously control two cars. Some participants struggled with the second part of the task, which involved keeping control of two cars at once, leading to some surprising results as highlighted in **Figure 40**. It is not possible to differentiate between participants who performed poorly due to inability to follow the task instructions, and participants who performed poorly due to poor *EMG skill* (such as inability to independently contract the two muscles).

Two significant correlations were found between the measures of *EMG skill* and user performance, however, these were at a very low level $\tau_b<0.4$, and the statistical power was very low (0.23); therefore, it is not possible to draw any strong conclusions from these relationships. Previous research has questioned the relationship between *EMG skill* and user performance with a myoelectric prosthesis. Although, with practice, improvements in abstract EMG controlled games have been demonstrated, this has not been shown to transfer to measures of functionality with the prosthesis, such as the length of the "**reach plateau**" [70]. The absence of significant correlations between the measures of *EMG skill*, *functionality* and *prosthesis usage* in this current study supports the theory that high performance on

abstract EMG tasks may not transfer to high clinical *functionality* or daily use of the prosthesis. The tracking tasks used in this study were designed to represent the tasks used in the early stages of clinical myoelectric training. These results question whether these training measures are relevant to the use of an actual prosthesis.

5.4.2. *Measures representing unpredictability introduced at the interface*

Based on the data presented in **Section 5.3.2.4**, it would be suggested that the **undesired activations** of the hand is the factor most in need of further investigation. 75% of participants experienced undesired activations of the prosthetic hand during the testing period. This supports the findings of Head [15]; in Head's thesis he presented example EMG plots for 5 participants undertaking 3 arm movements. When a load was added to the prosthesis all participants demonstrated EMG signals above the threshold to activate the hand. Only one participant was able to perform a reach movement with their prosthesis without an undesired signal being generated. This is a notable finding and illustrates well how far current myoelectric prostheses are from offering the almost perfect predictability of hand response anatomically intact people take for granted.

Furthermore, during the reaction time task, only six participants managed to complete all 40 trials successfully when wearing their own prosthesis, with eight participants failing to complete more than a quarter of the trials. Where failed trials involved an incorrect response, it is not possible to differentiate between an incorrect response by the user and an incorrect response of the hand. Interestingly two participants found that when concentrating on the reaction time LED the hand would respond in a manner contrary to their intention. For example if they intended to open their hand it would close; surprisingly when these participants looked at the hand it would respond how they desired. There is no clear explanation as to why this occurred.

The measures employed to assess the **desired activation** of the hand were not able to provide high quality data for a variety of reasons which will be addressed in more detail below.

The median reaction times were similar to/slightly longer than the median reaction times for the assessment of *EMG skill*. For the socket conditions, when opening the hand, the minimum RT was 107 ms. As noted previously, RTs faster than 100 ms were excluded from the analysis as an early response [129]; the *delay* in the response of the prosthesis was not considered. In future, the *delay* should be removed from the RT before early and late responses are excluded, however, for this study this was not possible as *delay* data was not available for all prostheses tested. More information on the removal of early/late reactions is provided by Whelan [149].

Furthermore, as different hands were used for the "ideal" interface and socket tests to avoid dismantling the user's own prosthesis, direct comparison between the RTs for each condition was not possible. To allow unbiased comparison between the reaction times using the "ideal" interface and the reaction times using the socket, the electromechanical delay introduced by each prosthetic hand would once again need to be removed. As d*elay* data was not available for all prostheses used in this study, this analysis has not been undertaken.

Rather than comparing the RTs themselves, unpredictability was assessed by comparing the spread of the RTs using the "ideal" interface against the spread of the RTs using the socket. The measure of spread was the standard deviation. Comparing two SDs is not a common measure; one alternative is to inspect the F ratio, which compares the variance between two groups of data. Neither of these methods account for incorrect responses. Consequently a person who only completed two trials may have been shown to have less unpredictability in the desired activation than someone who had completed ten correct trials. In a traditional reaction time experiment, participants may be asked to continue the trials until a particular number of successful trials have been completed. In this study time restrictions (and for some participants, the inability to activate their prosthesis under particular conditions) prevented the collection of matching numbers of successful trials from each participant.

When assessing the difference in the spread of the reaction times between the conditions, an increase in the spread for the socket conditions was suggested to

correspond to a poor fit between the electrodes and the skin. For 70% of participants, the spread in the reaction times was smaller when wearing the socket; this improvement provides no useful data on the quality of the socket, and is likely a measure of improvement in performing the task (these participants likely had either a well fitted socket which did not increase the unpredictability of the response, or a socket with such a poor fit that they were unable to complete many trials successfully). In future a larger number of RT tests would be recommended. In this study only 5-10 trials were assessed for each part of the task, whereas some larger scale studies assess up to 50 trials per condition [150, 151].

5.4.3. *Measures representing the delay in the prosthesis*

The data shows that the electromechanical *delay* varies between prostheses. It is important to note that this *delay* cannot be represented by a single number. For almost all of the hands tested, the $delay_{O\_C}$ to the onset of hand opening from a fully closed position was over twice as long as the *delay* to the onset of hand movement from the other tested starting apertures. The only exception was prosthesis 9 (see **Figure 44**); this prosthesis demonstrated a similar trend to the threshold controlled Steeper Select hand tested in **Appendix 4**. The participant was unable to inform as to whether the hand employed threshold or proportional control, however, the hand was manufactured by Steeper, and therefore it is possible that it may have been the same hand. On average, aside from the $delay_{O\_C}$, delays were within the bounds proposed by Farrell [76] of 100-120ms.

A longer *delay* in the response of the hand to a muscle signal would be expected to be a negative trait (previous work has attempted to minimise this delay). However, this study suggested that users whose prostheses exhibited a longer electromechanical *delay* demonstrated less time spent looking at the hand and GCA during the “transport” phase, and more time spent looking at the LCA and the tube. This result is difficult to interpret and in future it may be worth looking into more detail at the relationship between *delay* and patterns in gaze behaviour over a range of tasks.

The results showed that participants who used a prosthesis with a longer $delay_{O\_C}$ to open the hand from fully closed, and $delay_{C\_N}$ to close the hand from neutral, demonstrated a shorter "**reach plateau**". It is possible that these participants have learnt to plan their reach, beginning to close around the object earlier than users whose prosthesis includes a shorter delay.

5.4.4. *Clinical functionality*

The data collected from the **cylinder task** suggested that the participants assessed had a wide range of *functionality* levels. The data relating to the patterns in the hand aperture during "reach-to-grasp" showed similar patterns to those detected by Bouwsema et al. [85]. Rearranging the data presented for the six participants in Bouwsema's study suggests a mean "**delay plateau**" equivalent to 25.5% of the "reach-to-grasp" phase, and a mean "**reach plateau**" equivalent to 26% of the "reach-to-grasp" phase. Our figures of 24% and 29% support Bouwsema's findings. Unlike Bouwsema's study, we did not find a correlation between the length of the "**reach plateau**" and the task **duration** (the measure most similar to the SHAP score used in her study), however we did find a correlation between the "**delay plateau**" and the task **duration**.

The temporal variability in acceleration of the forearm varied significantly between participants. In Thies' earlier work [120], healthy anatomically intact controls performed a 'drinking' from a glass task with a warp cost of 13.71, whilst participants who had suffered a stroke were more variable with a warp cost of 44.63 (for a task where they were asked to move a plate the warp cost was higher). In another study, Thies et al. [87] inspected the variability in a cohort of prosthesis users performing tasks such as carton pouring, lifting a weighted container, and a tray transfer task. In this study the warp costs were higher ranging from 55.23 for the tray transfer task up to 174.24 for the carton pouring task. Thies' work suggests that the warp cost is highly affected by task. As we do not have control data for the **cylinder task** it is not currently possible to directly compare performance to anatomically intact subjects, however it is clear that the range of warp costs showed a clear difference between

the most and least variable participants. Similarly to Thies' work, we found **variability** to be positively correlated with task **duration**.

In the work of Parr et al. [89] the importance of the timing of gaze fixations during the task is highlighted, for example looking at the GCA during "reach-to-grasp" has a different significance to looking at the GCA during the "transport" phase. The gaze data presented here demonstrated that almost all prosthesis users spent some amount of time looking at their hand, either during the "reach-to-grasp", or at the end of the "transport" phase. Bouwsema [85, 86], Sobuh [88], and Parr [89] have all previously shown the gaze behaviour of prosthesis users to differ from anatomically intact controls in this way. Bouwsema suggested that a lower level of skill (demonstrated by lower performance on the SHAP) was generally accompanied by more monitoring of the hand [85], however this was not the case for all participants, with some who wore the prosthesis less often demonstrating high SHAP scores combined with large amounts of hand monitoring. This may help to explain the surprisingly few correlations between the gaze measures and the other measures of *functionality* in the study results presented here.

5.5. Limitations and future work

This study is one of the largest experimental studies of myoelectric prosthesis users to date, nevertheless, it is still underpowered. As demonstrated by the power calculations, the twenty participants involved in this study only allow for a statistical power of 0.8 when the correlation coefficient is greater than 0.6. A power of 0.8 was achieved for many of the correlations between the measures of *unpredictability* (see **Table 8**), between the temporal **variability** in the functional task and the task **duration** (τ_b=.653, p<0.001, n=20), and between the total number of undesired activations of the hand during the *unpredictability* assessment and the task **duration** for the functional task (τ_b=.649, p=0.001, n=20). Some of the correlations with smaller sample sizes still achieved a power of 0.8, including the relationship between the delay to close the hand from a fully open and a neutral position (τ_b=.789, p=0.001, n=14), the time spent looking at the hand and/or GCA during the "transport" phase and the time spent looking at the LCA and/or tube (τ_b=-.692, p<0.001, n=19), and

finally the relationship between the delay to close the hand from a fully open position and the time spent looking at the LCA and/or tube during the "transport" phase (τ_b=.805, p<0.001, n=13). All other correlations presented here were underpowered, and hence, confidence in the findings was low, and interpretation of the results is not straightforward in places. In future, studies attempting to evaluate all of these control factors should aim to recruit 50+ participants.

We initially proposed to undertake a multiple regression analysis to establish the relative impact of each control factor. Having analysed the data it was established that the measures constituting each factor were not able to be reduced into single measures of *EMG skill*, *unpredictability* and *delay*. Therefore, correlation analyses were undertaken for each measure individually.

Large scale recruitment of prosthesis users is not a trivial task, we would therefore recommend that efforts are concentrated on establishing in more detail the reasons for undesired prosthesis activations. This may include movement when the user does not desire it, incorrect responses (opening rather than closing), or no response.

The number of repeats of the RT tasks were too few. In **Chapter 3** we noted that the number of responses was constrained by the length of the testing period, however, in future we would recommend increasing these numbers or providing a longer practice period to avoid the effects of learning. We would also recommend that an alternative method of measuring the **desired activation** of the prosthesis is developed, making sure the different prostheses used for the "ideal" and socket interfaces are accounted for.

It is also possible that other unknown factors may have affected the results, such as the mechanical response of the hand, or the exact location of the electrodes (for some participants the electrode location within the socket was not the 'optimal' location, however on occasions the best signal was found in a location where the electrode could not be placed within the socket due to trim lines). Two participants in the study had wrist rotators on the prosthesis which they were asked not to use whilst in the clinic to allow comparison of their results with other users. During pilot testing it was noted that when using a wrist rotator the functional task duration

increased significantly. Therefore if future studies were to evaluate hands with multiple degrees of freedom, then the number of DOFs should also be considered within the evaluation.

5.6. **Summary**

This study set out aiming to establish whether *EMG skill*, *unpredictability* introduced at the skin-electrode interface, or the electromechanical *delay* in the prosthesis had the greatest impact on user *functionality* and everyday *prosthesis usage*. The small sample size meant that this study was unable to answer this question; nevertheless, some control factors did show stronger relationships with performance than others (such as the relationship between the number of undesired responses of the hand, and the time taken to perform the functional task). The findings suggest that future efforts should be concentrated on better understanding why the prosthesis responds unexpectedly, and how the electrode interface could be improved to reduce the number of undesired activations of the hand.

Additionally we have shown that for the majority of prosthesis users, the delay to open the hand from a fully closed position is significantly longer than the delay from any other starting aperture. Further work would be recommended to establish the impact this has on user performance.

6

Results

Upper limb activity in myoelectric prosthesis users compared with anatomically intact participants, and an initial exploration of the relationship between clinical functionality and everyday upper limb activity

As noted in the earlier chapters, activity monitors offer an objective measure of prosthesis use outside of the clinical environment. In this chapter data is presented from 20 myoelectric prosthesis users collected over a 7 day period. This data provides a first look at how people use their prostheses during an average week, and compares this to the upper limb activity of 20 anatomically intact subjects. Furthermore, prosthesis use is compared against measures of user *functionality* as presented in the previous chapter.

6.1. Introduction

Over-reliance on one upper limb may lead to overuse injuries [43-45]. People with upper limb absence are twice as likely to experience musculoskeletal complaints compared to the general population, with up to 65% of people affected [152]. For a person with upper limb absence, one of the aims of prescription of a prosthesis is to restore a degree of function to the affected limb. In people with unilateral upper limb absence, a prosthesis which facilitates the execution of functional tasks may reduce the over-reliance on the anatomically intact side and this may, in turn, be reflected in upper limb activity patterns which are closer to those seen in anatomically intact individuals.

To date, studies of the effectiveness or otherwise of prosthetic hands have involved assessing user performance on functional tasks in the lab/clinic [77, 81, 85, 88, 101], sometimes combined with questionnaires to elicit data on usage in the real world. It is well established in other fields that questionnaires on real world behaviours are subject to bias and recall errors [153] and, at best, provide only averaged data on activity [154].

Previously [109] (**Chapter 3**), building on a technique introduced by Bailey et al. [108] to study upper limb activity in people with impairments following stroke, we introduced the use of wrist-worn activity monitoring sensors for the objective assessment of the upper limb activity of prosthesis users. The approach was illustrated with data collected from two trans-radial users of myoelectric prostheses and one anatomically intact participant, showing that in contrast to the data from the anatomically intact participant, the upper limb activity in both prosthesis users was heavily skewed towards their anatomical limb. However, it was not known whether these patterns of upper limb activity reported in Chadwell et al. [109] (**Chapter 3**) are seen in larger groups of myoelectric prosthesis users and anatomically intact participants. To address this question, we report data collected over a 7-day period describing the upper limb activity of twenty people with upper limb absence who have been provided with a myoelectric prosthesis and twenty anatomically intact participants. Using our novel approach to visualising the temporal patterns in upper

limb activity data [154] (**Chapter 4**) we also investigate the extent to which previous self-report approaches [91] are capturing the true patterns of upper limb activities in the real world.

In the second part of the chapter, we investigate a question which has been previously studied by Bailey et al. [108] in a stroke population. Bailey [108] showed that performance on lab-based assessments of *functionality* (specifically the Action Research Arm Test – ARAT) did not strongly reflect the real world *usage* of the affected arm. In this chapter, we investigate whether measures of clinical *functionality* evaluated using a multi-stage functional task correlate with different measures of upper limb activity (*usage* measures) in the same group of twenty people with upper limb absence who have been provided with a myoelectric prosthesis.

6.2. Methods

6.2.1. *Participants*

Twenty participants (14 male, 6 female) with unilateral upper limb absence at a trans-radial level were recruited from six (4 NHS, 2 University) sites across the UK. All participants had a single degree of freedom myoelectric prosthesis (e.g. Steeper Select or Ottobock DMC Plus/VariPlus/Sensor Speed).

The age of the prosthesis users ranged from 18 to 75 years (mean age 53 years). Eleven people had congenital limb absence (6 Right/5 Left), and nine had an amputation (6 Right/3 Left); six of the amputations had occurred on the dominant side. Time since amputation ranged from 8-47 years (mean 25 years). Time since prescription of a myoelectric prosthesis ranged from 1.5-39 years (mean 20 years).

A group of twenty anatomically intact participants (9 male, 11 female, age 23-61, mean age 43, 3 left handed) with no upper limb impairments were also recruited through the University of Salford.

Ethical approval for this study was granted by the University of Salford School of Health Sciences Research Ethics committee (REF: HSCR 16-25), by the University of Strathclyde Department of Biomedical Engineering Ethics Committee

(DEC.BioMed.2017.220) and through the NHS IRAS system (IRAS Project ID: 193794). Informed consent was gained from all participants.

6.2.2. *Equipment*

To evaluate upper limb activity in the real world, we used Actigraph activity monitoring sensors from the GT3X range (GT3X+, wGT3X, wGT3X-BT). These sensors provided continuous logging of acceleration across three axes at 30 Hz.

Functionality of the prosthesis users was assessed using during performance of a multistage task [109]. An electronic goniometer (Biometrics Ltd) was attached across the proximal knuckle of the index finger (on the prosthetic hand) to measure hand aperture. An Inertial Measurement Unit (IMU) (Xsens MTw) was fixed on the forearm to measure wrist motion. A head-mounted eye tracker (Dikablis Professional Wireless) was worn to capture gaze behaviour. A button was placed beneath the hand in the starting position for synchronisation purposes. Full details of the task are provided in **Chapter 5** and the **Appendices**.

6.2.3. *Protocol*

The methods for the assessment of everyday activity used in this study are described in Prosthetics and Orthotics International [154] (**Chapter 4**), however, since this publication a couple of amendments were made to the protocol. A newer version of the Actilife software was used (Actilife6 for compatibility with the newer sensors) and an updated non-wear algorithm was developed as detailed in **Appendix 7b**.

6.2.3.1. DATA COLLECTION – EVERYDAY ACTIVITY

The sensors were initialised using Actilife6 software and programmed to record data for 7 days at 30Hz. The start time was set so that the participant was wearing the sensors at the onset of data recording.

Participants were asked to wear the sensors, one on each wrist, for a 7-day period. The monitors were labelled to indicate on which wrist, and in which orientation they should be worn. Participants were requested to remove the monitors, only when they may become wet. As the myoelectric prosthesis would not be worn during

bathing or showering, participants were instructed to leave the prosthesis-worn monitor on throughout the testing period.

Participants were asked not to alter their behaviour during the data collection period and to keep a simple diary, which would be used to assist with the interpretation of the data. This diary included the recording of sleep/wake times, periods of sensor removal, and for the prosthesis users, periods of prosthesis removal.

At the end of the 7-day period, participants were asked to return the sensors and the completed diary either in person or by post.

6.2.3.2. DATA COLLECTION – FUNCTIONALITY

To evaluate the skill with which the prosthesis user was able to perform a functional task they were asked to reach to grasp a cylinder, lift and rotate it through 90° to the horizontal, then place it inside a tube [109] (**cylinder task**). Participants were asked to attempt the task ten times.

Task onset (the start of reach to grasp) was defined as the onset of movement (either lifting the arm or opening the hand), the end of reach to grasp was defined as the point at which the fingers finished closing around the cylinder, and task completion was defined as the moment the fingers began to open to release the cylinder after it had been placed into the tube (see **Appendix 5**).

6.2.3.3. ACTIVITY DATA PREPARATION PROPRIETARY TO ACTILIFE SOFTWARE

Data were downloaded using Actilife6 software. A low frequency extension filter (proprietary to the Actilife software) was employed [143]. The filtered accelerations were grouped into one minute epochs and converted into activity counts (for each of the three axes) using proprietary algorithms [140]. For each epoch, the resultant of the activity counts across the three axes was calculated generating the Vector Magnitude (VM). The VMs were exported to MATLAB (v. 2016a) for further analysis.

6.2.3.4. LIMB DOMINANCE TERMINOLOGY

As this chapter reports data from both anatomically intact participants and persons with upper limb absence who have been prescribed a myoelectric prosthesis, we define the terminology used to describe the limbs as follows.

The upper limb of each anatomically intact subject with which they self-reported to write was defined as the dominant, with their other being the non-dominant.

To reduce the number of equations used to characterise upper limb activity, we use the same variable names when referring to both anatomically intact participants and the prosthesis users. Therefore, we label both the anatomically intact upper limb of participants with unilateral upper limb absence and the dominant limb of the anatomically intact participants as the dominant limb; we label the other limb as the non-dominant limb [155]. However, within the text of the Results and Discussion sections, we refer to the **anatomical arm** and the **prosthesis** for ease of understanding.

6.2.3.5. REMOVAL OF PROSTHESIS NON-WEAR TIME

As we were interested in how the prosthesis was used during the periods when it was worn, a method of removing the non-wear periods was required. "*Prosthesis non-wear*" was assumed to correspond to the times when the monitor worn on the wrist of the prosthesis recorded prolonged inactivity. In our earlier paper [109] (**Appendix 7a**) we developed an algorithm for removal of these "*prosthesis non-wear*" periods, which required some visual inspection of the data. Subsequently a more automated algorithm for the removal of "*prosthesis non-wear*" periods was developed (see **Appendix 7b**).

6.2.3.6. DATA ANALYSIS – EVERYDAY ACTIVITY

For the prosthesis users we calculated the amount of time (in hours) spent wearing the myoelectric prosthesis over the 7-day period. This is referred to as "***Prosthesis wear time (C)***" calculated by subtracting the "*prosthesis non-wear*" periods from the overall recording time. We use the letter C in parentheses to distinguish wear time

calculated using the non-wear algorithm "***Prosthesis wear time (C)***" from self-reported wear time "***Prosthesis wear time (SR)***".

For both cohorts we also calculated the balance of activity across both limbs. First, for every epoch, the percentage reliance on the dominant side ("***% Reliance$_{Dom}$***") was calculated based on the VM values from the sensors on each arm. Where the VM was **equal to 0** on both arms, the 1-min epoch was marked as '**both arms at rest**'. For all other 1-min epochs the VM on the dominant side was divided by the sum of the VM across both arms to calculate the percentage reliance on the dominant side:

$$[\%Reliance_{Dom} = round(VM_{Dom}/(VM_{Dom} + VM_{NonDom}) \times 100)]$$

Two summary measures were calculated to characterise the balance of activity, one considering all data during which either or both arms were moving ("***Median %Reliance$_{Dom}$***"), and one considering only the data during which activity was seen on only one limb ("***Unilateral ratio***"). Epochs previously marked as '**both arms at rest**' were excluded from this analysis. For prosthesis users, "*prosthesis non-wear*" periods (calculated using the non-wear algorithm) were also excluded.

1) "***Median %Reliance$_{Dom}$***" defined as the median of all of the "***%Reliance$_{Dom}$***" values
2) "***Unilateral ratio***" defined as the ratio between the unilateral activity on the dominant and non-dominant sides ("***UL$_{Dom}$***" : "***UL$_{NonDom}$***"). Here, unilateral dominant activity ("***UL$_{Dom}$***"), was defined as the number of minutes where activity counts were only recorded on the sensor on the dominant limb (VM_{NonDom}=0); Unilateral non-dominant activity ("***UL$_{NonDom}$***") was defined as the number of minutes where activity counts were only recorded on the non-dominant sensor (VM_{Dom}=0)

6.2.3.7. DATA ANALYSIS – FUNCTIONALITY

For each participant, *functionality* measured during performance of the **cylinder task**, was evaluated using a series of previously reported measures:

1) **Task success** – The total number of successful trials (out of 10). Trials where the movement was not smooth (e.g. the hand opened and closed more than once

during "reach-to-grasp"), and trials where the cylinder was not placed all of the way into the tube (but remained in place once released) were counted as successful but only scored half a point. Trials where the cylinder was knocked over or dropped were counted as unsuccessful.

2) **Task duration** – The mean duration of the successful attempts (in seconds)
3) **"Delay plateau"** – Bouwsema [86] found that prosthesis users demonstrate a delay in the onset of hand opening at the start of "reach-to-grasp" not generally seen in anatomically intact subjects. For those trials where the user successfully achieved a grasp, the time between the task onset and the onset of hand opening was calculated and expressed as a percentage of "reach-to-grasp". A mean value was reported for each participant.
4) **"Reach plateau"** – Bouwsema [85] also found that prosthesis users demonstrate a characteristic plateau in their hand aperture during "reach-to-grasp". The length of this plateau was shown to reduce with improved *functionality* (measured using the Southampton Hand Assessment procedure). For those trials where the user successfully achieved a grasp, we identified the plateau periods based on the hand aperture being within two degrees of the maximum, and calculated the durations as a percentage of "reach-to-grasp". A mean value was reported for each participant.
5) **Acceleration temporal variability** – Prosthesis users have been shown to demonstrate increased trial-trial temporal variability in the trajectories of wrist-worn accelerometer data when compared to anatomically intact subjects [119]. Furthermore, this variability has been shown to decrease with practice [87]. Here we assessed the temporal variability in the acceleration of the forearm between successful trials (calculated according to the methods of Thies et al. [120])
6) **Gaze patterns** – Prosthesis users have been shown to spend a proportion of the "reach-to-grasp" phase focussing on their hand and/or the area of the object to be grasped (grasp critical area or GCA); by contrast anatomically intact participants generally look ahead to plan subsequent parts of the task, rarely looking at their hand or the GCA [88, 89]. During the "transport" phase, similar patterns of behaviour are seen, with prosthesis users focusing on the hand and/or GCA. Here we report:

- The % of the "reach-to-grasp" phase spent looking at:
  - the hand
  - the grasp critical area (GCA bottom half) of the cylinder
  - the location critical area (LCA top half) of the cylinder, or the tube
- The % of the "transport" phase spent looking at:
  - the hand or the GCA of the cylinder
  - the LCA of the cylinder, or the tube

6.2.3.8. DATA ANALYSIS - CORRELATIONS

Due to the size of the dataset and some measures containing a large number of tied ranks (e.g. success rate), Kendall's Tau-b (2-tailed) was used to establish whether any significant correlations existed between the clinical measures of *functionality* and the everyday upper limb activity measures. Analysis was undertaken using IBM SPSS Statistics software v24.0.0.1.

6.2.3.9. DATA VISUALISATION – EVERYDAY ACTIVITY

Two types of data visualisation were used to display the activity data. Archimedean spiral plots [154] were used to illustrate temporal patterns in the upper limb activity, and histograms were produced to characterise the distribution of activity between the two upper limbs.

To generate the spiral plots the "$\%Reliance_{Dom}$" values for each epoch were categorised according to the values in **Table 14**. The colour coded data were plotted using the spiral time series visualisation introduced in our earlier paper [154] (see **Chapter 4**). Working outwards, each revolution signified 24 hours, with midnight at the top and midday at the bottom.

A histogram of the "$\%Reliance_{Dom}$" values for each epoch was also produced. The data were grouped into activity bins (in 1% increments), and the number of minutes of data within each bin was plotted on the y-axis. For ease of visualisation, the time was displayed on a $\log_{10}$ scale.

N.B. "*Prosthesis non-wear*" periods (according to the non-wear algorithm) and times when both arms were at rest were not included in the histogram.

Table 14. Allocation of activity monitoring data (per epoch) into categories based on the values for the percentage reliance on the dominant side. A colour is assigned to each category.

% Reliance on dominant side	Categories	Colour
0 %	Unilateral non-dominant (prosthesis)	
1-10 %	90-99 % non-dominant	
11-20 %	80-89 % non-dominant	
21-30 %	70-79 % non-dominant	
31-40 %	60-69 % non-dominant	
41-59 %	Even contribution from both arms	
60-69 %	60-69 % dominant	
70-79 %	70-79 % dominant	
80-89 %	80-89 % dominant	
90-99 %	90-99 % dominant	
100 %	Unilateral dominant	
VM on both sides = 0	Both arms at rest	

6.3. Results

6.3.1. *Everyday upper limb activity of myoelectric prosthesis users*

In this section the results of the analysis for the twenty myoelectric prosthesis users are presented. It is important that we distinguish between the amount of time the prosthesis was worn during the week ("***prosthesis wear time (C)***") and the actual *usage* of the prosthetic arm (quantified using "**Median %Reliance$_{Dom}$**") during these periods; these two points are therefore addressed separately.

6.3.1.1. SELF-REPORTED PROSTHESIS WEAR TIME

The quality of the self-report data differed between subjects. Five participants failed to report a full set of times for the removal of the prosthesis and/or monitors (for example the participants would self-report the prosthesis to be removed, but not report it being put back on); additionally, one participant did not complete the diary at all and instead provided a written account of their non-wear from memory.

For the 14 remaining prosthesis users, the self-reported "***prosthesis wear time (SR)***" was compared to the calculated "***prosthesis wear time (C)***". On average (median) the algorithm calculated the "***prosthesis wear time (C)***" over the 7 days to be 4.4 hours shorter than self-reported (Maximum negative difference = -52.6 hours (calculated shorter), maximum positive difference = 6.3 hours (calculated longer), Q1

= -9.5 hours, Q3 = 0.8 hours). Approximately 35% of participants showed a difference between self-reported and calculated wear times of less than 5% of the total "***prosthesis wear time (C)***".

For all subsequent analysis, the "*prosthesis non-wear*" periods were removed using the non-wear algorithm.

6.3.1.2. PROSTHESIS WEAR TIME CALCULATED USING THE NON-WEAR ALGORITHM

Five of the participants wore the prosthesis all day, every day, removing it only to sleep ("***prosthesis wear time (C)***" > 91 hours / 13 hours per day, maximum = 106.9 hours per week). Two participants wore the prosthesis for less than 3 hours over the 7 day period (minimum "***prosthesis wear time (C)***" = 2.8 hours per week). The remainder of the participants either wore the prosthesis during the daytime removing it in the evenings each day, altered their wear pattern throughout the week, or wore the prosthesis only for short periods. The median "***prosthesis wear time (C)***" was 45.6 hours per week (Q1=25.4, Q3=88.7) (**Figure 46**).

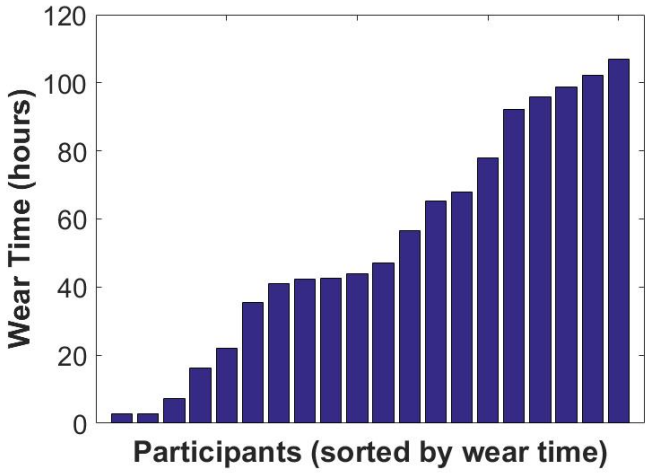


Figure 46. "***Prosthesis wear time (C)***" as calculated using the non-wear algorithm for each of the 20 participants. Median = 45.6 hours (IQR = 63.4).

6.3.1.3. PROSTHESIS USAGE

The primary measure of *prosthesis usage* was the "***Median %Reliance$_{Dom}$***". For each participant this median value was calculated based only on the times the prosthesis was worn. Histograms were plotted based on the percentage reliance on the

anatomically intact side for each minute of data collected (50% signifying an equal Vector Magnitude recorded on each sensor for that minute).

All of the prosthesis users demonstrated a skew in the histogram towards the anatomical side (>50%). This was supported by "***Median %Reliance$_{Dom}$***" values ranging from 66.8% up to 87.3% reliance on the anatomical side (median=79.9%, Q1=74.5%, Q3=84.7%). **Figure 47** presents example histograms for three of the participants: **(A)** the person least reliant on the anatomical side, **(B)** a person from the middle of the dataset, and **(C)** the person most reliant on the anatomical side.

We found there to be a medium negative correlation between time since prescription of a myoelectric prosthesis and the "***Median %Reliance$_{Dom}$***" (Kendall's τ_b= -.464, p = .005, n=20).

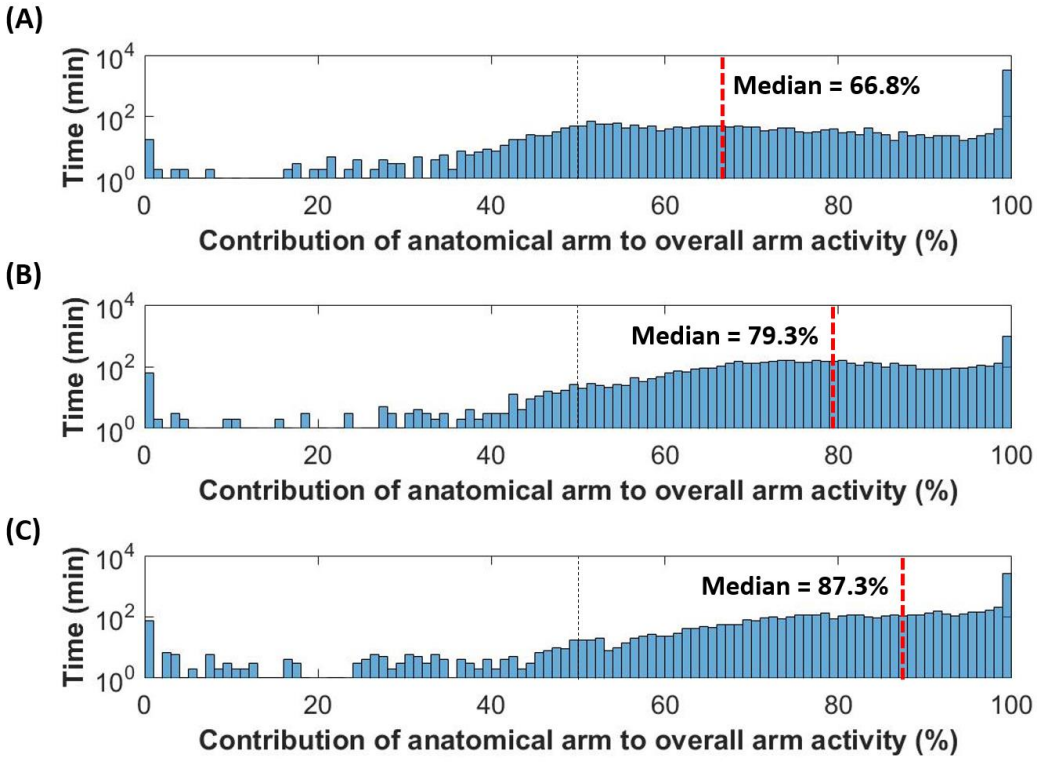


Figure 47. Histograms representing the reliance on the dominant arm over the 7-day period. Data is displayed for the participants with **(A)** the lowest "***Median %Reliance$_{Dom}$***" value, **(B)** the "***Median %Reliance$_{Dom}$***" value closest to the mean and median of all twenty participants, and **(C)** the highest "***Median %Reliance$_{Dom}$***" value (the person most reliant on their anatomical arm). NB. The time (y-axis) is displayed using a $\log_{10}$ scale to mitigate for large amounts of unilateral activity.

A secondary measure of *prosthesis usage* was the "***unilateral ratio***", defined as the ratio between unilateral activity on the dominant and non-dominant sides. The time spent using the anatomical arm alone (the bar at 100%) was higher than the unilateral use of the prosthesis (the bar at 0%) for all participants. The minimum "***unilateral ratio***" was 4.3 minutes of unilateral use of the anatomical side for each minute spent using the prosthesis in a unilateral manner (356 mins anatomical, 82 mins prosthesis, "**prosthesis wear time (C)**" = 98.7 hours). Two participants demonstrated 0 minutes of unilateral prosthesis use resulting in an undefined "***unilateral ratio***". For the remaining eighteen participants, the "**unilateral ratios**" of "UL_{Dom}": "UL_{NonDom}" were as follows: minimum = 4.3:1, first quartile = 9.6:1, median = 11.5:1, third quartile = 21.8:1, and maximum = 73:1.

6.3.1.4. PROSTHESIS WEAR TIME VS PROSTHESIS USAGE

It is important to note that increased "***prosthesis wear time (C)***" does not necessarily correspond to a more symmetrical arm *usage* pattern during the times when the prosthesis was actually worn (Kendall's τ_b= .032, p = .846, n=20). **Figure 48** shows the spiral plots for all twenty prosthesis users ordered according to the "***Median %Reliance$_{Dom}$***" values (shown in red), calculated based only on the data from the times when the prosthesis was worn; the associated "***prosthesis wear time (C)***" is also reported (shown in blue and rounded to the nearest hour).

The five 'all-day wearers' ("***prosthesis wear time (C)***" > 91 hours) are actually spread throughout the group (**Figure 48 C**, **I**, **J**, **N**, and **T**); whilst the person with the most symmetrical arm *usage* (**Figure 48A**, "***Median %Reliance$_{Dom}$***" = 66.8% reliance on the anatomical arm) donned and doffed the prosthesis regularly throughout the day ("***prosthesis wear time (C)***" = 41 hours).

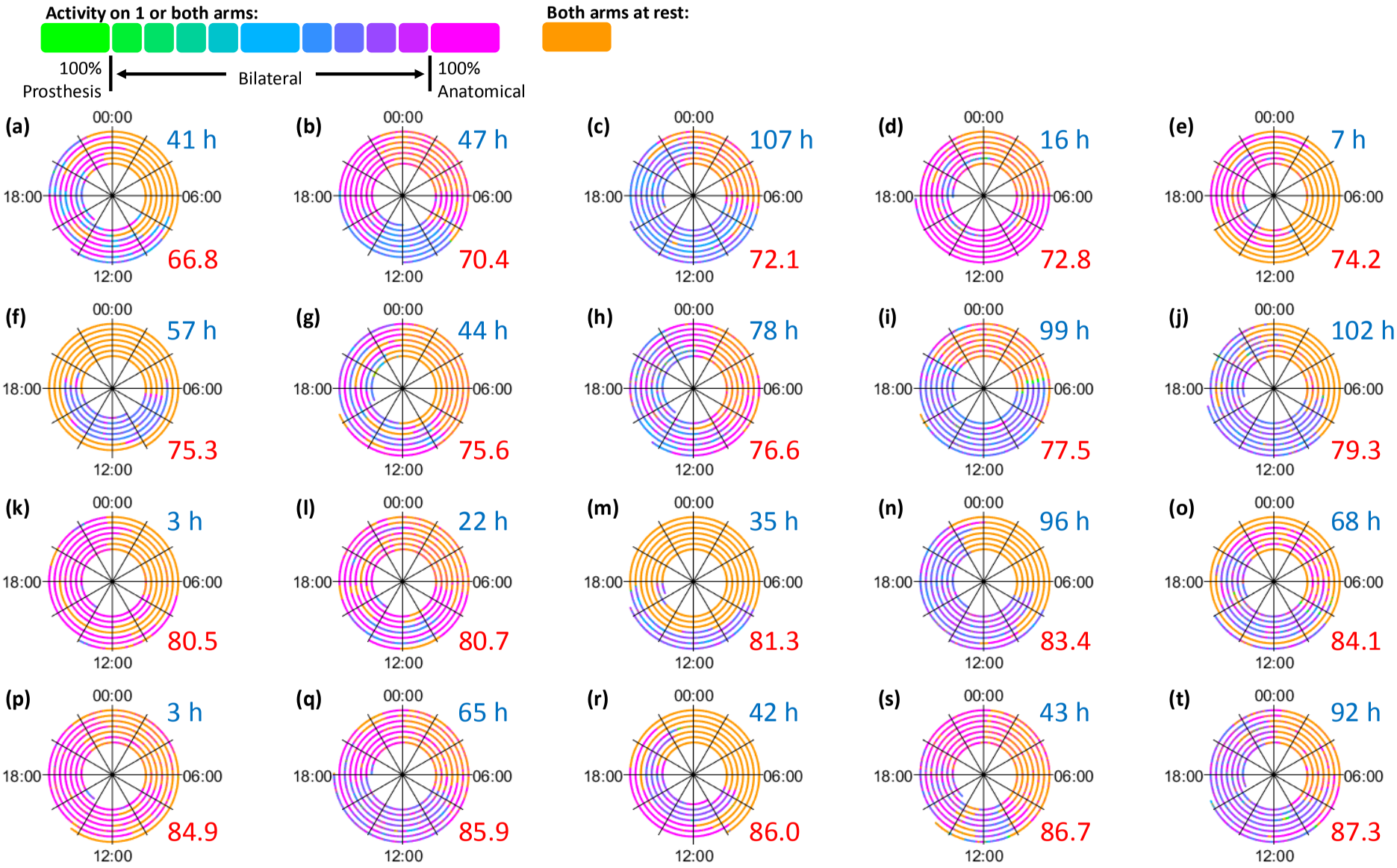


Figure 48. Spiral plots for all 20 myoelectric prosthesis users. The plots are ordered according the "***Median %Reliance$_{Dom}$***" values (calculated based on the times the prosthesis was worn) from the person who is the least reliant on the anatomical side to the person who is the most reliant. The "***prosthesis wear time (C)***" for each user is shown in blue (rounded to the nearest hour), and the "***Median %Reliance$_{Dom}$***" is shown in red.

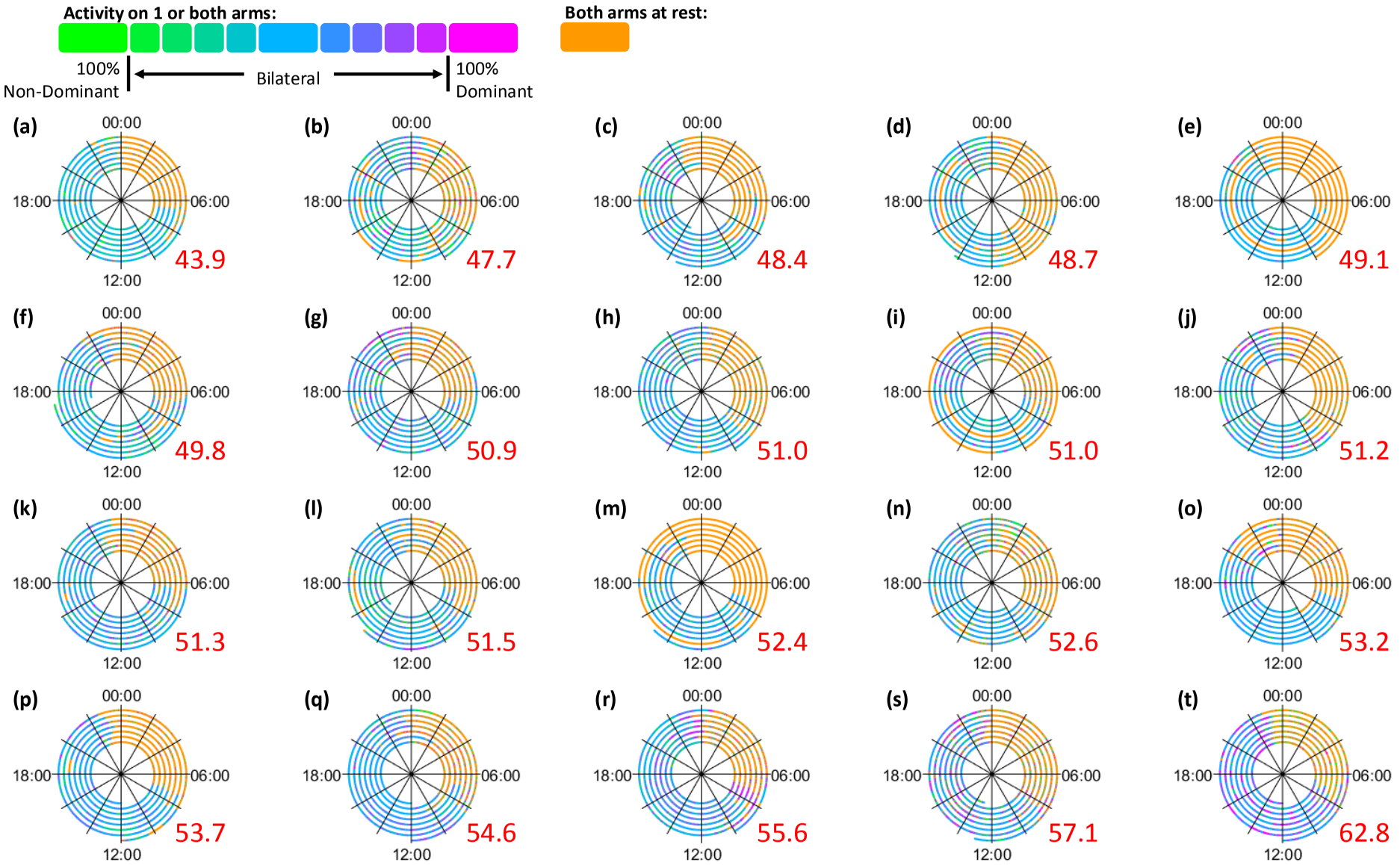


Figure 49. Spiral plots for all 20 anatomically intact subjects. The plots are ordered according the "***Median %Reliance$_{Dom}$***" values from the person who is the least reliant on the dominant side to the person who is the most reliant. The "***Median %Reliance$_{Dom}$***" is shown in red.

6.3.2. *Upper limb activity of anatomically intact participants*

Most anatomically intact participants were slightly more reliant on their dominant side ("***Median %Reliance$_{Dom}$***" >50%), whilst some showed a slight preference towards their non-dominant side ("***Median %Reliance$_{Dom}$***" <50%). Across the twenty participants, the "***Median %Reliance$_{Dom}$***" values ranged from 43.9% to 62.8% (median=51.3%, Q1=49.3%, Q3=53.6%).

The anatomically intact subjects showed a high frequency of unilateral activity at 0% (unilateral non-dominant) and 100% (unilateral dominant). The height of these bars were similar on both sides of the histogram; the "***unilateral ratio***" of "***UL$_{Dom}$***": "***UL$_{NonDom}$***" can be described as follows: minimum = 0.42:1, first quartile = 0.79:1, median = 1.31:1, third quartile = 1.74:1, and maximum = 2.08:1.

6.3.3. *Comparing the upper limb activity of prosthesis users to the anatomically intact participants*

Figure 49 shows the spiral plots for all twenty anatomically intact participants. An immediate colour difference can be seen when comparing these plots to the spirals for the prosthesis users in **Figure 48**. The spirals for the anatomically intact subjects tend to be primarily blue, with portions of both green and magenta corresponding to activities where each arm is used in a unilateral manner. The spirals for the prosthesis users tend to be purple, with large portions of magenta, and very little green (corresponding to a preference towards the prosthesis).

To provide an overview of this *usage* data, in **Figure 50A** the data recorded for all twenty anatomically intact subjects is grouped into a single histogram with an overall "***Median %Reliance$_{Dom}$***" value of 51.5%. When comparing this group histogram to the grouped data recorded from the twenty prosthesis users (**Figure 50B**) ("***Median %Reliance$_{Dom}$***" = 79.1%), a clear difference in the shape of the histogram can be seen. As noted previously, the prosthesis users are heavily reliant on the anatomically intact arm, and periods where more activity occurs on the prosthetic side than on the anatomical side (% contribution < 50%) are comparatively rare (≈18 min >50% for each minute ≤50% compared to ≈1:1 in the anatomically intact group).

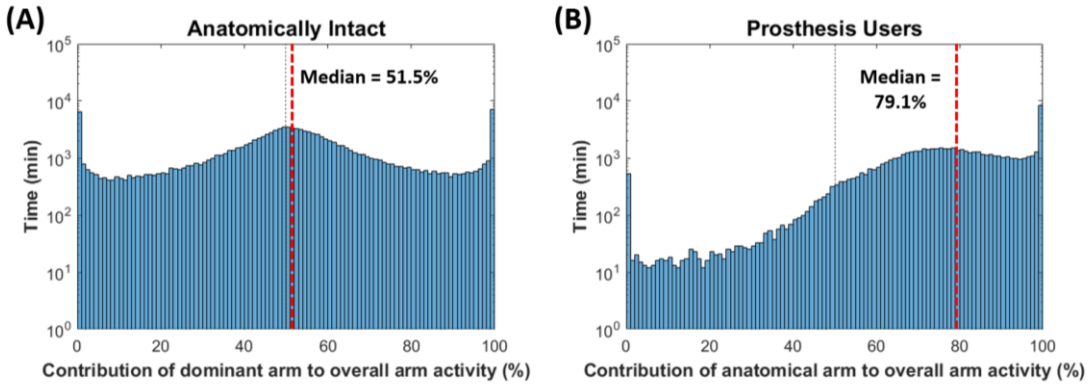


Figure 50. Histograms showing the grouped data for **(A)** all 20 anatomically intact subjects and **(B)** all 20 prosthesis users. The anatomically intact participants are similarly reliant on both arms ("***Median %Reliance$_{Dom}$***" = 51.5%), whilst the prosthesis users are significantly more reliant on the anatomically intact side ("***Median %Reliance$_{Dom}$***" = 79.1%).

It is worth noting that for the prosthesis users, the data included in the histogram and "***Median %Reliance$_{Dom}$***" calculations are only from the times when the prosthesis was worn, consequently the overall number of data points was lower than that used in the calculations for the anatomically intact subjects.

To illustrate the differences between prosthesis users, **Figure 51** presents data from two prosthesis users who wore the prosthesis all day every day, and for comparison, an average anatomically intact participant. Both prosthesis users demonstrated a skew in the histogram with a preference towards their unaffected arm, however the participant in **Figure 51B** showed more pronounced curvature than the participant in **Figure 51A** with a peak around 65-75%. As participants use their prosthesis more, this peak would be expected to shift towards the centre as seen in the anatomically intact example (**Figure 51C**).

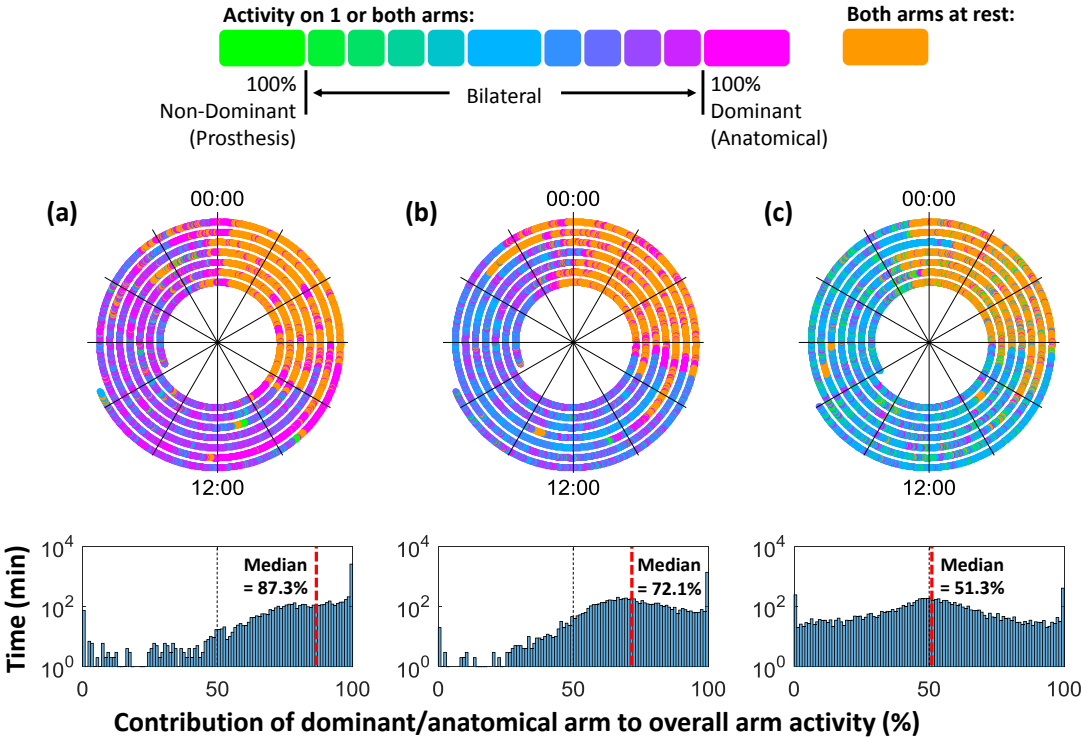


Figure 51. (A) The all-day prosthesis wearer with the highest "***Median %Reliance$_{Dom}$***" value (=87.3%), **(B)** the all-day prosthesis wearer with the lowest "***Median %Reliance$_{Dom}$***" value (=72.1%), and **(C)** an average anatomically intact participant ("***Median %Reliance$_{Dom}$***" = 51.3%)

6.3.4. *Correlations between clinical functionality and everyday upper limb activity*

Table 15 presents the results of the Kendall's Tau-b correlations between the measures of clinical *functionality* (incl. task success, duration and kinematic and gaze based measures of performance) and the measures of everyday upper limb activity (signifying prosthesis wear and *usage*) for the twenty prosthesis users. **No significant correlations ($p<0.05$) were found** between any of the measures of *functionality* and the measures of everyday activity evaluated using the activity monitors.

Table 15. Kendall's Tau-b (2-tailed) correlations between the clinical measures of *functionality* and the measures of everyday activity. NB. The calibration of the eye tracker failed for 1 participant, and the "***Unilateral Ratio***" for 2 participants was undefined (no unilateral prosthesis activity); these participants were excluded from the relevant correlations (n = number of values included in correlation). ** Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed). NB: GCA = Grasp Critical Area of the cylinder, LCA = Location Critical Area of the cylinder

	Success Rate	Task Duration	Delay Plateau Length	Reach Plateau Length	Acceleration Variability	Reach-to-grasp %Hand	Reach-to-grasp %GCA	Reach-to-grasp %LCA/Tube	Transport %Hand/GCA	Transport %LCA/Tube
Median %Reliance Dominant	τ = .071 p = .681 n = 20	τ = .105 p = .516 n = 20	τ = .158 p = .330 n = 20	τ = -.074 p = .650 n = 20	τ = -.053 p = .746 n = 20	τ = .030 p = .860 n = 19	τ = .076 p = .649 n = 19	τ = -.041 p = .807 n = 19	τ = -.129 p = .441 n = 19	τ = .181 p = .278 n = 19
Unilateral Ratio	τ = .200 p = .272 n = 18	τ = -.150 p = .384 n = 18	τ = .020 p = .910 n = 18	τ = .020 p = .910 n = 18	τ = -.255 p = .140 n = 18	τ = -.260 p = .155 n = 17	τ = -.015 p = .934 n = 17	τ = .309 p = .084 n = 17	τ = -.199 p = .266 n = 17	τ = .088 p = .621 n = 17
Prosthesis Wear Time	τ = .047 p = .784 n = 20	τ = .000 p = 1.000 n = 20	τ = .053 p = .746 n = 20	τ = -.158 p = .330 n = 20	τ = -.011 p = .948 n = 20	τ = .066 p = .697 n = 19	τ = .251 p = .132 n = 19	τ = -.263 p = .115 n = 19	τ = -.117 p = .484 n = 19	τ = .287 p = .086 n = 19
Unilateral Dominant	τ = .083 p = .632 n = 20	τ = .116 p = .475 n = 20	τ = .126 p = .436 n = 20	τ = -.232 p = .153 n = 20	τ = .105 p = .516 n = 20	τ = -.042 p = .805 n = 19	τ = .088 p = .600 n = 19	τ = -.053 p = .753 n = 19	τ = -.235 p = .161 n = 19	τ = .263 p = .115 n = 19
Unilateral Non-dominant	τ = -.191 p = .273 n = 20	τ = .281 p = .085 n = 20	τ = .143 p = .380 n = 20	τ = -.207 p = .205 n = 20	τ = .218 p = .183 n = 20	τ = .128 p = .457 n = 19	τ = .130 p = .441 n = 19	τ = -.201 p = .233 n = 19	τ = -.065 p = .700 n = 19	τ = .118 p = .483 n = 19

6.4. Discussion

6.4.1. *Sample size*

Although there are no national statistics on upper limb prosthesis provision in the UK, based on our clinical contacts we estimate that there are approximately 800-1000 myoelectric prosthesis users registered to NHS limb centres in the UK. This multi-site study of twenty people who have received a myoelectric prosthesis is one of the largest experimental studies of this population undertaken in the UK to date.

6.4.2. *Prosthesis wear time*

Prosthesis users ranged from people who rarely wore their prosthesis through to people who wore the prosthesis all day every day.

6.4.2.1. ACCURACY OF SELF REPORTED PROSTHESIS WEAR TIME

Self-report has been shown in some cases to have the potential to provide an extremely accurate measure of '*prosthesis wear time*', however, the reliability of the person providing the data cannot be guaranteed (in this study 30% of participants failed to provide completed diaries), and consequently the use of automated algorithms based on the data from the activity monitors is preferable and was used for all subsequent analysis.

6.4.2.2. DISADVANTAGES OF REPORTING AVERAGE PROSTHESIS WEAR TIME

Until now the primary measure of prosthesis wear has been the average daily '*prosthesis wear time*'. For some participants, the wear patterns varied in a complex manner over time. For example, the participant represented in **Figure 48G** demonstrated a highly variable wear pattern. On some days this participant wore the prosthesis for 9-11 hours, whilst on other days they chose to wear the prosthesis for less than 4 hours, or even not at all. Consequently, a single value constituting the average daily "***prosthesis wear time (C)***" would provide limited insight into the long-term wear pattern for this user.

Similarly, two users who exhibit the same average "***prosthesis wear time (C)***" may wear their prosthesis in a very different manner. For example, the two participants represented in **Figure 48A** and **Figure 48R** have weekly "***prosthesis wear times (C)***" of 41 and 42 hours respectively; nevertheless their wear patterns are visibly very different with one user regularly taking the prosthesis on and off, whilst the other wore it for the full day, but only on 4 of the days of testing.

The spiral plot time series visualisations provide context to the "***prosthesis wear time (C)***" to help understand the patterns of wear.

6.4.3. *Quantifying prosthesis usage*

As mentioned in the introduction, it is reasonable to suppose that provision of a myoelectric prosthesis to a person with unilateral upper limb absence may lead to a lower reliance on their anatomically intact side. Not only does this mean that we should be evaluating whether the prosthesis is worn, but also the actual *usage* of the prosthesis should be measured (no significant correlation ($p<0.05$) was found between these measures).

The techniques used in this chapter allow us to both visualise and quantify a prosthesis user's progression towards the symmetrical upper limb use demonstrated by anatomically intact participants. Nevertheless, as can be seen in **Figure 51B**, there is still a clearly visible difference between the prosthesis user who displayed the longest "***prosthesis wear time (C)***" combined with the highest level of *prosthesis usage*, and the anatomically intact example (**Figure 51C**).

All of the prosthesis users demonstrated an increased reliance on their anatomically intact side. However, we noted that participants who had been prescribed a myoelectric prosthesis for longer tended to be less reliant on their anatomically intact side ("***Median %Reliance$_{Dom}$***" closer to 50%).

Previous work has suggested that a person with no upper limb impairments is equally reliant on both of their arms during daily life [108, 109, 154] (with a very slight preference towards the dominant side equivalent to 52% reliance [108]). Similar to the findings of

these other studies we found our anatomically intact participants to be evenly reliant on each of their arms (51% reliance on dominant side).

6.4.4. *The relationship between clinical measures of functionality and everyday upper limb activity*

It has been established that the primary method of evaluating the 'success' of a prosthesis is through the use of clinical *functionality* assessment tasks. Outcome measures often include task success and duration, or more recently measures such as gaze behaviour, kinematic variability or patterns in hand aperture.

In this study we found there to be no significant correlation ($p<0.05$) between any of the measures of clinically assessed *functionality* and the measures of *prosthesis wear* and *usage*. A simple assumption might be that the better a prosthesis user performs on a functional task, the more likely they are to use the prosthesis to perform everyday tasks. Our findings begin to question this assumption and suggest the need for further work to explore how we assess prostheses.

6.5. Limitations and future work

Our previous paper [154] (see **Chapter 4**) highlighted some of the limitations with these methods for the assessment of upper limb prosthesis users outside of the clinic using activity monitors. Most notably, our current measure of *prosthesis usage* does not account for the active use of the prosthetic hand (as opposed to its use to, for example, simply stabilise an object). Future studies should complement the wrist-worn accelerometer data with a log of activations of the hand.

It is also worth noting that at present the automated non-wear algorithm is not able to differentiate between the prosthesis or the monitors being carried and being worn, therefore, it is possible that the algorithm may provide a slight over-estimate of the "*prosthesis wear time*". Furthermore, there is currently no way to determine whether the monitor has been removed from the wrist of the prosthesis; consequently if the prosthesis was worn but the sensors were not then this was counted as "*prosthesis non-wear*" (see **Appendix 7b**). One participant self-reported removing the sensors from the prosthesis during one of the days of data collection.

Further work (and potentially some additional sensors [156]) would be required to provide an entirely accurate measure of the "*prosthesis non-wear*" periods.

In the case of a person not demonstrating any minutes of unilateral prosthesis use over the recording period, the methods presented in this chapter do not allow the calculation of the "***unilateral ratio***". The two participants who showed no unilateral prosthesis use were observed to wear their prosthesis for very short periods over the 7-day monitoring period ("***prosthesis wear time (C)***" = 2.2 hours and 22 hours over the 7 days), which is perhaps unsurprising. It may be worthwhile in the future exploring alternative methods of representing unilateral activity.

In this chapter we have begun to question the relationship between clinical measures of *functionality* and upper limb activity outside the clinic. Our task was an extension of the task used by Bouwsema et al. [86] and in common with many other tasks used to explore *functionality*, involved a "reach-to-grasp" phase. However, future studies may want to consider using validated *functionality* assessments such as the Southampton Hand Assessment Procedure (SHAP) [101] or the clothespin relocation test [157] to confirm or refute our finding of no clear correlations between measures of *functionality* and real world use of a prosthesis. Additionally, future work should aim to develop a novel clinical outcome measure, which does correlate with everyday *prosthesis usage*.

Activity monitoring offers a quick and easy way of evaluating actual "*prosthesis wear*" and "*usage*" outside of the clinical environment. This information would be useful across the industry, from the development of new devices, to the commissioning and prescription processes, the evaluation of intervention effectiveness, and as part of the rehabilitation process. Through the further development of these measures, we have the opportunity to gather data from a large dataset of prosthesis users, expanding our understanding of the factors affecting everyday prosthesis use.

6.6. Summary

In this chapter we have introduced data exploring the everyday upper limb activity (using activity monitors) of twenty myoelectric prosthesis users, and compared these to twenty adults with no upper limb impairments.

The findings in this chapter all question the way in which user performance with a myoelectric prosthesis is currently evaluated. We have demonstrated that longer "***prosthesis wear time (C)***" (the most common method of assessing how a person uses their prosthesis outside of the clinic), does not necessarily correspond to greater '*usage*' of the prosthesis relative to the anatomically intact arm (quantified based on the "***Median %Reliance$_{Dom}$***"). Furthermore, we found no significant correlations ($p<0.05$) between measures of clinically assessed *functionality* and our measures of everyday upper limb activity.

We conclude that our methods using activity monitoring sensors offer a more objective and accurate outcome measure for the assessment of prosthesis user performance outside of the clinic. We suggest that further work is needed to enhance these outcome measures, and to increase the size of the dataset to develop standards for the representation of data on real-world upper limb activity.

7

Discussion, conclusion and future work

7.1. **Thesis aims**

This thesis aimed to:

- Identify the key factors affecting prosthesis control

From the literature three key factors affecting the control of myoelectric prostheses were identified. These were the "*EMG skill*" of the user, the "*unpredictability*" introduced at the interface between the skin and the electrodes by the socket mounted electrodes, and the electromechanical "*delay*" in the response of the prosthetic hand to the muscle signals.

- Establish which of these control factors had the greatest impact on user performance

Protocols were developed to allow the assessment of each of the identified factors. Correlation analyses were undertaken on the data from twenty prosthesis users to establish the relationship between the control factors and measures of user performance (clinical "*functionality*" and everyday "*prosthesis usage*"). Each factor was comprised of a number of different measures; correlation analysis showed that the measures were not suitable for reduction into single control factors. This, combined with the small sample size, meant that the data was not suitable for inclusion in a multiple regression analysis. Nevertheless, individual correlations between the measures constituting each control factor and the performance measures suggested that the prosthesis responding incorrectly, or when the user did not desire it, are likely to be the most important factors affecting user performance.

- Objectively measure prosthesis use outside of the clinic

Data were collected using wrist-worn activity monitors over a period of 7-days. Novel techniques were developed for the analysis and visualisation of these data.

- Establish the relationship between clinical functionality and real world prosthesis usage

Kinematic and gaze based measures of *functionality* recorded during performance of the functional task were compared against measures of everyday *prosthesis usage* (including measures of prostheses wear and of the symmetry of upper limb activity). Correlations between the measures were examined, and no significant correlations ($p<0.05$) were found between the measures. It is worth noting that if the threshold was relaxed slightly to highlight correlations with less than a 10% probability that the effect occurred by chance ($p<0.10$), three weak correlations ($\tau_b \approx 0.3$) exist.

7.2. **Novelty**

The data presented in **Chapters 5 & 6** of this thesis were collected from a cohort of twenty unilateral trans-radial users of myoelectric prostheses. We believe this to the largest experimental study of myoelectric prosthesis users which has been undertaken in the UK to date (other large studies involve fewer than 10 users [101, 158]).

Additionally, many experimental studies undertaken within the lab have involved the construction of specific prostheses for use in the study. Participants generally all use the same prosthetic hand, and where sockets are used, they would often be made to the same design, by the same prosthetist. Although this allows direct comparison of a particular approach between the participants, it does not reflect the reality of clinically prescribed prostheses. In this thesis, novel protocols were developed to classify the user's own prosthesis and their performance with this prosthesis. Participants were recruited from six different sites across the UK. Prosthetic hands included those made by Ottobock, and those made by Steeper. Significant differences were seen in the sockets themselves, especially in relation to the location of the trim lines (see **Figure 52A** for an example from one participant with very restricted elbow flexion which caused undesired activation of the hand at the -45° position). Suspension was achieved through suction, self-suspension, and for one participant a liner with a pin lock ratchet mechanism; some participants also made use of an external roll on sleeve to assist with suspension. Inside the socket, one participant had a leather shim which appeared to impact on the contact of the electrodes with the skin (**Figure 52B**). Furthermore, one participant involved in the

study was still using the old round style of myoelectrodes and self-reported not to have updated their prosthesis for just over 20 years (**Figure 52C**). Participants were included regardless of the quality of their socket fit, or the regularity of wear of the myoelectric prosthesis. In this way, for the first time we have been able to evaluate a wide range of different performance, allowing us to inspect the possible control factors affecting user *functionality* and everyday *prosthesis usage*.

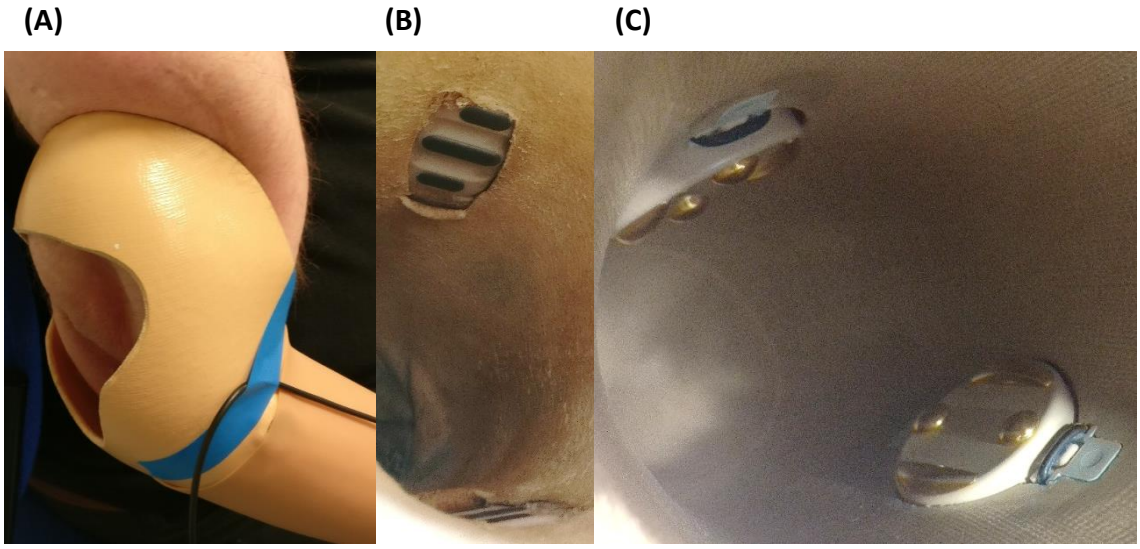


Figure 52. The clinical reality of myoelectric prostheses; examples of prostheses encountered during this study where: **(A)** the trim lines and the suspension of the socket, limited the amount of elbow flexion achievable, **(B)** a leather shim on the inside of the socket affected the quality of electrode-skin contact, **(C)** a 20 year old prosthesis still utilised outdated components.

The assessment of the user's own prosthesis led to a couple of limitations. Protocols were designed in such a way as to avoid the need to tamper in any way with the user's own prosthesis; removal of the glove, adjustment of the electrode settings, adjustment of the hand settings and disconnection of the prosthetic hand from the socket were all avoided so as not to risk damage, or affecting the performance of the prosthesis. This meant that different prosthetic hands were used for different parts of the assessment.

In **Chapter 3** new methods for the assessment of *EMG skill*, *unpredictability* and *delay* were introduced. The techniques used to capture these measures were developed to be portable, allowing for recruitment from a number of different sites, thus increasing the potential sample size. The **signal tracking tasks** were designed to

be directly transferred into clinic; for example, if the primary finding of the thesis was that the performance on the "car game" corresponds to improved user performance with the prosthesis, then additional training could be implemented with the equipment already used in the clinic (Myoboy).

This has been the first study to characterise the full system from the generation of the muscle signal, through to the onset of hand movement. The protocols were developed to assess each measure at a high level, for example, we assessed whether the hand activated unexpectedly, not precisely why.

Finally this was the first study to objectively evaluate the use of the prosthesis outside the clinic using wrist-worn activity monitors. In **Chapter 4** a new method of quantifying and visualising upper limb activity data was introduced, and in **Chapter 6** the upper limb activity of 20 prosthesis users and 20 anatomically intact adults were presented. These measures show significant promise for use by researchers, clinicians and developers in the assessment of upper limb prostheses.

7.3. Key findings / contribution to knowledge

The results of the *EMG skill* assessments presented in **Chapter 5** questioned whether tasks designed to train the user to control the amplitude of the EMG signals are relevant to their ability to use the prosthesis functionally and patterns of use of the prosthesis in the real world. These findings are consistent with the work of researchers at the University of Groningen who have previously shown that improvements in performance on abstract on screen EMG tasks does not relate to improved *functionality* with the prosthesis, such as a shorter "**reach plateau**" during "reach-to-grasp" [70]. Furthermore, this thesis suggests that complex EMG tasks which involve additional cognitive challenges (such as the 2-car task within the PAULA software) may be unsuitable for some users. If the participant is unable to cope with the cognitive challenge of the task, it is no longer possible to assess their *skill* in controlling the EMG signal as the performance is detrimentally affected by other factors.

One of the key findings within this thesis was the high number of users who experienced undesired activations of the prosthesis (see **Chapter 5**). These undesired activations were mostly recorded when participants were wearing their prosthetic socket, however for some participants, undesired activations of the hand also occurred using the "ideal" electrode-skin interface. 75% of users tested experienced at least 1 undesired activation of the hand (out of 24 movements – "ideal", "normal" and "additional load" conditions) and over all the tests for all users ≈12% of the transitions resulted in an undesired activation of the hand. Furthermore when attempting to activate the prosthetic hand, the number of incorrect responses increased from 4% with the "ideal" electrode interface to 13% when wearing the socket (although it is not possible to attribute all of these incorrect responses to a poor interface, it is likely that this would be the cause of a significant number). This thesis suggests that the *unpredictability* at the interface between the skin and the electrodes may be the most important of the control factors studied in terms of the effect on user performance. Significant correlations were found between the total number of undesired activations of the hand and the success rate, task duration, and temporal kinematic variability during the **cylinder task**. Furthermore, when α was increased to 0.1, correlations were also found with the time spent looking at the hand and the GCA during reach-to-grasp, and the time spent looking at the LCA/Tube during the "transport" phase. This finding is in support of the work of both Head [15] and Saunders [14], proposing that regardless of the skill of the user, or the delay within the prosthesis, or even the complexity of the hand itself, if the signal cannot be reliably detected from the muscle, user performance will be limited.

The work presented in **Chapters 3 & 5**, and within **Appendix 4** raises new questions about the extent of electromechanical *delay* in the prosthesis. Previously no data on the delay in the prosthesis has been published. These findings suggest that the mean *delay* to the onset of movement of a myoelectric prosthesis when starting with the hand in a neutral (neither fully open nor closed) hand aperture is 116 ms. The mean $delay_{C\_O}$ to the onset of hand closing from a fully open hand aperture is 109 ms, and the $delay_{O\_C}$ to open the prosthesis from a fully closed position is significantly higher (mean = 240 ms). The *delay* cannot therefore be characterised by a single

measurement, and future studies should consider the mechanical properties of the hand when evaluating the effects of a *delay* in hand response. In this study *delay*, was only characterised up to the point of movement onset; in future, the speed of hand movement should also be assessed alongside the time to fully open/closed.

The data presented in **Chapter 6** demonstrated the differences in the upper limb activity between prosthesis users and anatomically intact adults. Anatomically intact adults demonstrated fairly symmetrical upper limb usage, whilst prosthesis users demonstrated a large preference towards their intact arm demonstrated by a skew in the histograms.

In **Chapter 6** the relationship between clinically assessed *functionality* and everyday *prosthesis usage* was also assessed. No significant correlations were found between any of the measures, suggesting that the ability of a person to use the prosthesis in the clinic may have no relationship with how often and how much they choose to use the prosthesis outside the clinic. This raises questions around the ways in which upper limb prostheses are currently evaluated, and should be investigated further.

Finally to date the primary measure of the effectiveness of a prosthesis outside of the clinic has been through self-reported prosthesis wear time. In **Chapter 6** data was presented which suggested that users who wear the prosthesis for a longer amount of time over a week, do not necessarily have a more symmetrical pattern of upper limb activity whilst the prosthesis is being worn than people who only put the prosthesis on to perform specific tasks. The visualisations proposed in **Chapter 4** allow the upper limb activity to be interpreted in more detail than a simple measure of the average daily wear time.

7.4. Limitations and recommendations for future work

As noted in **Chapter 5** twenty participants only provided enough power for correlations with a coefficient of 0.6 and above. In future, if the whole control chain were to be characterised, at least 50 participants should be recruited. Alternatively fewer measures should be evaluated for each factor.

Based on the findings of this research, we would recommend that future studies aim to break down *unpredictability* to establish the exact causes of poor user performance and to further investigate this relationship. To characterise the unpredictability in the desired activation of the prosthesis to a control signal, a new protocol should be developed; it was not clear whether the measures of spread used in this study were ideal (see **Chapter 5**).

The measures introduced in this thesis for the characterisation of the prosthesis control chain have not yet been validated. Future work should use test/retest, and comparison against other validated measures (where available) to establish the validity of these new measures. The outcome measures used in this study have been previously used to assess the *functionality* of prosthesis users [85, 87-89]. Although the specific values have been shown to differ depending on the task (for example, variability is highly affected by the task being performed), several of the functional measures, such as variability, hand aperture patterns, and gaze have been shown to correlate against performance on SHAP; furthermore, "reach-to-grasp" is a common factor to all tasks used to assess *functionality*, and is used heavily in everyday life [159]. In future it would be recommended that "healthy" control data are collected for the **cylinder task** to allow a direct comparison of the performance of the prosthesis users. Furthermore, in the current assessment we do not analyse the grip force control of the participants, in future this may also be a useful avenue to explore.

Finally this thesis introduced a new outcome measure using wrist-worn activity measures. As noted in **Chapter 2**, prostheses can cause discomfort to the user due to factors such as their weight, and the heat build-up within the socket. The benefits provided by the prosthesis (such as functionality and cosmesis) must outweigh the disadvantages (or perceived disadvantages). Consequently an understanding of how the prosthesis is used outside of the clinic is a valuable measure of the success of the prosthesis. Further work is needed to improve this measure, such as integrating a measure of hand activation (a key factor in the evaluation of expensive multi-grip hands), and expansion of the measure to activity monitors other than the Actigraph (based on evaluation of the raw accelerometer data). Future studies should use activity monitors to evaluate the differences in everyday upper limb activity of

prosthesis users with different types of prostheses (e.g. cosmetic, body-powered hooks/hands, and multi-grip myoelectric prostheses). These could be useful data with respect to the future prescription of these devices; furthermore agreed standards for the representation of usage data should be developed, which will allow for comparison of devices.

Appendix 1

Experimental setups

This appendix provides a brief introduction to the experimental setups, including signposting to the relevant appendices providing additional detail on the designs.

A1.1. Background

This thesis involves a number of complex experimental setups for the assessment of each of the factors affecting control of the prosthesis and the assessment of user performance with the prosthesis. This appendix will provide an introduction to the experimental setups, and introduce the challenges addressed in the following appendices.

A1.2. Experimental setups

The protocols used in this thesis were designed to be portable. This allowed assessment of prosthesis users at multiple centres across the country. All of the experiments were controlled from a single laptop. **Figure 53A** shows the complete experimental setup.

The arrows in **Figure 53** represent the direction of data transfer or synchronisation signals between each piece of hardware. For example, in **Figure 53B** a signal is sent from the laptop to either "*Arduino 1*" or the IMU base station (depending on the test); a trigger is then sent to "*Arduino 2*", instructing it to begin sending the data coming from the goniometer, back to the laptop. Each of these setups are explained in more detail in the relevant appendices (see below).

A1.2.1. *Myoboy and PAULA*

Ottobock's Myoboy® alongside the associated PAULA software (Prosthetist's Assistant for Upper Limb Architecture) were used in the assessment of the user's level of "*skill*" in controlling the EMG signals. As this equipment was used according to the manufacturers' guidelines, no further detail is provided in the appendices.

A1.2.2. *Reaction time tasks*

Reaction time tasks were used both in the assessment of the user's level of "*skill*" in controlling the EMG signals, and in the assessment of the level of "*unpredictability*" introduced by the socket mounted electrodes. To determine the reaction time, we first had to provide a stimulus, and we then had to record the response of the

prosthetic hand. The experimental setup for the reaction time task is shown in **Figure 53C**.

A1.2.2.1. GENERATING A STIMULUS FOR THE USER TO RESPOND TO

The stimuli chosen for these tasks were red LEDs (Light Emitting Diodes); LEDs illuminate with negligible delay, therefore providing an ideal stimulus. A reaction time box was developed allowing the illumination of the LEDs to be controlled from the laptop. The design of this box is detailed in **Appendix 3**.

A1.2.2.2. RECORDING THE MOVEMENT OF THE HAND

The movement (opening/closing) of the prosthetic hand was detected using an electronic goniometer attached across the proximal knuckle of the index finger. **Appendix 2** details the method of recording data from the goniometer. For these reaction time tasks, the data was logged using Matlab to allow for immediate analysis. More detail is provided in **Appendix 3**.

A1.2.2.3. DETECTING THE ONSET OF HAND MOVEMENT AND CALCULATING THE REACTION TIME

As noted above, the LED stimuli were controlled from the laptop and the data relating to the movement of the hand were then returned to the laptop. An algorithm was developed to detect the onset of hand movement (opening/closing) based on the data from the goniometer. The reaction time was then displayed to the user through the reaction time box. Full details on the detection of hand movement are reported in **Appendix 3**.

A1.2.3. *Measuring the delay in the response of the prosthetic hand*

In order to determine the electromechanical "*delay*" to the onset of movement introduced within the prosthesis, we first needed to find a method to artificially stimulate the electrodes. Using the same methods as introduced for the reaction time tasks, we were then able to detect the movement of the hand in response and calculate the delay. The experimental setup is shown in **Figure 53D**.

A1.2.3.1. ARTIFICIALLY STIMULATING THE ELECTRODES

In **Appendix 4** a method of stimulating the electrodes using short pieces of wire is introduced. An electromechanical relay switch was used to allow the stimulation of the electrodes to be controlled from the laptop.

A1.2.3.2. RECORDING THE MOVEMENT OF THE HAND

The movement of the hand was recorded using a goniometer as in the reaction time tasks above. **Appendix 2** details the method of recording data from the goniometer.

A1.2.3.3. DETECTING THE ONSET OF HAND MOVEMENT AND CALCULATING THE DELAY

The hand movement data was analysed using Matlab allowing detection of the moment of movement onset. Further details on the measurement of the "*delay*" are supplied in **Appendix 4**.

A1.2.4. *Assessment of functionality (cylinder task)*

The measurement of user "*functionality*" involved four separate pieces of equipment: (1) Xsens MTw Inertial Measurement Units (IMU), (2) a button placed beneath the hand in the starting position, (3) a Dikablis Professional wireless eye tracker, and (4) a Biometrics Ltd electronic goniometer. The connections between the hardware are shown in **Figure 53E**.

A1.2.4.1. SYNCHRONISING ALL OF THE SENSORS

The first step involved synchronising the different pieces of equipment. In **Appendix 5** the methods of synchronising the systems are introduced.

A1.2.4.2. SEGMENTING THE TASK INTO DIFFERENT PHASES

To evaluate the measures of "*functionality*" it is important that accurate methods exist to locate task onset and completion, and the end of "reach-to-grasp". In **Appendix 5**, a range of segmentation methods are assessed, and conclusions are drawn as to the optimal methods for the detection of task onset, completion and the end of "reach-to-grasp".

A1.2.4.3. DEVELOPMENT OF A CODING SCHEME FOR THE EYE TRACKING DATA

In this study, the **cylinder task** was split into Areas of Interest (AOIs), such as the hand or the grasp critical area of the cylinder. A set of rules were generated to allow each frame to be coded as one of the AOIs (**Appendix 6**). An inter-rater reliability study was undertaken to establish the agreement between raters and the results of this are also presented in **Appendix 6**.

A1.2.5. *Real world prosthesis usage*

A1.2.5.1. DETECTING PERIODS OF PROSTHESIS NON-WEAR

In order to evaluate the use of the prosthesis during the times it was worn, it is important that an accurate method of removing the prosthesis non-wear periods exists. For the results presented in **Chapter 3** non-wear of the prosthesis was removed through visual inspection of the accelerometer data; this method is introduced in **Appendix 7a** and was previously published as supplementary material alongside the publication of **Chapter 3** [109]. Subsequently an automated algorithm was developed for the removal of prosthesis non-wear periods. This algorithm (see **Appendix 7b**) was used in **Chapters 4**, **5** and **6**.

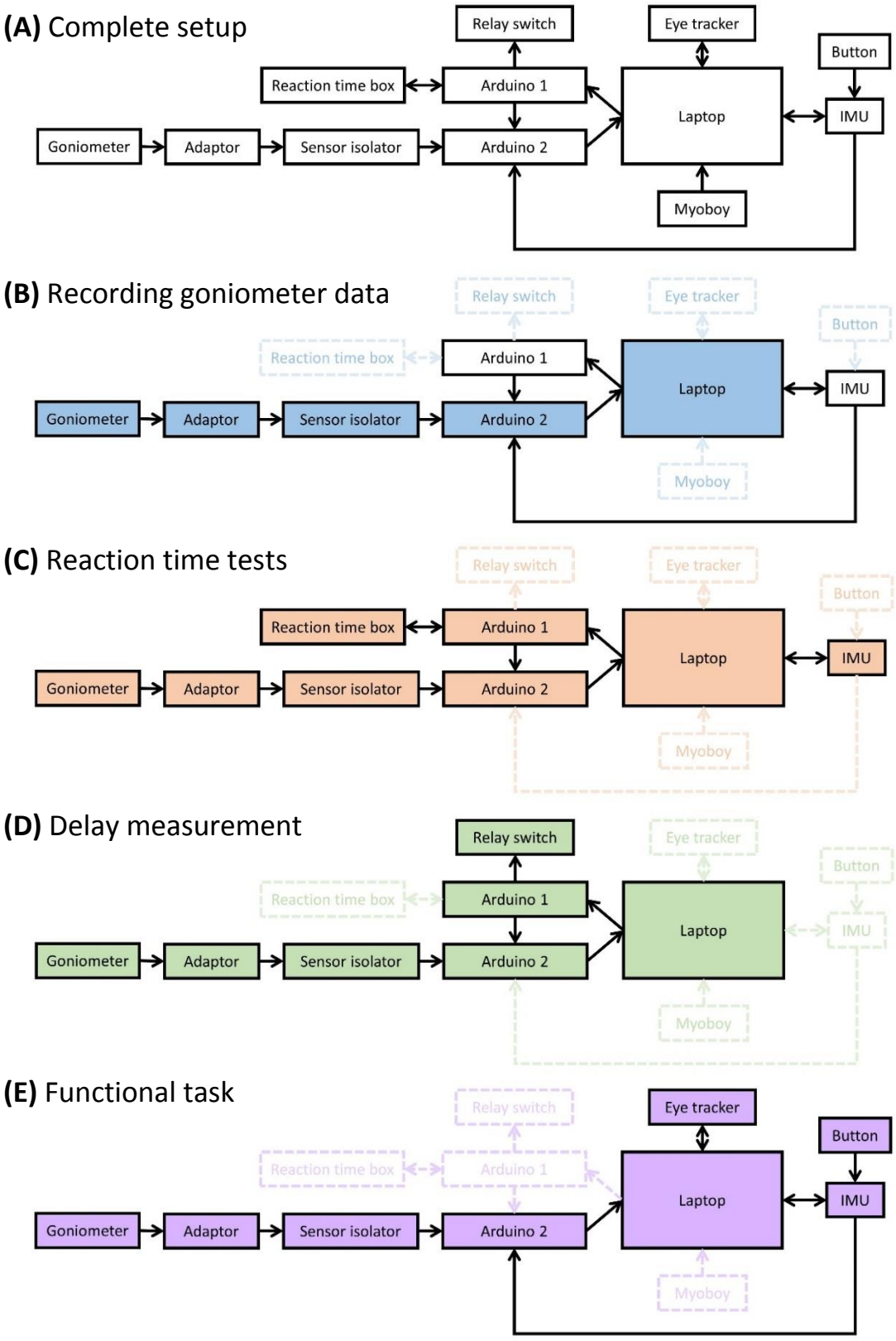


Figure 53. Experimental setups: **(A)** complete setup, **(B)** equipment for the recording of goniometer data, **(C)** equipment for the reaction time tests, **(D)** equipment for the measurement of delay, and **(E)** equipment for the assessment of user functionality. In **(B-E)** equipment not included in the individual experimental setup has been faded out with dotted lines. The arrows show the direction of data transfer between the hardware.

Appendix 2

Methodology for the recording of goniometer data

A2.1. Aims

The aims of the work were to develop a method to read data recorded by a Biometrics goniometer using an Arduino (**Section A2.2**), and to send this data using serial communication to a computer for analysis. Two methods of receiving the serial data were used in this thesis: (1) Matlab (**Section A2.3**), and (2) the serial monitor built in to the Arduino computer software (**Section A2.4**).

To convert the readings sent by the Arduino into degrees, a calibration process was undertaken; this is detailed in **Section A2.5**.

Figure 54 shows a block diagram of the equipment used for data collection. Data from the goniometer is sent via an adaptor and isolator unit (developed by Thought Technologies) to an Arduino ("*Arduino 2*"); the Arduino acts as an ADC sending the data serially to the laptop. Serial communication between "*Arduino 2*" and the laptop is controlled using TTL signals supplied by either a second Arduino ("*Arduino 1*" is the primary Arduino running all of the different tests for this study) or by the hardware associated with the Inertial Measurement Unit.

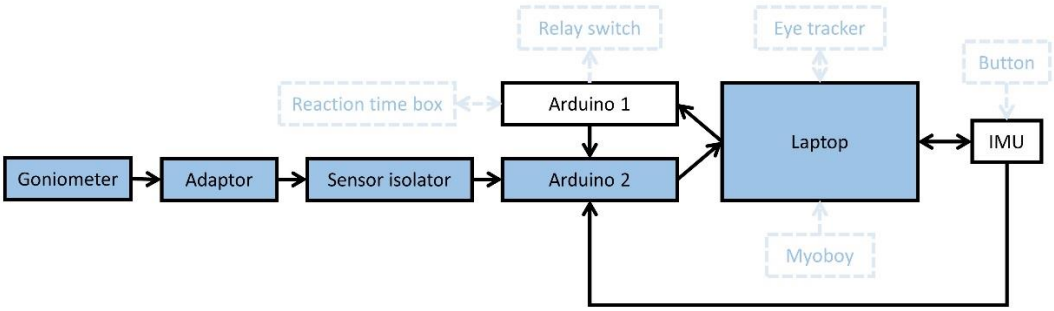


Figure 54. Block diagram showing the setup for the logging of data from the electronic goniometer. Logging is controlled using TTL signals sent from either "*Arduino 1*" or the Awinda base station used with the Xsens MTw Inertial Measurement Units (IMU); these 2 options are shown in white. Equipment from the overall experimental setup which is not included in the recording of the goniometer data has been faded out with dotted lines. The arrows show the direction of data transfer between the hardware.

A2.2. Using an Arduino as an analogue-to-digital convertor and managing communication with a computer

In this section, the method of collecting data from the goniometer using an Arduino ("*Arduino 2*") and sending it to the laptop is described.

Using the goniometer adaptor (T9545) developed by Thought Technology Ltd. the data recorded by the Biometrics goniometer was output as a voltage between 2.2 and 3.4V. To isolate the goniometer and the participant from the laptop, the signal was passed through a sensor isolator, also from Thought Technology Ltd. (ST9405AM).

The analogue to digital convertor (ADC) on the Arduino board was designed to map input voltages between 0 and 5 volts into integer values between 0 and 1023 at a maximum rate of 10,000 times per second.

"*Arduino 2*" was configured to send data over serial at a rate of 115200 bits per second. One of the digital pins ("*Record Pin*") was configured as an input in order to allow control of the serial communication; when the "*Record Pin*" was set as "HIGH", the data would be sent over the serial port.

When data collection was initiated (when the "*Record Pin*" was set to HIGH), the Arduino *analogRead()* function was used to detect the current value of the "*Analogue Pin*" into which the goniometer signal was input. The microsecond clock time was used to timestamp this data point, and a millisecond timer was started. The "*Analogue Pin*" reading and its associated timestamp were sent over serial using *Serial.print()*. Once 1ms had passed (detected using a while loop based on the timer started previously), the next reading was taken and the loop continued until the "*Record Pin*" was set as "LOW".

A2.3. Using Matlab to read data from the serial port

In this section the method of reading the data from the serial ports of the computer using Matlab is described. Matlab allows the data to be quickly analysed;

consequently the results can be checked and feedback can be provided to the participant. This approach was used for the Reaction Time tasks, and for the measurement of "*delay*".

As real time functionality was not required, the approach taken was to store data being read from "*Arduino 2*" in a buffer on the computer. Using the Matlab *serial()* function, the serial port connected to "*Arduino 2*" was configured with an input buffer size of 90000 bytes. The port was opened using the *fopen()* function.

At the start of each trial, the buffer was cleared using *flushinput()*. Once all of the data for the trial had been sent to the buffer (i.e. the number of bytes in the buffer stopped increasing), *fread()* was used to read all of the data from the buffer into a Matlab variable for analysis. A function was written to convert the data from bytes back into the analogue readings sent by the Arduino.

A2.4. Using Arduino software to read data from the serial port

The **cylinder task** performance was not analysed during the testing session; therefore, a more simple method of collecting the serial data was employed for this task. The Arduino software contained a serial monitor, allowing all data received by the serial port to be recorded without the need for any additional code to be written. For each task difficulty level, the serial monitor was capable of recording the data for all 10 trials of the **cylinder task**. Once the task was complete (all 10 trials), the data was saved into a text file for subsequent segmentation and analysis.

A2.5. Conversion of analogue readings into degrees

As noted above, the angle data recorded by the goniometer was sent to the computer as an integer in the range 0:1023. A calibration process was used to establish the conversion factor between the integer values and degrees.

A manual goniometer was used for calibration purposes. The electronic goniometer was taped to the manual goniometer (**Figure 55**). To ensure flexion/extension was measured accurately two right angled blocks were placed on the manual goniometer

to thicken its surface and avoid rotation of the electronic goniometer against the edge.

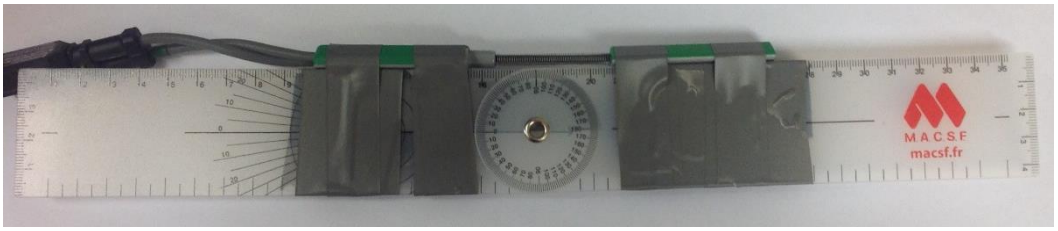


Figure 55. The electronic goniometer was attached to a manual goniometer for calibration

The two goniometers were moved through the range 0° (flat) to -90° (flexion) in 10° increments. This range was chosen as it is comparable to the angles which will be experienced during opening and closing of the prosthetic hand (**Figure 56**).

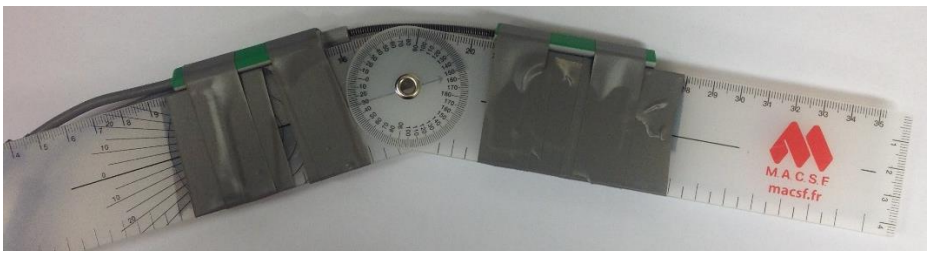


Figure 56. The goniometers were moved through a range of angles from 0° to -90° pausing every 10°.

Figure 57 provides an example of the data output from this process. Whilst the goniometer was stationary (represented by the flat sections of the graph), the integer readings fluctuated by approximately 1-2. The mean value of each of the flat portions (represented by the horizontal black lines) was calculated. The process was repeated 10 times.

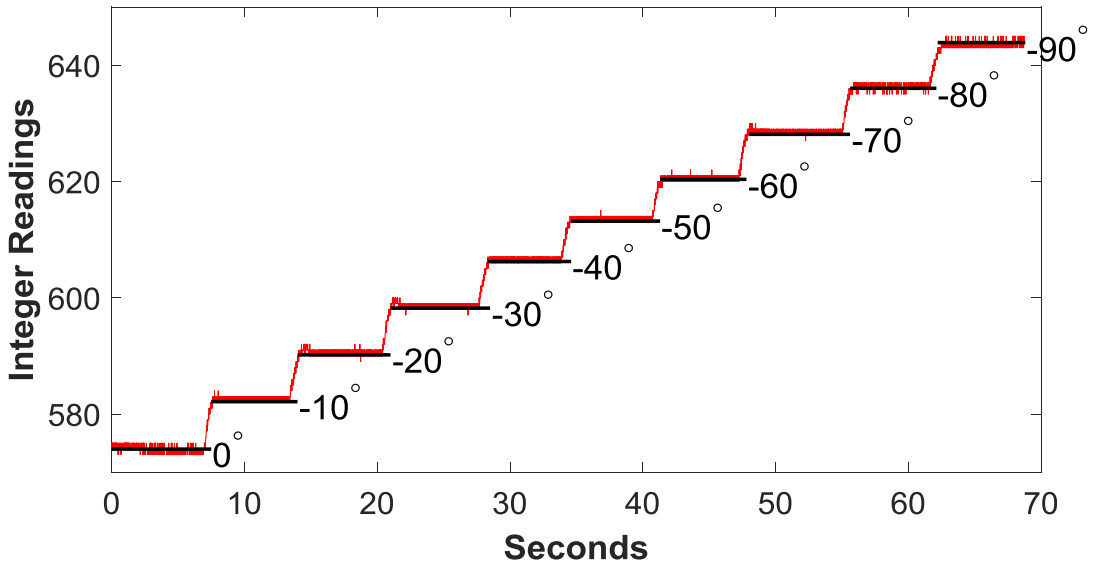


Figure 57. Integer values returned by the step test for one of the ten trials. Each flat portion represents a 10 degree marker.

The integer values for the task (all 10 trials) were plotted against the corresponding angle (**Figure 58**). A linear trend line was placed through these points (total 100 points). The equation of the line was rearranged to calculate the conversion factor for the integers representing the analogue readings.

$$\boldsymbol{DEGREES = -1.29 \times ANALOG\ READING + 741}$$

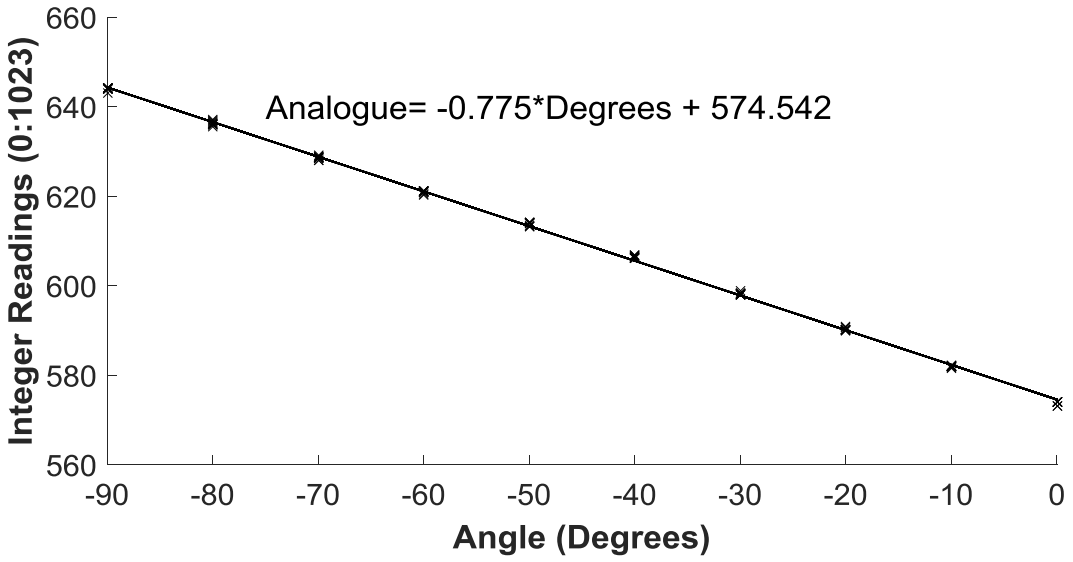


Figure 58. Step test results; integer readings recorded at each angle in 10 degree increments (over 10 trials). The conversion equation was taken from the line of best fit through all 100 points.

Appendix 3

Development of the experimental setup for the measurement of participant's reaction times

This appendix details the design of the reaction time box and the algorithms used for the detection of the onset of hand opening/closing in response to stimuli. The flowcharts in this appendix detailing the algorithms were previously published as supplementary material in Frontiers in Neurorobotics alongside the publication of **Chapter 3**.

Chadwell A, Kenney L, Thies S, Galpin A, Head J; ***(2016);*** *The reality of myoelectric prostheses: Understanding what makes these devices difficult for some users to control;*
Frontiers in Neurorobotics; *DOI: 10.3389/fnbot.2016.00007*

A3.1. Aims

The aims of the work were to develop a method of measuring the time taken for the prosthesis user to respond to a stimulus by either opening or closing the prosthetic hand.

In this appendix the design of the reaction time box (**Section A3.2**) and the reaction time task (**Section A3.3**) are presented. Additionally the method of detecting hand movement onset and incorrect responses is detailed (**Section A3.4**) (this last part of the appendix was previously published as supplementary material in Frontiers in Neurorobotics [109]). Data on the opening/closing of the hand was recorded using the electronic goniometer detailed in **Appendix 2**.

Figure 54 shows a block diagram of the experimental setup. The task is controlled through "*Arduino 1*" which receives information from the laptop. Information is provided to the participant through a display screen on the Reaction Time Box, and they are able to acknowledge commands using a button on the box. Once the task begins a signal is sent to "*Arduino 2*" to begin sending data from the goniometer to the laptop. For the tests of the "*unpredictability*" introduced by the socket mounted electrodes, an Inertial Measurement Unit (IMU) is also used to determine the orientation of the arm relative to the horizontal. Further detail on the reaction time task procedure is included in **Section A3.3**.

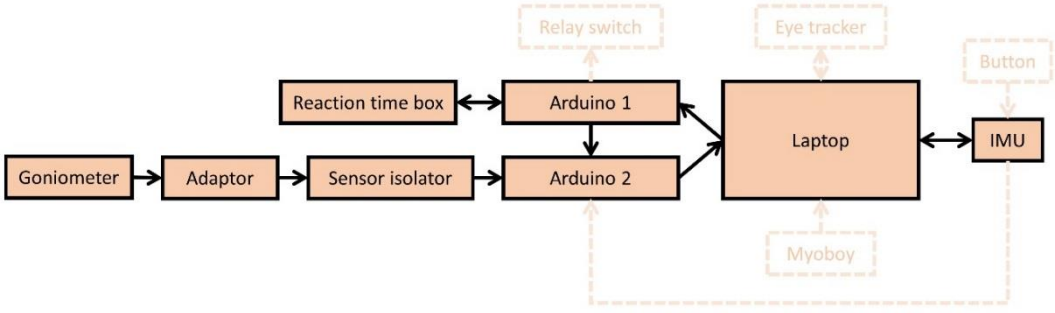


Figure 59. Block diagram showing the setup for the recording of participants' reaction times. The task is controlled via "*Arduino 1*". An IMU is used during the assessment of "*unpredictability*" to inform on the orientation of the arm. Equipment from the overall experimental setup which is not included in the measurement of reaction times has been faded out with dotted lines. The arrows show the direction of data transfer between the hardware.

A3.2. Reaction time box design

A3.2.1. *Design requirements and decisions*

A3.2.1.1. STIMULUS DESIGN

Requirement 1: instant display of stimuli

Initially stimuli displayed on the laptop monitor were explored, however the standard screen refresh rate of 60 Hz led to a decision to use Light Emitting Diodes (LEDs), which illuminate with a negligible delay.

Requirement 2: two separate stimuli (one for open, one for close)

Although the delay in the illumination of an LED could be considered as negligible, reaction time has been shown by some researchers to vary with LED colour and luminescence [160]; possible reasons include fractionally different illumination speeds, and different mental processing times for different colours. Two separate LEDs of matching colour and size were therefore chosen.

Requirement 3: central focal point

To allow comparison between the simple and choice reaction time tasks, a central focal point was required. Here a further smaller LED was used.

A3.2.1.2. AN INTERFACE FOR THE PARTICIPANT

Requirement 4: a method of the participant acknowledging they are ready

Between each response the participant was required to reset the hand to the correct position. To ensure the test did not continue before they were ready, a button was added to the box for the participant to acknowledge that they were ready to begin.

Requirement 5: a method of informing the participant of their reaction time

A display screen was added to allow information to be provided to the participant, such as feedback of their reaction time.

A3.2.2. *Final box design*

Figure 60 shows the reaction time box. On the top half of the box, two large red LEDs (10 mm diameter), were equally spaced 4 cm above and below a smaller (5 mm diameter) LED. The top LED was used as a stimulus for hand opening, whilst the bottom LED was used as a stimulus for hand closing. The central LED was used to focus the participant's attention.

On the bottom half of the box was a 7-segment display used to provide commands and feedback on the reaction time to the participant (such as the examples provided in **Figure 60**). Additionally a large arcade style button was placed on the box to allow the participant to acknowledge that they were ready to progress.

Figure 60. Reaction time box with example displays informing the participant as to whether they are undertaking practice or assessed trials, asking if they are ready to begin and returning their reaction time.

A3.2.3. *Electrical circuit*

The reaction time task was controlled using an Arduino (see **Section A3.3**). **Figure 61** represents the circuitry contained within the reaction time box. The dotted lines

represent the path of the control signals, whilst the solid lines represent the path of the main circuit. The illumination of each LED was determined by a connection to digital output pins on the Arduino through a transistor connected to the 5V pin. This ensured that the voltage to illuminate the LED was taken from the 5V output of the Arduino and not drawn from the digital output pins. Appropriate resistors were chosen based on the specification of the LEDs.

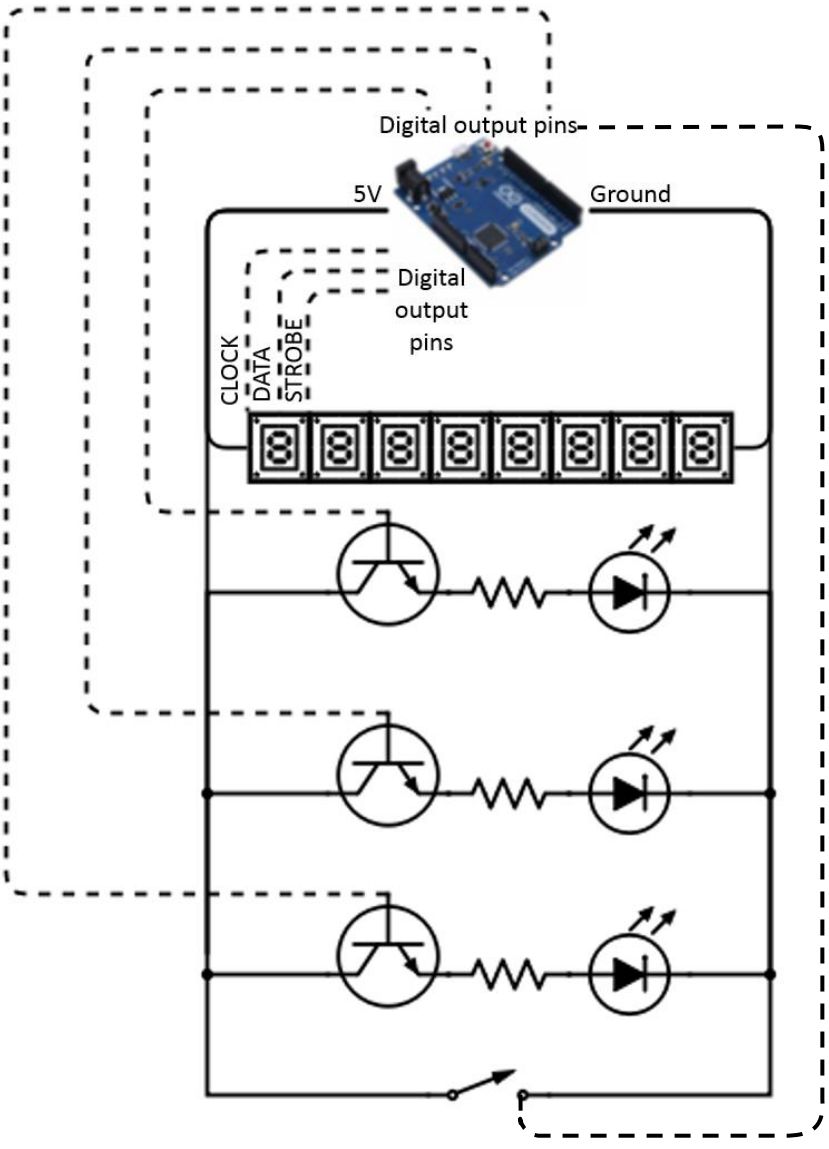


Figure 61. Circuit diagram for the reaction time box

A3.3. Reaction time task procedure

The reaction time task was controlled from the Mathworks Matlab software. Each trial of the reaction time task first involved the generation of a random waiting time

between 2 and 3.5 seconds [116]. Using serial communication, "*Arduino 1*" was instructed of this waiting time and which LED to illuminate (top or bottom); on receiving this information "*Arduino 1*" displayed the word "ready" to the participant. Meanwhile, the Matlab serial buffer was emptied using the *flushinput()* command.

The participant was instructed to acknowledge the "ready" command using the button once the hand was in the starting position. When the button was pressed, "*Arduino 1*" initiated the LED illumination sequence, sent a signal to "*Arduino 2*" to begin sending the goniometer data to the Matlab buffer (see **Appendix 2**), and sent a signal via serial to Matlab to inform the main code that the sequence had begun.

The LED illumination sequence involved illuminating the small central LED for 1s, and then after the full waiting time had passed since the beginning of the sequence, the pre-specified larger LED was illuminated for 1s. At this point the participant should respond by opening or closing their hand. "*Arduino 1*" then sent a signal to "*Arduino 2*" to stop sending the goniometer data to the Matlab buffer.

Once all of the bytes had arrived in the Matlab buffer, the *fread()* function was used to extract the data from the buffer into a Matlab variable for analysis. The data was converted into degrees according to the methods introduced in **Appendix 2**, and segmented using the waiting time to leave the hand movement data recorded after the stimulus had been presented. **Section A3.4** details the method of determining the reaction time from this data. This time was then sent back to "*Arduino 1*" and displayed on the 7-segment display to the participant.

A3.4. Methods for the identification of movement onset and exclusion of incorrect responses

Algorithms were developed to examine the data recorded from the goniometer to identify, early reactions (<100ms [129]), incorrect reactions and to calculate the reaction time. These algorithms are detailed in the flowcharts in **Figure 62**, **Figure 63**, and **Figure 64**.

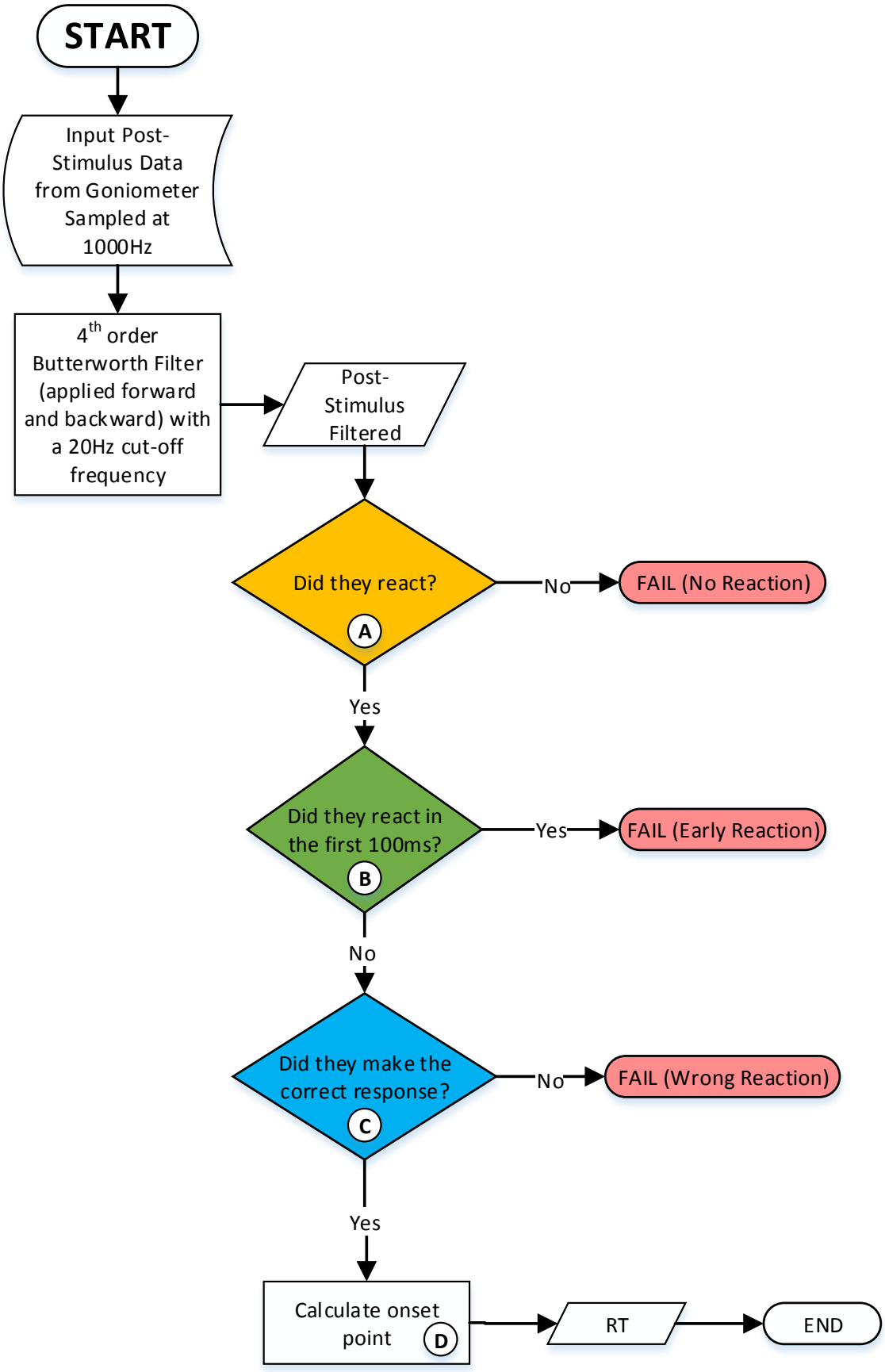


Figure 62. General overview of the analysis of the data for the reaction time task

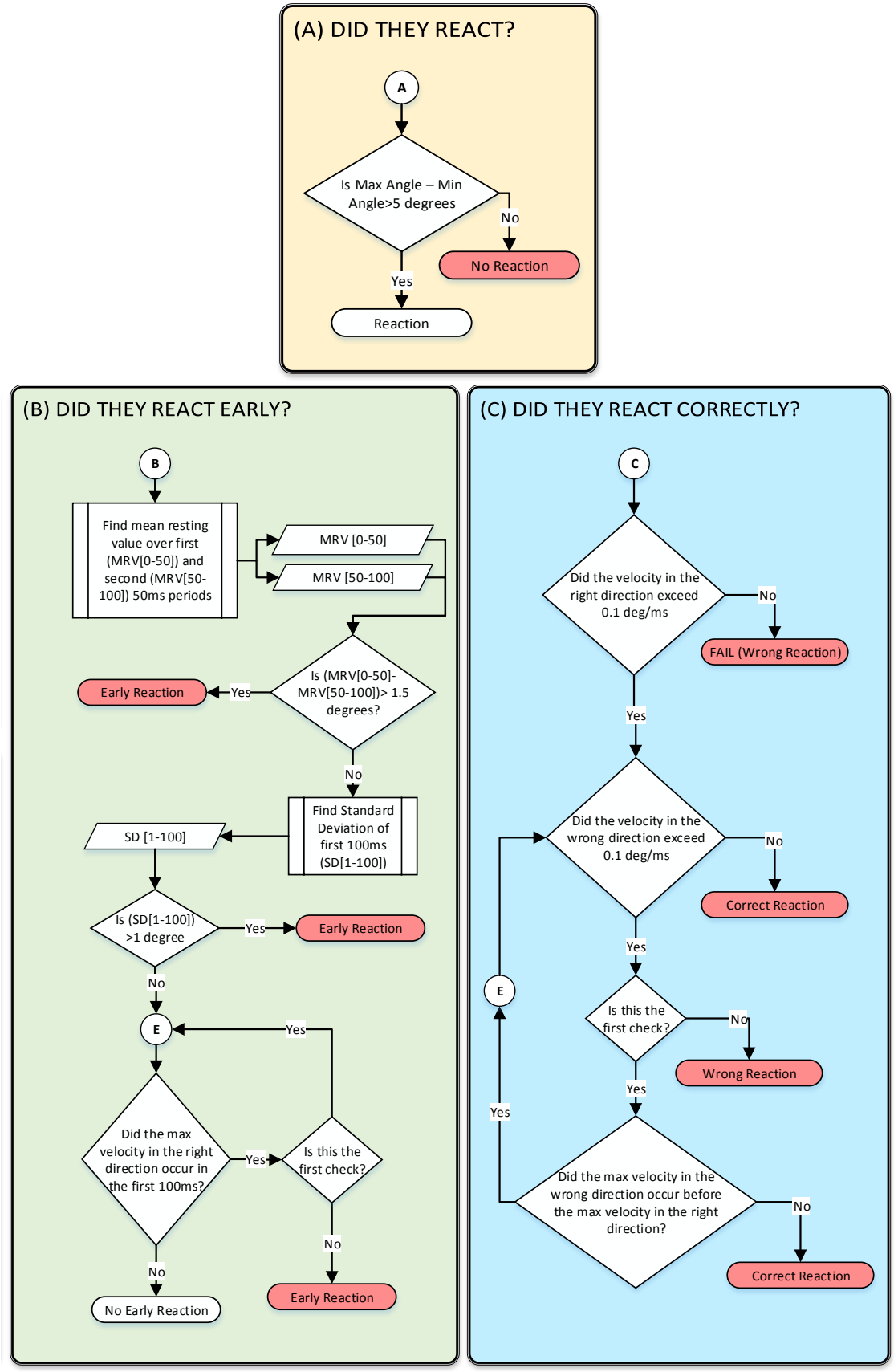


Figure 63. More detailed breakdown of the methods used by the software for determining whether a person has reacted accurately to the stimulus

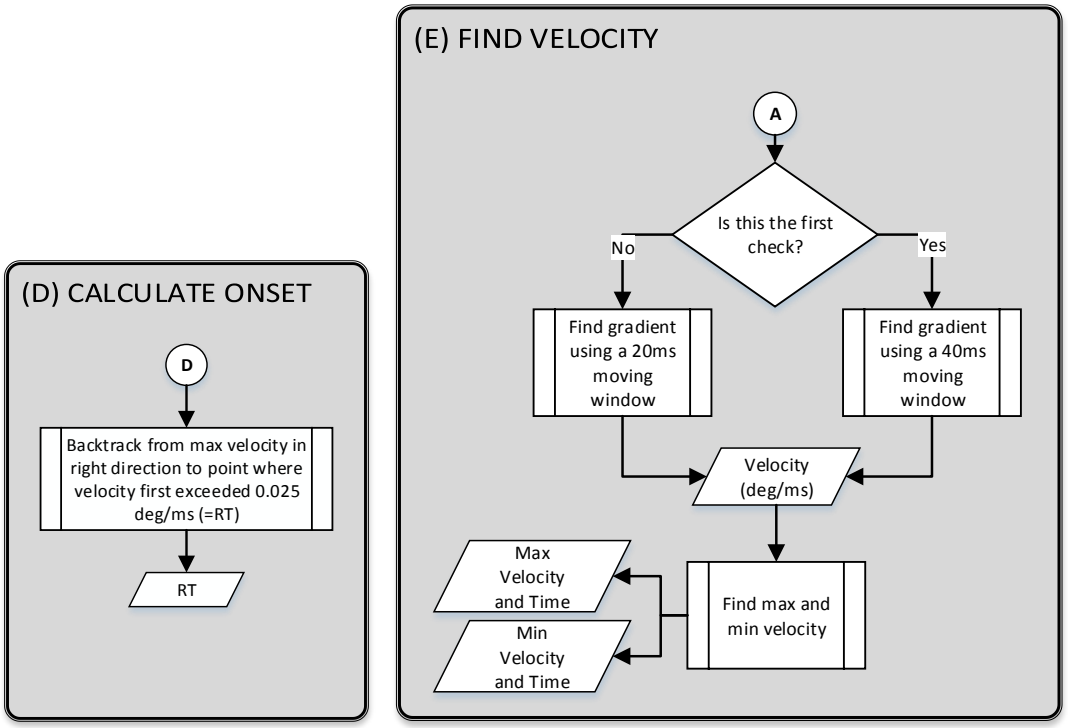


Figure 64. More detailed breakdown of the methods used by the software for detecting the onset of movement and determining the velocity of hand movement

Appendix 4

Development of the protocol for the measurement of delays

A4.1. Background

In this study we defined the "*delay*" in the response of the myoelectric prosthesis to be the time difference between stimulus presentation and the onset of hand movement. Stimulus presentation is the first moment a differential voltage is provided to the electrodes. The onset of movement is defined as the point where the goniometer placed across the index finger has moved by 1 degree.

In order to measure the "*delay*" in the response, an experimental setup was required in which the electrodes could be artificially stimulated, and the time taken for the hand to move in response measured.

Figure 65 shows a block diagram of the experimental setup. When a signal is received from the laptop, "*Arduino 1*" controls the task, opening the relay switch to stimulate the electrodes (**Section A4.3**), and initiating data recording from the goniometer (**Section A4.4**).

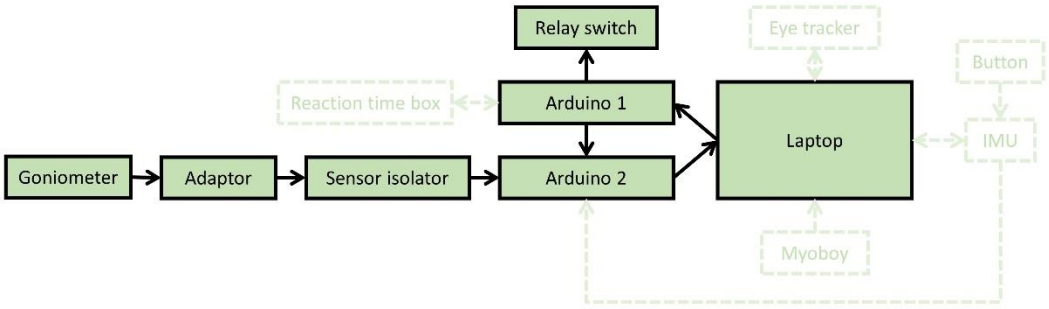


Figure 65. Block diagram representing the setup for the measurement of the electromechanical delay in the prosthesis response to a stimulus. Equipment from the overall experimental setup which is not included in the measurement of delays has been faded out with dotted lines. The arrows show the direction of data transfer between the hardware.

A4.2. Aims

The aims of the work were:

a) To develop an experimental setup which allowed the electrodes to be artificially stimulated.
b) To ensure the stimulation of the electrodes was synchronised with the recording of the data from the goniometer.

c) To assess whether the gain setting of the electrode impacted on the recorded "*delay*".

And finally, pilot work suggested that the "*delay*" recorded from a closed position for one participant was longer than the reaction time for that participant, therefore the final aim of this work was:

d) To establish whether the starting hand aperture impacted on "*delay*".

A4.3. Artificial stimulation of the electrodes

In order to activate the myoelectrode, a voltage difference between the two outer electrodes is required. Early pilot work demonstrated that it was possible to achieve this voltage difference by touching an ungrounded wire to one of the electrodes. This wire acts like an aerial with a voltage induced by electromagnetic fields in its surroundings.

In this section a simple circuit is proposed where the two outer electrodes are connected via a switch. Whilst the switch is closed the voltage across the two electrodes is the same. When the switch is open, there is a voltage difference and the electrode is activated.

A4.3.1. *Experimental setup*

A4.3.1.1. THE CIRCUIT DESIGN

The experimental setup for the artificial stimulation of the electrodes is shown in **Figure 66**. To ensure good contact with the electrodes, two flat conductive plates (stripboard) are used. These are connected to the normally closed poles of a relay switch using 10cm lengths of copper wire. A piece of insulating foam is placed over the stripboard to allow the plates to be held against the electrodes during the test without the conductivity of the finger affecting the voltage induced in the plates.

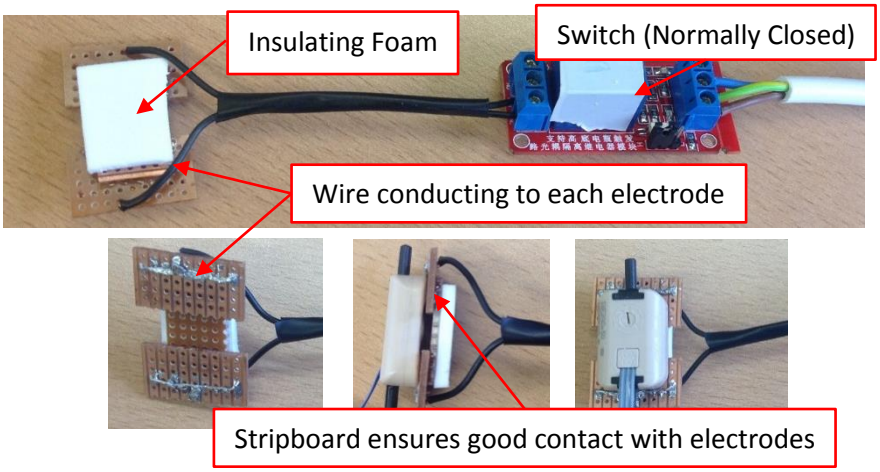


Figure 66. Experimental setup for the assessment of delays

A4.3.1.2. RELAY SWITCH OPERATION

The switch is opened when current is passed through an electrical coil. **Figure 67** shows a 5V Songle switch with its outer casing removed. As the switch is activated the common terminal is pulled onto the coil, contacting the normally open part of the switch; when the current is removed the common terminal returns to contacting the normally closed terminal. The activation of the switch can be controlled by a signal sent from an Arduino to the input pin of the switch.

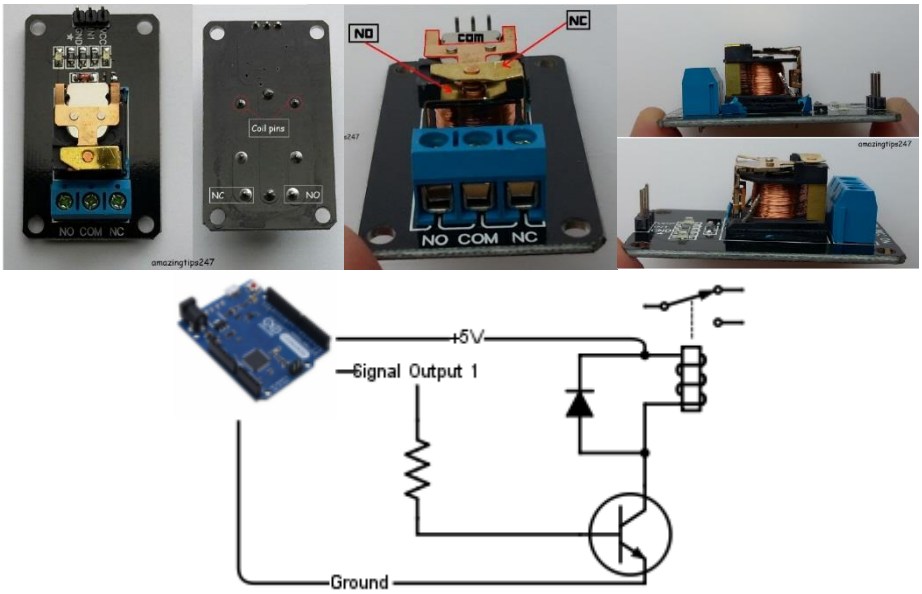


Figure 67. Internal view of the Songle SRD-05VDC-SL-C switch with circuit diagram taken from www.amazingtips247.co.uk article from 27/07/2015 entitled 'Inside of a SRD-05VDC-SL-C relay and how to wire it up?'

A4.3.2. *Checking the artificially generated signal level*

To establish whether the voltage induced in the plates using the setup introduced in **Section A4.3.1.1** was of a suitable level to activate the prosthetic hand, a short test was undertaken.

The amplitude of a naturally generated myoelectric signal is different for each person, therefore, in clinical practice the myoelectrode gain settings are adjusted using the potentiometer on the rear of the myoelectrode, to produce a suitable post-processed signal to operate the prosthesis. To guide the clinician in selecting a suitable gain setting, clinicians typically use the Ottobock Myoboy® system to display the magnitude of the processed signal. To activate the prosthetic hand, a user should be able to comfortably achieve a processed myoelectric signal above a threshold, set within the Myoboy system by the manufacturers, at 24 (units undefined).

During the data collection for this thesis, as the researcher was not clinically qualified the gain settings on the users own prosthesis were not adjusted. Therefore, expert advice was sought as to the likely gain settings used in clinical practice, which were reported to lie between 3.5 and 5 for the majority of users.

To establish the amplitude of the signal that would be supplied to the hand by the experimental setup for electrodes configured with each gain setting, an electrode was connected to the Myoboy software (PAULA), allowing the post-processed signal level to be recorded. Due to the fact that some users may have their gain settings outside of the suggested 3.5-5 region, the whole range of available gain settings were evaluated. The gain was initially set at 1 and the electrode was activated using the circuit described in **Section A4.3.1.1** for a period of 5s, the switch was then closed for 5 seconds before re-opening a total of 4 times (**Figure 68**). This was repeated for each gain setting increasing in increments of 0.5 each time until the maximum gain setting of 7 was reached.

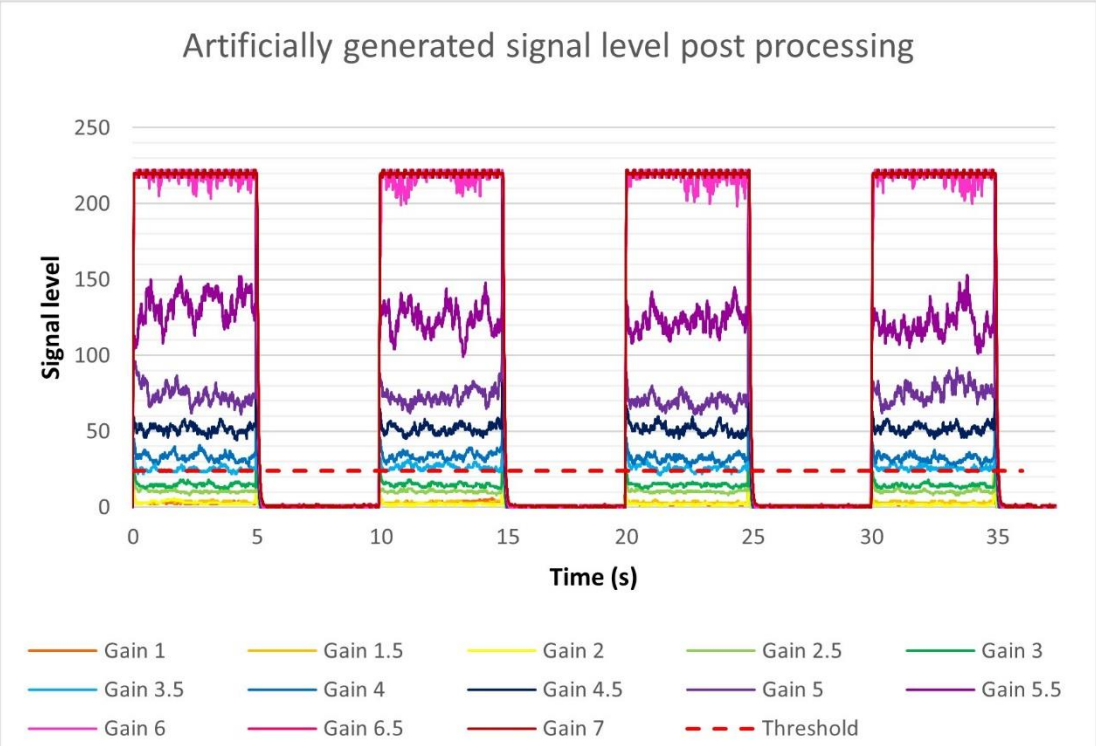


Figure 68. Output signal level recorded in Myoboy (PAULA) software for each electrode gain setting; when the gain setting reached 6, the signal exceeded the limit measurable using the Myoboy, explaining the clipping. The signal is sustained above the threshold (24) for gain settings >3.5.

Figure 68 presents the resulting post-processed signal for each gain setting; the signal was sustained above the threshold level for gain settings >3.5 suggesting the experimental setup would be able to activate the prosthetic hand successfully for the majority if not all users.

Further testing was undertaken to establish exactly how the gain setting (and resulting signal amplitude) would impact on the measured "*delay*" (see **Section A4.7**).

A4.4. Sensing the movement of the hand

Movement of the hand was measured using an electronic goniometer (Biometrics Ltd) attached across the proximal knuckle of the index finger (accuracy ± 2° measured over a range of ± 90°). A T9545 goniometer adaptor (Thought Technology Ltd accuracy ± 5%) and TT Sensor Isolator ST9405AM were used to return readings from

the goniometer to an Arduino (referred to as "*Arduino 2*") (see **Appendix 2** for more details).

The angle data from the goniometer was relayed to Matlab for analysis via a serial interface. For each measurement the mean resting value (MRV) was calculated based on the first 80ms of data. A threshold of movement was set 1 degree above the MRV for hand opening, or 1 degree below the MRV for hand closing. The angle data was then double pass filtered using a 4th order Butterworth filter with a cut off frequency of 20Hz. Onset of hand movement was taken as the moment the filtered angle data exceeded the threshold, and continued to increase by at least 5 degrees above the MRV (**Figure 69**).

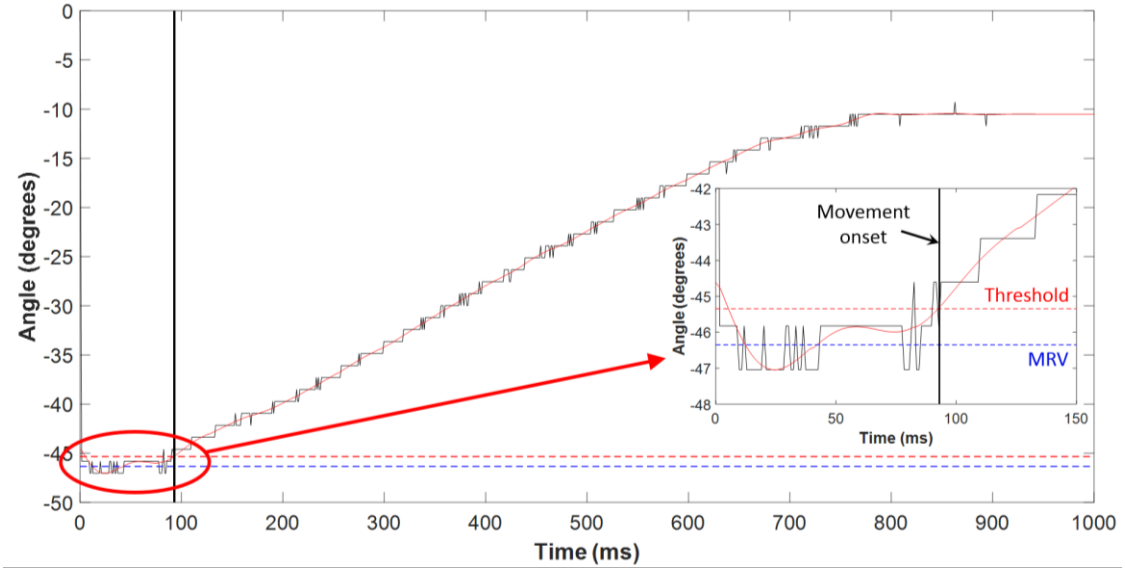


Figure 69. Example data (hand opening) showing the detection of hand movement onset.

A4.5. Checking for undesired delays introduced by the measurement equipment

In this section the potential delays introduced by each part of the measurement system are addressed, specifically:

- Is there a delay in the activation of the switch?
- Is there a delay in the voltage rise of the wires?
- Is there a delay in the time taken to initiate the goniometer recording?

A4.5.1. *Measuring the delay in switch activation*

To measure the delay in activation of the switch, a simple circuit was designed using the relay switch and a single Arduino (**Figure 70**). The normally closed poles of the relay switch were connected between two of the digital pins on the Arduino. One pin was configured as an output ("*Signal Output 2*") and set to HIGH; the other was configured as an input pin ("*Signal Input 1*"). "*Signal Input 1*" was also connected to the Arduino's ground pin via a resistor.

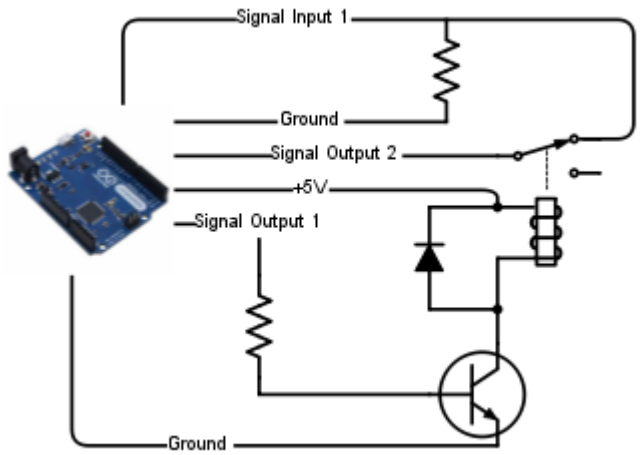


Figure 70. Diagram of circuit used to test the delay in the relay switch

A simple code was produced where the Arduino reported the clock time in microseconds before activating the relay switch and breaking the circuit. When the polarity of "*Signal Input 1*" was pulled from HIGH to LOW by the connection to ground (i.e. the switch had opened), the Arduino again reported the clock time in microseconds. The difference in these two timestamps represents the time taken to open the switch. This was repeated 50 times.

The mean switching delay measured over the 50 repeats was **2.675ms** (SD 0.032ms, min 2.612ms, max 2.776ms). This switching delay was highly consistent and could therefore be accurately accounted for in the overall delay measurement.

A4.5.2. *Measuring the delay in stimulation of the wires*

With the equipment available, it was not possible to measure the time taken between the switch opening, and the wires producing the appropriate voltage

differential to activate the electrodes. The capacitance of a typical wire is minimal, and for the purposes of this study this delay was therefore assumed to be negligible.

A4.5.3. *Measuring the delay in the goniometer*

As noted above, goniometer data collection is controlled by "*Arduino 2*". Using the equipment available, it was not possible to measure the delay between the movement of the goniometer and the movement data being received by the Arduino; furthermore, Biometrics do not report whether there is a significant delay between onset of movement and the outputting of voltages in their system. It can therefore be assumed that any delays are minimal and not worthy of reporting.

A4.6. Measuring the delay in prosthesis response

This section brings together the method of stimulating the electrodes detailed in **Section A4.3** and the method of detecting the onset of hand movement detailed in **Section A4.4** to calculate the electromechanical "*delay*" in the onset of hand movement (**Figure 65**).

Two Arduino Leonardo development boards (www.arduino.cc) were used to run the "*delay*" measurement setup. The setup was controlled via "*Arduino 1*", whilst "*Arduino 2*" acted as an ADC for the goniometer (see **Appendix 2** for full details).

A digital pin on "*Arduino 1*" was configured as an output and was connected via a wire to the "*Recording Pin*" on "*Arduino 2*" (see **Appendix 2**). For each repeat of the "*delay*" measurement, "*Arduino 1*" first initiated data collection through "*Arduino 2*" and then immediately set the input pin of the switch high, opening the switch and stimulating the electrodes. After 1 second "*Arduino 1*" sent a signal to "*Arduino 2*" to stop the data recording, and then immediately set the input pin of the switch low, closing the switch and stopping the stimulation of the electrodes.

The angle data from the goniometer was imported from the recording buffer into Matlab for analysis. The "*delay*" was taken as the time from the onset of the goniometer data recording until the identified moment of hand movement onset

(see **Section A4.4**), 2.675ms was then subtracted from this value to account for the delay in the switch activation (see **Section A4.5.1**).

A4.7. Establishing how the gain setting affects the delay

In **Section A4.3.2** it was highlighted that as the gain of the myoelectrode is adjusted, the post-processed signal amplitude will change. To understand how this change in signal amplitude would affect the "*delay*" in the onset of hand movement, a short study was undertaken.

A4.7.1. *Methodology*

The hand was placed in a fully closed position and the electrode gain was set at the lowest setting (=1). The "$delay_{O\_C}$" to the onset of hand opening was measured 5 times. The gain was increased in increments of 0.5 up to the maximum gain setting of 7 and the "$delay_{O\_C}$" was measured 5 times at each of these gain settings.

The hand was then placed in a fully open position, and the "$delay_{C\_O}$" to the onset of hand closing was measured 5 times at each gain setting (1-7 in increments of 0.5).

This test was undertaken for each of: (1) a threshold controlled Steeper Select hand (owned by the research team), (2) a proportionally controlled Ottobock Myohand Variplus Speed (owned by the research team), and (3) the prosthesis owned by one of the pilot participants (Ottobock).

A4.7.2. *Results*

For the threshold controlled hand (Steeper Select) (**Figure 71**) the mean "$delay_{O\_C}$" to the onset of hand opening (from fully closed) was 91ms (SD = 17ms), whilst the mean "$delay_{C\_O}$" to the onset of hand closing (from fully open) was slightly shorter at 74ms (SD = 17ms). The gain setting did not appear to have an impact on the time taken for the hand to begin to move.

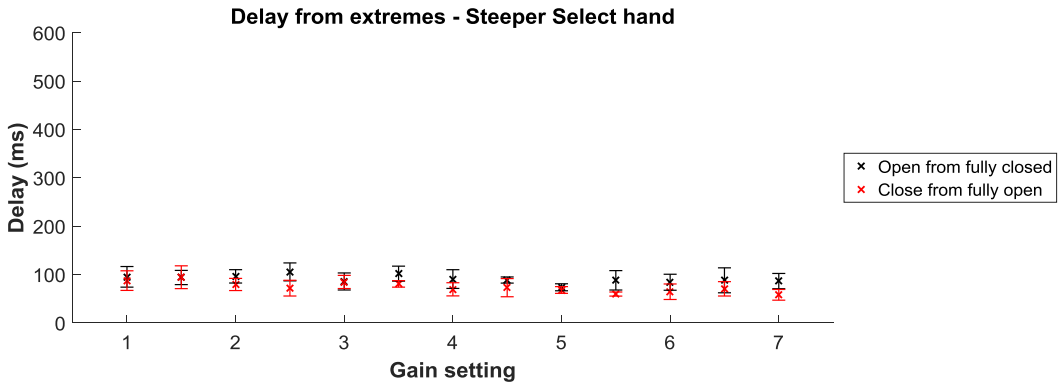


Figure 71. "*Delay*" recorded at each gain setting for a threshold controlled Steeper Select hand. "*Delays*" were measured from the extremes of hand open or closed.

Figure 72 shows the results of the same test for a proportionally controlled hand (Ottobock Myohand Variplus Speed). Proportional control means that the motor torque is adjusted in relation to the amplitude of the myoelectric signal. At the lower gain settings (corresponding to lower motor torques for a given physiological EMG signal) the "*delay*" is significantly longer ("*delay*" at a gain of 1 = 474ms for opening or 203ms for closing). Once the torque exceeds a certain (unspecified) level the hand responds in a similar manner to the threshold controlled hand. It is worth noting that the "$delay_{O\_C}$" to the onset of hand opening (from a fully closed position) is approximately double the "$delay_{C\_O}$" to the onset of hand closing (from fully open). It is possible that this is caused by the time taken to achieve the required motor torque to overcome the resistance and backlash in the system. Additionally in a fully closed position some deformation of the metal fingers occurs, the "$delay_{O\_C}$" may therefore be increased due to the time taken for the metal to return to its unloaded position before the fingers begin to open.

Finally **Figure 73** presents the results of the same test for the prosthetic hand used by one of the pilot prosthesis users. For this hand the gain setting does not appear to impact on the measured "*delays*" suggesting that the hand is configured to use threshold control. Similarly to the proportionally controlled hand, the "$delay_{O\_C}$" to the onset of hand opening (from a fully closed position) is significantly longer than the "$delay_{C\_O}$" to the onset of hand closing (from fully open). The mean "*delay*" to open the hand was 453ms (SD = 48ms) and to close it was only 91ms (SD = 15ms).

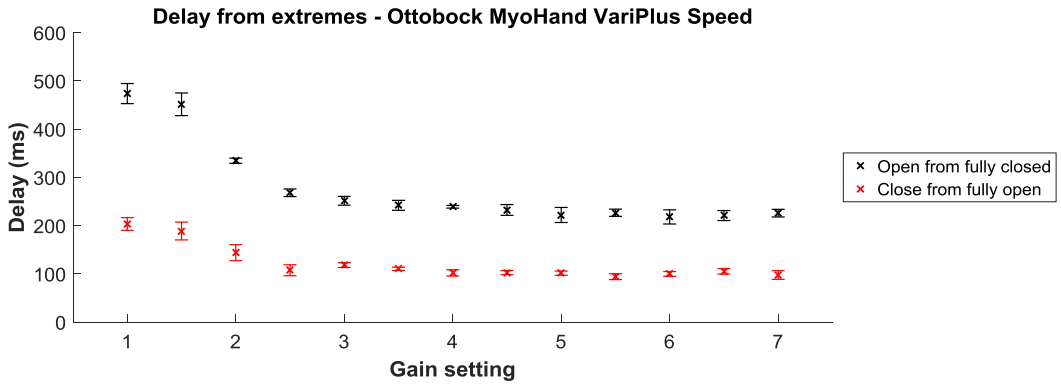


Figure 72. "*Delay*" recorded at each gain setting for a proportionally controlled Ottobock MyoHand VariPlus Speed. "*Delays*" were measured from the extremes of hand open or closed.

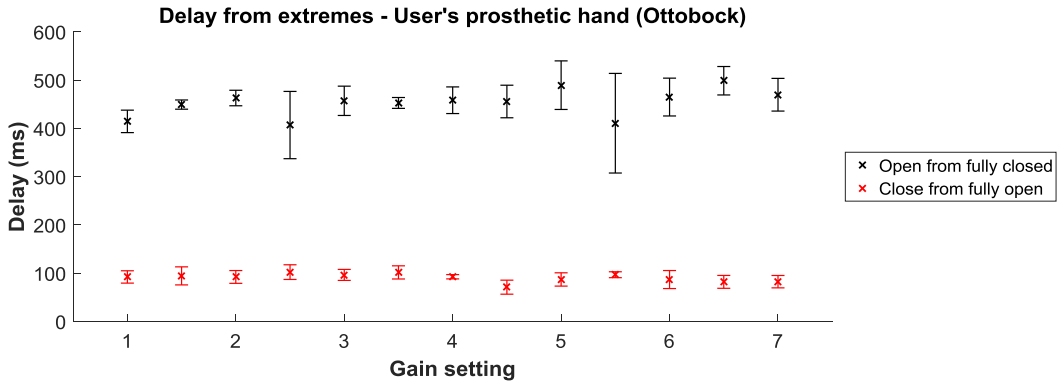


Figure 73. "*Delay*" recorded at each gain setting for a user owned prosthesis. "*Delays*" were measured from the extremes of hand open or closed.

A4.7.3. ***Conclusion***

For a threshold controlled hand the gain setting does not appear to affect the "*delay*" in the time taken for the hand to start opening/closing; whereas, for a proportionally controlled hand, the "*delay*" to the onset of hand movement is longer at lower gain settings, until a plateau is reached.

It was also noted that for two of the three hands the time for the hand to begin opening from a fully closed position was significantly longer than the time taken for the hand to begin closing (from fully open). It was suggested that one of the primary reasons for this may be that when in a fully closed positon, the motor torque causes the metal finger/thumb to slightly deform. The "$delay_{o\_c}$" in the onset of hand opening may therefore be increased due to the additional time required for this deformation to relax before the finger/thumb begin to separate from each other.

A4.8. Establishing how the hand aperture affects the delay

In the previous section, the "*delay*$_{O\_C}$" to the onset of hand opening from a fully closed position (for the user's prosthesis) was measured to be 453ms. In part of the early pilot work with the same prosthesis user (see **Chapter 3**) the mean reaction time (made up of the user's reaction time and the "*delay*" in prosthesis response) measured for the onset of hand opening was <300ms. The reaction time task was undertaken with the hand starting in a neutral position (neither open nor closed) suggesting that the hand starting aperture may have an impact on the "*delay*" to movement onset.

To allow a better understanding of the impact of the hand starting aperture on the measured "*delay*", three short studies were undertaken.

1) Comparing the "*delay*$_{O\_N}$" in the onset of hand opening from different neutral hand apertures
2) Comparing the "*delay*$_{O\_N}$" in the onset of hand opening from a neutral position to the "*delay*$_{O\_C}$" in the onset of hand opening from fully closed
3) Comparing the "*delay*$_{C\_N}$" in the onset of hand closing from a neutral position to the "*delay*$_{C\_O}$" in the onset of hand closing from fully open?

A4.8.1. *Delay to open measured from different neutral apertures*

This section addresses the "*delay*$_{O\_N}$" in the onset of hand opening, as measured with the hand starting at a number of different neutral (neither open nor closed) hand apertures. The following tests were undertaken for the proportionally controlled (Ottobock Variplus) hand, and for the user's own prosthesis.

For each measurement the hand was placed in a neutral aperture (neither open nor closed) and the "*delay*$_{O\_N}$" to begin opening the hand was measured (see **Section A4.6**). The hand was then returned to a different neutral aperture, and the measurement was repeated; in total 20 measurements were undertaken, all at different starting apertures (excluding the extreme of fully closed). The full test (20 measurements) was undertaken at each gain setting (1-7 in increments of 0.5).

For the user's own prosthesis, the results suggest that the initial (neutral position) hand aperture does not affect the delay in the time taken for the prosthetic hand to begin opening (for each gain setting $p>0.05$, and max Pearson's R^2 over all gain settings=0.17). **Figure 74** shows the results for 3 of the gain settings (1, 4, and 7).

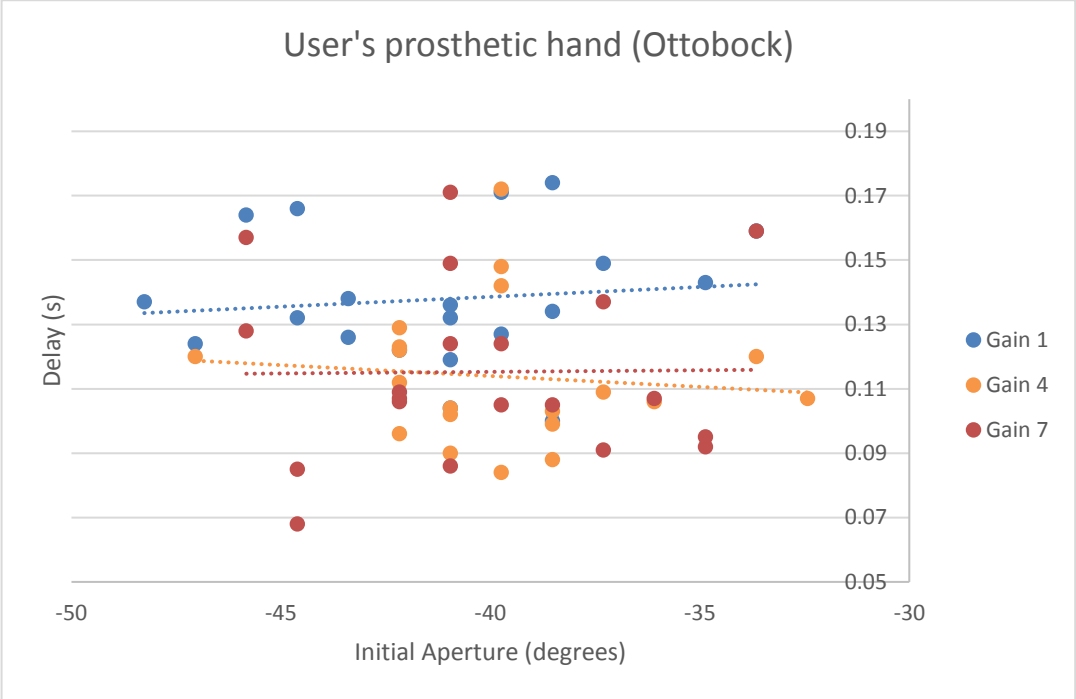


Figure 74. Comparison of initial hand aperture against the delay to the onset of hand opening at a selection of gain settings for the user owned hand.

Similarly for the Ottobock Variplus hand, there was no clear correlation between the starting aperture and the "$delay_{O\_N}$" in the onset of hand opening (for each gain setting $p>0.05$, and max Pearson's R^2 over all gain settings=0.22). **Figure 75** presents the data for three of the gain settings (1, 4, 7). This figure supports the earlier findings (**Section A4.7**) that the "*delay*" is longer at the lower gain settings (gain = 1).

In summary, it was concluded that provided the hand was in a neutral starting position, the **specific aperture had no impact on the "$delay_{O\_N}$"** to the onset of hand opening.

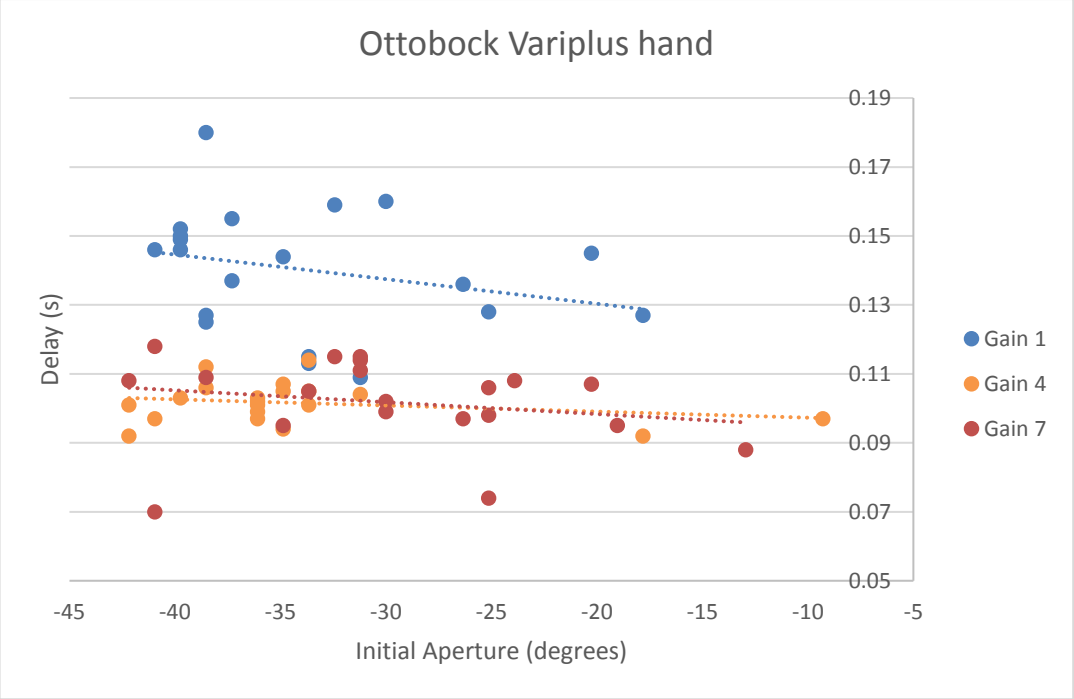


Figure 75. Comparison of initial hand aperture against the delay to the onset of hand opening at a selection of gain settings for the Ottobock MyoHand VariPlus Speed.

A4.8.2. *Delay to open measured from neutral aperture vs fully closed*

Having established that there is no clear correlation between the hand aperture and the "$delay_{O\_N}$" in the onset of hand opening when starting in a neutral hand position, this section compares the "$delay_{O\_N}$" from a neutral position to the "$delay_{O\_C}$" from the extreme (fully closed).

Here the previously measured mean "$delays_{O\_N}$" to open the hand from a neutral position (from 20 measurements at each gain setting – see **Section A4.8.1**) are compared against the previously measured mean "$delays_{O\_C}$" to open the hand from a fully closed position (from 5 measurements at each gain setting – see **Section A4.7.1**).

In **Figure 76** the results for the user's own prosthesis are displayed, whilst **Figure 77** displays the results for the Ottobock Variplus hand.

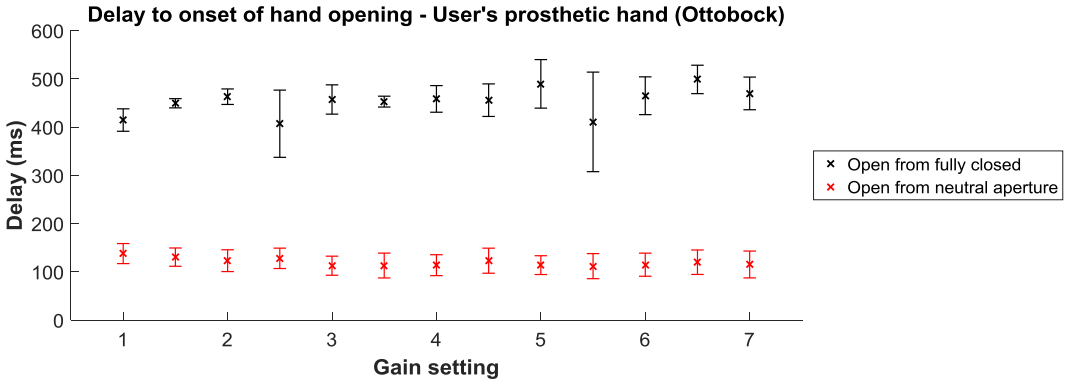


Figure 76. "*Delay*" to the onset of hand opening recorded at each gain setting for a user owned prosthesis. "*Delays*" were measured from the extreme of hand fully closed and from a range of neutral positions.

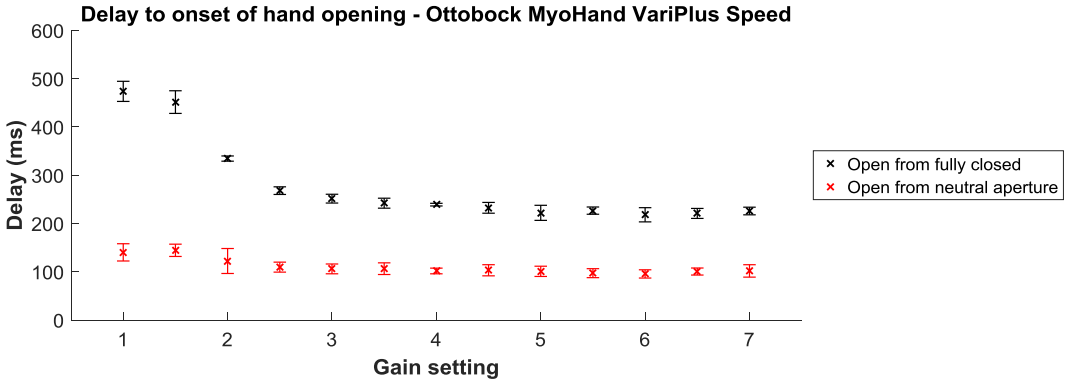


Figure 77. "*Delay*" to the onset of hand opening recorded at each gain setting for a proportionally controlled Ottobock MyoHand VariPlus Speed. "*Delays*" were measured from the extreme of hand fully closed and from a range of neutral positions.

For both hands, the "*delay*" in the onset of hand opening was significantly shorter when measured from a neutral aperture than when measured from a fully closed position. In **Section A4.7** it was demonstrated that the "$delay_{O\_C}$" was significantly longer than the "$delay_{C\_O}$". These results show the length of the "$delay_{O\_N}$" to be similar to the previously measured "$delay_{C\_O}$".

It was suggested previously that this additional "*delay*" to open the hand from a fully closed position may relate to the deformation of the metal fingers when the prosthesis is fully closed, and the backlash in the gears. These results support this theory.

A4.8.3. *Delay to close measured from neutral aperture vs fully open*

For the proportionally controlled Ottobock Variplus hand it was noted that at the lower gain settings, the "$delay_{O\_N}$" to open from a neutral position was in fact shorter than the "$delay_{C\_O}$" to close from a fully open position. The "$delay_{C\_N}$" to close from a neutral position was therefore also measured (20 times at each gain setting). The results were comparable to the hand opening from a neutral position (**Figure 78**).

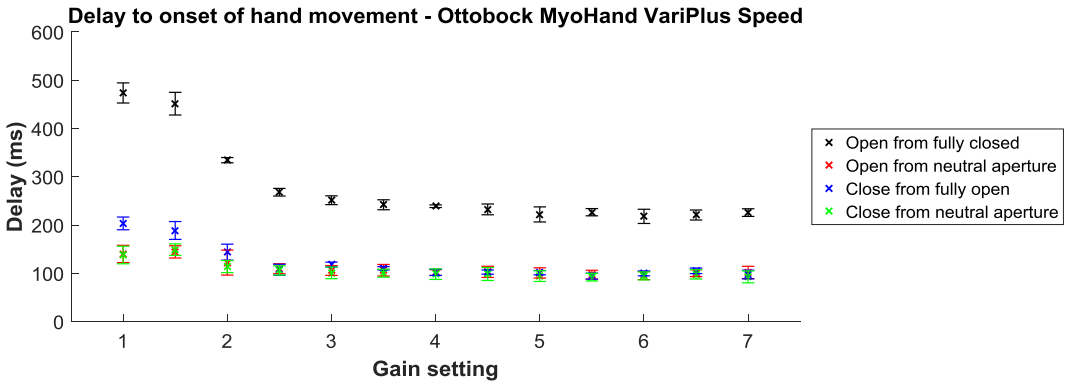


Figure 78. "*Delay*" recorded at each gain setting for a proportionally controlled Ottobock MyoHand VariPlus Speed. "*Delays*" were measured from the extremes of hand open or closed. Both opening and closing were also measured from a range of neutral starting hand apertures.

From these results it is possible to conclude that the "*delay*" is significantly affected by hand posture (neutral vs the extremes). As in everyday life users may be opening their hands or closing their hands from a variety of different starting postures, it is clear that **the "*delay*" of any given prosthesis cannot be simply characterised by a single value**. In an attempt to address this, it was proposed that in the main study, "*delay*" values would be measured with the hand starting from both the extremes of aperture, and from a neutral hand aperture.

A4.9. Conclusions

These results of these short studies suggest that the measurement of "*delays*" is repeatable.

Due to the significant difference in the time to movement onset from the extremes of hand aperture when compared to the neutral positions, all four conditions will be

assessed; this includes hand opening from fully closed and neutral, and hand closing from fully open and neutral. This may provide some useful information when assessing the onset delay for the functional task. During the main study it is proposed that the "*delay*" for each condition is measured five times.

Appendix 5

Synchronisation and segmentation of the cylinder task

A5.1. Aims

The aims of the work were:

a) To synchronise the data collected using the following systems:
   - Xsens MT Manager Software for the measurement of data recorded from the Inertial Measurement Unit (Xsens MTw IMU).
   - Biometrics goniometer (data collected according to the methods introduced in **Appendix 2**).
   - Ergoneers D-lab software for the measurement of data from the Dikablis Professional Wireless Eye Tracker.
   - An arcade style button placed under the hand at the start of the task.

Figure 79 presents a block diagram of the experimental setup for the **cylinder task** showing how these four systems are connected.

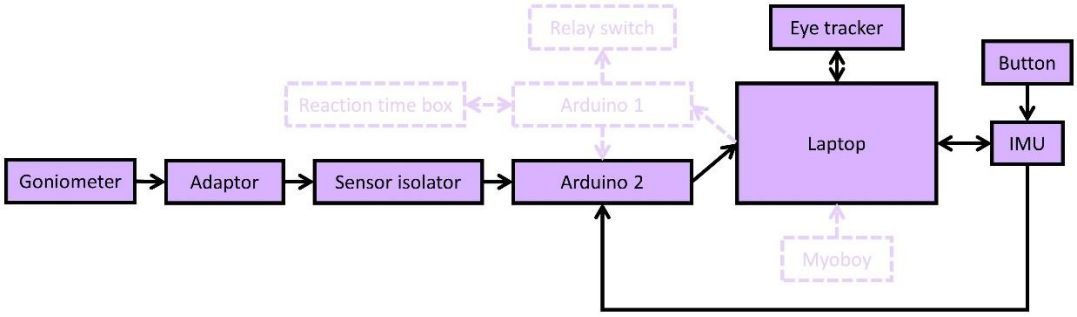


Figure 79. Block diagram of the experimental setup for the functional task sensors. Equipment from the overall experimental setup which is not included in the functional task has been faded out with dotted lines. The arrows show the direction of data transfer between the hardware.

b) To develop automated/semi-automated methods for the identification of the start and end points of the **cylinder task**, and the end of the "reach-to-grasp" phase, based on observation of the recorded data.

In order to address task segmentation (**part b**), clear text-based definitions were developed:

- Task onset:

  Defined as the onset of movement (either lifting the arm or opening the hand)

- End of "reach-to-grasp":

  Defined as the point at which the fingers finish closing around the cylinder. If the grasp was not smooth e.g. the hand re-opened and closed again during grasping, the first time the fingers finished closing around the cylinder was taken as the end of "reach-to-grasp" for the assessment of the length of the "delay plateau" and the "reach plateau".

- Task completion:

  Defined as the moment the fingers begin to open to release the cylinder after the "transport plateau".

A5.2. Synchronisation

Two synchronisation approaches were implemented, as detailed below.

A5.2.1. *Synchronising the goniometer with the IMU*

A5.2.1.1. TTL SYNCHRONISATION WITH XSENS AS MASTER

The Xsens Awinda station provides for synchronisation of the IMU's with external third party devices using TTL levels (0-3.3V). The Awinda station was configured to act as a master (sync out), changing the TTL level each time the recording was either started (rising edge) or stopped (falling edge) on the MT Manager software. The TTL levels were used to control the recording of data from the goniometer through "*Arduino 2*" (see **Appendix 2**), thereby allowing for synchronisation between the 2 systems. "*Arduino 2*" began goniometer data collection when the TTL level was set high, and stopped when it returned to 0.

A5.2.1.2. CHECKING THE SYNCHRONISATION

In order to confirm that the goniometer and IMU were accurately synchronised, a small study was undertaken. The IMU was taped to one end of the goniometer, with the z-axis of the IMU aligned with extension of the goniometer, and the y-axis of the IMU aligned with the lateral movements of the goniometer (see **Figure 80**). The other end of the goniometer was taped to the table. In line with the data collection during the functional task, the sampling rate was set at 100Hz for the IMU and 1000Hz for

the goniometer. Data collected using both systems were subsequently downsampled to 50Hz.

Data recording was initialised in the MT Manager software and the IMU was oscillated in the flexion/extension direction through 10 cycles (**Figure 81**), recording was then stopped; the trial was repeated 10 times (total 100 cycles). It would be expected that every time the movement direction changed, the flexion/extension data collected from the goniometer would peak/trough (represented by the black vertical lines on the figure), and the angular velocity measured around the y axis would be equal to zero (represented by the green circular markers). Angular velocity was chosen rather than the acceleration data due to the oscillations being rotational in nature.

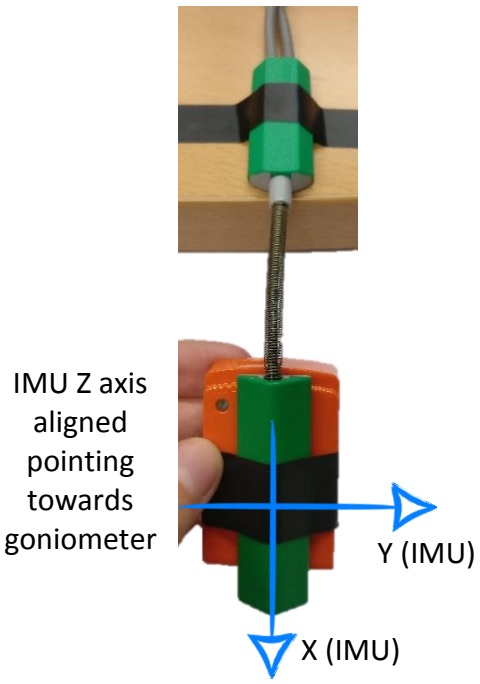


Figure 80. To synchronise the IMU and goniometer with each other, the IMU was taped to the underside of one end of the goniometer with the x-axis of the IMU aligned along the long axis of the goniometer. The other end of the goniometer was taped to the table top. The sensors were then cycled through the flexion/extension direction of the goniometer.

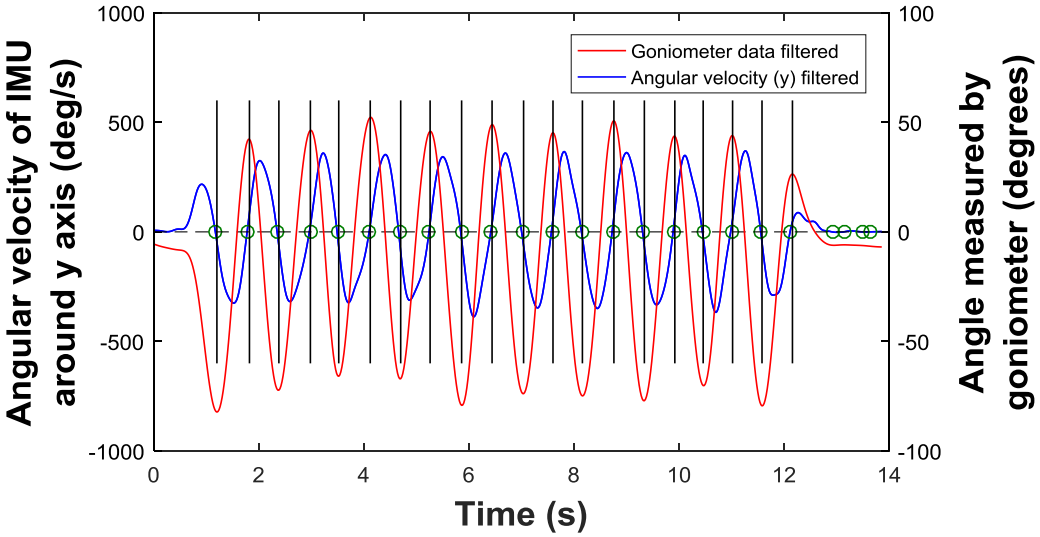


Figure 81. Plot of the IMU and goniometer data recorded from a single recording. The sensors were oscillated in the flexion/extension direction through 10 cycles. The goniometer data (red line) is the data recorded on the flexion/extension channel. The IMU data is the angular velocity around the y-axis (blue line). The black vertical lines represent the peaks/troughs in the goniometer data, whilst the green circles represent the IMU data zero crossings.

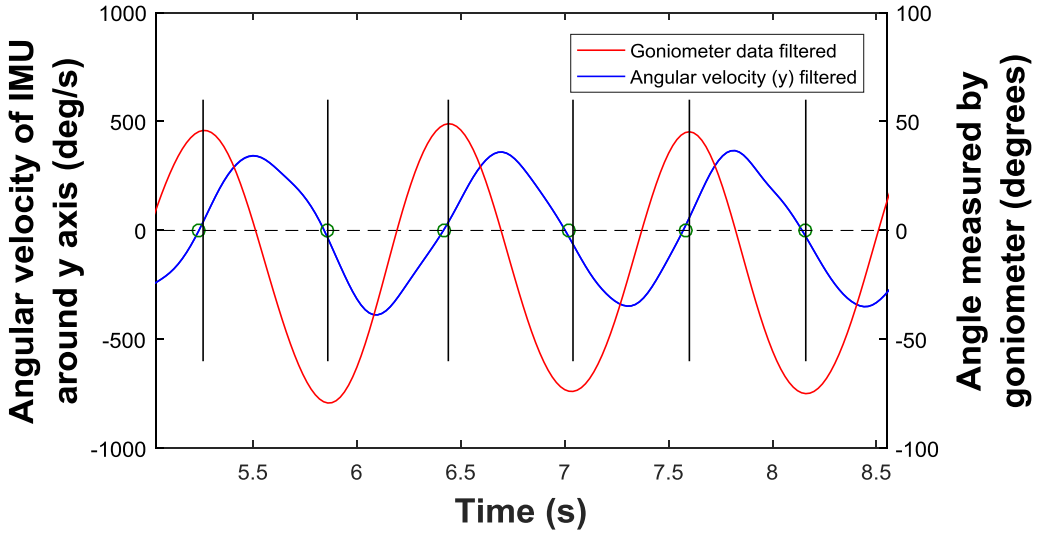


Figure 82. Zoomed in section of the plot in **Figure 81**. The vertical lines show the peaks and troughs in the goniometer data, whilst the circular markers represent the zero crossings for the angular velocity data.

The goniometer data recorded on the flexion/extension channel was double pass filtered using a 4th order Butterworth filter with cut-off frequency 2Hz. Peaks and troughs were located using the Matlab (v2016a) *findpeaks()* function with a minimum peak prominence of 20 degrees.

The angular velocity data from the IMU was double pass filtered using a 2nd order Butterworth filter with cut-off frequency 2.5Hz. The zero crossings were located by multiplying each data point by the previous data point. If the resulting value was less than or equal to 0 (i.e. positive*negative) the position was marked as a zero crossing.

Figure 82 shows a zoomed portion of the graph in **Figure 81**. The dotted red line shows the data from the flexion/extension channel of the goniometer, whilst the thick blue line shows the angular velocity data recorded by the Y-gyro in the IMU. The vertical black lines show the identified peaks and troughs in the goniometer data, whilst the green circles show the zero crossings for the IMU data. It is worth highlighting that, in the case that the zero crossing occurs between timestamps, the method of detecting the zero crossing will always allocate the point to the timestamp just after the zero crossing.

The difference between the timestamps (goniometer peak/trough – IMU zero crossing) was calculated for each of the ten trials, providing a total of 200 points for comparison (10 peaks and 10 troughs per trial). **Figure 83** shows the full results for the 10 trials. Across the 200 points examined, the timestamps identified by the IMU and goniometer matched for 67 points. For 123 points the timestamp identified by the goniometer was 20ms (1 frame) later than the IMU. For 7 points the goniometer identified a timestamp 40ms (2 frames) later than the IMU, and for 3 points the goniometer detected a timestamp 20ms (1 frame) earlier than the IMU. The mean difference between the two timestamps across the 200 trials was **13.4ms (<1 frame)** with a standard deviation of 11.4ms.

It can therefore be concluded that synchronisation between the IMU and the goniometer was successful.

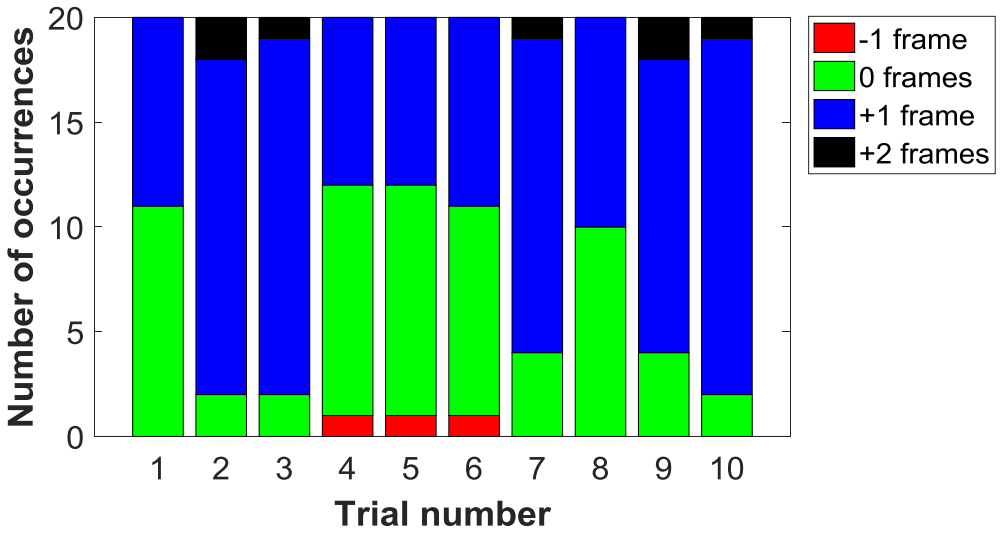


Figure 83. Timestamps were identified for the zero crossing points of the angular velocity (around the Y axis), these were subtracted from the peaks and troughs identified in the goniometer data. The number of frames difference (-1 to 2) is plotted here for each of the 10 oscillations (total 20 points), for the 10 trials. The colours of the bar show the number of frames difference, whilst the height of each bar shows the number of occurrences of each difference for each trial.

A5.2.2. *Synchronising the button and eye tracker with the IMU*

A5.2.2.1. TTL SYNCHRONISATION WITH XSENS AS SLAVE

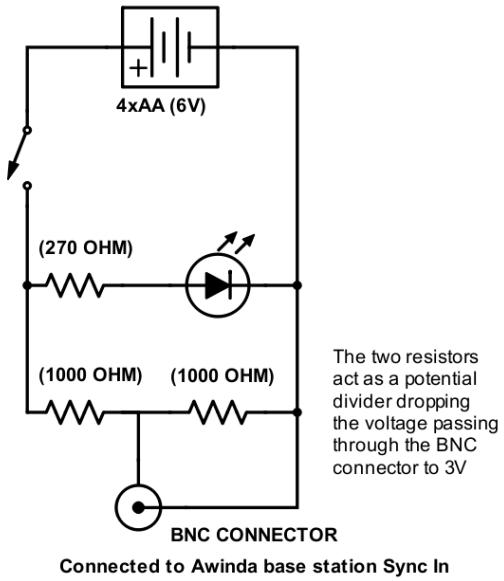


Figure 84. Circuit design for the button used to add a timestamp to the IMU data. The two 1000 Ω resistors were used to create a 50% voltage drop. The BNC connector was connected to the sync in port on the Xsens Awinda base station.

A simple method of determining task onset is to place a button under the hand which is used to timestamp the sensor data. A circuit was designed (**Figure 84**) in which the button acted as a switch, completing the circuit when pressed and breaking it when released. This circuit delivered either a rising or falling edge signal to the sync-in port of the Awinda station (acting as a slave). The MT Manager software was configured to add a timestamp to the IMU data each time a rising or falling edge signal was received.

A5.2.2.2. SYNCHRONISATION OF EYE TRACKING DATA WITH XSENS

The eye tracking data was collected using the Ergoneers D-lab software. D-lab is unable to send or receive TTL signals. An LED was therefore connected in line with the button (see **Figure 84**), which illuminated when the button was pressed and turned off as the hand left the button. This LED could be seen in the videos recorded from the eye tracker and used for manual synchronisation with the timestamps generated by the button.

The field of view (scene) camera for the Dikablis Professional Wireless Eye Tracker gave video with a frame rate of 30Hz, whilst the two eye cameras' frame rate were both 60Hz. The IMU data was sampled at 100 Hz.

A5.2.2.3. CHECKING THE SYNCHRONISATION

A short study was undertaken to establish whether the LED (visually detected from the scene camera videos) was synchronised with the timestamps in the IMU data (generated by the button).

Data recording was initiated through both pieces of software (D-lab and MT Manager). The button was then held down and released 10 times (duration approximately 0.5s). Recording was then stopped on both systems. This was repeated 20 times. A total of 400 timestamps were detected over the 20 repeats for comparison between the two systems.

The full task duration for each of the 20 repeats, from the first time the LED illuminated until the last time it turned off (mean duration = 9.9s), was calculated using the LED and button timestamps. The mean difference between the task

durations for the two measures (LED-button) was **0.004s** (SD=0.015s), with a maximum difference of **0.030s (less than 1 frame at 30Hz)**.

The duration of each shorter period where the LED was turned on/off was also calculated (Total 380 comparisons). The mean difference between the durations calculated using the two measures (LED-button) was **0s** (SD=0.015s), with a maximum discrepancy of **0.057s (less than 2 frames at 30Hz)**. The difference was greater than 1 frame (less than 2 frames) for 8/380 comparisons.

It can therefore be concluded that the timestamps placed in the IMU data provide an accurate representation of the on/off status of the LED detected in the scene camera video.

A5.3. Potential segmentation methods

To allow evaluation of the task performance, a consistent and reliable method of segmenting the task is required. This includes the detection of the task onset, the end of the "reach-to-grasp" phase and task completion as defined above (**Section A5.1**).

Previously the sensors used for the data collection and synchronisation were introduced; these included a button, eye tracker, goniometer, and IMU. Using these sensors, numerous methods are available to segment the task into different movement phases, some of which are introduced below (**Sections A5.3.3, A5.3.4 and A5.3.5**). Several of these methods require prior manipulation of the data recorded by the goniometer and the IMU; this includes the calculation of the hand opening and closing speed throughout the task (**Section A5.3.1**), and the calculation of the norm of the angular velocity at the wrist (**Section A5.3.2**).

A5.3.1. *Calculation of hand opening/closing speed*

To calculate the speed of hand movement, the angle data recorded from the goniometer was first double passed through a 4^{th} order Butterworth filter with a cut-off frequency of 2Hz. Hand speed was then calculated as the gradient of the filtered data using a 40ms moving window.

A5.3.2. *Calculation of angular velocity norm*

The norm of the angular velocity was calculated according to the methods of Carpinella et al. [161]. Each axis of angular velocity data was double passed through a 2nd order Butterworth filter with a cut-off frequency of 2.5Hz. The norm of the filtered velocities was then used for the task segmentation.

A5.3.3. *Methods of detecting task onset*

As defined above, task onset is taken as the onset of movement which could come from the lifting of the arm from the starting position or the opening of the hand, whichever occurs first. Six methods of detecting movement onset were evaluated as follows.

Option 1 – Button: A timestamp is placed in the IMU data when the prosthesis leaves the button (situated under the hand). The change of state of the button (pressed to not-pressed), also lights up an LED, visible in the scene camera of the eye tracker for synchronisation purposes.

Option 2 – Video: Visual inspection of the scene camera video from the eye tracker to establish the first moment of hand/arm movement; this may be the hand being opened, or the arm being lifted.

Option 3 – Goniometer method 1: Find the 1st point where the angle exceeds the Mean Resting Value (MRV) from the first 500 ms by +1°, and continues to increase by ≥5° over next 200 ms.

Option 4 – Goniometer method 2: Find the 1st point where the angle exceeds the MRV +1SD, and continues to increase by ≥5° over next 200 ms.

Option 5 – IMU method 1: Method used by Carpinella et al. [161] Find the 1st peak in the norm of the angular velocity (see **Section A5.3.1**) which exceeds a value of 5.73°/s. Onset = 1st point the norm exceeds 25% of the peak value.

Option 6 – IMU method 2: Find 1st point at which the norm of the angular velocity (see **Section A5.3.1**) exceeds 5.73°/s.

A5.3.4. *Methods of detecting the end of reach-to-grasp*

The end of "reach-to-grasp" was defined as the point at which the fingers finish closing around the cylinder. This information is not possible to obtain using the IMU or the button, therefore two methods of detecting the end of "reach-to-grasp" were assessed; one using the video, and one using the goniometer.

Option 1 – Video: Visual inspection of the scene camera video from the eye tracker to establish when the fingers finish closing around the cylinder.

Option 2 – Goniometer method 3: Find 1st point where the hand closing speed (see **Section A5.3.1**) reduces to 2.5°/s. If the hand closes around the cylinder at a slower rate than 2.5°/s, the end of "reach-to-grasp" is taken as the point when the hand closing speed reaches its maximum.

A5.3.5. *Methods of detecting task completion*

Task completion was defined as the moment the fingers begin to open to release the cylinder after the "transport plateau". Four methods of detecting the opening of the hand were assessed as described below.

Option 1 – Video: Visual inspection of the scene camera video from the eye tracker to establish when the hand begins to open releasing the tube.

Option 2 – Goniometer method 4: Find the last peak in hand opening speed (occurring before the final peak in the norm of angular velocity as the hand returns to the start point) which exceeds a height of 0.0125°/s. If the hand opens at a slower rate than 0.0125°/s, task completion is taken as the point when the hand opening speed reaches its maximum.

Option 3 – Goniometer method 5: Find 1st point after the "transport plateau" where angle exceeds the Mean Resting Value (MRV) during the plateau +1°.

Option 4 – Goniometer method 6: Find 1st point after the "transport plateau" where angle exceeds the Mean Resting Value (MRV) during the plateau +1SD.

A5.4. Choice of segmentation method

To decide on which segmentation method to use, the functional task data from 15 participants (total 150 trials) performing the medium difficulty task were segmented according to each of the methods introduced in **Section A5.3**. This number was chosen based on the number of participants whose data had been collected at the time of this analysis. The segmentation according to the video data was only undertaken for 5 participants (total 50 trials) due to the process being very time consuming, an issue which is addressed further below.

A5.4.1. *Task segmentation using video*

In previous studies task segmentation based on video data has often been considered as a gold-standard approach. However, in this study there are a number of downsides to using the scene camera video from the eye tracker for segmentation. If the head is moving, the field of view camera (sampled at 30Hz) can become blurred making it difficult to see whether the hand is moving or not. Furthermore, although a macro lens was used, the field of view camera cannot capture everything the participant can see; depending on the head position, the hand may move outside of the camera's field of view. This means that in certain cases the hand cannot be seen clearly at the start and end of the task making segmentation impossible. Finally, using a video-based approach the segmentation of the video data is not automated, therefore it is a very time consuming process. Consequently it was decided that the video data would not be used for the segmentation of the functional task during the main study. Nevertheless, the video offers an accepted standard, upon which we can base a decision as to which of the automated methods should be used.

A5.4.2. *Automated methods of detecting movement onset*

Participants were not constrained as to whether they should, at the start of the movement first lift or open their hand, and the approach used varied between participants and trials; consequently onset of movement must be detected by employing a combination of measures.

Five methods of automatically detecting the onset of the task were evaluated; these included using the data from the goniometer to detect the onset of hand opening (2 methods) (see **Section A5.4.2.1**), using the button to detect the moment the hand lost contact with the table (see **Section A5.4.2.2**), and using the IMU data to detect the onset of forearm movement (2 methods) (see **Section A5.4.2.3**).

Through visual inspection and comparison with the videos, a decision was made as to which methods will be used to detect the onset of hand opening and arm movement in the main study.

A5.4.2.1. DETECTION OF HAND OPENING USING THE GONIOMETER

Two methods were evaluated to detect the onset of hand opening (goniometer methods 1 and 2 see **Section A5.3.3**). The onset of hand opening identified by each method was the same for 89% of trials (133/150). For the other 17 trials, goniometer method 1 (MRV+1°) detected the onset of hand opening 20-160ms later (SR = 50Hz) than goniometer method 2 (MRV+1SD).

Of the 150 trials assessed, in only 4 trials did a participant open the hand before movement of the forearm was detected by the IMU. Consequently, due to the very small data set, the decision on which method to use was not based on a comparison of goniometer data with video data. Instead the decision was based on a visual inspection of the goniometer data for the 17 trials where the onset detected by the two methods differed. For these 17 trials goniometer method 1 appeared to be more consistently accurate at detecting the onset of hand opening; the moment of onset detected using goniometer method 2 was too early.

It was therefore decided that the method to be used to detect the onset of hand opening would be ***goniometer method 1***.

A5.4.2.2. DETECTION OF ARM LIFT USING THE BUTTON

Using the button it is possible to definitively state that the arm has been lifted from the table. However, the onset identified by the button may vary compared with physical behaviour of the hand, based on the initial placement of the prosthesis on the button. Visual inspection of the plotted IMU and goniometer data suggests that

in some instances the fingers started opening or the forearm began to lift from the board whilst the hand was still in contact with the button; therefore using the button as a measure of task onset will be affected by the participant's technique and does not necessarily detect the first instance of movement. For these reasons it was decided that the button would not be used to identify task onset. This leaves IMU Methods 1&2 to detect the onset of movement of the forearm caused by the lifting of the prosthesis.

A5.4.2.3. DETECTION OF ARM LIFT USING THE IMU

Two methods of detecting the lifting of the arm according to the IMU data were evaluated (IMU methods 1 and 2 see **Section A5.3.3**). Using Bland Altman tests, these two methods are compared against each other and against the moment of movement onset detected using the video data, to establish which method most accurately detects the first moment of forearm movement.

IMU method 1 was only able to detect an onset for 97% of the trials (145/150); whilst IMU method 2 was able to detect an onset point for all 150 trials. The 5 trials where IMU method 1 was unable to detect the onset of arm lift were excluded from the comparisons below.

Onset of forearm movement according to the two methods was the same for 14/145 trials. As noted by Carpinella et al. [161] reach to grasp generates a distinctive peak in the norm of the angular velocity. IMU method 1 detects onset using a threshold which is based on a percentage of this peak; consequently, dependant on the peak value, onset may be detected earlier or later than with IMU method 2 (which uses a specific threshold).

A Bland Altman test [162] was undertaken to establish the limits of agreement between these two methods (**Figure 85**), resulting in a lower limit of -108ms, an upper limit of 150ms and a mean difference of 21ms (Mean task duration = 5185ms, SD = 1879ms, sampling rate = 50Hz). It would therefore be reasonable to use either method.

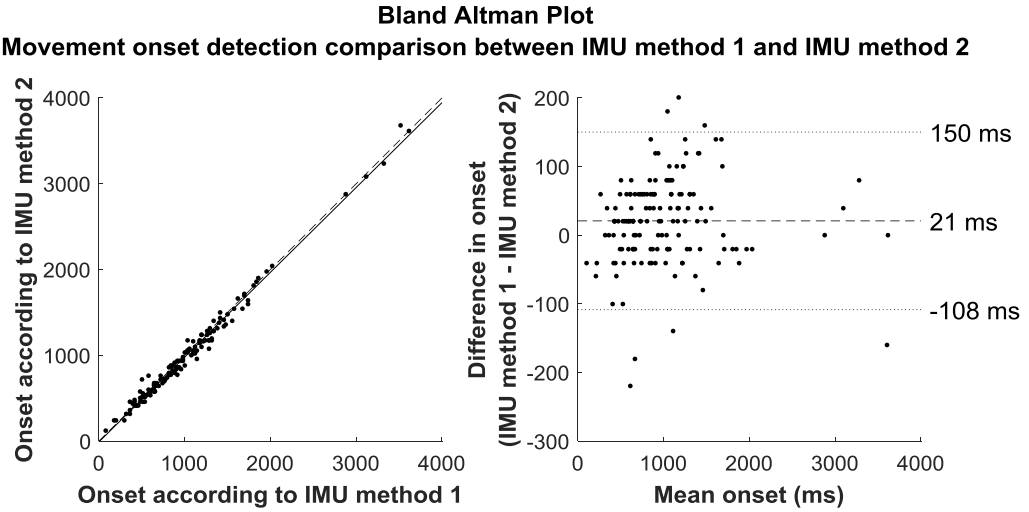


Figure 85. A Bland Altman plot of the mean onset between IMU methods 1 and 2 plotted against the difference in onsets (IMU method 1 – IMU method 2). The limits of agreement are -108 and 150, with a mean difference of 21ms.

To allow a decision to be made as to which of these two methods most accurately detects movement onset, both measures were individually compared against the onset detected using the video data. As noted in **Section A5.4.2.1**, for 4 of the trials the hand began opening before the arm was lifted from the table, these 4 trials were therefore excluded from the comparison against the video data. The 50 trials where video analysis was undertaken also included two of the trials where IMU method 1 was unable to detect movement onset. 44 trials were therefore included in the following comparisons.

Inspection of the Bland Altman plots (**Figure 86** and **Figure 87**) shows narrower limits of agreement between the video and IMU method 2 (-87 and 229 ms see **Figure 87**) than between the video and IMU method 1 (-138 and 217 ms see **Figure 86**).

It is worth noting that the onset of movement detected using IMU method 2 (which uses the specific threshold) was detected on average 71ms (≈ 2 frames) earlier than in the video (Mean task duration = 4870ms, SD = 1712ms, IMU sampling rate = 50Hz, Video sampling rate = 30Hz), whilst IMU method 1 detected movement onset on average slightly closer to the time identified by the video (mean = 39ms before video ≈ 1 frame). Nevertheless visual inspection of the data from all 150 trials showed that IMU method 2 only detected onset incorrectly for two of the trials, whilst as noted above, IMU method 1 was unable to detect a moment of movement onset for five of

the trials. For the two trials where IMU method 2 detected an incorrect moment of movement onset, the participant was subtly moving their arm before the task had begun and generating peaks in the angular velocity norm which exceed the threshold value. For these two trials it is possible to manually input the location of the correct peak in the angular velocity norm. This is clearly visible through visual inspection of the data.

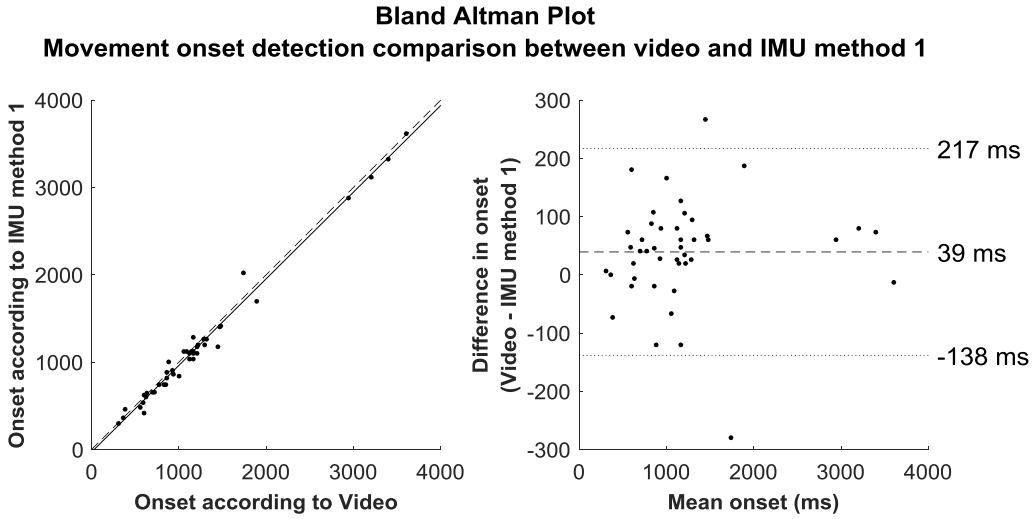


Figure 86. A Bland Altman plot of the mean onset between the video data and IMU method 1 plotted against the difference in onsets (video – IMU method 1). The limits of agreement are -138 and 217ms, with a mean difference of 39ms.

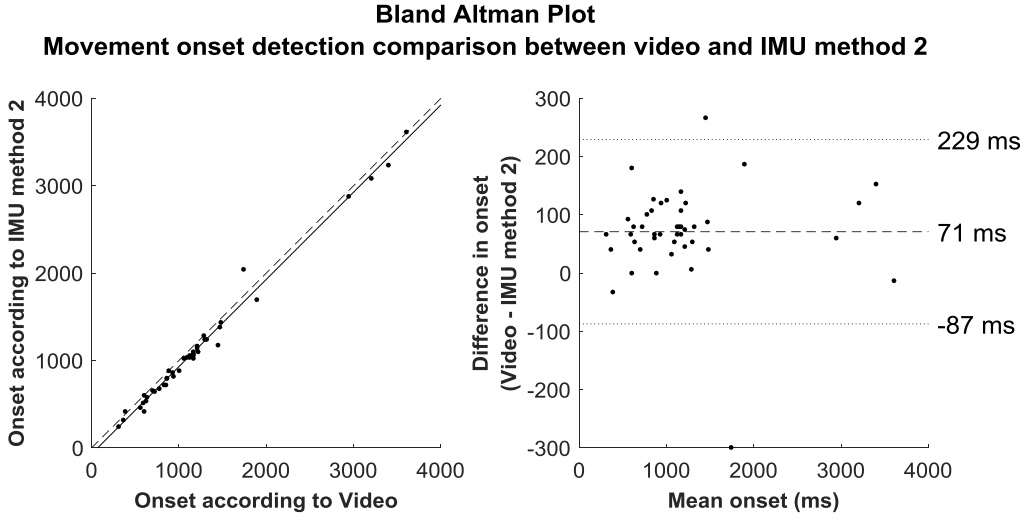


Figure 87. A Bland Altman plot of the mean onset between the video data and IMU method 2 plotted against the difference in onsets (video – IMU method 2). The limits of agreement are -87 and 229ms, with a mean difference of 71ms.

In summary, IMU method 2 (based on the specific threshold) provides a more accurate measure of the onset of arm movement. Despite detecting onset earlier than the video data, the values are more consistent, with limits of agreement equal to approximately 6% of the total task duration. **IMU method 2** will therefore be used for the detection of the onset of the arm being lifted from the table, combined with **goniometer method 1** (detecting hand opening); task onset will be taken as the first of these two movements to occur.

A5.4.3. *Automated methods of detecting the end of reach-to-grasp*

Besides the video data, only one method of detecting the end of the "reach-to-grasp" was investigated. Here we evaluate whether goniometer method 3 (see **Section A5.3.4**) accurately detects the end of "reach-to-grasp" when compared against the video data. In one of the 50 video trials analysed, the cylinder was knocked over during "reach-to-grasp", this trial was therefore excluded from the comparisons.

For the majority of participants, visual inspection of the goniometer data shows two phases to the hand closing around the cylinder: a fast movement phase, and a slower movement phase as the fingers meet the cylinder and tighten, deforming the foam (**Figure 88**).

Visual inspection of this data suggests that the threshold employed in goniometer method 3 causes detection of the end of reach to grasp slightly late when compared to the video data; this is supported by the skew of -188ms in the Bland Altman plot (**Figure 89**). A threshold of 5°/s (as opposed to 2.5°/s) was therefore also tested and did reduce this skew; however using this higher threshold prevented automatic detection for the few participants with slower hand movements, or those who did not change hand aperture excessively between the "reach plateau" and the "transport plateau" such as the participant presented in **Figure 90**. This higher threshold was therefore discarded.

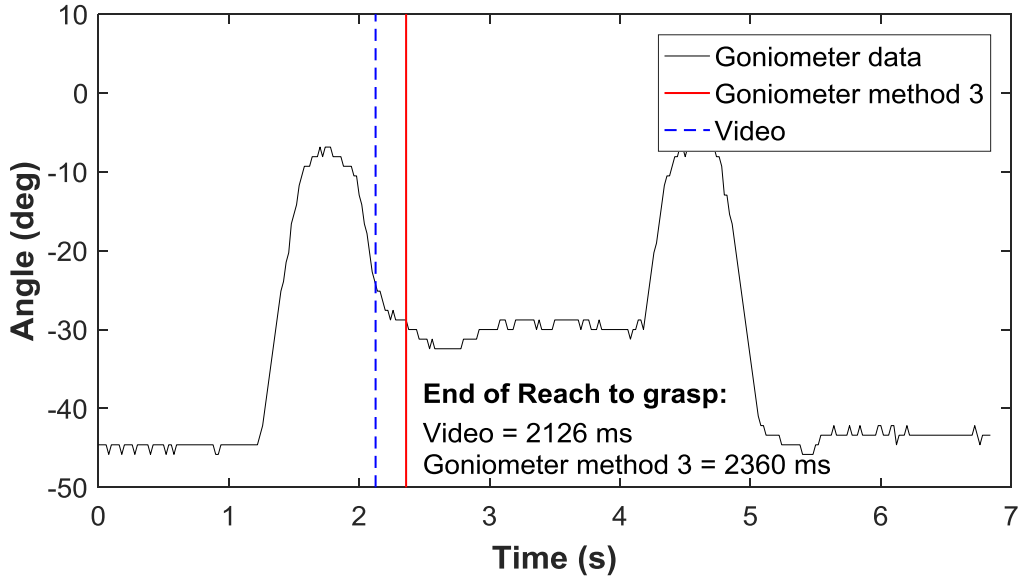


Figure 88. Example plot showing the goniometer data recorded during the functional task. The first peak shows the opening and closing of the hand during the reach to grasp, whilst the second peak shows the release of the cylinder and the closing of the hand as it returns to the starting position. The vertical lines show the moments identified as the end of "reach-to-grasp" using the video (blue dotted) and goniometer method 3 (red). In this example the two phases to the closing of the hand around the cylinder can be clearly identified.

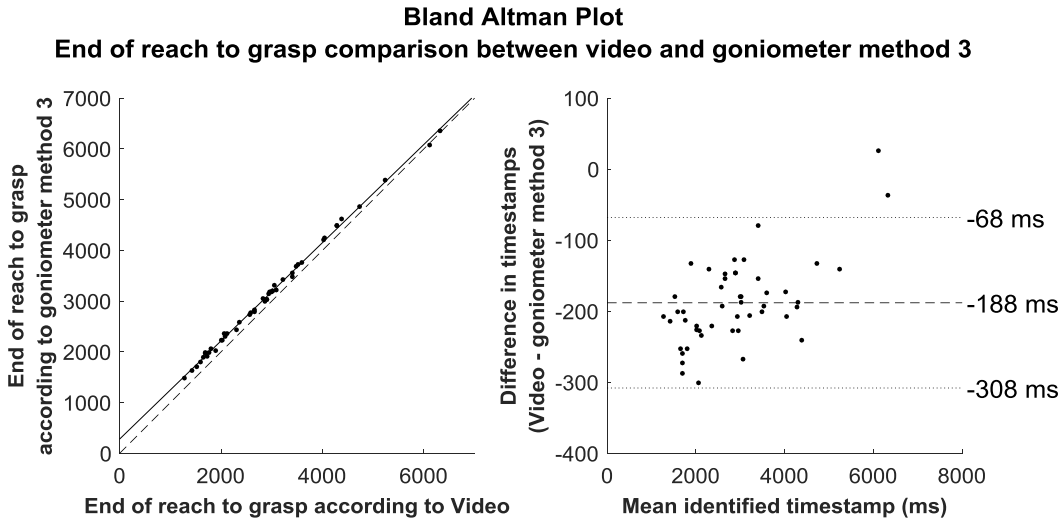


Figure 89. A Bland Altman plot of the mean timestamp identified as the end of reach to grasp using the video data and goniometer method 3 plotted against the difference in timestamps (video – goniometer method 3). The limits of agreement are -308 and -68ms, with a mean difference of -188ms.

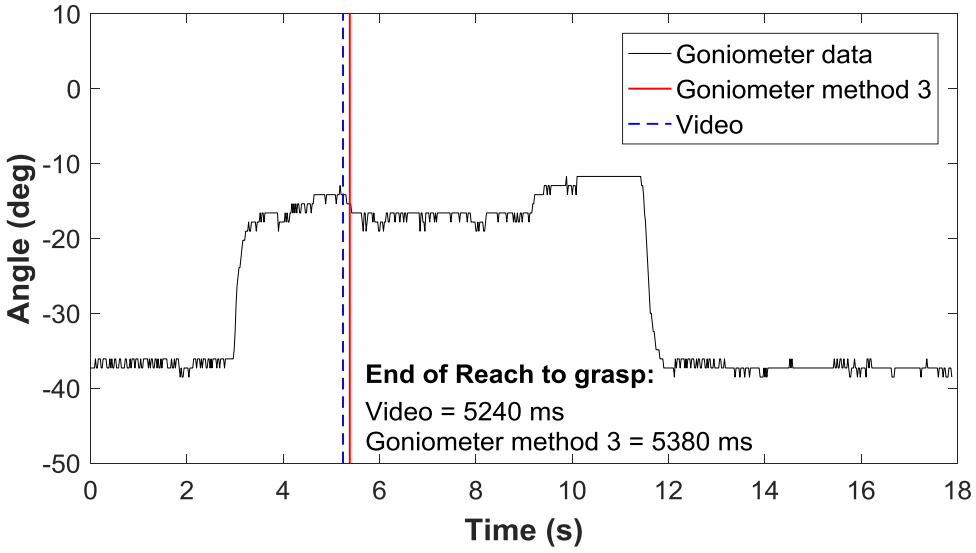


Figure 90. Example plot for a participant with very little movement of the hand when closing around the cylinder at the end of reach to grasp. The first peak shows the opening and closing of the hand during the reach to grasp, whilst the second peak shows the release of the cylinder and the closing of the hand as it returns to the starting position. The vertical lines show the moments identified as the end of reach to grasp using the video (blue dotted) and goniometer method 3 (red).

The limits of agreement between goniometer method 3 and the video were -308 and -68 ms, which is 5% of the mean task duration of 4823ms (SD = 1861ms, IMU sampling rate = 50Hz, video sampling rate = 30Hz). Visual inspection of the goniometer data for each trial suggest that goniometer method 3 detects a consistent point; therefore **goniometer method 3** will be used to detect the end of the "reach-to-grasp" phase.

A5.4.4. *Automated methods of detecting task completion*

Here the three automated methods of identifying task completion (goniometer methods 4, 5 and 6 see **Section A5.3.5**) were assessed against each other and compared to the video data. Task completion was defined as the moment the fingers begin to open to release the cylinder after the "transport plateau".

Bland Altman plots were generated comparing the instance identified using the three goniometer methods to each other (**Figure 91**, **Figure 92**, and **Figure 93**). Eight trials where the cylinder was dropped during the "transport" phase were excluded leaving a total of 142 trials (48 for the video analysis). Goniometer method 5 (MRV+1°) and goniometer method 6 (MRV+SD) showed the most similar results to each other

(limits of agreement -114 and 66ms, mean task duration = 5165ms, SD = 1849ms, sampling rate = 50Hz, see **Figure 91**). When each of these two methods were compared against goniometer method 4 (based on the hand opening speed) the limits of agreement were significantly larger (>300ms difference between the conditions see **Figure 92** and **Figure 93**).

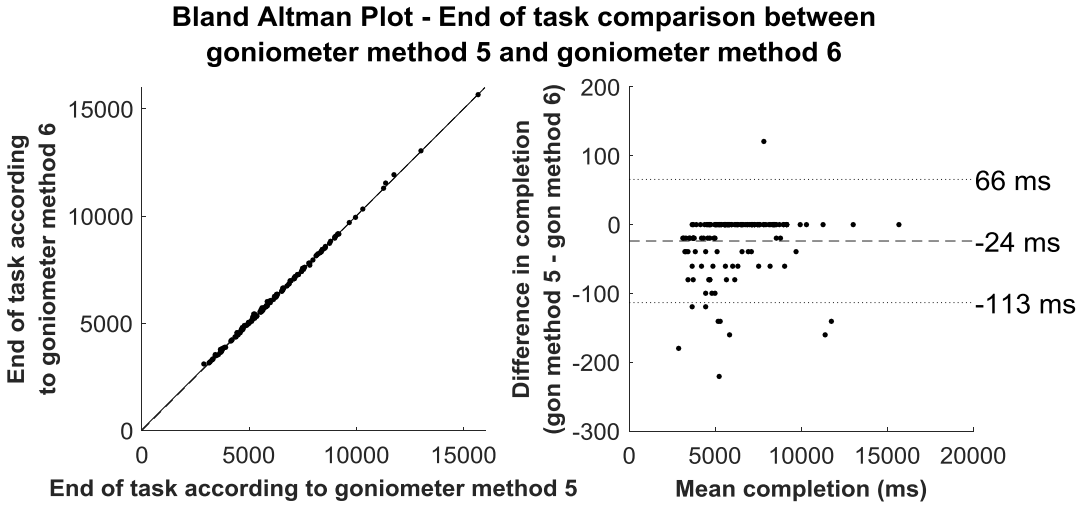


Figure 91. A Bland Altman plot of the mean task completion calculated according to goniometer method 5 and goniometer method 6 plotted against the difference in completion timestamps (goniometer method 5 – goniometer method 6). The limits of agreement are -113 and 66, with a mean difference of -24ms.

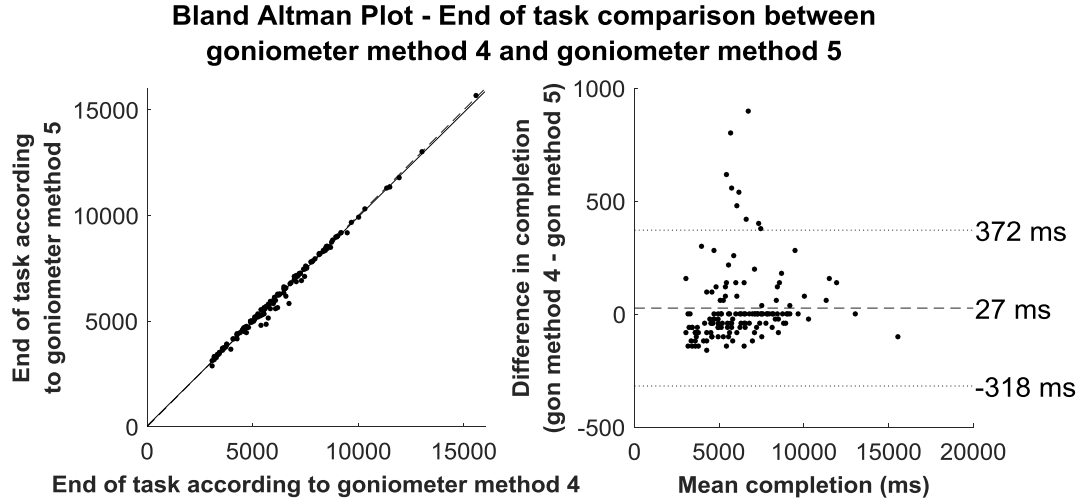


Figure 92. A Bland Altman plot of the mean task completion calculated according to goniometer method 4 and goniometer method 5 plotted against the difference in completion timestamps (goniometer method 4 – goniometer method 5). The limits of agreement are -318 and 372, with a mean difference of 27ms.

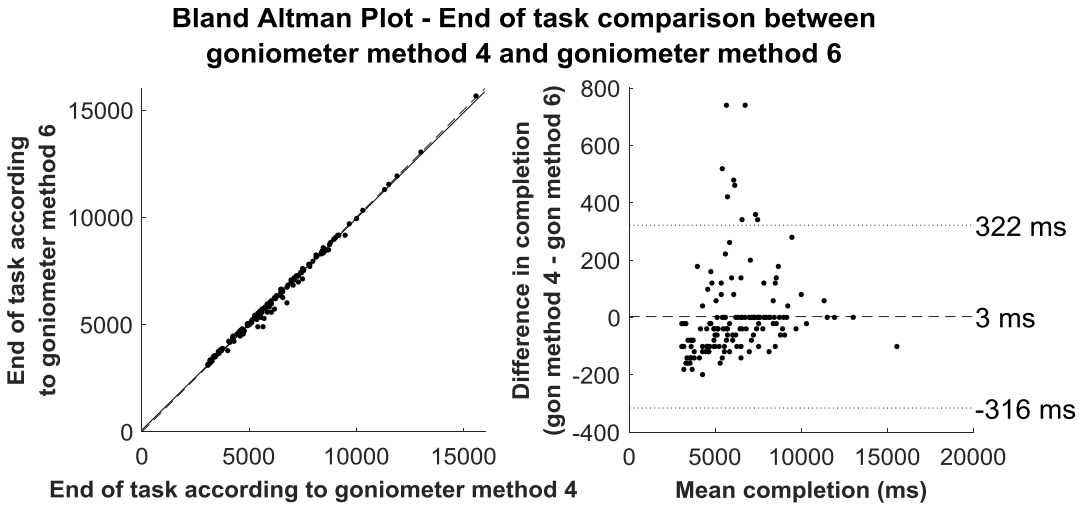


Figure 93. A Bland Altman plot of the mean task completion calculated according to goniometer method 4 and goniometer method 6 plotted against the difference in completion timestamps (goniometer method 4 – goniometer method 6). The limits of agreement are -316 and 322, with a mean difference of 3ms.

Goniometer method 4 also showed the largest limits of agreement when compared against the moment identified as the onset of cylinder release in the video data (limits of agreement = -357 and 324ms, mean task duration = 5032ms, SD = 1744ms, IMU sampling rate = 50Hz, video sampling rate = 30Hz); goniometer method 4 was therefore excluded as a method of detecting task completion.

Goniometer methods 5 and 6 were also compared against the video data using the Bland Altman method; Goniometer method 6 (MRV+SD) offered the narrowest limits of agreement (limits = -358 and 251ms, mean difference = -53ms) (**Figure 94**). Visual inspection of the plot shows three values where the point of completion according to the video was more than 400ms before the point of completion identified by goniometer method 6. These three points were all recorded from the same participant; visual analysis of the video data for this participant was not straightforward. During release of the cylinder the prosthetic hand was situated slightly outside of the video frame for the scene camera, consequently it is possible that some errors were made in the visual detection of hand opening for this subject. If this subject (10 trials) is excluded leaving only 4 participants (37 trials) the limits of agreement reduce to 156 and -165 ms (mean task duration = 4669ms, SD = 1781ms, IMU sampling rate = 50Hz, video sampling rate = 30Hz).

In summary, **goniometer method 6** was chosen to be the best method of detecting the hand opening from around the cylinder and was therefore used to establish the point of task completion.

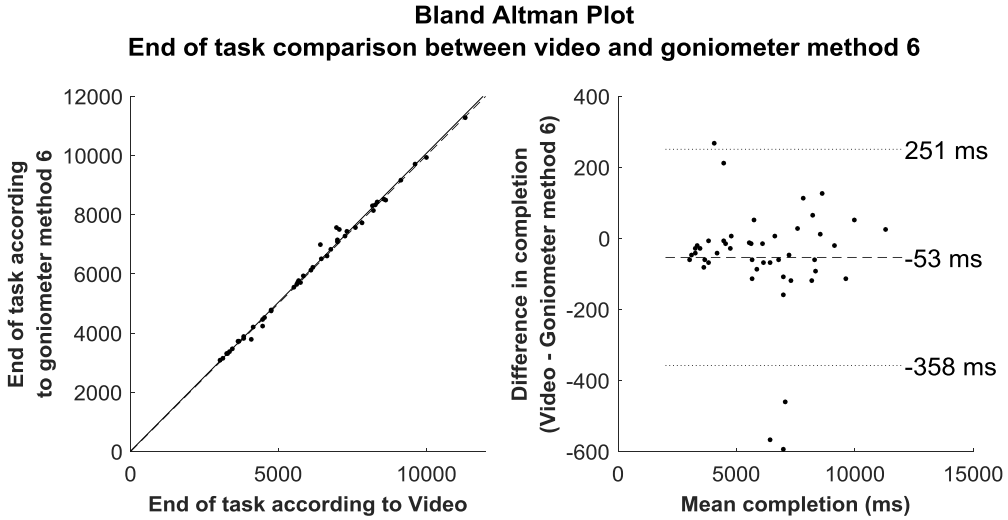


Figure 94. A Bland Altman plot of the mean task completion calculated according to the video and goniometer method 6 plotted against the difference in completion timestamps (video – goniometer method 6). The limits of agreement are -358 and 251, with a mean difference of -53ms.

A5.5. Conclusion

In **Section A5.4** methods for the detection of task onset, the end of the "reach-to-grasp" phase, and task completion were assessed to establish the optimal segmentation methods for use in the analysis of the functional task data.

The chosen methods were:

- The onset of hand opening will be detected using **goniometer method 1**.
- The first moment of forearm lift will be detected using **IMU method 2**.

NB: Task onset will be taken as the first point of movement detected using ***goniometer method 1*** *and* ***IMU method 2***

- The end of "reach-to-grasp" will be detected using **goniometer method 3**.
- Task completion will be detected using **goniometer method 6**.

Figure 95 shows data from an example participant segmented using these four methods. The data presented comes from a participant who completed each phase

of the movements in a smooth manner, as demonstrated by the clear peaks and troughs in the IMU and goniometer data.

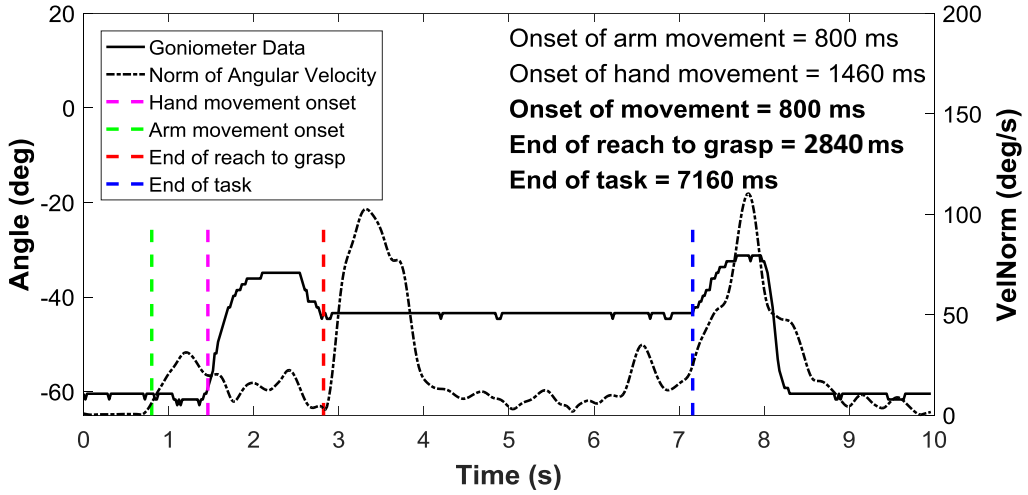


Figure 95. Example of timestamps identified by the chosen algorithms. This example shows a smooth completion of the task. The bold solid line shows the angle data recorded by the goniometer worn across the proximal knuckle of the index finger, the dashed line shows the norm of the angular velocity recorded from the IMU worn on the wrist. The onset of arm movement (green) is detected using IMU method 2, the onset of hand opening (magenta) is detected using goniometer method 1, the end of reach to grasp (red) is detected using goniometer method 3, and task completion (blue) is detected using goniometer method 6.

Appendix 6

Gaze coding scheme inter-rater reliability study

A6.1. Background

The gaze patterns of people performing upper limb functional tasks using a prosthesis have been shown to differ markedly from the anatomically intact hand [85, 88, 89, 163]. Using a head mounted eye-tracker it is possible to record and analyse these gaze patterns. During a multistage task, the skill of a prosthesis user can be quantified based on the amount of time spent looking at the prosthetic hand, compared to the time spent looking ahead to later portions of the task.

In this thesis we introduce a **cylinder task** where users reach-to-grasp a cylinder and place it into a tube. The 'field of view' camera on the eye-tracker captures data in two dimensions; consequently, there are times when the identification of what the participant is looking at can be ambiguous and open to misinterpretation [90]. For example, during "reach-to-grasp" if the user is focussed on the cylinder, the hand may move in front of the cylinder, but the gaze may not necessarily shift to the hand itself. We have therefore developed a set of rules (coding scheme) for identification of the fixation point, and here the results of an inter-rater reliability study are presented.

A6.2. Inter-rater reliability study methodology

In the main study 20 participants each attempted the medium difficulty **cylinder task** 10 times (see **Chapter 3**). For one participant (10 trials) it was not possible to successfully calibrate the eye tracker due to problems with the automated pupil detection. For 16 trials the participants did not complete the full task. To assess the reliability of the coding scheme 20 trials were chosen at random from the remaining 174 trials.

Gaze data was collected using a Dikablis Professional Wireless Eye Tracker. D-lab software was used to analyse the data. Due to bugs in the programme, the software was updated a couple of times during the data collection for the study (starting with v3.01), however, the final analysis was undertaken using D-lab v3.5. The D-lab software placed a crosshair over the position of gaze fixation.

The data was independently coded by two separate people. The two raters agreed on a set of rules in advance (see **Section A6.3.2**).

In total 6517 frames of data were coded by each rater. Statistical analysis of the coded data was undertaken using IBM SPSS statistics (v 24.0.0.1). The agreement between the raters was assessed using Cohen's Kappa.

A6.3. Coding scheme

A6.3.1. *Areas of interest*

The task area was split into five areas of interest (AOI): (1) the prosthetic **hand**, (2) the Grasp Critical Area (**GCA**) of the cylinder, (3) the Location Critical Area (**LCA**) of the cylinder, (4) the **tube**, and (5) **other** (**Figure 96**).

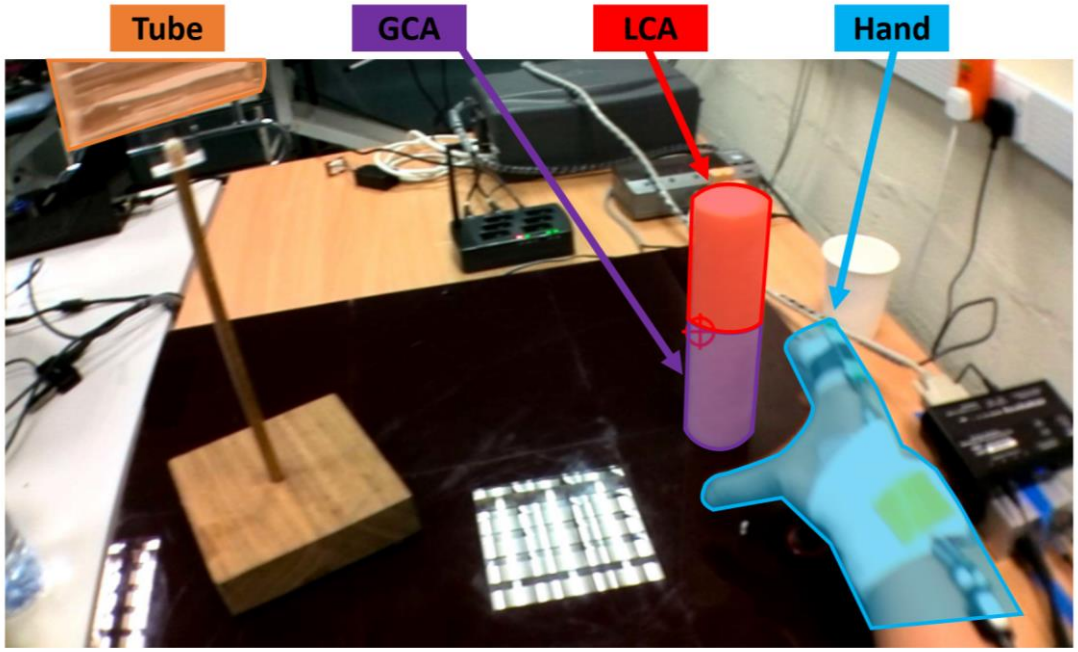


Figure 96. Areas of interest (AOIs) for **cylinder task**

A6.3.2. *Rules*

The task was split into the "reach-to-grasp" phase, and the "transport" phase (see **Appendix 5**); the coding scheme was slightly different for each phase. Using the location of the centre of the crosshair, each frame of video data (SR=60Hz) was coded according to these rules.

A6.3.2.1. REACH-TO-GRASP

During "reach-to-grasp" the **LCA** and the **tube** were combined into a single AOI. Gaze at either of these areas corresponded to looking ahead to future portions of the task.

Coding options included: **Hand**, **GCA**, **LCA/Tube**, **Other** or **Missing data**.

The AOI **Hand** included any part of the prosthetic hand.

The **GCA** was defined as the bottom half of the cylinder, and the **LCA** was defined as the top half of the cylinder (**Figure 96**).

The **Tube** did not include the stand or the plastic block, however, if the crosshair was within 5mm of the opening of the tube (video size = 14.95*8.4cm) this was marked as **LCA/Tube**.

If the gaze was transitioning between positions, or the participant was looking at any other part of the task, this was coded as **Other**.

Data was marked as **Missing Data** if the participant blinked, or if the centre of the crosshair was outside of the field of view.

The following additional rules were put in place to cover periods during "reach-to-grasp" where the hand may move in front of the cylinder:

1) If the gaze is on the GCA and the hand moves into the area where the crosshair is this should continue to be coded as **GCA**, unless the pupils and the crosshair flick to a different location.
2) If the gaze is on the hand tracking its movement to the cylinder this should be coded as **Hand**, unless the pupils and the crosshair flick to a different location.
3) If the gaze is flicking between the hand and the cylinder, the coding should be consistent even if the hand and cylinder both fall under the crosshair. The rules above should be used as a guide.

A6.3.2.2. TRANSPORT

During the "transport" phase the **LCA** and the **Tube** were combined into a single AOI. As the tube was transparent it was not possible to differentiate gaze at these two AOIs. The **Hand** and the **GCA** were also combined.

Coding options included: **Hand/GCA**, **LCA/Tube**, **Other** or **Missing data**.

The video data was two-dimensional, consequently when lifting and rotating the cylinder there were times when it was not clear which part of the cylinder the participant was looking at. The AOIs were therefore re-defined in a more restrictive manner. A line was drawn through the points where the index finger and thumb contact the cylinder (**Figure 97A**). The **LCA** included areas of the cylinder above this line, and the **GCA** included areas of the cylinder below this line (**Figure 97B**).

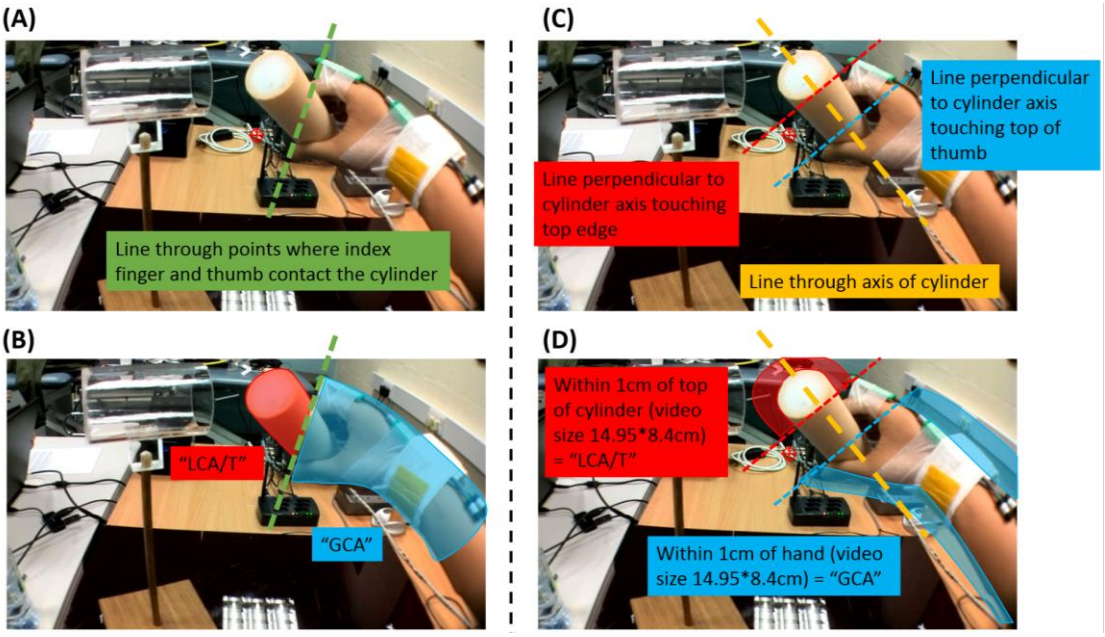


Figure 97. Re-defining the Areas of Interest (AOIs) for the "transport" phase. **(A)** and **(B)** relate to frames where the crosshair is on the hand or cylinder. **(C)** and **(D)** relate to frames where the crosshair is in the area surrounding the hand or cylinder.

Furthermore, as the participants tracked the movement of the cylinder the crosshair would hover just off the edge of the cylinder. We therefore added a boundary region around the top of the cylinder and around the hand; if the crosshair hovered around the centre of the cylinder it was not clear which region they were looking at so this was left as **Other**. A line was drawn through the long axis of the cylinder (**Figure 97C**);

perpendicular lines were then drawn which touched the top of the thumb, and the top edge of the cylinder (**Figure 97C**). If the crosshair was within 1cm of the top of the cylinder (video size = 14.95*8.4cm), and above the top line this was included in the **LCA** (**Figure 97D**). If the crosshair was within 1cm of the hand (video size = 14.95*8.4cm), and below the bottom line this was included in the **Hand/GCA** (**Figure 97D**).

The following rules were applied with respect to these boundary regions:

1) If the centre of the crosshair is within 5mm of the opening of the tube (video size = 14.95*8.4cm) code as **LCA/Tube**
2) If the centre of the crosshair is within 1cm of the top of the cylinder (defined according to a perpendicular line through the cylinder axis touching the edge of the cylinder – see **Figure 97C**) code as **LCA/Tube**
3) If the centre of the crosshair is within 1cm of the bottom of the cylinder/hand (defined according to a perpendicular line through the cylinder axis touching the top of the thumb– see **Figure 97C**) code as **Hand/GCA**
4) Once the cylinder begins to enter the tube rules 1 and 2 should be replaced by the following: If the centre of the crosshair is within 5mm of any part of the LCA or tube code as **LCA/Tube** (unless rule 3 is met)

If the gaze was transitioning between positions, or the participant was looking at any other part of the task, this was coded as **Other**.

Data was marked as **Missing Data** if the participant blinked, or if the centre of the crosshair was outside of the field of view.

A6.4. Results

The results showed near perfect agreement between the two raters ($\kappa = 0.909$, $p<.001$). The gaze sequence from each of the two raters for each of the 20 assessed trials is presented in **Figure 48,** and **Table 16** shows the crosstabulation of the agreement between the two raters output from SPSS. As can be seen in both **Figure 48** and **Table 16**, the main discrepancies between the two raters were between the **Hand** and the **GCA** during "reach-to-grasp", and between the **LCA/Tube** and the **Hand/GCA** when releasing the cylinder at the end of the "transport" phase.

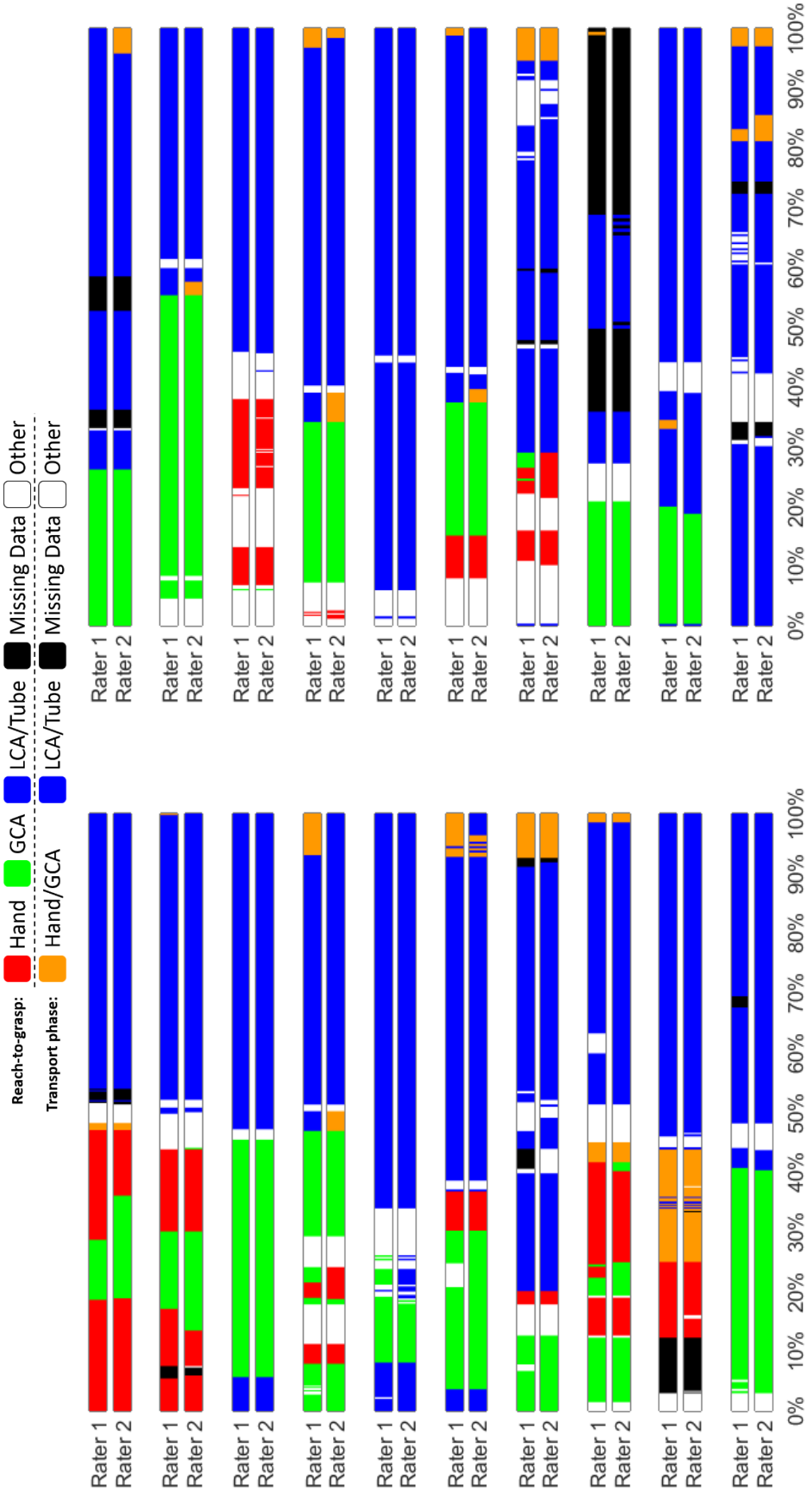


Figure 98. Coding plots for each trial to allow visual comparison of the gaze sequence between the two raters.

Table 16. Crosstabulation table for the agreement between the two raters

		Rater 2						
		Hand	**GCA**	**Hand/GCA**	**LCA/Tube**	**Missing Data**	**Other**	**Total**
Rater 1	**Hand**	545	55	0	0	0	8	608
	GCA	24	1021	0	17	0	2	1064
	Hand/GCA	0	0	170	68	2	1	241
	LCA/Tube	0	0	69	3686	6	7	3768
	Missing Data	2	0	0	8	177	12	199
	Other	7	23	0	53	1	553	637
	Total	578	1099	239	3832	186	583	6517

A6.5. Conclusion

The coding scheme detailed above was shown to be consistent between raters and was therefore used to analyse the patterns of gaze for the main study (**Chapter 5**).

Appendix 7a

Non-Wear Algorithm

Removal of prosthesis non-wear time based on visual inspection of accelerometer data

This appendix details the non-wear algorithms used in **Chapter 3**. This appendix was previously published as supplementary material in Frontiers in Neurorobotics alongside the publication of **Chapter 3**. Since publication an automated non-wear algorithm has been produced for use in the main study. This second algorithm is detailed in **Appendix 7b**.

Chadwell A, Kenney L, Thies S, Galpin A, Head J; ***(2016);*** *The reality of myoelectric prostheses: Understanding what makes these devices difficult for some users to control;*
Frontiers in Neurorobotics; *DOI: 10.3389/fnbot.2016.00007*

A7.1. Methods for identification of prosthesis non-wear periods

As far as the authors can tell, there are no published detailed algorithms to distinguish wear time from non-wear time for wrist worn Actigraph GT3X+ monitor (Actigraph Corp) data. To address this, we first applied the approach taken by Bailey [108] to remove periods when the "*bilateral magnitude*" was equal to 0. This allowed exclusion of periods when it can be assumed that both activity monitors were removed. It appears that Bailey assumed that participants were wearing either both of the monitors or neither and hence no further analysis of wear were employed in Bailey's study.

The monitoring of amputees introduces additional challenges to the ones faced by Bailey. The monitor worn on the prosthesis may be isolated from the anatomical upper limb by either removing the monitor from the wrist of the prosthesis, or removing the socket (with the monitor still attached) from the anatomical residual limb, so it is difficult from the monitor data alone to distinguish prosthesis non-wear time from monitor non-wear time. However, participants were asked to keep the monitor on the prosthetic socket throughout and, unlike the anatomical limb, there would be no obvious reason why the participants would not comply with this; it is reasonable to assume that, when bathing, showering, or sleeping, the prosthetic socket – not the monitor - would be removed. The only exception to this was the last day of recording, where in one case the participant (Prosthesis User 2) removed the monitor in the morning to return it to us (**Figure 99**). We also invited participants to complete an activity diary, recording sleep times, the times when the prosthesis was worn, and the times when the monitors were removed from either arm and this record was also used in the analysis, as described below.

To address the challenge of detecting periods when the prosthesis was not worn, we used both diary record and visual inspection of both the activity count data and "raw" accelerometer data. We used diary record to exclude periods where there was activity evident from the accelerometer data, but the diary indicated the prosthesis was not worn (e.g. final day's data for Prosthesis User 2). We used visual inspection

of the monitor data to identify periods where we believed the participant to have removed their prosthesis. As discussed above, we assumed that all participants would remove their prosthesis (if worn) prior to going to sleep. The figures below show the data recorded from both activity monitors. The red, green and blue lines show the raw accelerometer data measured in g (1g = 1 unit of gravity or 9.81m/s^2), whilst the black line represents the Vector Magnitudes (VM, the residual of the Activity Counts on all three axes) generated by the proprietary algorithm in the Actilife software (these have been divided by 100 to allow them to be plotted alongside the raw data). All data from the activity monitor worn on the anatomical hand has been shifted vertically upwards by 10g, to illustrate the synchronous data from the two activity monitors, one plotted above the other. Overnight removal of the prosthesis was identified as being the period from the last VM>0 registered on one day until the first VM>0 on the next day. Single, isolated VM spikes during this period were ignored, such as the spike at 65 hours in **Figure 99**.

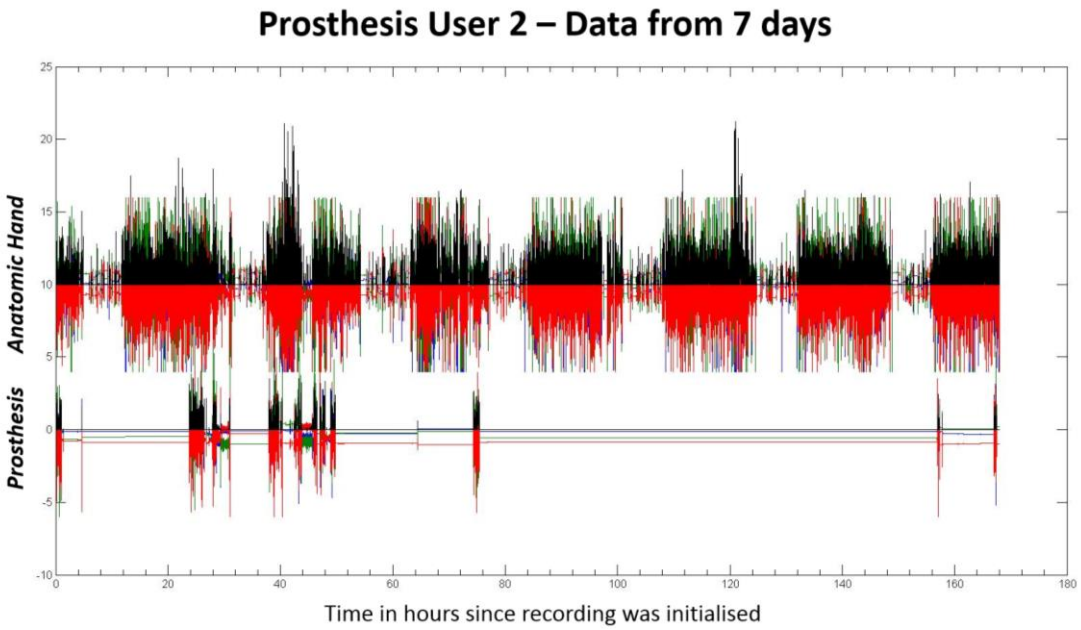


Figure 99. Activity Monitoring Data from 1 week of prosthesis wear for Prosthesis User 2. The red, blue and green lines show the raw accelerations in g, whilst the black lines signify the Vector Magnitudes (divided by 100 to scale). The data for the anatomic hand has been shifted upwards by 10g for visual purposes.

Figure 100 shows day 3 data in more detail. Although the activity diary did not provide information on removal of the prosthesis during the day, the raw data would suggest that the device was not always worn. The yellow bars in Figure 2 represent the length of the 'quiet' periods for the prosthesis in minutes. We decided to label one of these periods as non-wear based on the raw data as there was no movement of the prosthesis for a period of 133 minutes (>2 hours), whilst the anatomical hand was still very active. As both arms exhibited similar accelerometer profiles, we did not label the 131 minute long period of low amplitude activity at 44-46 hours as non-wear, even though the number of activity counts during this period was very low. It is possible that the participant was travelling during this period and therefore was very inactive.

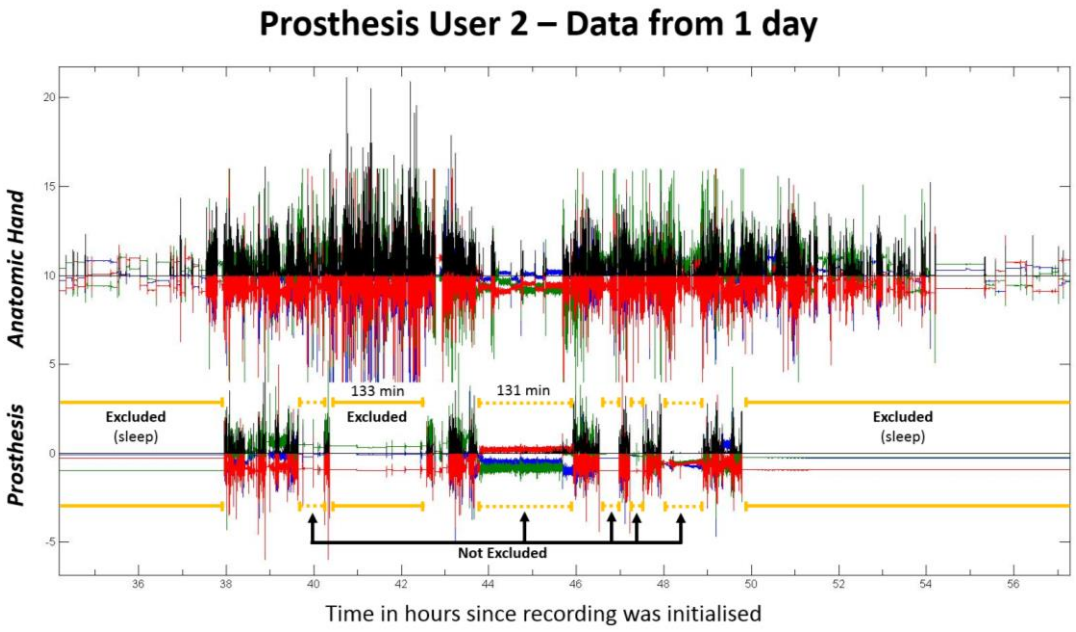


Figure 100. Activity Monitoring Data from day 3 of prosthesis wear for Prosthesis User 2. The red, blue and green lines show the raw accelerations in g, whilst the black lines signify the Vector Magnitudes (divided by 100 to scale). The data for the anatomic hand has been shifted upwards by 10g for visual purposes. The yellow bars show periods where the prosthesis was very inactive; solid lines represent the periods which were treated as non-wear time. 1 period during the day was excluded, all other periods were left in and assumed to be passive wear.

None of the other periods marked in **Figure 100** were labelled as non-wear. For comparison, the raw accelerometer data from Prosthesis User 1 who wore the device every day is presented in **Figure 101**.

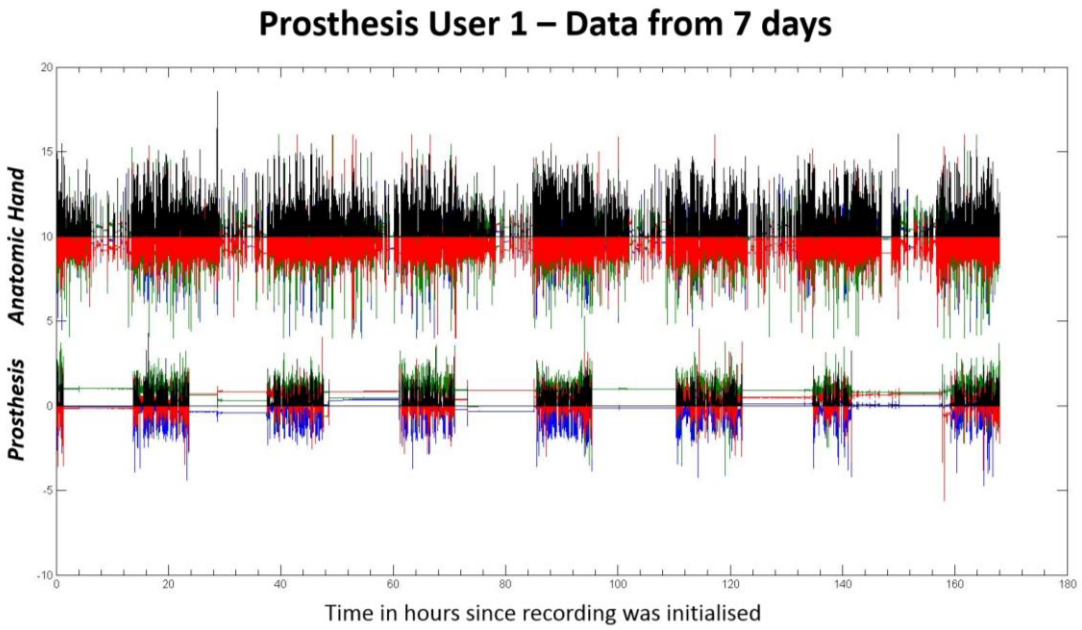


Figure 101. Activity Monitoring raw acceleration data from 1 week of prosthesis wear for Prosthesis User 1. The red, blue and green lines show the raw accelerations in g, whilst the black lines signify the Vector Magnitudes (divided by 100 to scale). The data for the anatomic hand has been shifted upwards by 10g for visual purposes.

Appendix 7b

Non-Wear Algorithm

Algorithm for the automated removal of prosthesis/monitor non-wear time

This appendix details the automated non-wear algorithm produced for use in the main study (**Chapter 4** onwards).

A7.2. Background

This study uses wrist-worn activity monitoring sensors to record the upper limb activity of prosthesis users and anatomically intact adults. To accurately analyse upper limb activity, it is important to determine the periods when the monitors are, and are not, worn.

Anatomically intact participants were instructed to remove the monitors if they were likely to get wet. Therefore it can be assumed that when either monitor was removed (for example, to shower), both would be removed (resulting in no activity counts being recorded on either monitor VM=0). These periods where no activity is recorded on either arm are excluded as part of the data analysis. The algorithm described below was therefore only applied to data from the prosthesis users.

Prosthesis users are likely to remove the prosthesis for periods during the day, leaving the second monitor on the intact wrist. Without further processing, the data from these periods would present incorrectly as unilateral activity on the anatomically intact side, thereby biasing the results. Therefore, a method is needed to identify periods when the prosthesis and the attached monitor were removed. We refer to these periods as "***prosthesis non-wear***", although we are currently unable to differentiate between removal of the prosthesis, and removal of the prosthesis monitor from the wrist of the prosthesis.

As participants were instructed to leave the monitor on the wrist of the prosthesis at all times, it can be assumed that when showering etc. the myoelectric prosthesis itself would have been removed. Furthermore, as there would be no discomfort associated with wearing the monitor on the wrist of the prosthesis, it is reasonable to assume that participants complied with this instruction.

"***Prosthesis wear time***" therefore refers to the times when both the prosthesis *and* the monitor on the prosthetic 'wrist' were worn; "***prosthesis non-wear***" was calculated based on the activity counts recorded on the prosthesis worn monitor.

For the results presented in **Chapter 5**, the algorithm presented here was only used to remove the periods "***prosthesis non-wear***" in order to avoid the potential bias discussed earlier.

To differentiate between self-reported wear times and wear times calculated using the algorithm the suffixes "***(SR)***" and "***(C)***" are used.

A7.3. Aims

No standardised method exists to distinguish wrist worn accelerometer wear from non-wear [156]. In the pilot stages of this work, "***prosthesis non-wear***" periods were removed through a combination of automated event detection, diary data, and visual inspection [109]. Here we report on the development of a fully automated method of "***prosthesis non-wear***" detection.

A7.4. Proposed algorithm for the detection of prosthesis non-wear

The algorithm has been developed on the assumption that prolonged periods of activity recorded on the prosthesis worn monitor constitute "***prosthesis wear***", and that prolonged periods of inactivity correspond to "***prosthesis non-wear***". As noted in our previous work (see **Appendix 7a**) [109], occasionally isolated spikes may be seen in the Vector Magnitude data which may not correspond to "***prosthesis wear***", and similarly, short periods of inactivity may occur during "***prosthesis wear***" periods. The algorithm is therefore designed to inspect surrounding data points during the classification of each epoch.

Data were collected using Actigraph activity monitoring sensors from the GT3X range (GT3X+, wGT3X, wGT3X-BT) and downloaded using the Actilife 6 software where they were filtered using the low frequency extension filter (proprietary [143]) and grouped into 60s epochs. For each epoch, acceleration data were converted into activity counts (proprietary [140]), and summed across the three axes to generate Vector Magnitudes of the activity counts ($VM = \sqrt{x^2 + y^2 + z^2}$). The Vector Magnitude values were imported into Matlab for the removal of non-wear periods.

Each epoch was classified as either wear or non-wear according to the steps below (see also **Figure 102**).

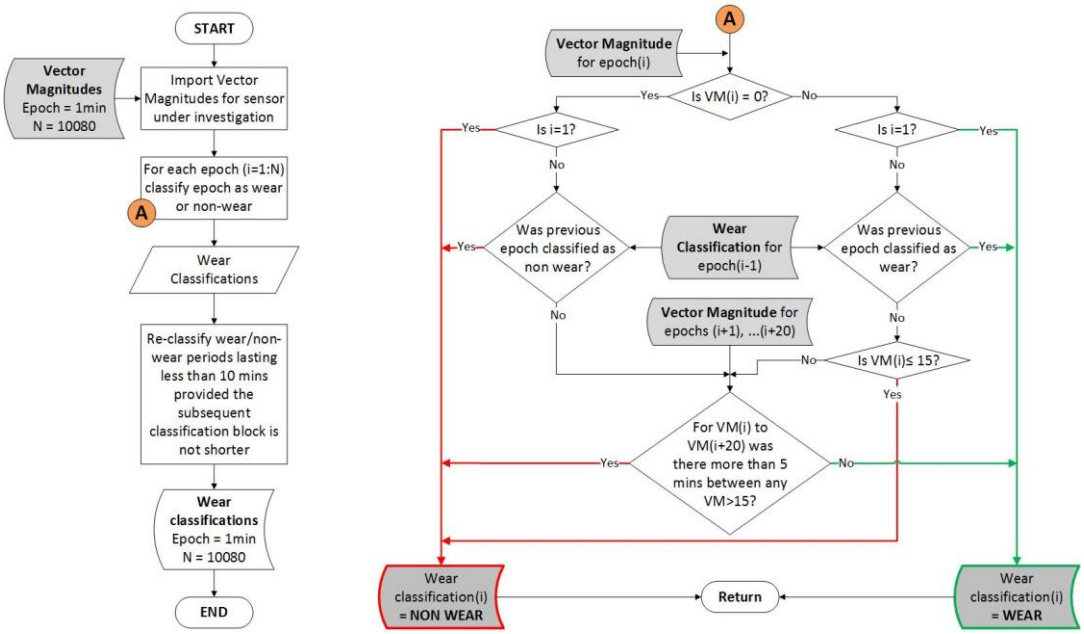


Figure 102. Automated non-wear algorithm.

Step 1: For the first epoch (minute 1), if the Vector Magnitude was equal to zero (no counts recorded) the epoch was classified as non-wear, otherwise it was classified as wear.

Step 2: Working from the second epoch (minute 2) to the last (minute 10080), each epoch was compared to the previous epoch, if no counts were recorded (VM=0) and the previous epoch had been classified as non-wear, it was assumed the monitor was still not being worn and this epoch was also classified as non-wear. Similarly if counts were recorded, and the previous epoch had been classified as wear, it was assumed the monitor was still being worn and this epoch was also classified as wear. If the epoch was identified as a possible transition between wear and non-wear (e.g. VM=0 but previous epoch=wear; or VM>0 but previous epoch=non-wear) the epoch was assessed according to Step 3.

Step 3: Transitions between wear and non-wear periods were more complex to detect. Step 3 aims to avoid misclassification based on isolated spikes of data or short periods of inactivity.

A possible transition from non-wear to wear: Where activity was recorded for the epoch under inspection (VM>0), but the previous epoch had been classified as non-wear, the following checks were used to establish whether the current epoch should be categorised as wear.

1. If the Vector Magnitude of the epoch under inspection was greater than 15[15], and the monitors continued to show activity over the subsequent 20 minutes[16], demonstrated by no-more than 5 consecutive minutes of VM≤15, the epoch was classified as wear.
2. Otherwise, if the Vector Magnitude of the epoch under inspection was less than or equal to 15, or the monitors showed prolonged inactivity over the subsequent 20 minutes, demonstrated by more than 5 consecutive minutes of VM≤15, the epoch was classified as non-wear.

A possible transition from wear to non-wear: Where no activity was recorded for the epoch under inspection (VM=0), but the previous epoch had been classified as wear, the following checks were used to establish whether the current epoch should be categorised as non-wear.

1. If the monitors continued to show inactivity over the subsequent 20 minutes[17], demonstrated by no-more than 5 consecutive minutes of VM>15, the epoch was classified as non-wear.
2. Otherwise, if the monitors showed prolonged periods of activity over the subsequent 20 minutes, demonstrated by more than 5 consecutive minutes of VM>15, the epoch was classified as wear.

Step 4: Initial testing of the algorithm suggested that some epochs had been misclassified; this occurred where two 'isolated' spikes occurred within 5 minutes of each other during a non-wear period resulting in an incorrect classification of wear.

[15] This threshold was chosen through visual inspection of the data spikes generated by picking up the sensors/prosthetic arm.
[16] This ensured that isolated spikes of activity within a non-wear period were not incorrectly coded as wear.
[17] This ensured that short periods of inactivity within a wear period were not incorrectly coded as non-wear.

This was remedied by undertaking a second classification phase; periods of wear/non-wear lasting for less than 10 minutes were re-classified unless they were immediately followed by a shorter block of wear/non-wear.

A7.5. Comparison to self-reported prosthesis non-wear

Participants were asked to complete a wear diary to assist with the development of the non-wear algorithm. Nineteen participants returned the wear diary; the self-reported prosthesis and/or monitor wear times were incomplete for five of these participants. For the remaining fourteen participants "***prosthesis wear time (C)***" calculated using the algorithm was plotted against the self-reported "***prosthesis wear time (SR)***". The discrepancy between the measures was highlighted.

Over the 7 days "***Prosthesis wear time (C)***" was on average (median) 4.4 hours shorter than "***Prosthesis wear time (SR)***" (min = 52.6 hours shorter, Q1 = 9.5 hours shorter, Q3 = 0.8 hours longer, max = 6.3 hours longer) (**Figure 103**).

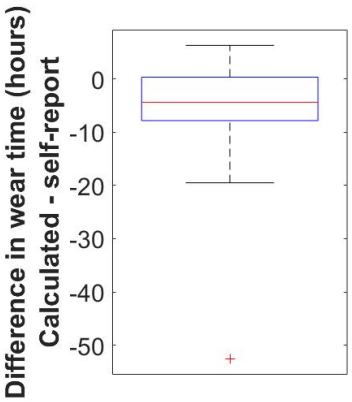


Figure 103. Box plot representing the difference between the "***prosthesis wear time (C)***" and "***prosthesis wear time (SR)***" for 14 participants.

There are some limitations to the algorithm, one participant self-reported to remove the prosthesis when driving each day; and this can be seen in a reduction in the Vector Magnitude during these periods (**Figure 104A**); these periods were not detected as "***prosthesis non-wear (C)***" by the algorithm. Similarly periods where the prosthesis or monitors were removed for less than 20 minutes (e.g. a quick shower) (**Figure 104B**) were not detected as "***prosthesis non-wear (C)***" using this algorithm. Further work would be needed to ensure that this algorithm was robust to all

situations, however this was outside of the scope of this study. For the majority of participants, the algorithm appeared to calculate "***prosthesis non-wear***" more accurately than self-reported (**Figure 104C**).

A7.6. Checking the performance of the algorithm to detect monitor removal on anatomically intact subjects

The data presented above suggests that on average the algorithm was able to accurately detect "***prosthesis non-wear***"; although there were some periods that were self-reported as "***prosthesis wear***", which the algorithm allocated as "***prosthesis non-wear***". To further evaluate the ability of the algorithm to detect non-wear periods, the same algorithm was used to analyse the "***anatomical monitor non-wear***" for the cohort of anatomically intact participants. The algorithm was used to detect the removal of the monitor worn on the dominant wrist.

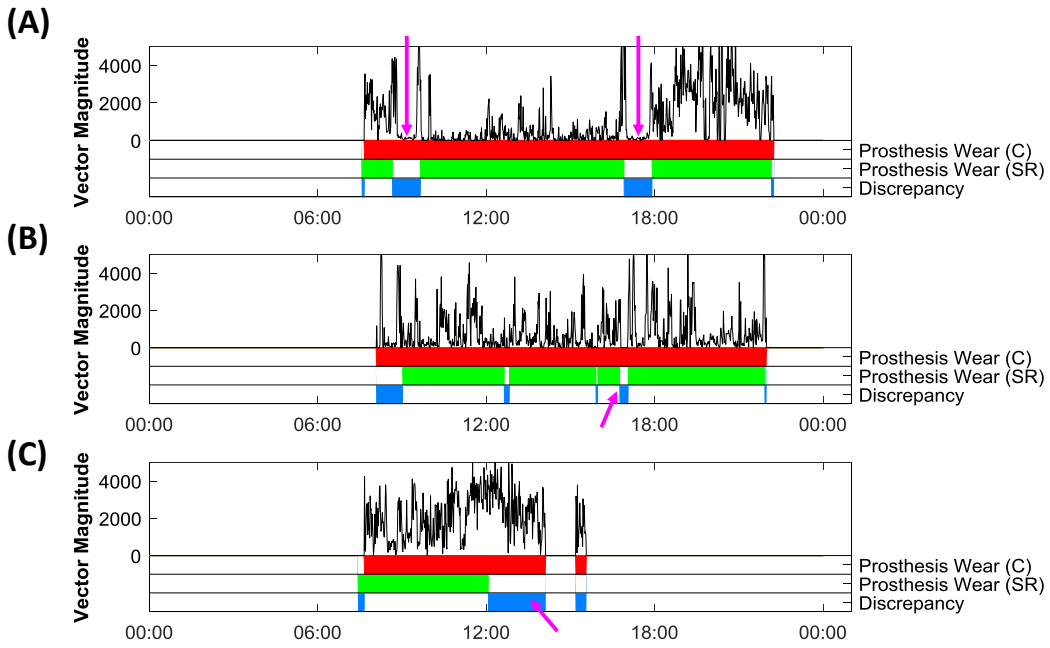


Figure 104. Each figure presents the Vector Magnitude data recorded by the monitor worn on the wrist of the prosthesis over 24 hours. The bars below allow comparison of the "***prosthesis wear time (C)***" (red), and "***prosthesis wear time (SR)***" (green). The discrepancy between the two measures is shown in blue. The magenta arrows indicate specific points discussed in the main text: **(A)** the participant self-reported to remove the prosthesis when driving, **(B)** the participant self-reported to remove the prosthesis for 14 minutes, and **(C)** the participant self-reported to remove the prosthesis at midday.

All twenty anatomically intact participants involved in the study returned completed diaries. Data was plotted and the discrepancy between the "***anatomical monitor wear time (SR)***" and the "***anatomical monitor wear time (C)***" was highlighted. Visual inspection suggested that although the algorithm was consistent in the detection of "***anatomical monitor wear time***" during the daytime, whilst the person was asleep, the algorithm was not very accurate (see **Figure 105**). For the purposes of this study, it was not important that the non-wear algorithm was able to accurately detect the monitor wear status during the times the person was asleep; the self-reported sleep times were therefore excluded from the following analysis.

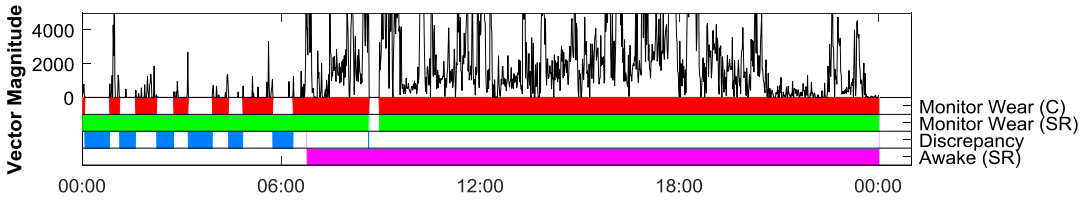


Figure 105. Example plot displaying 24 hours of data recorded from one of the monitors worn by an anatomically intact participant. During the times the participant self-reported to be awake (magenta) the "***anatomical monitor wear time***" calculated using the algorithm (red) matched the self-reported "***anatomical monitor wear time***" (green). Whilst the participant was asleep, the algorithm was less accurate.

During the times the participants self-reported to be awake (over the 7 days), the "***anatomical monitor wear time (C)***" was on average (median) 1 minute shorter than the "***anatomical monitor wear time (SR)***" (min = 8.0 hours shorter, Q1 = 1.7 hours shorter, Q3 = 0.7 hours longer, max = 1.5 hours longer) (**Figure 106**).

For the three outliers shown in **Figure 106**, the large discrepancy between the "***anatomical monitor wear time (SR)***" and "***anatomical monitor wear time (C)***" could possibly be explained by: (1) lying in bed in the morning (one participant self-reported to wake up to 3 hours before the monitor detected large amounts of movement), (2) sitting still for long periods of time, or (3) removing the monitor without reporting its removal (See **Figure 107** for examples of large discrepancies).

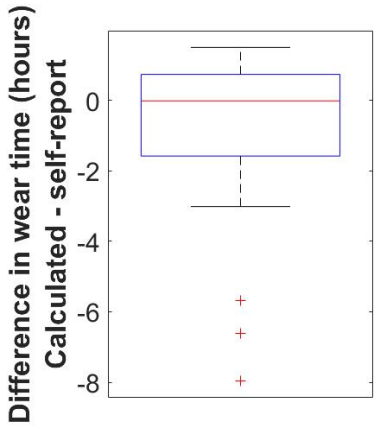


Figure 106. Box plot representing the difference between the "***anatomical monitor wear time (C)***" and "***anatomical monitor wear time (SR)***" for 20 anatomically intact participants.

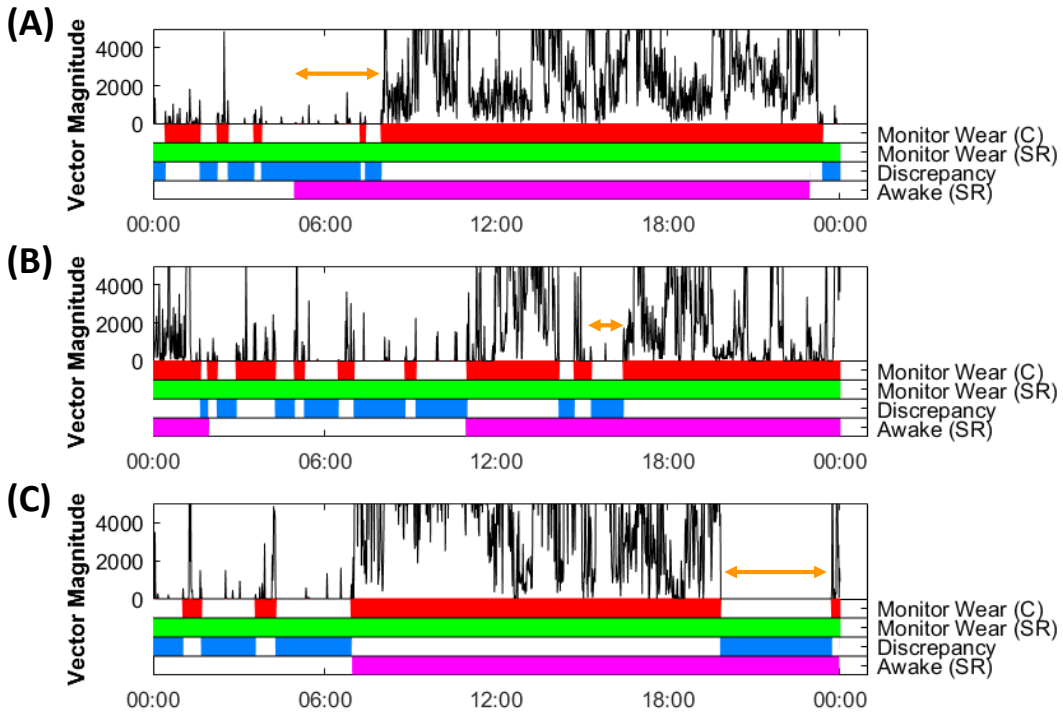


Figure 107. These three plots demonstrate some of the large discrepancies between "***anatomical monitor wear time (SR)***", and "***anatomical monitor wear time (C)***". The Vector Magnitude data (over 24 hours) is presented from the monitor worn on the dominant wrist. The bars below allow comparison of the "***anatomical monitor wear time (C)***" (red), and "***anatomical monitor wear time (SR)***" (green). The discrepancy between the two measures is shown in blue. The magenta bar signifies the time the participant self-reported to be awake. Possible explanations for the large discrepancies, marked with the orange arrows could be: **(A)** the participant remained in bed, **(B)** the participant sat very still, and **(C)** incorrect self-report, it is possible the monitor was not actually worn.

A7.7. Conclusion

Detection of "***prosthesis non-wear***" is a complex task. The prosthesis may be carried or transported resulting in movement detection on the activity monitor; furthermore, detection of short periods of prosthesis removal is difficult without misclassifying periods where the person may have been sat still (for example watching TV). For the majority of participants, visual inspection of the plots suggested that the automated non-wear algorithm was more accurate than the self-report data. Self-report generally overestimated the wear time.

In future, a more complex algorithm for the detection of "***prosthesis non-wear***" would be beneficial.

Appendix 8

Principle component analysis

A8.1. Can the number of variables used to represent the delay in the prosthesis be reduced?

As noted in **Chapter 5**, correlation analyses suggested that the measurements constituting the electromechanical "*delay*" in the prosthesis may be suitable for reduction into fewer components. Here the results of a Principle Component Analysis (PCA) on the "*delay*" measures is presented to investigate the possibility of reducing the number of variables.

Significant correlations were found between:

- The "$delay_{O\_N}$" to the onset of hand opening from a neutral starting aperture
- The "$delay_{C\_N}$" to the onset of hand closing from a neutral starting aperture
- The "$delay_{C\_O}$" to the onset of hand closing from a fully open starting aperture

N.B. As no significant correlation was found with the "$delay_{O\_C}$" to the onset of hand opening from a fully closed starting aperture this was not included in the PCA.

The Kaiser-Meyer-Olkin measure of sampling adequacy (0.619) and Bartlett's test of sphericity ($p = 0.001$) suggest that the variables are suitable for PCA [164].

The first component had an eigenvalue of 2.643 and explained 88.1% of the variance. The second component only had an eigenvalue of 0.319. Therefore, based on Kaiser's criterion [165] one component should be extracted.

After extraction of the first component, all communalities were greater than 0.7 and as there were less than 30 variables, Kaiser's criterion was shown to be valid [164]. The component matrix is shown in **Table 17**. After reproducing the correlation matrix using the extracted component, 2 (out of 3) residuals had absolute values greater than 0.5; these were the residuals related to the "$delay_{O\_N}$" to open from the hand from a neutral aperture. Consequently [164] this data would **not be recommended for PCA** with single component extraction.

Table 17. Component matrix – one component extracted using PCA

	Component 1
Delay to close from neutral	0.980
Delay to close from open	0.948
Delay to open from neutral	0.886

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