The Role of Visuomotor Behaviours in Understanding the Functionality of Upper Limb Prostheses

by

Kodi Cheng

A thesis submitted in partial fulfillment of the requirements for the degree of

Master of Science

in Biomedical Sciences

Department of Biomedical Engineering

University of Alberta

Abstract

Introduction: Upper limb prostheses aim to restore the complex capacities of the human hand. Coordinated hand and arm function relies on an intact visuomotor system during object interaction. However, unlike individuals with intact arm function, prosthesis users face additional challenges due to an absence of the natural channels for motor control and feedback sensations from the amputated limb. These challenges necessitate constant visual monitoring of the prosthesis and lend to disruptions to normal patterns of eye-hand coordination. Novel prosthetic interventions are thus developed to facilitate increased functionality, while also minimizing the attentional demand associated with operating these devices. To evaluate this visual demand, eye tracking is a technology that has enabled researchers to delve into our understanding of the visuomotor behaviours of upper limb prosthesis users and provides the potential of quantifying the usability of prosthetic devices.

Objectives: The first objective of this thesis was to employ a scoping review in order to understand how eye tracking metrics have been used in the literature to date to describe the visual behaviours of upper limb prosthesis users. The review aimed to characterize the visuomotor behaviours of upper limb prosthesis, summarize the eye tracking metrics and variables used to describe these behaviours, and identify gaps in the literature and potential areas for future research. Building on the research gaps presented in the scoping review, the second objective of this thesis was to explore the relationship between gaze behaviour and prosthesis skill level using measures of hand movement. The goal was to understand whether improved motor planning, as reflected by eye gaze behaviour, was associated with more efficient hand movement patterns when performing object manipulation tasks with a prosthesis. Finally, the third objective of this thesis was to investigate the effects of an advanced myoelectric control strategy on the visuomotor behaviours of upper limb prosthesis users. That is, to determine whether a more reliable control strategy could reduce the visual demand associated with prosthetic control.

Methods: To tackle the first objective, a scoping review was performed, in which five online databases were searched for academic literature that involved the use of eye tracking and the assessment of visuomotor behaviours for upper limb prosthetic use. Data on the level of amputation, type of prosthetic device, type of eye tracker, primary eye metrics, secondary outcome metrics, experimental task, aims, and key findings were extracted to understand the ways in which eye tracking has been used to evaluate upper limb prosthesis use. For the second objective, participants without limb difference used a simulated myoelectric prosthetic device to perform an object manipulation task, while eye tracking and motion capture data were collected. Correlational analyses were carried out to investigate the relationship between measures of gaze behaviour (percent fixation and eye latencies) and measures of hand kinematic function (hand distance travelled, hand trajectory variability, number of movement units, and phase durations). Lastly, to accomplish the third objective, two myoelectric control strategies were compared, a baseline control strategy and an advanced control strategy that was designed to be more reliable in multiple limb positions. Participants without limb difference controlled a simulated myoelectric prosthesis on two separate days, with either the baseline or advanced control strategy. Eye tracking and motion capture data were collected, and the resulting visuomotor metrics were compared between control strategies.

Results: The research findings in this thesis indicated that prosthesis users have a characteristic visuomotor behaviour that differs from individuals with intact arm function, such that prosthesis users fixate more towards their hand and less towards target objects or locations. Additionally, measures of gaze behaviours were shown to be related to measures of hand kinematic function, which suggests that a reduced reliance on visual attention and improved motor planning is associated with improved grasp control. Furthermore, modulating prosthetic control demonstrated to be successful in improving the visuomotor behaviours of myoelectric prosthesis users.

Recommendations: Eye tracking technology has contributed significantly to our understanding of the visuomotor behaviours of upper limb prosthesis users. This thesis demonstrated, for the first time, the sensitivity of eye metrics in response to prosthetic control interventions. Future work should thus consider the inclusion of eye tracking as an outcome measure when evaluating novel prosthetic control strategies to ensure that research work is guided towards developing prostheses that are both functional and useable.

Preface

This thesis is an original work by Kodi Cheng. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board (Pro00054011 & Pro00086557), the Department of the Navy Human Research Protection Program, and the SSC-Pacific Human Research Protection Office.

This thesis contains information in three manuscripts that have been published or are in preparation for submission:

> Chapter 3 of this thesis has been published as Cheng KY, Rehani M, Hebert JS. A scoping review of eye tracking metrics used to assess visuomotor behaviours of upper limb prosthesis users. J NeuroEngineering Rehabil. 2023;20(1):1–22. I contributed as first author, conceptualized the study (together with Rehani M and Hebert JS), carried out the study selection process, performed data extraction, generated the tables and figures, and drafted the manuscript for the co-authors to review.
>
> Chapter 4 of this thesis has been published as Cheng KY, Chapman CS, Hebert JS. Spatiotemporal Coupling of Hand and Eye Movements When Using a Myoelectric Prosthetic Hand. In: 2022 International Conference on Rehabilitation Robotics (ICORR). Rotterdam, Netherlands, 2022. p. 1–6. The dataset that was analyzed in Chapter 4 was previously collected by Kuus T, Kalwajtys B and Kovic O. I contributed as first author, conceptualized the study (together with Chapman CS and Hebert JS), analyzed the experimental data, generated the tables and figures, and drafted the manuscript for the co-authors to review.
>
> The research conducted in Chapter 5 was part of a collaboration with a PhD candidate (Williams HE). The control strategies (baseline and transfer learning) were developed by Williams HE. Williams HE designed the experimental protocols and I assisted with developing these protocols. Chapter 5 of this thesis will be submitted as Cheng KY, Williams HE, Shehata AW, Pilarski PM, Chapman CS, Hebert JS. The Effect of an Advanced Myoelectric Control Strategy on the Visuomotor Behaviours of Upper Limb Prosthesis Users. I contributed as first author, conceptualized the study (together with Williams HE, Shehata AS, and Hebert JS), collected the data (with Williams HE and Shehata AS), analyzed the data, generated the tables and figures, and drafted the manuscript for the co-authors to review.

Acknowledgements

I would like to begin by acknowledging the individuals that I had the privilege of meeting over the years throughout my volunteer work. Engaging with individuals with disabilities and assisting with adaptive exercise programs and the rehabilitation process were transformative experiences that greatly motivated my journey in pursuing graduate studies. Their stories of resilience and positivity in the face of adversity were profound sources of inspiration. It was these encounters that fueled my passion for wanting to make a difference in the lives of people with disabilities and sparked my interest towards the field of assistive technologies. I want to dedicate this work to the individuals who use prostheses in their daily lives – I admire your strength and adaptability. My hope is that even the smallest contribution within this thesis may, in some way, positively impact the lives of prosthesis users.

I am extremely grateful for my supervisor, Dr. Jacqueline Hebert, for always believing in my capabilities and for providing me with this opportunity that many believed were beyond my reach. I want to thank Jacqueline for supporting my learning, for giving me the freedom to explore my own interests, and for being an incredible mentor. Upon entering my master's program, my aspiration was to translate my background in human movement physiology into applications in biomedical engineering. I aimed to gain technical expertise that would be critical for landing a research and development role in industry. Jacqueline's supervision fostered an interdisciplinary learning environment that supported my personal growth and skill development and has enabled me to acquire the necessary skills for transitioning into a professional career.

My professional development would not have been complete without the SMART-CREATE program, which was a program led by Jacqueline as the director. I'm thankful for the opportunity to have taken part in such a wonderful program and for the invaluable exposure to the broader field of assistive technologies. I want to extend my gratitude to all the Principal Investigators of the SMART-CREATE program, who dedicated their time and effort in curating enriching workshops that complemented and enhanced my research endeavours. The mentorship that I received through this program has been pivotal in my growth. Importantly, I'm grateful for the opportunity to have taken part in an internship, where I was able to apply my academic knowledge in an industry setting. I want to thank my industry supervisor, Amirali, and the entire team at Myant for their guidance during my internship tenure, as well as their continued support. I would also like to acknowledge the funding from the Natural Sciences and Engineering Research Council of Canada, Mitacs, and the Faculty of Graduate Studies and Research that made my participation in this program and my research work possible.

In addition to the support that I received from my academic and industry supervisors, I'm thankful for Dr. Craig Chapman, who was a member of my supervisory committee. Despite his busy schedule, I'm grateful for the time that Craig dedicated to support me throughout this journey. I could always rely on him for guidance, whenever I approached him with questions, he had the answers. I appreciated his willingness to challenge my thinking, offering diverse opinions and perspectives that broadened my approach. I also want to extend my gratitude to Dr. Patrick Pilarski, whose presence and influence truly enriched my academic experience. Although not directly supervising my work, Patrick's stimulating conversations were thought-provoking and his passion for the field inspired my work.

I want to thank Heather and Ahmed for the countless hours that we spent together during data collection. Their guidance and the opportunity to learn from them imparted invaluable skills and knowledge. I appreciate the willingness for Heather to involve me in her project and the immense amount of work that she has contributed to the project. Her contributions to machine learning control algorithms are remarkable and I sincerely hope her work continues to achieve great success. I also want to thank some key lab members who have been pivotal to this research work. Thank you to Quinn and Riley for their GaMA expertise and for always being available to assist with questions. Thank you to Mayank for his support with my review paper and thank you to Rory for his ongoing technical support. Thank you also to all the BLINC lab members who have always been nothing but welcoming and supportive. Throughout our shared journey in graduate school, their support and understanding have offered comfort during challenging times.

Finally, I want to thank my friends and family for being my biggest supporters. I'm fortunate to have such supportive and encouraging friends and family, who cheered me on through all the ups and downs. My parents have been the most wonderful supporters of my growth and learning. They have always nurtured my interests, whether it's scaling the side of a mountain, or diving headfirst into a research project. The values that they have instilled in me, and their lifelong support have led me to where I am today. I'm deeply grateful for the love and support of my partner, Matt. He supported me while I pursued my goals, celebrated my successes, and kept me grounded in challenging moments. As this chapter of my life comes to a close, I'm excited to start the next one together.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

1.1 Motivation

Upper limb prostheses provide individuals with upper limb difference a solution for restoring hand function and independence. Technological advances in recent decades have progressed the development of myoelectric prostheses and pattern recognition control systems to enable increased dexterity and functionality. However, despite ongoing research, the adoption of these devices remains low, as the high visual demand needed to operate these devices poses as a barrier to user acceptance[1]. While researchers continue to improve upper limb prostheses, through more reliable control strategies, integration of sensory feedback, and surgical interventions[2], there is a need for the accompanying assessment of visuomotor behaviours to determine the efficacy of these new technologies in reducing visual attention. Several studies to date have investigated the visuomotor behaviours of upper limb prosthesis users. Therefore, this thesis aims to first, understand the visual behaviours of upper limb prosthesis users and then, to address the research gaps pertaining to the visuomotor behaviours of these individuals.

1.2 Research objectives

The first objective of this thesis was to understand the ways in which eye tracking metrics have been used to evaluate the visual behaviours of upper limb prosthesis users. A scoping review was undertaken to identify the literature surrounding the visuomotor behaviours of prosthesis users. These behaviours, along with the eye tracking metrics used for analyses were summarized, and research gaps in the literature were identified. Two research gaps presented in the scoping review were selected for further investigation and are addressed in chapters 4 and 5.

To address the first research gap, the next objective of this thesis was to determine the relationship between gaze behaviour and prosthesis skill level, as it is unknown whether increased functionality is also associated with improved eye-hand coordination. To test this, measures of eye gaze behaviour and hand movement behaviour were collected during an object manipulation task performed with a myoelectric prosthetic hand. This approach served to provide an understanding of the measures of proficiency in the eye domain that correlate with the measures of proficiency in the hand movement domain of prosthesis users.

The last objective of this thesis addressed the second research gap – to determine whether addressing the unpredictability of myoelectric control can alleviate the visual demand of prosthesis users. An advanced myoelectric control strategy that was designed to address the limb position effect was tested in real-time. Eye tracking and motion capture data were recorded and analyzed to examine the effects of this control intervention in changing visuomotor behaviours of upper limb prosthesis users.

1.3 Chapter summary

Chapter 2 provides the relevant background information necessary for understanding the research objectives of this thesis. The chapter begins with an overview of the motor control of human grasping, which is then contrasted with the control of upper limb myoelectric prostheses and some of the challenges associated with these devices. This is then followed by a broad overview of the assessment tools used to evaluate novel prosthetic technologies, including the Gaze and Movement Assessment. Finally, a summary of experimental findings of eye gaze behaviour of individuals with intact arm function are presented.

Chapter 3 presents the manuscript titled *A Scoping Review of Eye Tracking Metrics Used to Assess the Visuomotor Behaviours of Upper Limb Prosthesis Users* published in the *Journal of NeuroEngineering and Rehabilitation*. This review paper characterized the visuomotor behaviours of upper limb prosthesis users, summarized the eye tracking metrics used to describe prosthetic behaviour, and identified gaps in the literature and potential areas for future research. Findings from this review guided the research presented in chapters 4 and 5.

The contents of Chapter 4 were published as *Spatiotemporal Coupling of Hand and Eye Movements When Using a Myoelectric Prosthetic Hand* in the 2022 proceedings for *IEEE International Conference on Rehabilitation Robotics*. The purpose of this study was to explore whether improved motor planning, as reflected by eye gaze behaviour, was associated with more efficient hand movement patterns. The introduction, methods, results and discussion pertaining to this research objective are presented in this chapter.

Chapter 5 presents the manuscript titled *The Effect of an Advanced Myoelectric Control Strategy on the Visuomotor Behaviours of Upper Limb Prosthesis Users* in preparation for submission. This chapter introduces the limb position effect and the potential for advanced myoelectric control strategies to reduce the reliance on vision when operating a prosthetic device. Introduction, methods, results and discussion sections are presented in this chapter to answer the question as to whether eye gaze behaviour is sensitive to prosthetic control interventions.

Chapter 6 summarizes and joins together the major contributions of this thesis. The implications of these research findings are discussed within the broader scope of the upper limb prosthesis research field in this chapter.

Chapter 2: Background

2.1 Motor control of human grasping

In humans with intact arm function, successful object manipulation relies on both feedforward and feedback control mechanisms[3]. Feedforward control operates in a predictive manner to program the necessary grip forces to grasp objects based on their physical properties[4]. Vision plays an important role in guiding the actions of the hand. Visual information about an object's location, size and texture inform the motor system to generate an appropriate motor plan[5]. Sensory feedback then plays an essential role in updating feedforward control mechanisms[6]. Discrepancies between expected sensory events and actual feedback information enable the motor command to be automatically adjusted in order to generate accurate grip forces[6]. In the absence of somatosensory feedback, anticipatory force control is maintained, however, the regulation of grip force magnitude according to actual loading demands is disrupted[3,7]. Instead, individuals rely on alternate feedback channels, such as vision to predict grip force levels, resulting in excessive or unstable grip forces[3].

2.2 Feedforward and feedback control of myoelectric prostheses

With upper limb prosthesis users, the natural feedback pathways from the hand are lost with amputation. Unlike normal arm function, myoelectric prostheses allow for feedforward control, however, lack feedback control. These devices operate on an open-loop control system, such that feedforward commands generated by the user are translated into actions of the prosthetic hand. However, feedback information about grip aperture, grip force, hand distance to the object, and properties of the object are not relayed back to the user through the hand to update the motor plan. Consequently, prosthesis users may face challenges with controlling their prosthesis and often rely on vision to monitor the activity of their prosthetic device[8–10]. In fact, Saunders et al.[11] demonstrated that visual and tactile feedback were required to successfully grasp objects when feedforward control was disrupted. However, when the control was optimized, feedback was not necessary to accurately control grip force[11]. Therefore, feedforward and feedback control demonstrated complementary roles in grasp performance[11], and continue to be areas of interest for prosthetic research and development[12].

2.3 Challenges associated with myoelectric control

Myoelectric prostheses are controlled using electromyography (EMG) signals that are generated by the muscles in a person's residual limb. Surface electrodes placed on the surface of the skin record EMG signals from the underlying muscles, which are then translated into specific movements of the prosthesis. Direct control is a simple myoelectric control method, in which the muscle signals from individual electrode channels are mapped directly to prosthetic movements, such as to activate hand open and close[13]. The prosthesis can either be activated at a constant speed when the signal amplitude exceeds a certain threshold, or can operate proportionally to the intensity of the signals generated by the user. However, this type of control is limited by the number of control signals available for multiple prosthetic functions and would require users to switch between activating different degrees of freedon[14]. As such, pattern recognition has become popular in recent years as a control method that combines information recorded from multiple electrodes to provide natural control with a high level of dexterity and functionality[14].

Pattern recognition leverages machine learning algorithms to recognize and interpret the complex patterns of muscle activity[13]. This approach comprises feature extraction from EMG signals to classify specific prosthetic movements[13]. Despite ongoing research, the robustness of recorded EMG signals remains a challenge for myoelectric control[14]. Numerous factors, such as changes in limb position[15], varying contraction intensity[15], and fluctuations at the skin-electrode interface[16–18], can affect the reliability of myoelectric control. Therefore, to overcome these challenges, researchers have been interested in advancing machine learning algorithms to accurately decode movement intent and effectively execute control commands[19]. The goal of these advanced machine learning algorithms is to develop control strategies that are adaptable to variations in EMG signals with different contraction strengths, limb positions, electrode placement, etc., while minimizing the burden on the user to repeatedly calibrate their device[12].

2.4 Current assessments

With the progression of more advanced technologies, there is a demand for accompanying outcome measures that adequately measure the efficacy and benefits of such technologies. Clinical assessments, such as the Southampton Hand Assessment Procedure[20], Assessment of Capacity for Myoelectric Control[21], Activities Measure for Upper Limb Amputees[22], Box and Blocks Test[23], and Clothespin Relocation Test[24] are commonly employed to provide a global measurement of function, and rely on rater-based measures or time-based measures to score performance[25]. These clinical assessments however, often do not include specific hand function metrics, such as grip aperture and movement variability[26], or corresponding measures of gaze behaviour that are important in understanding visuomotor behaviours during grasp control[27,28]. In the context of research developments, quantitative measurements of visuomotor behaviours can further enhance our understanding a user's functional abilities and aid in identifying specific areas for further research developments.

The Gaze and Movement Assessment (GaMA) is a repeatable and reproducible assessment tool that quantifies upper limb movements[26,29] and visual fixations[28] during functional tasks. GaMA involves collecting motion capture and eye tracking data, that are then synchronized and segmented into discrete movements and phases for detailed analysis of upper limb and hand kinematics, as well as visual behaviour during object interaction. Eye metrics inform as to visual attention and provide insights into movement planning. Since one of the primary goals of advanced prosthetics research is to reduce the attentional demand associated with prosthetic use[1], eye tracking provides a meaningful evaluation of novel interventions to reduce the visual attention towards the prosthetic hand. Overall, GaMA provides a collection of outcome measures that enable a comprehensive approach to evaluate eye and hand movements of upper limb prosthesis users.

2.5 Eye gaze behaviour of individuals with intact arm function

Head-mounted eye trackers have enabled researchers to study natural gaze behaviours during a wide variety of goal-directed tasks[30–32]. The eyes have consistently been shown to precede the actions of the hands and move in a predictive manner to direct and guide the hands towards the object[30–32]. The eyes have also been shown to rarely fixate the hand or task irrelevant objects, and shift away from grasped objects to allow haptic and proprioceptive feedback to take over[33]. In a study using GaMA, Lavoie et al.[28] combined eye tracking and motion capture to automate the data analysis process for a comprehensive assessment of eye gaze behaviour throughout the entire object manipulation task. Findings from this study further revealed that on average, participants fixated task relevant areas for 73% to 80% of the task, with the remainder consisting of blinks and saccades[28]. In addition, participants maintained their fixation on one location at a time, instead of shifting between target areas[28]. The eyes led the hand by an average of 0.53s to 0.90s and fixations towards the hand were maintained into the beginning of the transport phase before touch and proprioceptive feedback could take over[28]. In comparison to these findings involving intact limb individuals, the application of GaMA in an upper limb prosthesis user population could provide meaningful insights into the challenges and adaptations unique to prosthesis use[8].

Chapter 3: Literature Review

The material presented in this chapter was published in the Journal of NeuroEngineering and Rehabilitation as the article titled "A Scoping Review of Eye Tracking Metrics Used to Assess the Visuomotor Behaviours of Upper Limb Prosthesis Users":

> *Cheng KY, Rehani M, Hebert JS. A scoping review of eye tracking metrics used to assess visuomotor behaviours of upper limb prosthesis users. J NeuroEngineering Rehabil. 2023;20(1):1–22.*

The contents of this chapter are identical to the material presented in the published manuscript. Tables from the original manuscript are presented in the Appendix of this thesis.

3.1 Abstract

Advanced upper limb prostheses aim to restore coordinated hand and arm function. However, this objective can be difficult to quantify as coordinated movements require an intact visuomotor system. Eye tracking has recently been applied to study the visuomotor behaviours of upper limb prosthesis users by enabling the calculation of eye movement metrics. This scoping review aims to characterize the visuomotor behaviours of upper limb prosthesis users as described by eye tracking metrics, to summarize the eye tracking metrics used to describe prosthetic behaviour, and to identify gaps in the literature and potential areas for future research. A review of the literature was performed to identify articles that reported eye tracking metrics to evaluate the visual behaviours of individuals using an upper limb prosthesis. Data on the level of amputation, type of prosthetic device, type of eye tracker, primary eye metrics, secondary outcome metrics, experimental task, aims, and key findings were extracted. Seventeen studies were included in this scoping review. A consistently reported finding is that prosthesis users have a characteristic visuomotor behaviour that differs from that of individuals with intact arm function. Visual attention has been reported to be directed more towards the hand and less towards the target during object manipulation tasks. A gaze switching strategy and delay to disengage gaze from the current target has also been reported. Differences in the type of prosthetic device and experimental task have revealed some distinct gaze behaviours. Control factors have been shown to be related to gaze behaviour, while sensory feedback and training interventions have been demonstrated to reduce the visual attention associated with prosthesis use. Eye tracking metrics have also been used to assess the cognitive load and sense of agency of prosthesis users. Overall, there is evidence that eye tracking is an effective tool to quantitatively assess the visuomotor

behaviour of prosthesis users and the recorded eye metrics are sensitive to change in response to various factors. Additional studies are needed to validate the eye metrics used to assess cognitive load and sense of agency in upper limb prosthesis users.

3.2 Introduction

The goal of advanced upper limb prostheses is to restore the highly dexterous and complex capacities of the human hand. Vision is among one of the most important senses in controlling the hand during object interaction[34]. Both individuals with an anatomical hand[28] and prosthetic hand[8] use vison to preplan movements by gathering information about the external environment. Visual fixations are directed at areas of interest prior to generating a motor command. As such, visuomotor coordination is required to achieve coordinated hand and arm function. Prosthesis users have an additional requirement to visually monitor the prosthesis, given the lack of feedback sensations that are typically provided by the anatomical hand. Novel prosthetic interventions are developed to facilitate increased functionality, while also minimizing the attentional demand associated with operating these devices. However, attentional demand can be difficult to quantify. When the gaze is focussed on a target of interest, information is processed through the fovea with high visual acuity[35]. Generally, the direction of gaze corresponds with the location of overt attention, however, does not consider covert attention that is processed through the peripheral vision[35]. Nevertheless, this principle has enabled researchers to use eye movement behaviours to measure the allocation of overt visual attention and provide insights into movement planning. Indeed, it wasn't until recently that eye tracking research has become popular as a diagnostic tool aimed at measuring visual attention[27].

Eye tracking is a technology used to record eye movements to provide objective and unbiased insights into human gaze behaviour[36]. Modern video-based eye trackers use digital cameras to capture a series of images of the eyes. Different approaches have been employed to detect the pupil location in order to calculate the point at which the eyes are fixated[37]. By quantifying the timing and location of visual fixations, the coordination between eye and hand movements can be studied under different conditions to reveal important aspects of object interaction[28]. With the anatomical limb, the eyes precede the actions of the hands to provide movement planning information to successfully reach and grasp for target objects[33,38–40]. Eye tracking has been applied to identify biomarkers for cognitive impairment, as well as to track treatment progress in clinical populations such as autism spectrum disorder, schizophrenia, attention deficit hyperactivity disorder, and fetal alcohol spectrum disorder[41]. More recently, eye tracking has been utilized to evaluate the visuomotor behaviours of upper limb prosthesis users. Research in this area has further contributed to our understanding of human-machine interaction with prosthetic devices and provides a new way of potentially quantifying the usability of these devices. Currently, there is an absence of any review of eye tracking metrics within the upper limb prosthetic population. Therefore, with this growing body of literature surrounding the visuomotor behaviours of prosthesis users, there is an emergent need for a review of the literature.

A scoping review was designed to answer the question: what is known about the visuomotor behaviour of upper limb prosthesis users and which eye metrics have been used to evaluate prosthesis use? The aim of this scoping review was to identify the literature on the use of eye tracking to evaluate the behaviour of individuals using an upper limb prosthesis. In doing so, visual behaviours of prosthesis users were summarized, as well as the eye metrics used to describe these behaviours. Additionally, the literature search uncovered novel eye metrics beyond eye-hand coordination that show promise in assessing other features of prosthetic behaviour. This review paper serves to provide an understanding of how eye tracking metrics have been used to date in upper limb prosthetics research and to guide future research.

3.3 Methods

A scoping review protocol was published on the University of Alberta Education and Research Archive website detailing the methods for this scoping review[42]. The specific aims of this scoping review were: (i) to characterize the visuomotor behaviours of upper limb prosthesis users reported in the literature that have utilized eye tracking technology, (ii) to summarize the eye tracking metrics and variables commonly used to describe behaviours when manipulating a prosthetic hand, and (iii) to identify gaps in the literature and potential areas for future research. Five online databases: Medline, Embase, PsycInfo, ProQuest, and Google Scholar were searched for relevant academic literature published from the dates of their inception until December 1, 2021. The search strategy consisted of terms related to (i) upper limb amputation and prostheses and (ii) assessment of visuomotor behaviour using eye tracking technology. An example of the complete search strategy for Medline is included in the Appendix of the published protocol. Reporting for this scoping review follows the recommendations as outlined by the PRISMA-ScR statement and checklist[43].

Inclusion criteria were peer-reviewed journal articles in which (i) individuals with an upper limb amputation used a prosthesis or individuals with intact arm function used a simulated upper limb prosthesis, (ii) to accomplish an experimental task, (iii) while eye tracking data were collected. Conference papers and dissertations were included, however literature was excluded if the work was preliminary and later published in a peer-reviewed format, or if there were insufficient details to extract the required data. Literature reviews were excluded, as these were found to be summaries of included original papers on other topics, and no review papers were found on this review topic. Studies were excluded if eye tracking was not used as an outcome metric to describe visual behaviour, but rather for control in computer vision. Research on lower limb amputation or prosthesis use, and non-English articles were also excluded.

Title and abstract screening was performed independently by two reviewers (KC and MR). Although literature reviews were excluded from this scoping review, the reference list of two identified review papers were manually searched for relevant literature. This process was to ensure that the original literature was included in the review process. In addition, the following manual searches were conducted in Google Scholar: (i) upper limb prosthesis eye-tracking thesis, (ii) visuomotor control upper limb prosthesis, (iii) cognitive workload artificial limb, (iv) eye tracking artificial limb. All relevant literature was then selected for screening. Two reviewers (KC and MR) completed a full-text review to assess the eligibility of all retained literature. Any conflicts were resolved in consultation with the third reviewer (JH).

Data on the level of amputation, type of prosthetic device, type of eye tracker, primary eye metrics, secondary outcome metrics, experimental task, aims, and key findings were extracted to understand the ways in which eye tracking has been used to evaluate upper limb prosthesis use. Only data pertinent to the research question of this scoping review were reported in the results. Key themes from the literature were identified by grouping together common research goals and experimental methods. Subtopics were subsequently described as related to the overarching theme.

3.4 Results

3.4.1 Selection of sources of evidence

A database search in Medline, Embase, PsycInfo, ProQuest and Google Scholar produced a total of 204 articles. 65 duplicates were removed, resulting in 139 articles for further screening. After a title and abstract screening, 81 articles were excluded, and a full-text review was conducted on the remaining 58 articles. One article was added manually after reviewing the full text of identified literature. Once the articles were assessed for eligibility, a total of 17 studies were included in the review. The PRISMA diagram (Figure 3-1) serves to illustrate this process visually and it includes the details of the reasons for exclusion.

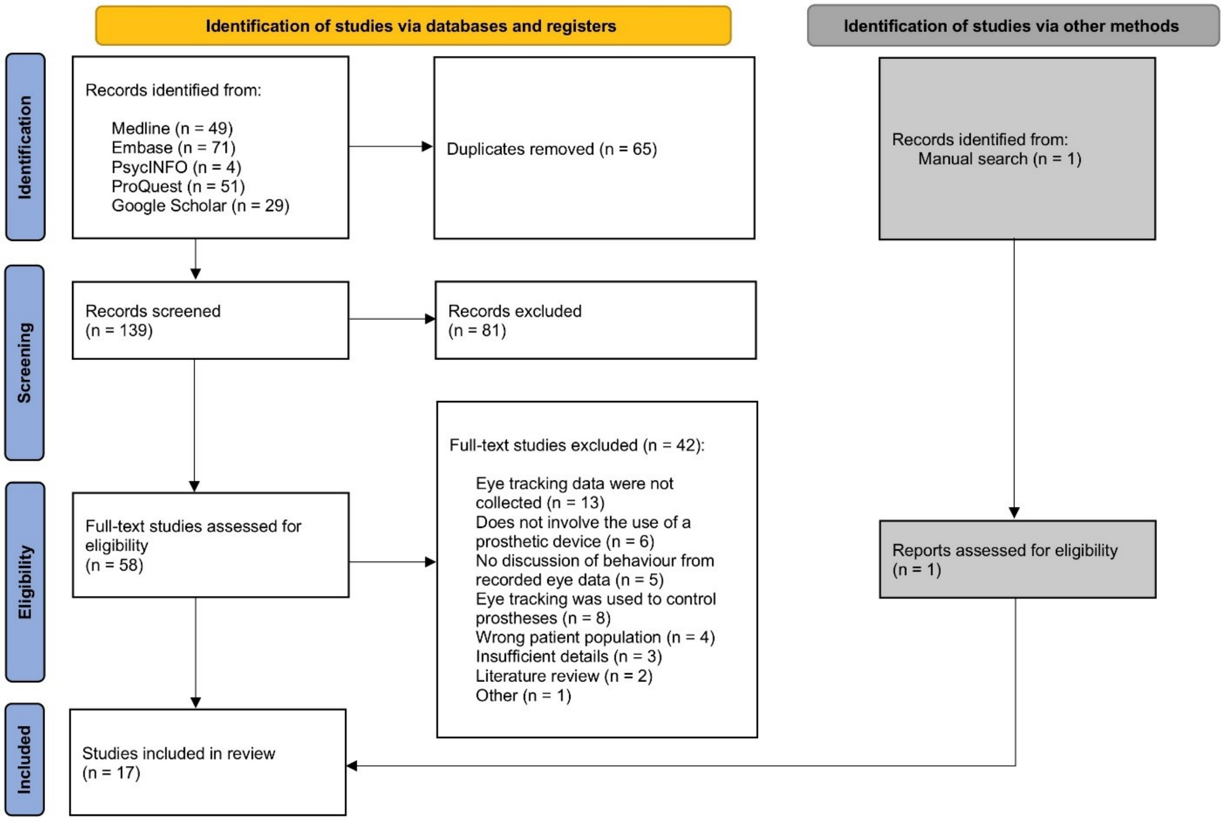


Figure 3-1: PRISMA flow chart

3.4.2 Characteristics of sources of evidence

Appendix A provides a summary of included study characteristics. All studies quantitatively assessed the behaviour of participants using eye tracking technology. Ten studies consisted of a cross-sectional design[8,10,44–51], 3 studies included a repeated-measures study design[9,10,52], 2 were crossover studies[53,54], and 4 were case studies[52,55–57]. Of the included literature, 1 was a conference paper[51] and 2 were dissertations[45,49].

3.4.3 Synthesis of results

Participant characteristics were diverse and are summarized in Appendix B. A total of 10 studies involved individuals with a limb difference, including 9 studies that tested individuals with transradial amputation[8,45–48,52,53,56,57], 3 with transhumeral amputation[8,45,55] and one with shoulder disarticulation[55]. Participants with an amputation had a myoelectric prosthesis in 8 studies[8,46–48,52,55–57], while others had a body-powered prosthesis in 2 studies[8,45]. Nine studies evaluated the visual behaviour of individuals with intact arm function. Of those, 7 studies had individuals perform tasks using a simulated myoelectric prosthesis[9,10,50–52,54,57]. The simulated device used myoelectric signals to control a terminal device that bypassed the anatomic hand. Alternatively, a simulated body-powered prosthesis was employed in one study[44] and a myoelectrically-controlled virtual reality arm was used in another study[49] with participants who had intact arms. Figure 3-2 summarizes the type of prosthetic device and level of amputation of participants.

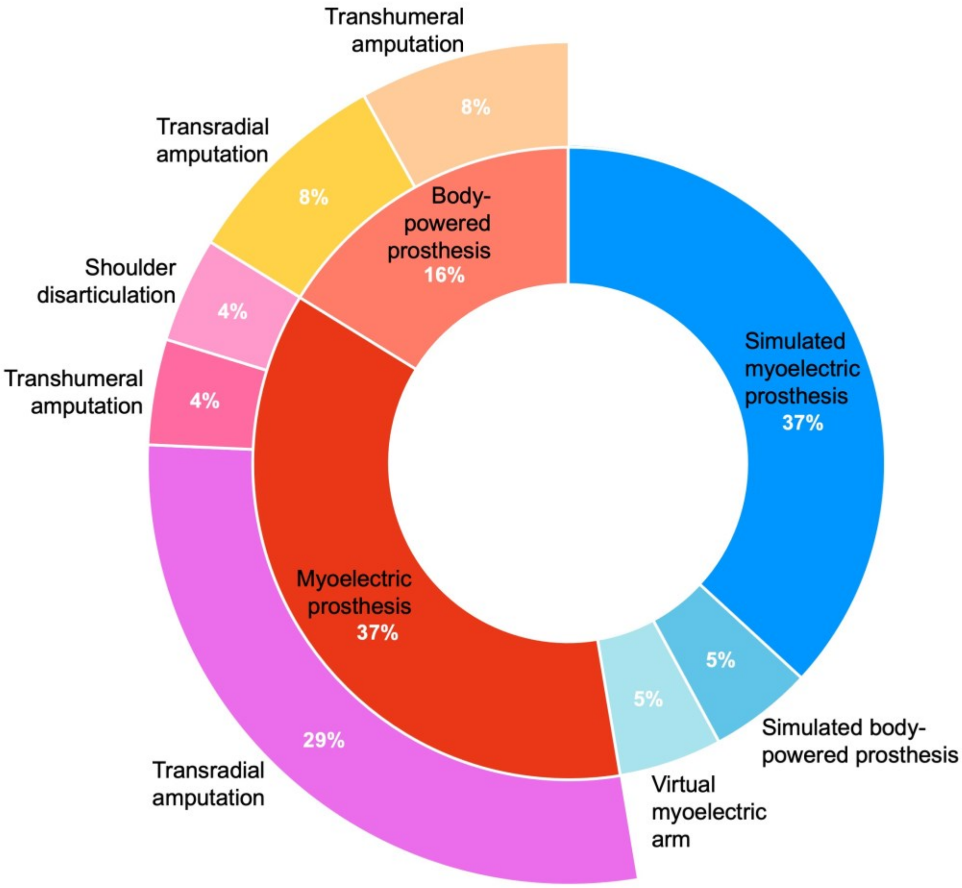


Figure 3-2: Type of prosthetic device and level of amputation of participants

Appendix C summarizes the experimental data collection methods. In general, object manipulation tasks were performed with the prosthetic hand while eye tracking data were collected. Tasks involved the Southampton Hand Assessment Procedure (SHAP)[20], as well as tasks modified from the SHAP[9,10,52]. Other experimental tasks included a dual task activity[53,54], a clothespin relocation task[50,51,56], a cylinder task[47,48,57], a cup transfer task[8,45,55], and a pasta box task[8,45,55].

To characterize the visual behaviours of participants, several eye metrics were recorded and are summarized in Appendix C. The direction of gaze was recorded to determine the location of overt visual attention[35]. Key areas of interest (AOI) were defined in each study that were relevant to the specific task demands. Since areas unrelated to the goal of the task are rarely fixated[33,38,39], areas such as the hand, start location, end location and objects being manipulated were usually defined as AOIs. Eye metrics used to describe prosthetic visuomotor behaviour included both spatial and temporal information, such as when and where someone was looking. In the spatial domain, these metrics included the number of fixations, gaze sequence, duration of fixation, percent fixation and target locking strategy (TLS), and in the temporal domain, these metrics included eye latency measures. Figure 3-3 presents the distribution of eye metrics that are reported in the literature.

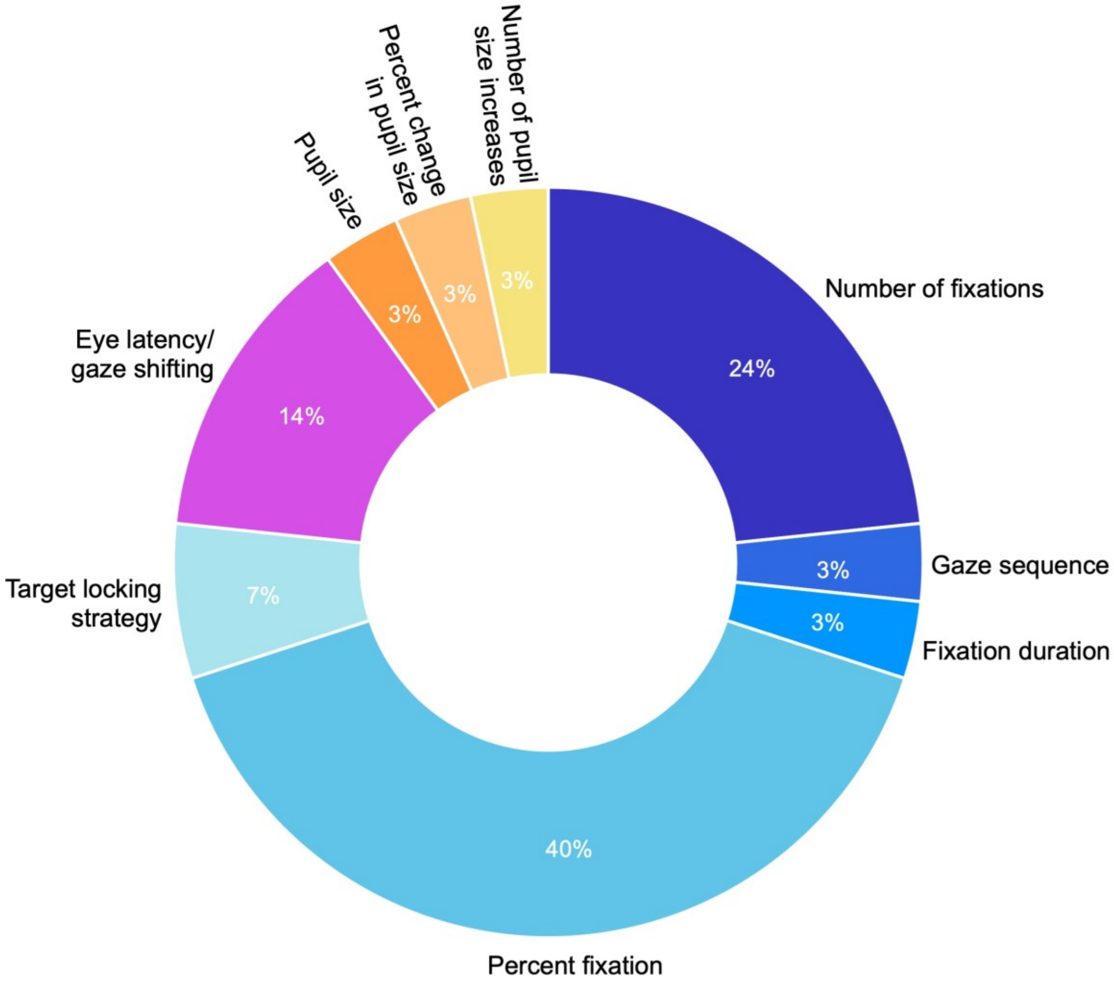


Figure 3-3: Eye metrics reported in the literature to evaluate prosthetic visuomotor behaviour

To describe the spatial allocation of gaze, the number of fixations referred to the frequency of visual fixations to defined AOIs and was used to indicate how often the gaze switched between the hand and the target to monitor the trajectory of the prosthetic hand[45,46,48,49,52,53,57]. While the number of fixations only reported the frequency of fixations, gaze sequence provided additional information about the order of visual fixations to AOIs in addition to the location, and demonstrated the pattern in which visual fixations occurred throughout each trial[52]. Fixation duration referred to the absolute time in seconds that the gaze fixated onto an AOI[49]. This metric is useful in comparing the absolute amount of attention towards an AOI during fixed time trials. However, for trials that are variable in length, percent fixation was generally used as a preferred metric to compare the relative allocation of visual attention to the hand and target areas. Percent fixation was defined as the amount of each phase that was spent fixating a given AOI and was represented as a percentage of each phase[8,9,44–48,52–55,57]. Additionally, TLS was the difference between the percentage of time spent fixating the target and the hand[9,10]. Using this metric, a more positive value reflected more time spent fixating the target, whereas a more negative value indicated more time spent fixating the hand[9,10]. A score close to zero represented a gaze switching strategy, in which equal amounts of time were spent fixating the target and the hand[9,10]. Together, these metrics provide a detailed description of the efficiency of gaze control and where upper limb prosthesis users predominantly focus their attention.

To describe the temporal relationship between eye and hand movements, eye latency measures were defined as the time in seconds that the eyes precede or follow the movement of the hand[8–10,45]. Eye arrival latency described the timing in which the eyes fixated the target location before the arrival of the hand[28]. Eye leaving latency referred to the timing to disengage gaze from the target of interest[28]. Note that Parr et al.[9,10] described the same metric which they referred to as gaze shifting. A negative time indicated that the eyes were ahead of the hand, while a positive time reflected the time in which the eyes lagged behind the hand. This metric is useful in understanding human-machine interactions, as it uncovers the temporal dynamics between the location of visual attention and the location of the prosthetic hand and objects.

Additional eye metrics described in the literature measured pupil dilation to describe the cognitive workload associated with prosthetic use. These metrics included pupil size, percent change in pupil size, and number of pupil size increases. Pupil size was measured as the average diameter of the pupil in millimeters during a trial[56]. Percent change in pupil size was measured as the difference between the maximum pupil diameter and minimum pupil diameter at baseline, relative to the baseline pupil diameter[51]. This metric did not account for differences in individual pupil sizes, which may not be appropriate for a between-subject design[51]. Number of pupil size increases, therefore, measured the number of times that the pupil diameter increased per second[50], as an index of cognitive activity[58] and was less susceptible to environmental factors[50].

3.4.4 Thematic synthesis

Three main themes were identified in the reviewed literature: (i) general visuomotor behaviours of prosthesis users, (ii) different experimental conditions across research groups, and (iii) changes in gaze behaviour in response to various factors. In addition, other exploratory areas of eye tracking in prosthesis research were uncovered in the literature that do not coincide with the aforementioned themes. Early studies aimed to characterize the visuomotor behaviours of upper limb prosthesis users. Across research studies, differences in experimental protocols revealed significant differences in these behaviours. Later work began to use eye tracking as an outcome measure to assess the effectiveness of novel prostheses interventions. Lastly, two additional areas of prosthetic behaviour, cognitive workload and sense of agency, used eye metrics for evaluation.

3.5 Discussion

3.5.1 Characteristics of Visuomotor Behaviours of Upper Limb Prosthesis Users

3.5.1.1 Eye-Hand Coordination of Prosthesis Users

When reaching and grasping with the anatomic limb, the eyes tend to fixate on a target ahead of the hand movement and maintain fixation on that target while executing the task. Thus the eyes rarely fixate on the hand[33]. Prosthesis users, however, have been shown to exhibit different patterns of visuomotor behaviour. The literature consistently demonstrated that when reaching and grasping for an object with the prosthetic hand, the eyes fixated more towards the hand and less towards the target[8–10,45,46,52]. Other studies further revealed increased fixations to the prosthetic hand when transporting an object[8–10,45]. The reliance on vision to monitor the hand was described to be due to grip insecurity and deficits in sensory feedback[8–10,45,57]. In addition, a gaze switching strategy was identified, in which prosthesis users continuously switched between visually monitoring the hand and the target, as indicated by an increased number of fixations[46,52] and a low TLS score[9,10]. Some studies further showed that there was a significant delay for the eyes to disengage from the current target and shift to the next target when manipulating objects with a prosthesis[8–10,45].

Disruptions to normative eye-hand coordination that have been highlighted in the literature are reflective of an increased visual dependency to compensate for difficulties associated with prosthetic use. The increased attentional demand that is needed to visually monitor the activity of the prosthesis can be one factor that is cognitively demanding and is often reported to be the primary reason for device dissatisfaction and rejection[1,59]. Since haptic and proprioceptive feedback are lost with amputation, it is likely that vision is used as a feedback mechanism to ensure a stable grip[11]. This reliance on vision prevents the eyes from looking ahead towards target objects to plan for upcoming actions[9,10]. Therefore, adjustments to the hand need to be actively controlled and can place a high cognitive demand on the user[10].

3.5.1.2 Gaze Behaviour as an Indicator of Skill Level

The development of eye-hand coordination during human development phases is well-defined. In the initial stages of motor learning, vision is used as a feedback mechanism to monitor the actions of the hands[60]. As skill develops, vision shifts to be predictive of hand movements and the eyes are able to look ahead towards the target[60]. Presumably then, the reliance on vision to monitor the prosthesis would decrease with experience and more highly skilled prosthesis users would demonstrate eye-hand coordination typically observed in individuals with intact arm function. Some studies[9,46,52] have suggested that more experienced prosthesis users behave similarly to individuals with intact limbs, however findings have been inconsistent.

Parr et al.[9] suggested that prosthetic eye and hand movements remain temporally coupled. Results of their study revealed that the timing of gaze shifts was a significant predictor of task performance time, therefore the ability to shift vision away from the hand towards the target resulted in faster movements[9]. Another study however, showed that the gaze strategies of experienced prosthesis users are highly variable[46]. While some experienced users fixated predominantly towards the target, others switched between monitoring the hand and the target. Measures used to describe the spatial allocation of visual attention, including percent fixation and number of fixations, thus were not related to skill level[46] or everyday usage[47]. Despite clear differences in the visuomotor behaviours of individuals with intact arm function and prosthesis users, it is unclear from the findings to date, whether behaviours that more closely resemble normative eye-hand coordination are indicative of a higher prosthesis skill level.

Disruptions to the development of typical patterns of eye-hand coordination reported in upper limb prosthesis users can also be attributed to the unreliability of prosthetic devices. A multitude of factors, such as electrode shift, electrode impendence, and fatigue affect the reliability of myoelectric control[14], preventing typical sensorimotor mapping rules from developing[61]. As a result, it is likely that vision maintains fixated on the prosthetic hand, even as skill progresses to compensate for the unpredictable control. Future work should investigate the relationship between gaze behaviour and skill level, and whether addressing the unpredictability of myoelectric control can alleviate demand on the visual system.

3.5.2 Experimental Conditions Can Influence Visuomotor Behaviours

The visuomotor behaviours of prosthesis users has been characterized across multiple research groups that have employed different experimental conditions. The general findings were largely in concordance with one another, apart from a few studies that indicated that the type of prosthetic device and experimental task produced notable differences in prosthetic behaviour.

3.5.2.1 Type of Prosthetic Device

Participants with intact arm function using a simulated prosthesis and individuals with amputation using a prosthesis have demonstrated similar eye and hand movement patterns when using a prosthetic device. Sobuh et al.[52] demonstrated that participants using a simulated myoelectric prosthesis and experienced myoelectric prosthesis users had similar gaze fixations, movement times, and SHAP scores. In addition to similarities in visuomotor behaviours between the two groups, the compensatory movement patterns of individuals using a simulated device have also been shown to be similar to individuals with an upper limb amputation when using a myoelectric prosthetic device[62]. Although this evidence suggests that the use of a simulator prosthesis is an acceptable proxy for studying upper limb prosthesis use, considerations should be made concerning the translatability of results to prosthesis users. The attachment of a terminal device to a simulated prosthesis presents several challenges. The position of the terminal device can affect the centre of mass or obscure the view of the prosthesis[63], which may affect visuomotor behaviour. In addition, the long-term use of a simulated prosthetic device has yet to be explored, therefore it is unknown whether visuomotor behaviours observed during initial testing sessions are representative of long-term device use for prosthesis users. However, recruiting participants with intact arm function as an alternative to upper limb prosthesis users allows a larger sample size to increase the statistical power of the results. Novice users are also assumed to have no experience with operating a prosthetic device, whereas prosthesis users typically have varied experience levels[46]. Using naïve participants allows researchers to control for level of experience when evaluating novel research interventions.

In general, myoelectric and body-powered prosthesis users demonstrated similar visuomotor behaviours. Both myoelectric and body-powered prosthesis users took longer to complete tasks with the prosthetic hand compared to the anatomical hand and a disproportionate amount of time was spent fixating the prosthesis when reaching and transporting objects[8,45,52]. However, some notable differences in gaze behaviour were observed that were unique to body-powered prosthetic use. A gaze switching strategy was not evident in transradial body-powered prosthesis users likely due to the mechanics of these types of devices[45]. Unlike the unreliable nature of myoelectric control that may cause the prosthetic hand to unexpectedly open, a voluntary open hook was used, which remained closed on objects once grasped. Since a relatively stable grasp can be achieved with this type of terminal device, vision was not required to monitor the prosthetic hand. This device, along with an intact elbow providing some proprioceptive feedback, enabled users to look ahead towards the drop-off target within a normative range of behaviour[45]. However, transhumeral body-powered prosthesis users faced an additional visual demand with increased fixations to the terminal device in transport that prevented the ability to look ahead to the drop-off target[45]. Researchers should therefore consider how the type of prosthetic device as well as the level of amputation might affect overall research outcomes.

3.5.2.2 Experimental Task Conditions

Across research groups, different experimental tasks were employed to study the visuomotor behaviours of prosthesis users. Interestingly, despite these differences, the observed gaze behaviours were consistent across studies[9,10,45,46,52]. This finding is in accordance with non-disabled eye-hand coordination studies that have also shown remarkable agreement across various functional tasks, which has led to important generalizations about human behaviour[33,38–40]. The majority of studies included in this review paper involved relatively simple tasks that were performed in a seated position and largely limited to the task space directly in front of the participant[9,46–48,52,57]. Individuals with upper limb amputation are known to use their prosthesis for a broad range of activities of daily living (ADL). The prosthesis is most frequently used in bimanual tasks to assist the intact limb[64]. In addition to desk procedures, similar to the experimental tasks of the included studies, common ADLs involving prosthetic use include housework, shopping, eating and cooking[65]. Therefore, the limited movements of these experimental tasks may, not be generalizable to prosthesis user functionality in everyday tasks[47].

Only one study specifically addressed the different task demands of two goal-oriented object manipulation tasks on the visuomotor system[8]. A pasta box task and a cup transfer task were developed to represent daily activities[26] and validated to quantify gaze behaviour[28]. The pasta box task required gross movements to transport a pasta box from various shelf heights, whereas the cup transfer task involved transporting compliant cups filled with beads[26]. The different task demands revealed differences in visuomotor compensatory strategies, in which the cup transfer task required more visual attention to the hand than the pasta box task during reach and transport phases. Since the cups are deformable, the authors explained that visual attention towards the hand was likely a cautious strategy to ensure contents of the cup were not spilled[8]. Therefore, the cup transfer task was applicable in evaluating gaze strategy in relation to grasping skills (including maintaining grasp during transport), whereas, the pasta box task challenged users in various planes of movement that required users to adapt their visual behaviours[8]. These findings highlight the importance of considering the task being used when measuring visual behaviour. Experimental conditions should include scenarios that represent activities of daily living, as lab-based tasks may not be representative of eye movement behaviours in the real world[66].

In addition to experimental task selection, the type of eye tracker should also be considered in the experimental design. Remote eye trackers restrict head and body movements to the area directly in front of the eye tracker for reliable gaze recording. Such postural constraints have been shown to affect gaze behaviour, specifically, the velocity of saccades was shown to increase when the head was restricted[67]. When the head was unrestrained and could move freely in the recording area of the remote eye tracker, data loss and spatial accuracy errors were apparent[68]. Head-mounted eye trackers, on the other hand, maintain ecological validity and allow for natural eye movements. In accompanying more functional tasks of daily living, researchers should consider preferentially using a head-mounted eye tracker to allow for natural eye, head, and hand movements that are representative of real-world scenarios.

3.5.3 Responsiveness of Eye Metrics to Various Factors

To date, the use of eye tracking technology has enabled researchers to establish a characteristic visuomotor behaviour of upper limb prosthesis users that differs from the behaviours of individuals with intact arm function. However, the question remains whether eye tracking metrics are sensitive enough to effectively assess functional improvements, such as to reduce the visual demand associated with prosthetic use. The following section will explore the effects of control systems, sensory feedback, and training on gaze behaviour and provide evidence that eye metrics are sensitive to various factors.

3.5.3.1 Prosthetic Control Chain

Myoelectric prostheses are challenging to control as there are many factors involved in controlling a prosthesis, which can explain why vision is drawn towards the prosthetic hand. Minimizing uncertainty in the controller can improve grasp performance[11] and also has the potential to reduce visual attention towards the hand. Research on the prosthetic control chain has investigated factors such as signal generation, signal acquisition, and device response[47,48,57].

To understand which control factors may contribute to improving user functionality, Chadwell et al.[47,48,57] investigated the relationships between each of these control factors and measures of functionality and everyday prosthesis usage. Their results showed that gaze behaviour was significantly disrupted by mechanical issues, such as unpredictability and electromechanical delay, and was not related to skill in controlling the electromyography (EMG) signal[48]. Unpredictability, as defined by a higher number of unwanted EMG activations, was significantly correlated to lower success rate, longer task duration, higher temporal kinematic variability, increased fixations to the hand, decreased fixations to target areas during reach to grasp, and increased gaze switches[48]. Longer electromechanical delay was also related to improved performance, such as shorter task duration, shorter length of aperture plateau, decreased fixations to the hand during transport, increased fixations to target areas during transport, fewer gaze switches, and longer prosthesis wear time[48]. This finding was in contrast to their hypotheses and is counterintuitive. The effect of device delay on user performance is not well understood, however the authors speculate that increased mechanical delays may actually reduce undesired activations of the prosthesis. Additional research is needed to investigate the interactions between mechanical issues and their influence on visuomotor behaviours.

The addition of a prosthesis introduces unpredictable control, which appears to drive the dependency on vision to monitor the hand. Gregori et al.[69] revealed that when individuals with a transradial amputation were asked to grasp and manipulate objects with their missing limb rather than their prosthesis, they demonstrated similar visuomotor behaviours as individuals with intact arm function. Therefore, it is likely that the complexities of translating muscle signals into actions of the prosthesis is what introduces the disruptions to gaze behaviours. Together, these findings point towards a need to address factors affecting control reliability and future work should consider including eye tracking as an outcome measure to assess the usability of novel control systems.

3.5.3.2 Sensory Feedback Systems

The integration of sensory feedback systems in myoelectric prostheses have shown promise in improving performance[70], and some researchers have investigated whether adding supplementary feedback can reduce the visual attention on the hand. One research group studied the potential of adding supplementary sensory feedback to normalize gaze behaviour[53,54]. In their testing paradigm, vibrotactile feedback had no effect on gaze behaviour in participants using a simulated myoelectric prosthesis[54] or myoelectric prosthesis users[53]. A dual-task was used to test differences in gaze behaviour, whereby performance on a primary task assessed the amount of cognitive effort exerted for that task, while performance on a secondary task assessed the remaining cognitive capacity[71]. This testing paradigm may not have been appropriate for discriminating differences between conditions with and without feedback, as the authors suggested that the secondary task was too simple and may not have adequately challenged the user[53,54]. In addition, the location of gaze may not discern attentional demand in a dual task, as the locus of attention can differ from the location of gaze, particularly when information is processed through the peripheral vision[35]. In the included studies, the effectiveness of sensory feedback was not tested over multiple training sessions. Markovic et al[72] demonstrated that the relevance of feedback is related to the prosthesis user's experience level. Feedback was only beneficial in reducing task completion time after subjects trained over multiple sessions to learn to control a prosthesis[72]. Therefore, the integration of supplemental feedback into the motor control loop may require time before feedback becomes useful in reducing the reliance on visual feedback.

Although prosthesis users lack touch and proprioceptive feedback, incidental feedback is relayed to the user through visual and auditory cues. Many studies have compared supplementary feedback to baseline conditions where vision is occluded. This method provides a means of isolating the effects of supplementary sensory feedback and has been shown to be useful in controlling grip aperture, grasping force, joint position, and object size and stiffness discrimination[73]. However, few of these studies have considered if supplementary feedback provides additional benefits in the presence of visual feedback. Sensinger and Dosen[73] recommended that the modality of feedback should be purposeful in relaying variables to the user that are not redundant with the information that is already provided through visual feedback. There is currently an absence of evidence to determine whether supplementary feedback is beneficial in reducing the reliance of vision to monitor the prosthesis.

However, one study[55] has demonstrated that restoring sensory feedback through natural channels can restore typical patterns of visuomotor behaviour. Targeted reinnervation is a surgical technique that provides intuitive bidirectional control by rewiring nerves from the amputated limb to new target sites in the muscles and skin[74]. Tactors were integrated into the prosthesis to provide physiologically matched touch and kinesthetic feedback to the reinnervated skin and muscle sites[55]. Compared to no feedback, providing kinesthetic and tactile feedback reduced fixations to the prosthetic hand when reaching and transporting objects, and increased visual fixations to the next target location[55]. In this study, eye tracking was shown to objectively assess visuomotor behaviours of prosthesis users during a goal-directed task and was sensitive to detect functional changes in response to a novel sensory feedback intervention. Given these findings, future work should incorporate the use of eye tracking to ascertain the ability for sensory feedback systems to reduce the burden on the visuomotor system.

3.5.3.3 Training Interventions

The goal of training is to improve functional outcomes of prosthesis users. Although training can improve speed[75] and performance[52], less is known about the effects of prosthetic training on gaze behaviour. The reviewed literature reveals that there are notable differences in the way in which persons learning to use an upper limb prosthesis are trained, which can affect functional outcomes. For example, different implicit gaze strategies were developed when observing an instructor with amputation demonstrate a task using a body-powered prosthesis, as opposed to an instructor with intact arm function who demonstrated the same task using their anatomic limb[44]. Those who were trained with observing the body-powered prosthesis user focussed primarily on the path of the prosthesis and the shoulders, which may have facilitated kinematic improvements when executing the task[44]. Therefore, guiding users to adopt gaze fixation patterns that are task specific may be beneficial in promoting more efficient motor learning during prosthesis use.

In fact, one study[10] explored the use of gaze training to teach novice prosthesis users. Gaze training is an implicit learning strategy that teaches users to adopt eye movement behaviours that are similar to expert users by encouraging users to look ahead towards the target instead of monitoring the hand. In contrast, traditional movement training instructs users on how to move their limbs, which can place a high attentional demand on using the prosthetic device. Gaze training resulted in greater fixations towards the target, shorter latencies for the eyes to shift to the next target and shorter performance times than movement training[10]. Not only did gaze training reduce the attentional demand that is associated with prosthetic hand use, but also the cognitive demand, as measured by EEG connectivity between T7 and Fz regions. The interaction between motor planning (Fz) and verbal-analytical (T7) regions of the brain were reduced with training, which reflected a reduction in conscious movement control[10]. Therefore, encouraging users to fixate the target improved neural efficiency and the usability of the prosthetic device. Importantly, those who received traditional movement training demonstrated no improvement in gaze behaviour, despite significant improvements in performance time[10]. The authors indicated that prosthesis users appear to maintain an overreliance on vision to compensate for prosthesis unpredictability and may not be capable of achieving feedforward gaze control through repeated practice. These results suggest that specific focus should be placed on teaching cognitive strategies during training that are aimed at reducing visual attention to improve functional outcomes.

3.5.4 Other Uses of Eye Tracking to Evaluate Prosthetic Behaviour

3.5.4.1 Pupil Dilation Used to Measure Cognitive Load

Eye tracking has also been applied to measure changes in pupil size during prosthesis use to assess cognitive workload. Previous studies have attributed visual attention towards the hand as a proxy for cognitive demand but did not provide a direct measure of this experience[9,52]. Pupil dilation could provide a direct, yet relatively unobtrusive method of measuring the cognitive workload associated with controlling a prosthesis. The pupils have been shown to dilate during mentally demanding activities, such as thinking and memory recall, and return to baseline following the mental task[76]. The benefit of measuring pupil dilation is that it is an objective and unbiased measure. Changes in pupil size are not voluntarily controlled by the user[77] and an eye tracker allows for natural movements. The drawback however is that pupillary size can respond to changes in light and can be confounded by other physiological factors such as anxiety and stress[78]. Other physiological measures (e.g. electroencephalography) require laborious experimental setup that can be obtrusive to the individual, can hinder their functional abilities, and may be susceptible to movement artefacts[79].

Measures of pupil diameter have been commonly used to measure cognitive load in the general population[78]. Recently, these metrics have also been applied to quantify cognitive load in the context of prosthesis use. Cognitive load was evaluated to compare the usability of two different control schemes: direct control and pattern recognition. Pattern recognition was determined to be less cognitively demanding than direct control, as indicated by a smaller change in pupil size[51] and fewer pupil size increases[50]. Since direct control requires additional mental steps to switch between control modes, the authors concluded that pattern recognition was more intuitive to use[50,51]. In addition, task performance increased across trials for both control modes[50,51], however pattern recognition was easier to learn and led to superior performance compared to direct control[50]. Zahabi et al.[56] further performed a cognitive modelling study using the average pupil size to predict the cognitive load of the two different control modes. Their predictions corroborated with the findings of previous studies[50,51] and indicated that fewer cognitive processes and motor commands were required for the pattern recognition control, making it less cognitively demanding than direct control. Evidently, pupil dilation shows promise as a means to non-invasively measure cognitive workload. Future work should address the reliability and validity of pupil dilations in quantifying cognitive workload of prosthesis users.

3.5.4.2 Fixation Duration Used to Measure Sense of Agency

The sense of agency towards a prosthetic limb can be described as the experience of voluntary control over a prosthetic limb to reliability perform movements as intended by the user[80]. This experience of agency is essential for the prosthesis to be embodied as part of one's own body[80]. Typically, to assess agency, explicit and implicit measures have been defined[81]. For example, questionnaires are used to explicitly report the experience of an experiment, but self-report relies on users to retrospectively recall the experiment and phrasing of the questions can influence outcome measures[81]. An example of an implicit measure is the intentional binding effect, in which the perceived time interval between a voluntary action and a resulting cue appear shorter than when the action is involuntary[81].

One preliminary feasibility study investigated the use of eye tracking to measure the sense of agency towards a prosthetic limb. Using gaze behaviour and reaction time in a simple detection task was shown to be feasible in assessing the perceived sense of agency[49]. Participants in this study simultaneously controlled four virtual onscreen arms that portrayed active grasp using EMG signals. Different noise levels were introduced to these virtual arms, to randomly reclassify the intended movements. Findings demonstrated that participants spent more time fixating on myoelectric-controlled virtual arms that were most controllable and corresponded to the actual movement intent recorded by EMG signals (i.e. no random noise)[49]. The authors suggested that visual attention is directed towards the virtual arm that provides the best sense of agency[49]. Although there was a significant difference in the allocation of visual attention to different virtual arms, the translatability of such evidence should be considered during functional tasks where visual monitoring of the prosthetic hand is undesirable[8–10,45,46,52]. Visual and proprioceptive cues about our bodily movements are needed to perceive control over one's voluntary actions[82]. In this experimental design, where a virtual arm was controlled, vision was the only mode of feedback, as participants did not receive proprioception from a physical arm to perform a functional task. It is therefore reasonable that participants fixated the most controllable virtual arms, however, the sense of agency cannot be confirmed with vision alone. To the best of our knowledge, eye tracking has not been otherwise implemented in prostheses research to measure the experience of agency. As this study is very preliminary, future work is needed to understand the role of vision towards the sense of agency and to test the validity of fixation duration as a metric to evaluate prosthetic agency.

3.5.5 Limitations and Future Work

Although this scoping review has compiled a collection of studies that have used eye tracking to assess the visuomotor behaviours of upper limb prosthesis users, we have not provided the reader with a critical discussion around the eye tracking technology itself. Many of the included studies provided limited details on their eye tracking setup. As such, future work should consider providing additional details on eye data collection, processing, and analysis methods for a more comprehensive insight into the technology. A review of the eye tracking technology applied to a wider population would serve useful in highlighting the limitations of eye trackers and the implications in understanding visuomotor behaviours.

To describe the visuomotor behaviours of prosthesis users, researchers have utilized visual fixations to infer cognitive effort. However, this metric only captures overt visual attention and does not encapsulate all of the cognitive, physical and emotional workload characteristics experienced by prosthesis users. Presently, only pupil dilations have been explored as an eye metric to directly quantify the cognitive workload of prosthesis users, although additional work is needed to verify the validity of this metric. Recent work has shown promise in developing a valid measure of cognitive workload and using eye tracking to correlate workload with visual attention[83]. Fixations towards the hand were related to a multitude of factors that represent mental workload, such as mental demands, physical demands, visual demands, conscious processing, frustration, etc.[83] This prosthesis user-specific workload measure may serve useful in future research to better understand the multifaceted challenges of prosthetic use.

An additional eye metric that has not yet been explored in prosthetics research is blink rate. Eye blink metrics have revealed cognitive processes in non-disabled populations, as these are known to be dependent on levels of mental activity[84]. In healthy humans, blinks occur around 15-20 times per minute[85] and have been shown to be reduced in mentally demanding tasks or when engagement levels were high[86]. Therefore, eye blink metrics may potentially provide researchers with another marker of cognitive effort in prosthesis users that could be explored in future work.

3.6 Conclusion

The literature revealed a remarkably characteristic visuomotor behaviour of upper limb prosthesis users across research studies. In contrast to the visuomotor behaviour of individuals with intact arm function, prosthesis users fixate more towards their hand and less towards target objects or locations. The reliance on vision to monitor the prosthetic hand prevents users from looking ahead towards future targets to plan for subsequent actions. Despite visuomotor behaviours that were mainly consistent, considerations should be made regarding the type of prosthesis and experimental task, as these may challenge the visuomotor system differently. Early work could not demonstrate that visuomotor behaviour was related to skill level or everyday usage. Therefore, it is unknown whether greater functionality is also marked by improved gaze behaviour and future work should investigate this gap in our knowledge.

Evidence has shown that gaze behaviour is related to prosthetic control and can be modulated with interventions, such as sensory feedback and training protocols. Importantly, eye tracking is a tool that provides a quantitative means of assessing human visuomotor behaviour and facilitates the understanding of the impact of prosthetic interventions to alleviate visual and cognitive demands. Research should thus consider including eye tracking as an outcome measure when evaluating novel interventions. Overall, the findings are promising, although more studies are needed with larger sample sizes to substantiate the repeatability and validity of the current findings. Eye metrics have also been used to study the cognitive load and sense of agency of upper limb prosthesis users. The literature to date suggests promising results in quantifying these phenomena, however more work is needed to validate the use of these eye metrics in an upper limb prosthesis user population.

Chapter 4: Relationship Between Eye and Hand Movements

The material presented in this chapter was published in the 2022 proceedings for IEEE International Conference on Rehabilitation Robotics as the article titled “Spatiotemporal Coupling of Hand and Eye Movements When Using a Myoelectric Prosthetic Hand”:

> *Cheng KY, Chapman CS, Hebert JS. Spatiotemporal Coupling of Hand and Eye Movements When Using a Myoelectric Prosthetic Hand. In: 2022 International Conference on Rehabilitation Robotics (ICORR). Rotterdam, Netherlands, 2022. p. 1–6.*

The contents of this chapter are identical to the material presented in the published manuscript, with the exception of Figures 4-1 and 4-2, which have been added to the body of the text for clarification of the methods.

4.1 Abstract

Upper limb prosthesis users have disruptions in hand-eye coordination, with increased fixations towards the hand and less visual allocation for feedforward planning. The purpose of this study was to explore whether improved motor planning, as reflected by eye gaze behaviour, was associated with more efficient hand movement patterns. Participants without limb difference wore a simulated prosthesis while performing a functional object movement task. Motion and eye tracking data were collected to quantify the eye gaze and hand movement during object interaction. The results of this study demonstrated that the latency of the eye to precede the hand at pick-up was correlated with measures of hand function, including hand variability, movement units, and grasp time, but not reach time. During transport and release, longer latency to disengage gaze from the grasped object and look ahead towards the target was correlated to hand kinematics of hand variability, distance travelled, and transport time. In addition, the latency of the eye to disengage the drop-off location was correlated to release time. Together these may point to control issues with opening and closing the prosthetic hand. Overall, increased feedforward fixations towards the target and reduced feedback fixations towards the hand were related to improved measures of hand function. Hence, coordination between eye and hand movements when using a myoelectric prosthesis may prove to be a useful metric to assess motor planning.

4.2 Introduction

Hand-eye coordination is fundamental to the way in which humans interact with the world around them. In normal reaching activities, it is well established that the eyes guide the actions of the hand. The eyes fixate on task-relevant objects and serve as a feedforward mechanism in motor planning prior to the hand movement[87]. Visual fixations are directed predominantly towards target objects and rarely towards the hand[33,38–40]. Once objects are grasped, feedback from another sensory modality such as touch, allows the eyes to disengage from the task and shift towards a future target[33,38,39]. Eye and hand movements are likely driven by a common neural mechanism[88] and have been shown to correlate with one another[89–91]. These studies demonstrated a temporal coupling between eye and hand movements across varying task demands. However, the experimental protocols were relatively simple and involved tasks where sensorimotor mapping rules were already learned.

When learning a novel skill, patterns of hand-eye coordination differ across different stages of learning. Sailer et al. described that in the early exploratory stage of motor learning, gaze tends to lag behind the movement of an onscreen cursor[60]. As skill acquisition progressed, the eyes retrieved feedforward control, and the ability to look ahead towards the target aligned with improved performance[60]. Similarly, motor learning during novel tool use is characterized by an initial monitoring of the hand and tool, that later shifts towards anticipatory visual fixations directed at the target[92]. This shift in gaze distribution was positively associated with improved performance[92]. However, unlike the relationship between skill level and visuomotor behaviour during motor learning, upper limb prosthesis users of varying skill level appear to employ different gaze strategies[46].

Disruptions to normal hand-eye coordination have often been reported in upper limb prosthesis users. Due to a lack of tactile and proprioceptive feedback, these individuals have the tendency to rely on visual feedback to monitor the prosthetic hand, a behaviour that is not typically observed with the anatomic hand. This behaviour is characterized by increased visual fixations towards the hand and reduced fixations towards the next target location[8,9,46,52]. The reliance on vision prevents users from looking ahead to plan for future actions, thereby shifting the use of vision for feedback control. Studies have suggested that there remains a temporal coupling between prosthetic hand and eye movements, however, findings have been inconsistent – visuomotor behaviour appears to be unrelated to functional performance[46] or everyday usage[47]. Chadwell et al. have attributed these inconsistent findings to the unreliability of myoelectric prostheses[48,57]. Unlike learning to use a simple tool, an upper limb prosthesis is a much more complex device. Many factors influence the reliability of the device and prevent normal motor learning from occurring[48,57]. Reduced learning, in combination with lack of inherent feedback, require users to rely on vision for feedback to monitor the activity of the prosthetic hand and to ensure the device performs as intended.

Although these previous studies have investigated the relationship between gaze behaviour and function or performance, investigation of the interaction of eye gaze and hand movement at specific timepoints of object manipulation could further elucidate the underlying mechanisms of prosthetic hand-eye coordination. Therefore, the aim of the present study was to explore whether improved motor planning, as reflected by eye gaze behaviour, was associated with more efficient hand movement patterns when performing object manipulation tasks with a prosthesis. This approach may provide further understanding of which measures of proficiency in the eye domain correlate with measures of proficiency in the hand domain in prosthesis users.

It was hypothesized that increased visual fixations towards the current target, reduced fixations towards the hand, as well as a shorter latency for the eye to disengage from the object and fixate the next target, would be associated with improved hand kinematics (i.e., shorter hand distance travelled, reduced hand trajectory variability, fewer number of movement units, and shorter phase durations).

4.3 Methods

4.3.1 Experimental Protocol

The data collected for this study follows the procedures as outlined by Williams et al.[62]. A bypass prosthesis (Figure 4-1) developed by Kuus et al.[93] was worn on the right forearm of right-handed participants without limb difference (11 male, 1 female; mean=23.8 years, SD=3.4 years). The device was meant to simulate a myoelectric upper limb prosthesis that is worn by an individual with a transradial amputation. The hand and wrist were immobilized in a brace, and a terminal device (MyoHand VariPlus Speed model: 8e38 = 9-R7 1⁄4; Otto Bock Healthcare Products) was attached on the palmar side with a radial offset. Electrodes (electrode model: 13E200=60; Otto Bock Healthcare Products; Duderstadt, Germany) were placed over the wrist extensor and flexor muscles to detect electromyography signals that were used to control the hand open and close of the device.

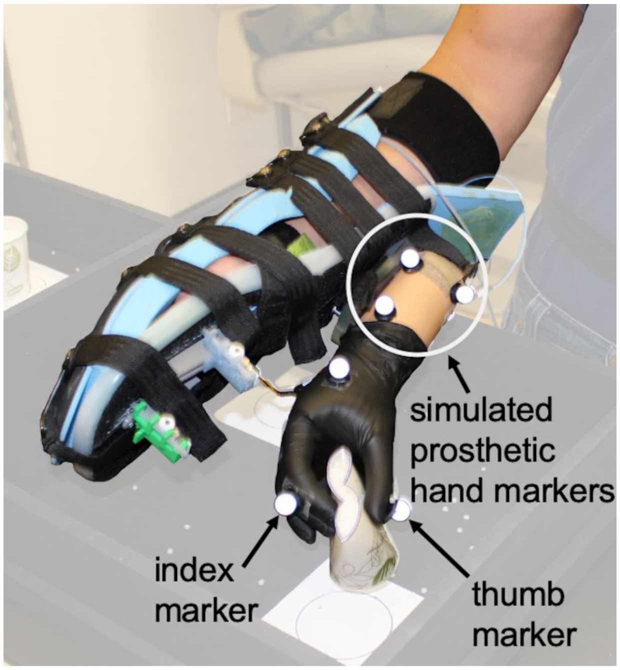


Figure 4-1: Bypass prosthesis worn on the right forearm of an intact limb participant. Motion capture markers were placed on the thumb, index finger, and on the medial side of the prosthetic hand.

A Gaze and Movement Assessment[26,28,94] was used to quantify eye fixations during object interaction. Participants performed a standardized Pasta Box Transfer Task that was meant to mimic activities of daily living[26,94]. The task consisted of three movements. Movement 1 involved moving a pasta box from a lower table on the right side of the body to a shelf in front of the participant. In movement 2, the pasta box was then moved around a barrier across the midline to a second higher shelf. Movement 3 consisted of a cross-body movement to return the pasta box to the initial starting point. All movements began and ended when the hand moved to a 'home' position. Refer to Figure 4-2 for a schematic of the Pasta Box Transfer Task. Participants were first trained to use the device and could practice the task until comfortable with executing it. Each participant performed 5 trials of the Pasta task. The data from one participant was discarded altogether due to poor data quality, resulting in data from 11 participants. If an error was made, the data from that trial was discarded. Each participant had a total of 3 to 5 trials that were included in the analyses, resulting in a total of 46 trials that were analyzed.

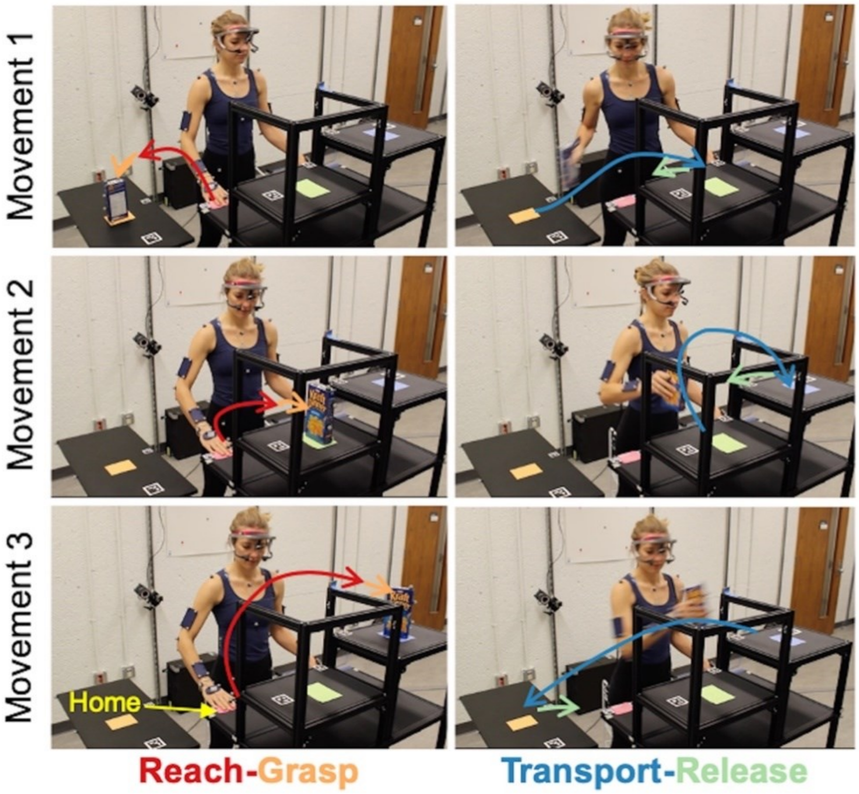


Figure 4-2: The Pasta Box Transfer Task involves three distinct movements to transport a pasta box to different locations. Each movement consists of a reach, grasp, transport, and release phase. Image reproduced from Valevicius et al.[26].

4.3.2 Experimental Setup

A 12 camera Vicon Bonita motion capture system (Vicon Motion Systems Ltd, Oxford, UK) was used to measure the 3-dimensional prosthetic hand movements at 120 Hz. Reflective markers were attached to the index finger, thumb, and the medial side of the prosthetic device as shown in Figure 4-1. Additional markers were placed on task-relevant areas of the workspace (pasta box, shelving unit, and side table) as described in Valevicius et al.[26]. A head-mounted binocular eye tracker (Dikablis Professional 2.0, Ergoneers GmbH, Manching, Germany) recorded pupil movements at 60 Hz. Two gaze and motion calibration trials were collected prior to the first trial to construct a gaze vector that represented the location of the participant's gaze in the task space.

4.3.3 Data Processing

Before motion capture and eye tracking data could be synchronized, the data were first cleaned to fill any gaps. Second-order, low-pass Butterworth filters with a cut-off frequency of 6 Hz for motion capture[26] and 10 Hz for eye tracking[28] were then applied to remove any noise that may have been introduced during data collection. The synchronized motion capture and eye data were divided into 'Reach', 'Grasp', 'Transport' and 'Release' phases as described in Lavoie et al.[28]. In addition, hand function measures were calculated according to 'Reach-Grasp' and 'Transport-Release' movement segments as defined in[26]. Precise segmentation of movements into object-related 'Pick-up' and 'Drop-off' events afforded the ability to reveal the temporal dynamics between the location of visual fixation and the hand and object, to provide insights into movement planning.

4.3.4 Data Analysis

All statistical analyses were performed in SPSS Statistics (Version 28.0; IBM, Armonk, NY, USA). Correlational analyses were carried out to investigate the relationship between gaze behaviour and hand kinematics. In reach and grasp, eye metrics (eye arrival latency (EAL) at pick-up and percent fixation to current) were correlated with hand kinematics (hand distance travelled, hand trajectory variability, number of movement units, reach time, and grasp time). In transport and release, eye metrics (eye leaving latency (ELL) at pick-up, EAL at drop-off, eye ELL at drop-off, percent fixation to current, and percent fixation to hand) were correlated with hand kinematics (hand distance travelled, hand trajectory variability, number of movement units, transport time, and release time). Mean values across trials for each participant were correlated between measures within each movement. The Pearson correlation coefficient was reported for measures that had no outliers and were determined to be normally distributed by the Shapiro-Wilk test. For measures that had outliers or a non-normal distribution, the Spearman rank correlation was reported. Correlations were significant if the p-value was less than 0.05. Within-subject variability for all measures had a minimum relative standard deviation of 0.003 and a maximum of 2.24.

4.3.5 Eye Metrics

Eye arrival latency refers to the time of eye arrival to the target location relative to the start of transport time for pick-up and relative to the end of transport time for drop-off. EAL at pick-up is related to the reach-grasp segment. EAL at drop-off is related to the transport-release segment.[28]

Eye leaving latency refers to the time of the eye leaving the target location relative to the start of transport time for pick-up and relative to the end of transport time for drop-off. A more positive number is attributed to a shorter ELL, whereas a more negative number is attributed to a longer ELL. ELL at pick-up relates to the transition point from grasp to transport and ELL at drop-off is related to the transport-release segment[28].

Percent fixation is the amount of time spent fixating either the hand or the current target in reach and transport phases as a percentage of the duration of that phase. During the reach phase, the current target refers to the pasta box and its starting location. During the transport phase, the current target refers to the drop-off location.

4.3.6 Hand Kinematics

Hand distance travelled was the total distance that the terminal device travelled. *Hand trajectory variability* was calculated as the maximum of the mean three-dimensional standard deviation at each time-normalized point. *Number of movement units* referred to the number of times that the hand acceleration profile crossed zero to produce a local velocity peak. The hand kinematic measures were calculated for reach-grasp and transport-release segments. *Phase durations* were the time for each phase of reach, grasp, transport, and release.

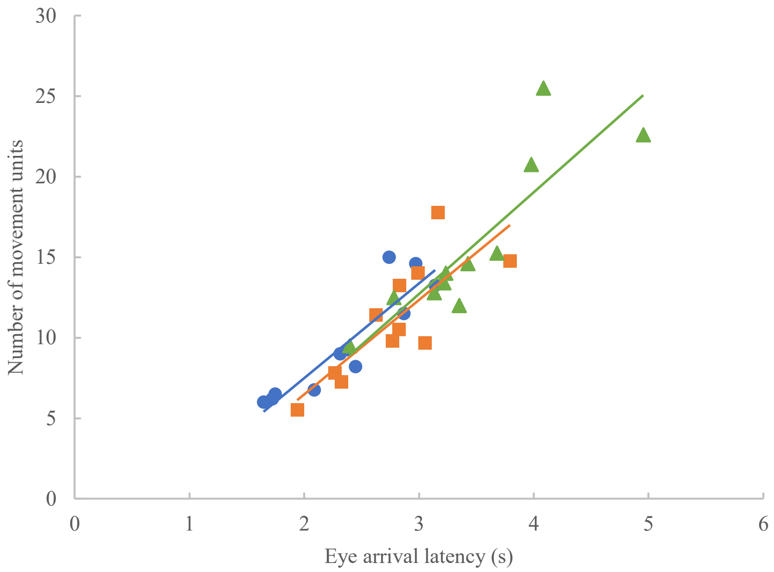
4.4 Results

4.4.1 Reach-Grasp

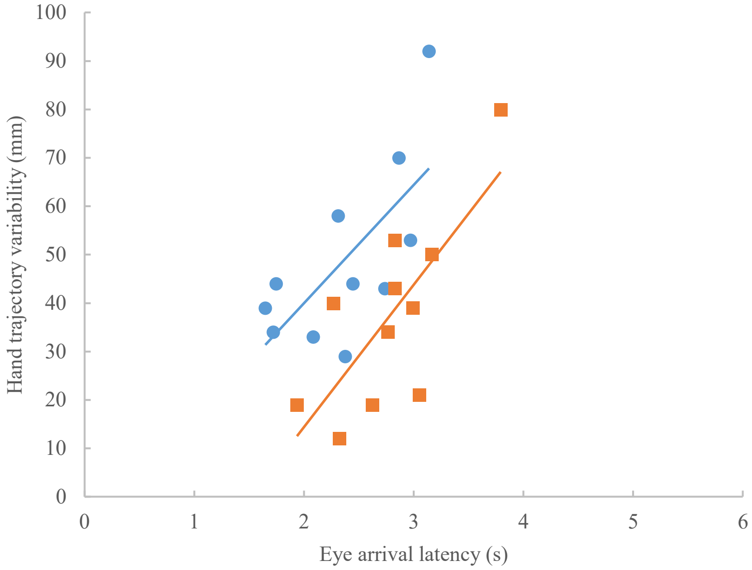
During the reach-grasp segment, EAL at pick up of the object had strong correlations to number of movement units (Figure 4-3a), hand trajectory variability (Figure 4-3b), and grasp times (Figure 4-3c). Specific positive correlations were found with the number of movement units in movement 1 ($r(9) = 0.908$, $p = <0.001$), movement 2 ($r(9) = 0.809$, $p = 0.003$), and movement 3 ($r(9) = 0.900$, $p = <0.001$) (Figure 4-

3a); and hand trajectory variability in movement 1 (*r*(9) = 0.690, *p* = 0.019) and movement 2 (*r*(9) = 0.749, *p* = 0.008) (Figure 4-3b). No significant correlations were shown between EAL and reach time. However, there was a strong positive correlation between EAL and grasp time in movements 1 (*r*(9) = 0.971, *p* = <0.001), 2 (*r*(9) = 0.923, *p* = <0.001), and 3 (*r*(9) = 0.845, *p* = 0.001) (Figure 4-3c). Percent fixation to current was not found to have any correlation to measures of hand function in reach-grasp. These correlations indicate that a longer EAL at pick-up is related to increased movement units, hand variability, and grasp time.

a)



b)



c)

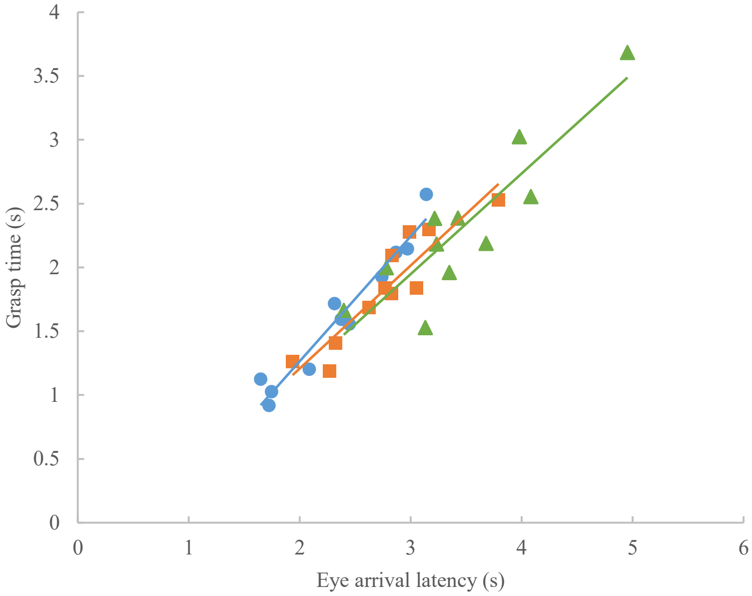
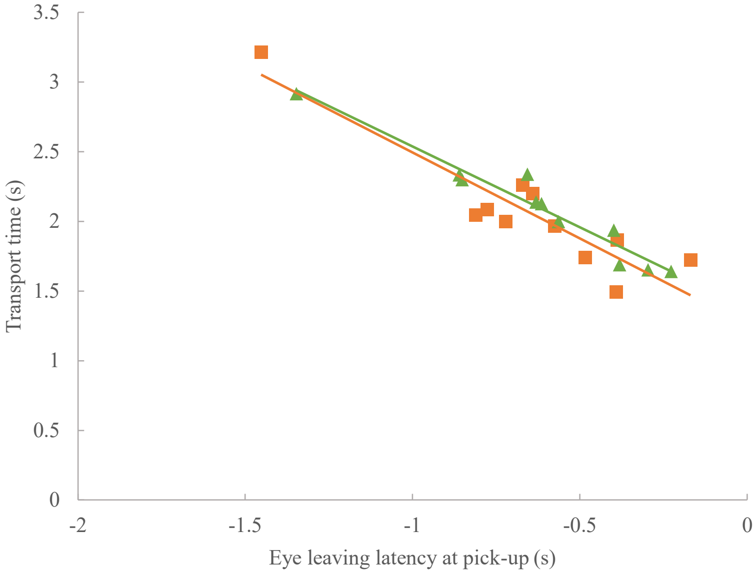


Figure 4-3: Relationship between eye arrival latency at pick-up and (a) number of movement units, (b) hand trajectory variability, (c) grasp time for movement 1 (blue circle), movement 2 (orange square), movement 3 (green triangle). Each data point represents the mean for each participant. Only significant correlations are shown in the figures.

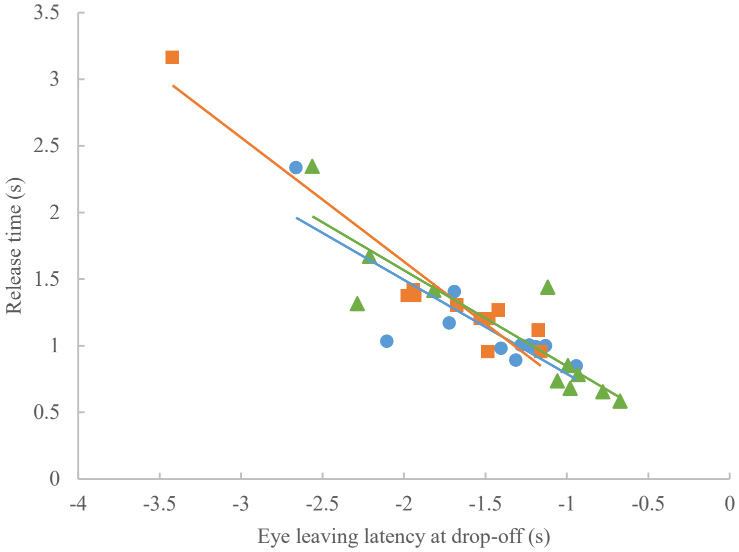
4.4.2 Transport-Release

During the transport-release segment, ELL at pick-up was negatively correlated to transport time in movements 2 (*r*(9) = -0.809, *p* = 0.003) and 3 (*r*(9) = -0.973, *p* = <0.001) (Figure 4-4a). In addition, ELL at pick-up was positively correlated to hand distance travelled (*r*(9) = 0.645, *p* = 0.032) in movement 2. At drop-off, EAL did not correlate with the hand kinematic variables, with the exception of a weak correlation to release time in movement 3 (*r*(9) = 0.620, *p* = 0.042). However, ELL at drop off showed a significant negative correlation to release times for all movements (movement 1 (*r*(9) = -0.736, *p* = 0.01); movement 2 (*r*(9) = -0.845, *p* = 0.001); movement 3 (*r*(9) = -0.891, *p* = <0.001) (Figure 4-4b). These correlations indicate that shorter ELL at pick-up and drop-off are related to shorter transport and release times, respectively.

a)



b)



c)

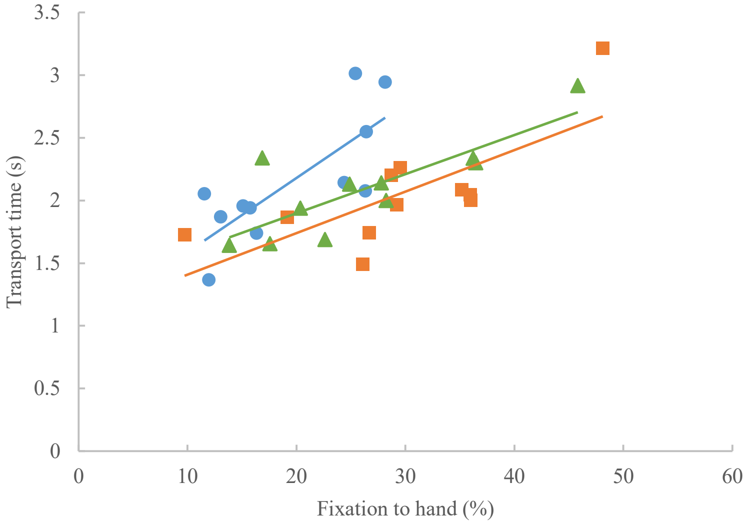
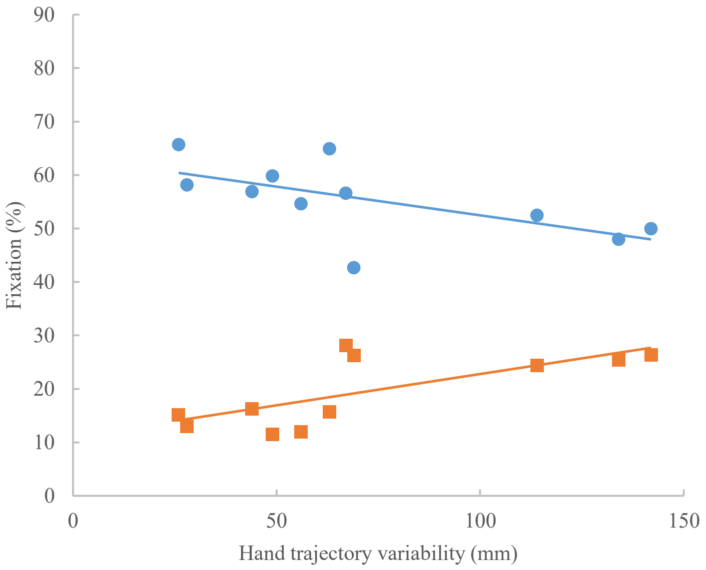


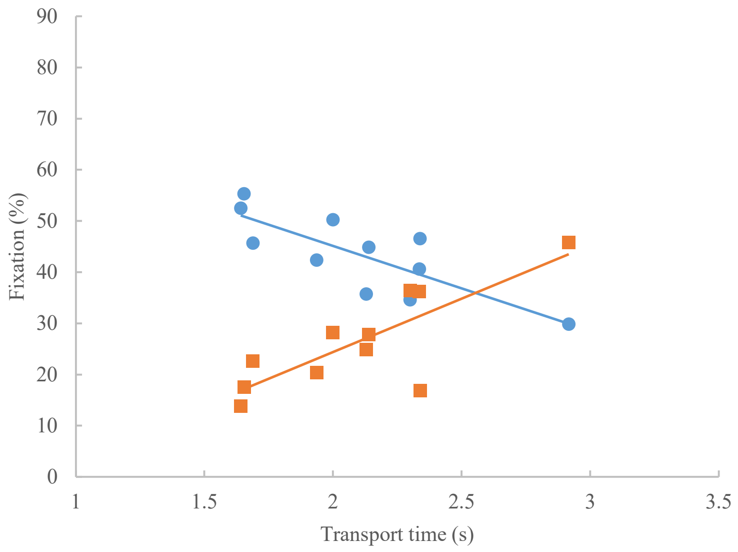
Figure 4-4: (a) Relationship between eye leaving latency at pick-up and transport time, (b) eye leaving latency at drop-off and release time, (c) percent fixation to hand and transport time for movement 1 (blue circle), movement 2 (orange square), movement 3 (green triangle). Each data point represents the mean for each participant. Only significant correlations are shown in the figures.

Percent fixation to the hand during transport showed positive correlations to the corresponding transport time for each movement (movement 1 ($r(9) = 0.727$, $p = 0.011$); movement 2 ($r(9) = 0.745$, $p = 0.008$); movement 3 ($r(9) = 0.808$, $p = 0.003$)) (Figure 4-4c). In addition, for movement 1, the percentage of hand fixation was positively correlated to the number of movement units ($r(9) = 0.673$, $p = 0.023$) and hand trajectory variability ($r(9) = 0.709$, $p = 0.015$), while percent fixation to the current target was negatively correlated to hand trajectory variability ($r(9) = -0.622$, $p = 0.041$) (Figure 4-5a). In contrast to the positive relationship between percent fixation to hand and transport time, percent fixation to current was negatively correlated to transport time in movement 3 ($r(9) = -0.800$, $p = 0.003$) (Figure 4-5b). The percentage of hand fixation showed a positive association with hand kinematic variables and the percentage of target fixation showed a negative association with hand kinematic variables in movements 1 and 3. In movement 2, the opposite relationships were observed to be significant. Percent fixation to hand was negatively correlated to hand distance travelled ($r(9) = -0.691$, $p = 0.019$) and percent fixation to current was positively correlated to hand distance travelled ($r(9) = 0.655$, $p = 0.029$) (Figure 4-5c). Participants that had greater hand trajectory variability, transport time, and hand distance travelled had longer fixations to the hand and correspondingly shorter fixations to the target.

a)



b)



c)

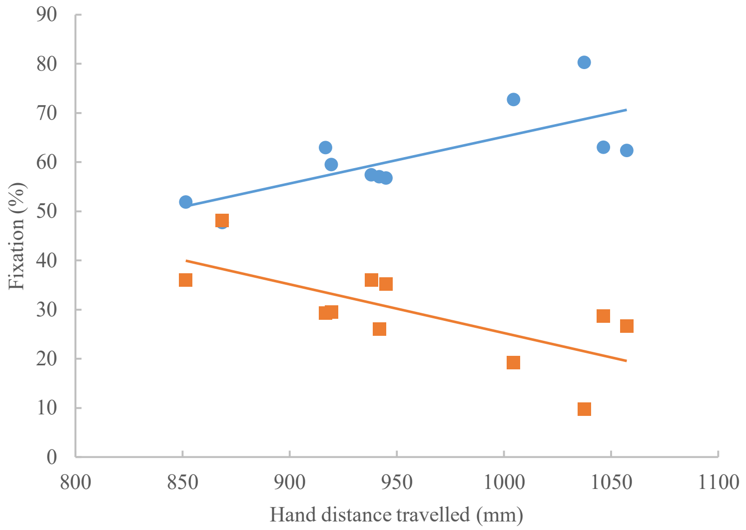


Figure 4-5: Relationship between percent fixation to current (blue circle) and hand (orange square) and (a) hand trajectory variability in movement 1, (b) transport time in movement 3, (c) hand distance travelled in movement 2. Each data point represents the mean for each participant. Only significant correlations are shown in the figures.

4.5 Discussion

The present study demonstrated that there is a correlation between the location and timing of gaze fixation and measures of improved hand function. Eye arrival and eye leaving latencies are temporal measures of gaze that describe the timing in which the eyes precede or follow the movement of the hand. Spatial measures of gaze refer to the location of visual fixation and include measures such as percent fixation to hand or to the next target. Both spatial and temporal measures of gaze showed significant correlations to kinematic hand metrics. Hand kinematic metrics such as hand trajectory variability, movement units, and phase durations are indirect indicators of motor control[95,96] and may represent motor skill (i.e. how well someone performs with their prosthesis).

4.5.1 Temporal Measures of Gaze Associated with Hand Function in Reach-Grasp

Eye arrival latencies inform as to the temporal allocation of gaze. In a normative population, the eyes generally fixate on the object half a second before the arrival of the hand[28,33,38–40]. Previous studies have shown that prosthesis users are often unable to look ahead when reaching and grasping for an object[9,46,52,57]. Here, participants demonstrated longer EAL at pick-up that deviated from normal[28]. Prolonged look-ahead fixations to the object were associated with greater hand trajectory variability and number of movement units, indicating worse motor control. A shorter EAL at object pick-up was associated with fewer movement units, reduced hand trajectory variability, and shorter grasp times, reflecting more efficient performance.

The temporal coupling of hand and eye movements that has been demonstrated in individuals with intact arm function[89–91] appears to prevail here, when using a myoelectric prosthesis to reach for and grasp an object. It should not be surprising that eye latencies were related to phase duration as these are both time-based measures that are inherently linked. Interestingly, the current study demonstrates that EAL is related to grasp time but not reach time. Parr et al. demonstrated that the timing of gaze shifts was a significant predictor of task performance time[9]. In line with their findings, the current study further highlights that the relationship between the eye gaze shift to the current object and the duration is pertinent to the grasp phase. The duration of grasp phase was likely influenced by difficulties in controlling the close of the prosthetic hand around the pasta box, whereas the reach time would not be affected by hand control issues as it involves proximal intact joint movements of the shoulder and elbow, hence the ability to maintain a feedforward gaze strategy.

4.5.2 Temporal Measures of Gaze Associated with Hand Function in Transport-Release

During the transport-release segment, shorter ELL at pick-up correlated to shorter transport times; whereas a longer ELL indicated a longer time for the gaze to shift away from the grasped object, which was associated with a longer transport phase. With the intact hand, the eyes are able to disengage from the current object when another sensory modality, such as touch, is able to confirm that the object has been grasped[33,38,39]. This usually occurs just after the object is adequately grasped and begins to move[28]. Prosthesis users lack the sensory feedback necessary to confirm the grasp of the object and tend to have longer eye leaving latencies[8]. Thus, a shorter ELL at pick-up indicates that the user was more confident in the prosthetic grip, which likely reflects improved motor control. An improved ability to disengage visual attention from the currently grasped object then allows the user to spatially attend to the next target.

Similar to the relationship between EAL at pick-up and grasp time, shorter ELL at drop-off correlated to shorter release times, while a longer latency for the eye to disengage from the drop-off location was associated with a longer release phase. A prolonged ELL at drop-off indicates that the eyes lingered on the pasta box after the object arrived at the drop-off location. This prolonged gaze time may have been needed to ensure that the box was placed correctly in an upright position. Analogous to the relationship between EAL at pick-up, a prolonged ELL at drop-off may also have been provoked by difficulties with controlling the opening of the prosthetic hand.

4.5.3 Spatial Measures of Gaze Associated with Hand Function in Transport-Release

Spatial allocations of gaze (locations of gaze fixation) had specific relationships to hand function during the transport-release segment of object manipulation. During transport and release, longer fixations on the drop off target location were associated with lower hand trajectory variability and shorter transport time, while longer fixations towards the hand were associated with an increased number of movement units, hand trajectory variability and transport time. These findings suggest that more effective motor planning, as indicated by greater target-fixations and less hand-fixations[97], are associated with better stability of control during transport of an object, as indicated by fewer movement units, reduced hand variability, and shorter transport times[95,96].

The highly variable movement patterns of prosthesis users stem from an uncertainty of the hand in space, as well as difficulties with controlling the prosthetic hand[48]. Chadwell et al. demonstrated that increased fixations towards the hand were correlated to undesired hand activations in reach and grasp[48]. In addition, we have shown that a cautious behaviour is adopted to monitor the hand through transport, likely to ensure that the hand remains closed on the grasped object. One factor contributing to visual monitoring of the hand is known to be the absence of sensory feedback. Indeed, prior study has shown that restoring touch and kinesthetic feedback for a prosthesis user can normalize gaze fixation patterns during transport[55]. In the current study, we have uniquely highlighted that an improved ability to maintain grasp of the object during transport is also related to the allocation of visual attention, with vision directed more towards the target and less towards the hand.

Contrary to our predictions, longer fixations towards the target and shorter fixations towards the hand during transport were associated with longer hand distance travelled in movement 2. This opposite relationship may have occurred due to an obstacle avoidance strategy uniquely required for movement 2; in which the box must be moved off the shelf, then around a barrier and on another shelf. To avoid hitting the barrier while moving from the pick-up location to the drop-off location, individuals that maintained feedforward gaze towards the target likely overcompensated by moving the hand further away from the barrier to reach the target location. Individuals that displayed a more conservative feedback strategy likely monitored the trajectory of the hand, thus able to take the shortest path towards the drop-off location. Although the hand travelled a longer distance when fixating the drop-off target, reduced fixations towards the hand, as well as the ability to disengage the gaze to fixate the next target resulted in a shorter transport time.

4.5.4 Limitations and Future Directions

These exploratory findings revealed important potential relationships between hand and eye movements while using a prosthetic hand. However, these correlational relationships do not point to causation. Furthermore, eye and hand metrics are known to be inter-related and with a larger data set, the specific weighting of each metric to hand or eye function could be more thoroughly explored. It would also be compelling to explore whether addressing variables of gaze through training could improve prosthetic hand kinematics and performance. Encouraging users to fixate on the target rather than the hand has been shown to improve learning and neural efficiency and may be a promising rehabilitation technique[10]. The participants of this study were free of any upper limb pathology and performed a functional task using a simulated prosthesis. Evidence suggests that individuals using a simulated prosthesis are an acceptable proxy for upper limb prosthesis users[52,62]. Moreover, we did not compare task performance both with without and the prosthetic hand. The assumption was that participants of the present study would exhibit similar hand-eye coordination strategies as those previously reported from a larger normative dataset. Future work should investigate whether similar relationships between hand and eye movements occur in upper limb prosthesis users of varying skill level, as evidence suggests that kinematics may vary in prosthesis users of different skill levels[98].

4.6 Conclusion

To summarize, in reach and grasp, the latency of the eye to precede the hand was related to hand trajectory variability, movement units, and grasp time. In transport and release, longer target-fixations and reduced hand-fixations were related to measures that reflected improved prosthetic grip during object transport. A corresponding ability to disengage visual attention from the grasped object enabled the gaze to fixate the next target in a feedforward manner and was associated with reduced phase duration time. Together, these correlations suggest a relationship of visual allocation with grasp control skill and reinforce the spatiotemporal coupling of hand and eye movement behaviours during prosthesis use. Key metrics of gaze behaviour (i.e., increased target fixations, reduced hand fixations, and shorter eye latencies) are identified as promising indicators of feedforward motor control, and future studies could explore these measures as a relevant metric of motor planning.

Chapter 5: Sensitivity of Eye Metrics to Control Interventions

The material presented in this chapter is in preparation for submission as the article titled "The Effect of an Advanced Myoelectric Control Strategy on the Visuomotor Behaviours of Upper Limb Prosthesis Users".

5.1 Abstract

Prosthesis users rely on vision to monitor the activity of their prosthesis, which can be cognitively demanding for the user. This compensatory behaviour may be attributed to an absence of feedback sensations from the missing limb or the unreliability of myoelectric control. Myoelectric prostheses behave unreliably due to variations in electromyography signals that can occur when the arm moves through different limb positions during functional use. Deep learning methods have been explored to include both arm position and movement intent predictions in order to provide users with a more robust control system. However, it is unknown to what extent control interventions can modulate gaze behaviours as previous work has not yet demonstrated the sensitivity of eye metrics to such interventions. The aim of this study was to evaluate the effects of an advanced myoelectric control strategy on the visuomotor behaviours of upper limb prosthesis users. Participants without limb difference controlled a simulated myoelectric prosthesis with a baseline control strategy and a novel transfer learning control strategy that was designed to address the limb position effect in real-time. Eye tracking and motion capture data were collected during an experimental task to assess the effectiveness of the novel transfer learning control strategy. The transfer learning control had shorter phase durations, increased smoothness of movements, and less visual attention towards the hand, compared to the baseline control. Differences between control strategies were revealed specifically in fully extended, cross-body arm positions. These findings indicated that a more reliable control strategy alleviated the reliance on vision to monitor the prosthesis as users had increased confidence in the prosthetic control.

5.2 Introduction

With amputation, the natural channels for motor control and feedback from the hand and arm are lost. Prosthesis users therefore need to compensate with vision to monitor the activity of their prosthesis, causing disruptions to normative patterns of eye-hand coordination[9,10]. Typically, the eyes lead the movement of the hands in a feedforward manner, thus individuals with intact arm function rarely fixate on the hand[33,38–

[40]. In contrast, prosthesis users typically show increased visual fixations towards the prosthetic hand and reduced fixations towards target areas[8–10,46,52]. In addition, prosthesis users have a significant delay to disengage visual attention from objects when picked up or dropped off[8–10]. The need to visually attend to the hand is often regarded by prosthesis users as being cognitively demanding and is one of the contributing factors to device dissatisfaction and rejection[1,59]. In fact, visual fixations towards the hand have been shown to encompass multiple workload factors, such as mental demand, physical demand, visual demand, conscious processing, and frustration[83]. Therefore, current prosthetic interventions should aim to reduce the attentional demand associated with prosthetic use while also increasing movement functionality.

Sensory feedback interventions have demonstrated the potential to alleviate this reliance on vision for prosthesis users. By restoring the natural feedback channels and providing users with touch and kinesthetic feedback, visual fixations towards the hand have been shown to be reduced[55]. Such evidence lends support to the hypothesis that a lack of sensory feedback contributes to the high visual demand associated with prosthetic use. However, the contribution of motor control cannot be understated. Chadwell et al.[48] revealed that a higher frequency of undesired activations (e.g. hand opening/closing when unintended, incorrect prosthesis response, or no prosthesis response) was linked to poor visuomotor behaviours, including increased fixations towards the hand, decreased fixations towards the target and an increased number of gaze switches, as well as decreased functionality. This evidence suggests that vision is continually drawn towards the prosthesis to ensure that the hand performs as intended. Therefore, addressing the unpredictability of myoelectric prosthesis control could potentially reduce the reliance on vision and thereby improve the usability of these devices.

One major factor affecting the accuracy and reliability of myoelectric control is the alteration of electromyography (EMG) signal patterns caused by limb positioning[99–101]. These variations in EMG signals can degrade prosthesis control and can cause unwanted hand and wrist movements to occur[99]. With a pattern recognition-based control, the user's muscle signals are decoded to generate control commands for the prosthesis. This method requires a training routine to learn the muscle signals of the user and relies on distinct, repeatable muscle contractions. Usually, individuals perform this training routine in one limb position that is comfortable for the user (i.e., with the arm resting at the side). However, when moving through a variety of limb positions to perform daily activities, changes in muscle recruitment to stabilize the limb, and changes in the shape and length of muscles can cause the original signal source to shift with respect to the electrodes[100]. As such, the EMG signals used to generate prosthesis commands during functional use differ from those used originally to train the control system. This problem is known as the limb position effect.

To overcome the challenges associated with the limb position effect, pattern recognition systems that are trained in multiple limb positions have been investigated to improve the classification accuracy and usability of prosthetic devices[99,100,102–107]. One caveat of using pattern recognition systems that are capable of accounting for multiple limb positions is that longer training routines are required, placing an additional burden on the prosthesis user[108]. Previous work has investigated the use of deep learning methods, namely transfer learning, to provide a promising solution for highly reliable movement predictions, while reducing the lengthy training process[109]. This deep learning model combines individual training data with a pre-trained model on a general dataset of defined hand gestures in multiple limb positions. The benefit of such a model is the potential to accurately predict movement intent when moving through different limb positions, while also shortening the time required to train the control system. Moreover, transfer learning has the potential to be highly individualized to the user, yet generalizable to a larger population of upper limb prosthesis users.

Williams et al.[109,110] previously demonstrated the feasibility of a transfer learning control strategy by reducing the time required to train the controller. This advanced control strategy improved overall task performance in real-time, suggesting the potential benefits of training in multiple limb positions to mitigate the limb position effect[110]. In addition to these performance measures, it would be valuable to assess whether such an advanced control strategy could also alleviate visual demand, as it is ultimately the usability of prosthetic devices that will determine whether users will adopt these devices. To date, no studies have investigated whether prosthetic control interventions have beneficial effects on modulating the gaze behaviour of prosthesis users[111] Therefore, we additionally propose visuomotor measurements to capture the user experience of upper limb prosthesis users.

In the current research, we aimed to investigate the effects of an advanced myoelectric control strategy in changing the visuomotor behaviours of myoelectric prosthesis users. Importantly, no studies to date have explored the impact of modulating prosthetic control on gaze behaviour. As such, this study is the first of its kind to demonstrate the sensitivity of eye metrics in response to prosthetic control factors. We further aimed to uncover limb positions in which control was challenging and to confirm the benefits of an advanced control strategy to improve functionality in these positions. It was hypothesized that an advanced control strategy that improves the accuracy and reliability of myoelectric control in various limb positions during functional use would also reduce the performance time, improve the efficiency of hand movements, and reduce the visual attention associated with prosthetic use. To test these hypotheses, collection of eye and hand movement data was used during an experimental task that challenged the user in various planes of movement when testing the effectiveness of a novel transfer learning control strategy that was designed to address the limb position effect in real-time.

5.3 Methods

5.3.1 Participants

A total of 9 participants with no upper limb pathology or history of neurological or musculoskeletal impairment were recruited. The data from one participant was incomplete due to technical issues. The eye data from another participant was considered to be poor quality as outlined in section 5.3.4. Therefore, two participants were removed from this study and the data of the remaining 7 participants were included for analyses. All participants were considered to be novice myoelectric prosthesis users, with little to no experience with controlling a prosthetic hand using EMG pattern recognition. Four of the included participants had normal or corrected-to-normal vision, while three individuals performed the tasks with uncorrected vision in order to wear the eye tracker without the interference of eye glasses. These individuals reported that their uncorrected vision was adequate to perform the tasks. The mean age was 23.4 ± 4.3 years and the mean height was 178.8 ± 6.4cm. Two participants were female and one individual self-reported to be left-handed. All participants provided written informed consent. This study was approved by the University of Alberta Health Research Ethics Board (Pro00086557).

5.3.2 Experimental setup

5.3.2.1 Simulated prosthesis

A simulated prosthesis originally developed by Hallworth et al.[112], was modified to be used in this study. The device was designed to simulate a myoelectric prosthesis that is worn by an individual with a transradial amputation. The simulated prosthesis consisted of 3D printed parts that were secured to the right forearm of intact limb individuals and a brace that restricted hand and wrist movements. A terminal device with two degrees of freedom (hand open/close and wrist rotation) was attached to the palmar side at the approximate location of the participant's anatomical hand, as shown in Fig 5-1a. A Myo armband (Thalmic Labs, Kitchener, Canada) was placed around the participant's right forearm, an average of 7.1 ± 1.2 cm distal to the medial epicondyle of the humerus (Fig 5-1b). The Myo armband collected EMG data from 8 embedded surface electrodes sampled at 200 Hz and positional data from one inertial measurement unit (IMU) sampled at 50 Hz. EMG data and accelerometer data from the IMU were collected and used to control the terminal device. Participants activated their wrist extensors to open the prosthetic hand and their wrist flexors to close the prosthetic hand. Wrist supination was performed to rotate the wrist motor clockwise and wrist pronation was performed to rotate the wrist motor counterclockwise.

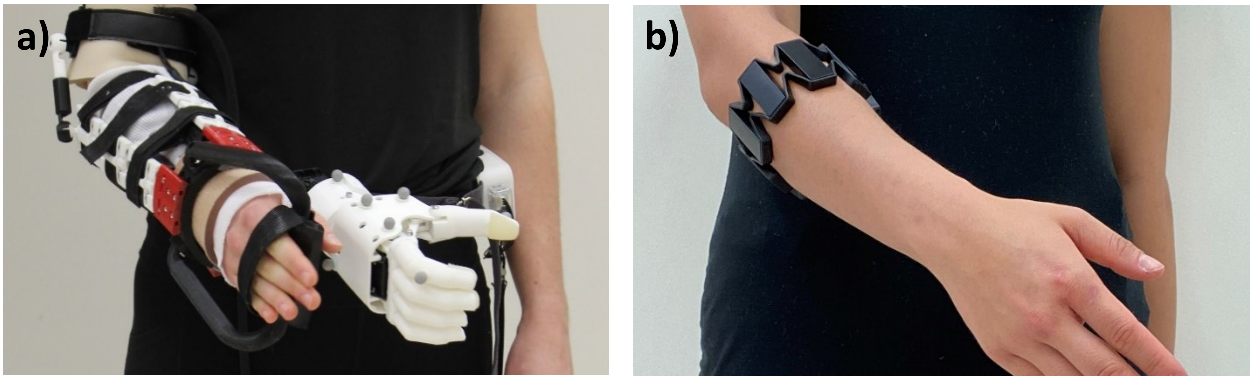


Figure 5-1: (a) Simulated prosthesis worn by an individual with an intact arm and (b) Myo armband worn around the forearm underneath the simulated prosthesis.

5.3.2.2 Motion capture and eye tracking setup

Gaze and Movement Assessment (GaMA) was performed to quantify hand kinematics and gaze behaviour during object interaction[26,28,29,94]. An 8-camera Optitrack Flex 13 motion capture system (Natural Point, OR, USA) was used to measure the 3-dimensional movements of the hand sampled at 120 Hz. Eight individual motion capture markers were attached to the prosthetic device on the thumb, index finger, and a rigid surface of the hand, as shown in Fig 5-2a. Additional individual markers were placed on task-relevant areas of the workspace (pasta box, shelving unit, and side table), as outlined in the supplementary materials of Valevicius et al.[26]. A head-mounted binocular eye tracker (Pupil Labs GmbH, Berlin, Germany) with 4 affixed motion capture markers (Fig 5-2b) was placed on the participant to record pupil movements sampled at 120 Hz. The cameras were optimally positioned, such that the pupils remained in frame when the eyes moved around the task space.

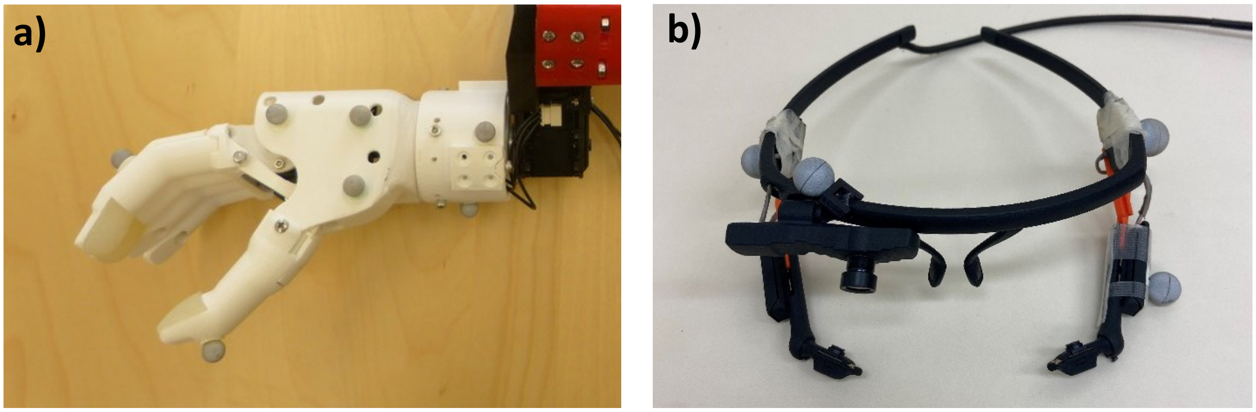


Figure 5-2: (a) Motion capture marker placement on the simulated prosthesis and (b) motion capture marker placement on the head-mounted eye tracker.

5.3.2.3 Pasta box task

A standardized Pasta Box Task, developed by Valevicius et al.[26], involved moving a pasta box from shelves at different heights to mimic a kitchen scenario. The task required participants to manipulate objects in different planes of movement. There were three movements: Movement 1 involved moving a pasta box from a lower table on the right side of the body to a shelf directly in front of the participant; Movement 2 involved moving the pasta box across the midline around a barrier to a second higher shelf; and Movement 3 consisted of a cross-body movement to return the pasta box to the initial starting position. Each movement began and ended when the hand was moved to a neutral 'home' position, which allowed for the motion capture and eye tracking data to be segmented into discrete movements. Each movement consisted of 4 phases: 'Reach', 'Grasp', 'Transport' and 'Release', which are defined in section 5.3.4. Fig 5-3 illustrates the movements and phases of the Pasta Box Task.

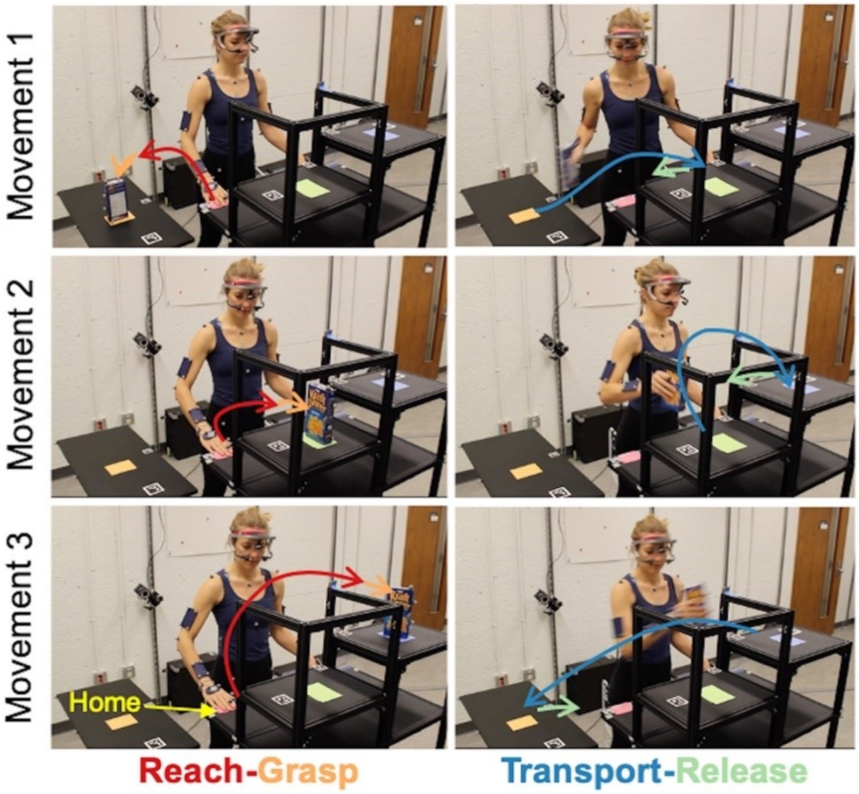


Figure 5-3: The pasta box task involves three movements in which a pasta box is moved to three different target locations. Each movement consists of a Reach (red arrow), Grasp (yellow arrow), Transport (blue arrow), and Release (green arrow) phase. The hand is moved to the labelled Home location between each movement. Image reproduced from Valevicius et al.[26].

5.3.3 Experimental procedure

On two separate days, participants performed functional tasks using the simulated prosthesis with either a baseline control strategy or a transfer learning control strategy. Testing sessions were separated by an average washout period of 27 ± 9 days to avoid any learning effects. Additionally, the order in which controllers were tested was randomized to counterbalance any potential learning effects. Four participants used the baseline strategy first, while the other three participants used the transfer learning strategy first.

5.3.3.1 Controller training

Before participants began controlling the prosthetic device, a controller training routine was performed to learn the muscle signals of the participant. EMG and IMU data were collected and streamed into Matlab using Myo Connect software. Custom Matlab scripts captured the data to learn an individual's intended movements from muscle patterns that were later used to send control signals to the prosthesis. Participants were instructed to perform moderate forearm muscle contractions while following onscreen instructions for specified wrist movements (rest, flexion, extension, pronation, supination).

The baseline control strategy used a statistical model (linear discriminant analysis) that was trained in one limb position. This training routine involved wrist at rest, flexion, extension, pronation and supination with the elbow bent at 90°, holding each muscle contraction for 5 seconds. This series of wrist movements were repeated twice. The EMG data resulting from this routine, along with the corresponding labels of wrist positions, were used to train the baseline control model.

The transfer learning control used a recurrent convolutional neural network (RCNN) model, developed by Williams et al.[109]. This model was originally trained with data from a large group of 19 individuals without upper limb impairment. These individuals performed a training routine involving each of the wrist movements in 4 arm positions (arm at side, elbow bent at 90°, arm out in front at 90°, and arm at 45° above shoulder height), as shown in Fig 5-4. Muscle contractions were maintained for 5 seconds and movements in each limb position were repeated twice. The EMG and accelerometer data from all 19 participants, along with the corresponding labels of wrist positions, were used to pre-train the transfer learning control model.

The transfer learning control model could then be retrained with data collected from each participant in this current study. The controller training routine involved repeating each of the wrist movements in 3 different arm positions (arm at side, elbow bent at 90°, arm at 45° above shoulder height), as shown in Fig 5-4. Muscle contractions were maintained for 2 seconds. Wrist movements in all 3 limb positions were repeated twice. Individual training data were then combined with the previously recorded larger training dataset to predict movement intent in different limb positions using deep learning models. The EMG and accelerometer data resulting from this routine, along with the corresponding labels of wrist positions, were used to train the transfer learning control model.

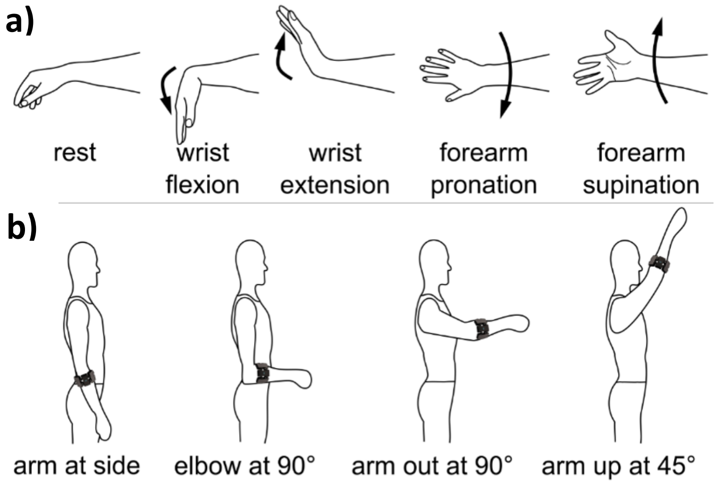


Figure 5-4: (a) Wrist movements and (b) arm positions used to perform controller training.

5.3.3.2 Prosthesis usage training

Each participant took part in a device usage training session to learn how to control the prosthetic hand using muscle activity. This training was completed for each testing session once the control strategy was trained. Participants progressed through a structured training protocol and were given the opportunity to practice functional tasks (including the Pasta Box Task) before the first trial where data was collected. There were 3 stages of training. Participants practiced controlling one degree of freedom (DOF) at a time – first, hand open and close only, followed by wrist rotation only. When successful with controlling each DOF separately, control over both DOFs was introduced in the last stage. A variety of picking up and placing objects, and object rotation tasks were presented to participants. As they carried out these tasks, verbal cues were given to help improve control of their device. Breaks were provided after each stage of training or as required. Full details of the prosthesis training protocol are outlined in Appendix D. To ensure that participants had sufficient control of the prosthesis, participants needed to demonstrate that they could successfully pick up a cup containing a ball and pour the ball into another cup. A 75% success rate after at least 10 trials within a 10-minute time period was required to continue onto the rest of the data collection.

5.3.3.3 Data collection

Prior to the first trial and immediately after the last trial of the Pasta Box Task, two gaze calibrations were collected to construct a gaze vector that represented the location of the participant's gaze in the task space. Participants were instructed to fixate on a motion capture marker attached to the tip of a calibration wand as the experimenter moved the wand through the task space. Additional details about the calibration process can be found in Appendix E. To synchronize the eye and motion tracking data, custom software was used to trigger the start and end of the recordings to temporally align the two data streams. Each participant performed 10 trials of the Pasta Box Task. If an error was made, the data from that trial was discarded. Errors included dropping the box, incorrect grasp, incorrect box placement, missing the drop off target, incorrect task sequence, hitting the task cart frame, movement hesitation, or undesired movements, such as a sneeze.

5.3.4 Data processing

Motion capture and eye tracking data were first cleaned to fill any gaps. Second-order, low-pass Butterworth filters with a cut-off frequency of 6 Hz for motion capture[26] and 10 Hz for eye tracking[28] were applied to remove any noise that may have been introduced during data collection. The motion capture and eye tracking data were then synchronized and divided in 'Reach', 'Grasp', 'Transport' and 'Release' phases for analysis, as described by Lavoie et al.[28] and Valevicius et al.[26].

The Reach phase began when the hand started moving away from the Home position and ended at the onset of Grasp. The Grasp phase began when the hand fell within a distance threshold to the pasta box and ended at the onset of Transport. The Transport phase began when the pasta box started moving and ended when the pasta box stopped moving. The Release phase began at the end of Transport and continued as the hand moved away from the pasta box, past a distance threshold, until the hand returned to the Home position. Distance thresholds values between the hand and the pasta box are defined in Lavoie et al.[28]. For hand kinematic measures, reach and grasp phases were combined into a reach-grasp segment, and transport and release phases were combined into a transport-release segment. Eye latency measures were defined relative to two key events: 'Pickup', which referred to the transition between grasp and transport as the object began moving and 'Drop off', which referred to the transition from transport to release as the object stopped moving. Using these object-related 'Pickup' and 'Drop off' events afforded the ability to reveal the temporal dynamics between the location of visual fixations and the location of the hand and object.

To ensure the accuracy and validity of the eye data, a set of rules were defined describing the quality of the best gaze vector and whether fixations were towards relevant areas of interest (AOIs). Firstly, a trial was removed if more than 15% of the best gaze vector data was missing or if the average distance to relevant AOIs for the best gaze vector was greater than 50mm. Secondly, a trial was removed if the total percent fixation (sum of percent fixation to current, hand and future) for any phase, except Reach in Movement 1 was less than 50%. In addition, a trial was removed if the total percent fixation in Reach of Movement 1 was less than 30%, as it is known that objects outside the field of view are fixated less[28]. Lastly, if more than 50% of a participant's trials from one testing session were removed, data from that participant was removed altogether. Therefore, one participant was removed due to poor quality of eye data. Fig 5-5 illustrates the steps taken to remove trials with poor eye data.

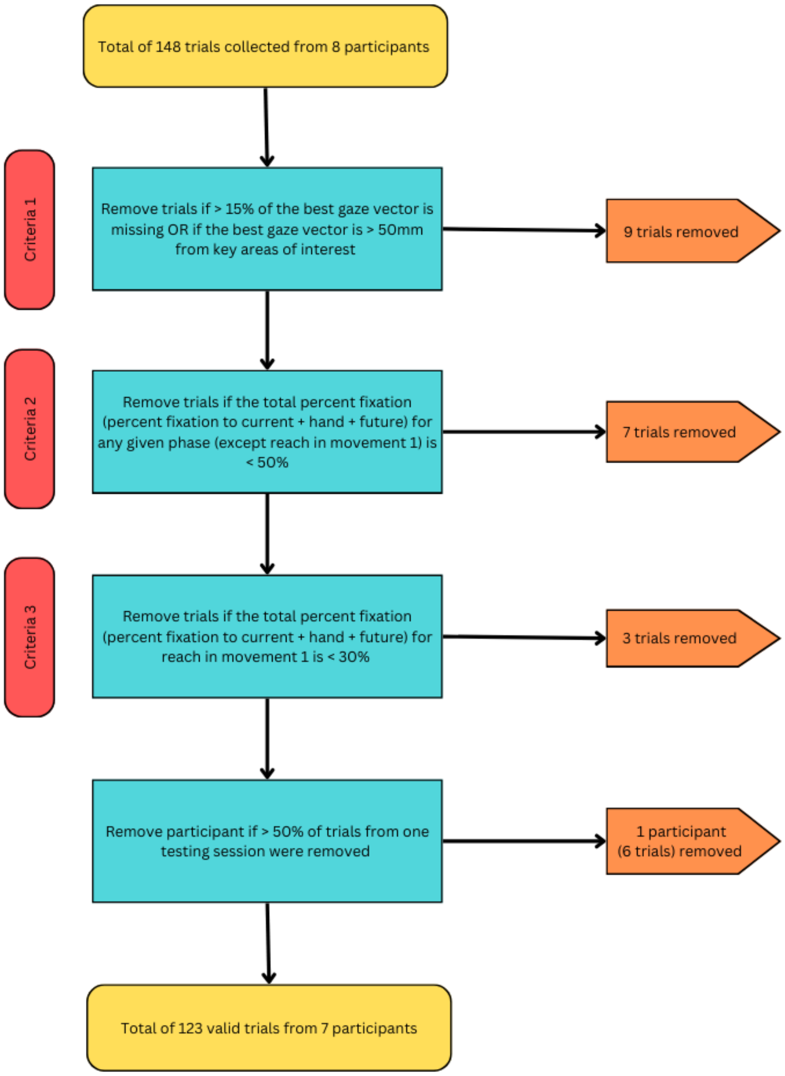


Figure 5-5: Flowchart outlining the steps taken to check the quality of the eye data. These criteria verified the amount of data loss and spatial accuracy of the best gaze vector that was constructed for each trial. A total of 25 trials out of 148 collected trials were removed (17% data loss). An average of 9 trials were retained for each participant for both control strategies.

5.3.5 Outcome metrics

5.3.5.1 Duration

Total task duration consisted of the total time in seconds to complete an entire trial. Phase duration was the time in seconds for each phase of reach, grasp, transport and release. Relative phase duration was the length of each phase represented as a percentage of the total movement time.

5.3.5.2 Hand kinematics

Peak hand velocity was defined as the maximum speed of the end effector (in any direction), given in mm/s. Number of movement units referred to the number of times that the hand acceleration profile crossed zero to produce a local velocity peak. Hand trajectory variability was calculated as the maximum of the mean three-dimensional standard deviation at each time-normalized point in millimetres. Grip aperture plateau was defined as the time in seconds between the end of hand opening and the start of hand closing. This was calculated when the grip aperture was < 90% of maximum and when the hand opening or closing velocity was < 20% of maximum. The definition for grip aperture plateau was adapted from Bouwsema et al.[46].

5.3.5.3 Gaze behaviour

Number of fixations referred to the number of continuous fixations (> 100 ms) to either the current target or the hand. Percent fixation was the amount of time spent fixating either the hand or the current target in reach and transport phases as a percentage of the duration of that phase. During the reach phase, the current target referred to the pasta box and its starting location. During the transport phase, the current target referred to the drop off location. A detailed description of the areas of interest for each phase of the pasta box task can be found in the supplementary materials of Lavoie et al.[28]. Eye arrival latency (EAL) was calculated as the difference between the time of eye arrival to the target location relative to the start of transport time for pickup and relative to the end of transport time for drop off. EAL values were positive if the eyes began fixating the target before the object was picked up or dropped off and negative if the eyes began fixating the target after the object was picked up or dropped off. EAL at pick-up was related to the reach-grasp segment. EAL at drop off was related to the transport-release segment. Eye leaving latency (ELL) was calculated as the difference between the time of the eye leaving the target location relative to the start of transport time for pick-up and relative to the end of transport time for drop off. A more positive number was attributed to a shorter ELL, whereas a more negative number was attributed to a longer ELL.

ELL at pick-up related to the transition point from grasp to transport and ELL at drop off was related to the transport-release segment.

5.3.5.4 General performance

The number of successes indicated the number of trials that were successfully completed without any errors, such as dropping the pasta box or an incorrect movement sequence. The NASA TLX[113] was administered to participants to measure subjective mental workload. The assessment involved rating the mental demand, physical demand, temporal demand, effort, performance, and frustration level involved in the Pasta Box Task on a 100-point scale. Participants then chose the factor that was perceived to be most relevant to workload and an overall task load index could then be calculated.

5.3.6 Statistical analysis

For each participant, the dependent measures were averaged across trials for each baseline control and transfer learning control. To investigate the within-subject differences between baseline and transfer learning, a series of repeated measures analyses of variance (RMANOVA) were conducted for each outcome measure. Significant interaction effects or main effects were followed up with additional RMANOVAs or pairwise comparisons. Only significant effects involving strategy were further investigated, as the primary focus was to determine whether different strategies had an effect on visuomotor performance. If the assumption of sphericity was violated, the Greenhouse-Geisser correction was used for the interpretation of results. Interaction effects or main effects were considered to be significant if the p value was less than 0.05 or if the Greenhouse-Geisser corrected p value was less than 0.05. Pairwise comparisons were considered to be significant if the Bonferroni corrected p value was less than 0.05. A detailed description of the statistical analysis methods can be found in Appendix F.

5.4 Results

5.4.1 Duration

5.4.1.1 Total task duration

There was no statistically significant difference in total task duration between control strategies $t(6) = 1.629$, $p = .154$, $d = 0.616$. Participants had an average total task duration of 28.6 ± 7.8s with the baseline controller and a total task duration of 24.0 ± 4.9s with the transfer learning controller, a mean difference of 4.6s (95% CI, -2.3 to 11.6s) [Table 5-6]. Although no difference was shown in the total task duration, there was a trend for movement times to be shorter with transfer learning. In movement 1, there was a mean difference of 1.0s (95% CI, -1.3 to 3.2s), in movement 2 there was a mean difference of 1.5s (95% CI, -0.5 to 3.4s), and in movement 3, there was a mean difference of 2.2s (95% CI, -0.6 to 4.9s) between baseline and transfer learning.

5.4.1.2 Phase duration

Overall, phase durations were reduced across all movement phases, with disproportionately large reductions in release time for movement 2 and grasp time for movement 3 with transfer learning compared to baseline, as shown in Fig 5-6. A significant three-way interaction ($F(1.974, 11.843) = 4.587$, $p = 0.034$) between strategy, movement and phase was revealed for phase durations. Simple two-way interactions were run for strategy x movement and strategy x phase. There was a statistically significant simple two-way interaction between strategy and movement for release ($F(2, 12) = 4.688$, $p = 0.031$). Pairwise comparisons revealed a mean difference of 0.866s (95% CI, -0.083 to 1.854s), $p = 0.066$ in release of movement 2 between baseline and transfer learning. Despite a non-significant difference at a Bonferroni adjusted $p < 0.05$, the magnitude of difference was large compared to other phases. In addition, a simple two-way interaction between strategy and movement for grasp was not found to be significant ($F(2, 12) = 3.080$, $p = 0.083$), however there was a large mean difference of 1.322s (95% CI, - .407 to 3.050s) in grasp of movement 3 between baseline and transfer learning, which was not observed in any other phases (Table 5-1). Therefore, release in movement 2 and grasp in movement 3 demonstrated trends towards shorter phase durations with the transfer learning controller compared to the baseline controller.

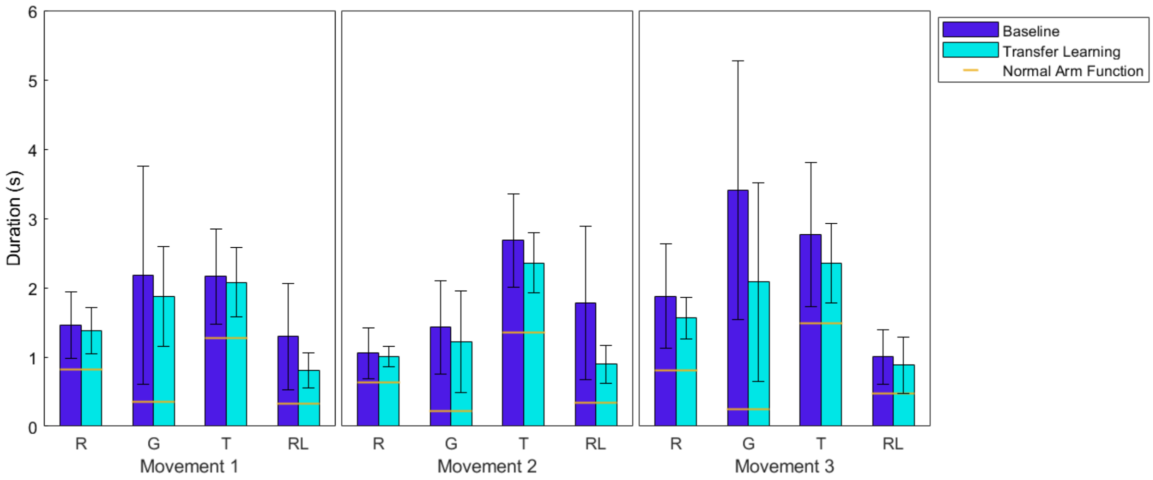


Figure 5-6: Mean phase durations with baseline (purple) and transfer learning (blue) control strategies for each movement and phase (R = Reach, G = Grasp, T = Transport, RL = Release) of the pasta box task. Normative values are represented by yellow lines. Error bars represent the standard deviation.

5.4.1.3 Relative phase duration

To accompany the changes in phase duration for release in movement 2 and grasp in movement 3, there was a corresponding decrease in relative duration for these phases. There was a trend in which transfer learning had a shorter relative duration of release in movement 2, which closely matched the normative value for relative release time as shown in Fig 5-7. A 3-way RMANOVA revealed a significant three-way interaction between strategy, movement and phase ($F(6, 36) = 3.313$, $p = 0.011$). Simple two-way interactions for strategy x movement and strategy x phase were run. There was a statistically significant simple two-way interaction between strategy and movement for release ($F(2, 12) = 7.756$, $p = .007$). Pairwise comparisons revealed there was a mean difference of 6.686% (95% CI, -.095 to 13.467%), $p = .052$ in release for movement 2 between baseline and transfer learning, although not significant at a Bonferroni adjusted $p < 0.05$ (Table 5-1).

In movement 3, the relative grasp duration was significantly reduced with transfer learning compared to the baseline control strategy. There was a statistically significant simple two-way interaction between strategy and phase for movement 3 ($F(3, 18) = 8.514$, $p < 0.001$). Pairwise comparisons revealed that there was a mean difference of 7.707% (95% CI, 4.276 to 11.138%), $p = 0.002$ between baseline and transfer learning for grasp in movement 3 (Table 5-1).

Similar to the differences in absolute phase durations, no other relative phase durations were found to be significantly different between transfer learning and baseline strategies. The large decrease in absolute release time for movement 2, in combination with a shorter total movement 2 duration of 5.5 ± 1.1s with transfer learning compared to 6.9 ± 2.2s with baseline, contributed to the trending decrease in relative release time for movement 2. A large mean difference in absolute grasp time for movement 3, together with a shorter total movement 3 duration of 6.9 ± 1.7s with transfer learning compared to 9.1 ± 2.9 with baseline, resulted in the significant decrease in relative grasp time for movement 3.

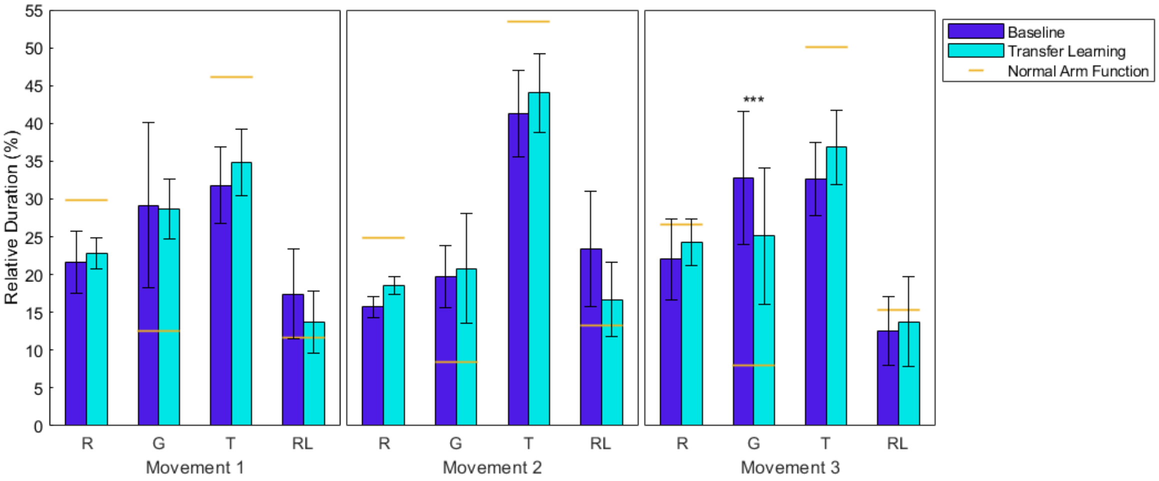


Figure 5-7: Mean relative phase duration with baseline (purple) and transfer learning (blue) control strategies for each movement and phase (R = Reach, G = Grasp, T = Transport, RL = Release) of the pasta box task. Normative values are represented by yellow lines. Error bars represent the standard deviation. Significant differences between control strategies are marked with asterisks with $p < 0.05$.

Table 5-1: Duration values for all movements and phases of the pasta box task with pairwise comparisons of baseline and transfer learning control strategies. A p value < 0.05 was considered to be significant, p values were given for observed trends, and ns indicates a p value that was not significant. Values are given as mean ± standard deviation.

		Phase duration (s)			Relative phase duration (%)		
Movement	Phase	*p*	Baseline	Transfer Learning	*p*	Baseline	Transfer Learning
1	Reach	ns	1.46 ± 0.48	1.38 ± 0.33	ns	21.6 ± 4.2	22.8 ± 2.0
	Grasp	ns	2.18 ± 1.57	1.87 ± 0.72	ns	29.1 ± 10.9	28.7 ± 4.0
	Transport	ns	2.16 ± 0.68	2.08 ± 0.50	ns	31.8 ± 5.0	34.8 ± 4.4
	Release	ns	1.30 ± 0.77	0.81 ± 0.25	ns	17.4 ± 5.9	13.8 ± 4.1
2	Reach	ns	1.06 ± 0.36	1.01 ± 0.15	ns	15.7 ± 1.5	18.5 ± 1.2
	Grasp	ns	1.43 ± 0.67	1.22 ± 0.73	ns	19.7 ± 4.1	20.8 ± 7.3
	Transport	ns	2.68 ± 0.67	2.36 ± 0.44	ns	41.3 ± 5.7	44.0 ± 5.2
	Release	0.066	1.78 ± 1.10	0.90 ± 0.28	0.052	23.3 ± 7.6	16.7 ± 4.9
3	Reach	ns	1.88 ± 0.75	1.56 ± 0.30	ns	22.0 ± 5.4	24.3 ± 3.1
	Grasp	ns	3.40 ± 1.87	2.08 ± 1.44	0.002	32.8 ± 8.8	25.1 ± 9.0
	Transport	ns	2.77 ± 1.04	2.35 ± 0.58	ns	32.6 ± 4.8	36.9 ± 4.9
	Release	ns	1.00 ± 0.40	0.88 ± 0.41	ns	12.6 ± 4.5	13.8 ± 6.0

5.4.2 Hand kinematic measures

5.4.2.1 Number of movement units

There were fewer movement units in all movement segments with the transfer learning controller than the baseline controller, however these differences were most notable in transport-release of movement 2 and reach-grasp of movement 3 (Fig 5-8). A 3-way RMANOVA revealed a statistically significant three-way interaction between strategy, movement and segment ($F(1, 6) = 10.622$, $p = 0.002$). Simple two-way interactions were run for strategy x movement and strategy x segment. A simple two-way interaction between strategy and movement for reach-grasp ($F(2, 12) = 4.730$, $p = 0.031$) was shown to be statistically significant, while there was no significant interaction between strategy and movement for transport-release ($F(2, 12) = 2.068$, $p = 0.169$). Pairwise comparisons revealed a trending mean difference of 9.860 (95% CI, -0.169 to 19.889), $p = 0.053$ movement units in reach-grasp of movement 3 between baseline and transfer learning (Table 5-2). In addition, although not significant, there was a disproportionately large mean difference of 8.341 (95% CI, -.552 to 17.235) movement units in transport-release of movement 2 (Table 5-2). These values represented large differences in movement units that were not observed in any other movement segments, therefore when using transfer learning, participants likely had increased smoothness of hand movements in transport-release of movement 2 and reach-grasp of movement 3.

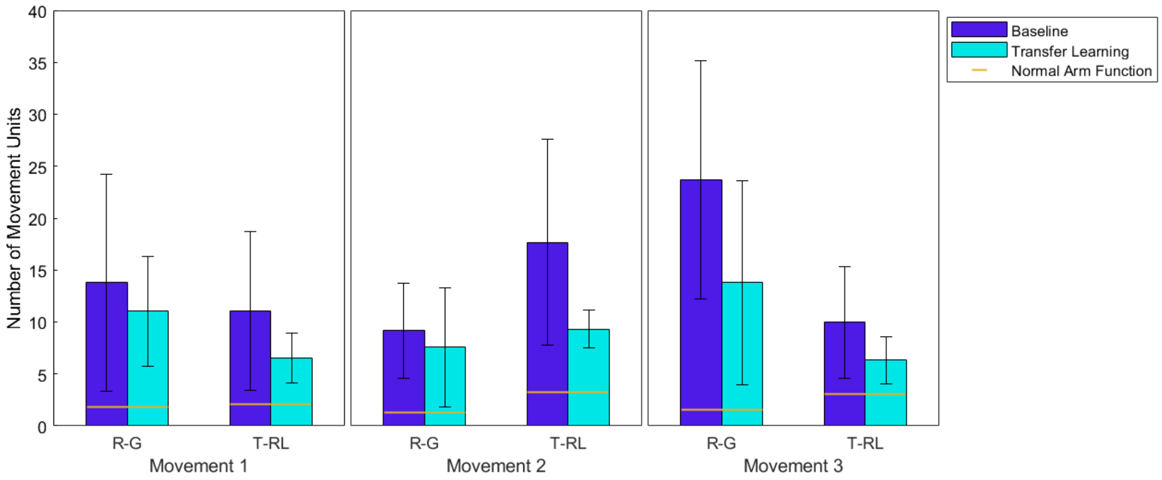


Figure 5-8: Mean number of movement units with baseline (purple) and transfer learning (blue) control strategies for each movement and movement segment (R-G = Reach-Grasp, T-RL = Transport-Release) of the pasta box task. Normative values are represented by yellow lines. Error bars represent the standard deviation.

5.4.2.2 Other hand kinematic measures

There were no significant interaction effects or main effects for hand trajectory variability, peak hand velocity and grip aperture plateau (Table 5-2).

Table 5-2: Hand metric values for all movements and phases of the pasta box task with pairwise comparisons of baseline and transfer learning control strategies. A *p* value < 0.05 was considered to be significant, *p* values were given for observed trends, and ns indicates a *p* value that was not significant. Values are given as mean ± standard deviation.

		Peak hand velocity (mm/s)		
Movement	Segment	*p*	Baseline	Transfer Learning
1	Reach-Grasp	ns	817.8 ± 159.7	789.2 ± 142.9
	Transport-Release	ns	851.1 ± 295.2	854.7 ± 220.5
2	Reach-Grasp	ns	714.4 ± 185.5	668.4 ± 170.0
	Transport-Release	ns	617.4 ± 158.9	644.5 ± 93.6
3	Reach-Grasp	ns	1002.4 ± 203.4	979.8 ± 147.5
	Transport-Release	ns	1097.4 ± 261.2	1158.6 ± 198.3
		Hand trajectory variability (mm)		
Movement	Segment	*p*	Baseline	Transfer Learning
1	Reach-Grasp	ns	69.4 ± 22.5	62.2 ± 31.7
	Transport-Release	ns	62.9 ± 35.1	52.9 ± 15.8
2	Reach-Grasp	ns	36.1 ± 14.1	35.4 ± 15.2
	Transport-Release	ns	65.0 ± 24.5	43.3 ± 15.3
3	Reach-Grasp	ns	95.8 ± 28.4	73.4 ± 43.9
	Transport-Release	ns	89.4 ± 33.2	81.5 ± 36.0
		Number of movement units		
Movement	Segment	*p*	Baseline	Transfer Learning
1	Reach-Grasp	ns	13.8 ± 10.4	11.0 ± 5.3
	Transport-Release	ns	11.0 ± 7.7	6.5 ± 2.4
2	Reach-Grasp	ns	9.2 ± 4.6	7.6 ± 5.7
	Transport-Release	ns	17.7 ± 9.9	9.3 ± 1.8
3	Reach-Grasp	0.053	23.7 ± 11.5	13.8 ± 9.8
	Transport-Release	ns	10.0 ± 5.4	6.3 ± 2.3
		Grip aperture plateau time (s)		
Movement	Segment	*p*	Baseline	Transfer Learning
1	Reach-Grasp	ns	1.87 ± 0.71	1.54 ± 0.61
2	Reach-Grasp	ns	1.49 ± 0.51	1.37 ± 0.60
3	Reach-Grasp	ns	2.66 ± 0.98	2.09 ± 0.95

5.4.3 Eye gaze metrics

5.4.3.1 Percent fixation

With transfer learning, there was a significant decrease in percent fixation to hand in movement 3 with transfer learning compared to baseline (Table 5-3). A 3-way RMANOVA revealed no significant three-way interaction between strategy, movement and phase ($F(2, 12) = 1.367$, $p = 0.292$). However, there was a statistically significant two-way strategy x movement interaction ($F(2, 12) = 5.231$, $p = 0.023$) and no significant strategy x phase interaction ($F(1, 6) = 1.339$, $p = 0.291$). Pairwise comparisons revealed a significant mean difference of 5.544% (95% CI, 0.448 to 10.639%), $p = 0.037$ between baseline and transfer learning in movement 3 (Table 5-3). Figure 5-9 demonstrates the decrease in percent fixation to hand occurred in both reach and transport phases in movement 3, while there was no difference in fixations towards the hand between controllers in any other movement. Therefore, when using the transfer learning controller, participants had a reduced reliance on vision to monitor the hand in movement 3. Decreased fixations towards the hand were not accompanied by increased fixations towards the current target. A 3-way RMANOVA revealed no other significant interaction effects or main effects for percent fixation to current (Table 5-5).

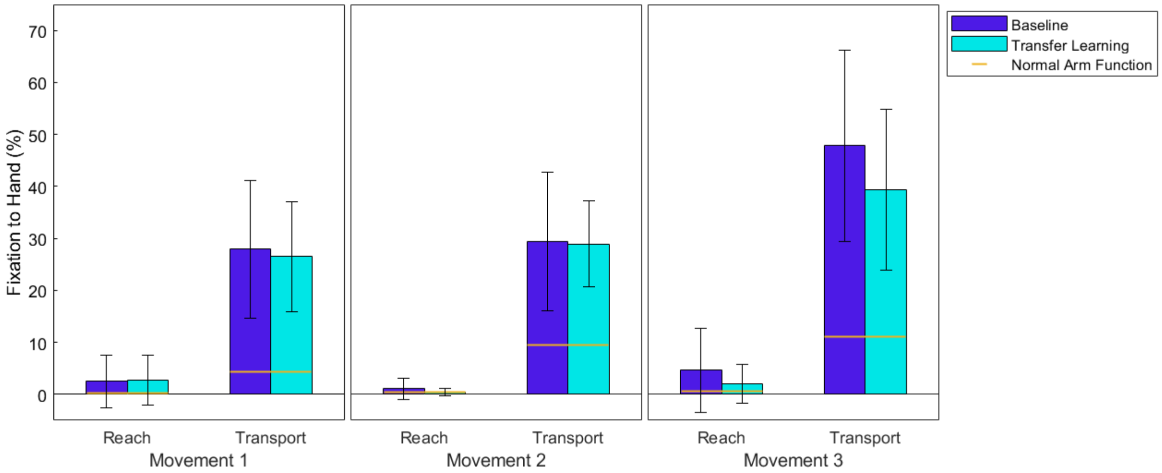


Figure 5-9: Percent fixation to hand with baseline (purple) and transfer learning (blue) control strategies for reach and transport phases of each movement of the pasta box task. Normative values are represented by yellow lines. Error bars represent the standard deviation.

Table 5-3: Percent fixation to hand values for individual movements collapsed across reach and transport phases of the pasta box task with pairwise comparisons of baseline and transfer learning control strategies. A *p* value < 0.05 was considered to be significant, *p* values were given for observed trends, and ns indicates a *p* value that was not significant. Values are given as mean ± standard error.

	Percent fixation to hand (%)		
Movement	*p*	Baseline	Transfer Learning
1	ns	15.2 ± 2.8	14.6 ± 2.7
2	ns	15.2 ± 2.7	14.7 ± 1.5
3	0.037	26.2 ± 4.4	20.7 ± 3.1

5.4.3.2 Eye leaving latency

In general, transfer learning resulted in shorter eye leaving latencies compared to the baseline control strategy (Table 5-5). A 3-way RMANOVA revealed no significant three-way interaction between strategy, movement and event ($F(2, 12) = 3.625$, $p = 0.059$). There was no significant two-way interaction between strategy and movement ($F(2, 12) = 3.274$, $p = 0.073$) or strategy and event ($F(1, 6) = 0.411$, $p = 0.545$). However, there was a significant main effect of strategy ($F(1, 6) = 6.419$, $p = 0.044$) with a mean difference of -0.468s (95% CI, -0.920 to -0.016s), $p = 0.044$ (Table 5-4). Figure 5-10 reveals that eye leaving latencies were consistently shorter across all movements and events with transfer learning compared to baseline, with a disproportionate difference of -1.081s (95% CI, -1.926 to -.236s) at drop off in movement 2. Therefore, the transfer learning control strategy required a shorter time for the eyes to disengage visual attention from pick up and drop off targets than the baseline control strategy.

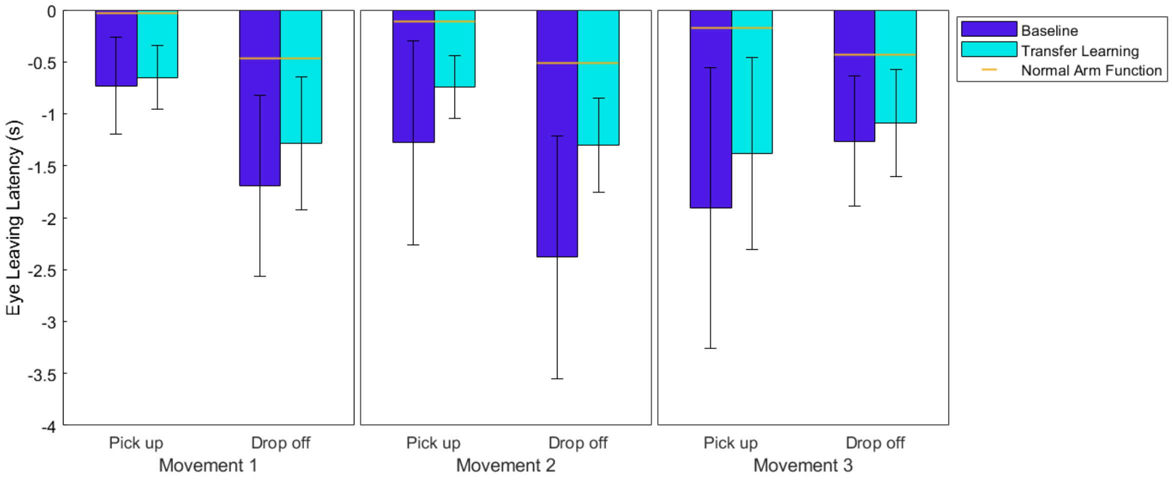


Figure 5-10: Mean eye leaving latency with baseline (purple) and transfer learning (blue) control strategies for each movement and event (pick up and drop off) of the pasta box task. Normative values are represented by yellow lines. Error bars represent the standard deviation.

Table 5-4: Eye leaving latency values collapsed across all movements and phases of the pasta box task with pairwise comparisons of baseline and transfer learning control strategies. A p value < 0.05 was considered to be significant, p values were given for observed trends, and ns indicates a p value that was not significant. Values are given as mean ± standard error.

Eye leaving latency (s)		
p	Baseline	Transfer Learning
0.044	-1.54 ± 0.28	-1.07 ± 0.14

5.4.3.3 Other eye gaze metrics

There were no other significant interaction effects or main effects for number of fixations to current or to hand, eye arrival latency at pick up, eye arrival latency at drop off, or eye leaving latency at drop off (Table 5-5).

Table 5-5: Eye metric values for all movements and phases of the pasta box task with pairwise comparisons of baseline and transfer learning control strategies. A p value < 0.05 was considered to be significant, p values were given for observed trends, and ns indicates a p value that was not significant. Values are given as mean ± standard deviation.

		Number of fixations to current			Percent fixation to current (%)		
Movement	Phase	*p*	Baseline	Transfer Learning	*p*	Baseline	Transfer Learning
1	Reach	ns	1.05 ± 0.09	0.99 ± 0.04	ns	60.5 ± 11.8	58.3 ± 13.8
	Grasp	ns	1.17 ± 0.26	1.11 ± 0.30	ns	97.6 ± 5.3	98.4 ± 4.3
	Transport	ns	1.11 ± 0.13	1.14 ± 0.18	ns	61.9 ± 7.7	60.9 ± 6.2
	Release	ns	1.04 ± 0.11	1.00 ± 0.00	ns	98.3 ± 3.2	98.1 ± 3.1
2	Reach	ns	1.19 ± 0.23	1.03 ± 0.05	ns	94.3 ± 6.2	96.3 ± 3.2
	Grasp	ns	1.10 ± 0.17	1.03 ± 0.05	ns	98.3 ± 2.6	99.3 ± 1.1
	Transport	ns	1.18 ± 0.15	1.07 ± 0.08	ns	67.1 ± 10.8	65.7 ± 6.9
	Release	ns	1.07 ± 0.13	1.00 ± 0.00	ns	99.0 ± 1.3	99.2 ± 1.3
3	Reach	ns	1.06 ± 0.10	1.04 ± 0.06	ns	87.4 ± 8.1	90.5 ± 6.8
	Grasp	ns	1.57 ± 0.98	1.10 ± 0.18	ns	98.1 ± 3.7	98.2 ± 3.7
	Transport	ns	1.08 ± 0.11	1.04 ± 0.06	ns	42.1 ± 9.1	45.5 ± 12.9
	Release	ns	1.01 ± 0.04	1.00 ± 0.00	ns	97.8 ± 3.1	98.0 ± 2.1
		Number of fixations to hand			Percent fixation to hand (%)		
Movement	Phase	*p*	Baseline	Transfer Learning	*p*	Baseline	Transfer Learning
1	Reach	ns	0.19 ± 0.34	0.15 ± 0.29	ns	2.5 ± 5.1	2.7 ± 4.8
	Transport	ns	1.21 ± 0.23	1.18 ± 0.39	ns	27.9 ± 13.2	26.5 ± 10.5
2	Reach	ns	0.05 ± 0.09	0.05 ± 0.06	ns	1.1 ± 2.0	0.4 ± 0.7
	Transport	ns	1.21 ± 0.18	1.13 ± 0.16	ns	29.4 ± 13.4	28.9 ± 8.2
3	Reach	ns	0.16 ± 0.22	0.15 ± 0.25	ns	4.6 ± 8.1	2.0 ± 3.7
	Transport	ns	1.26 ± 0.27	1.30 ± 0.32	ns	47.8 ± 18.4	39.3 ± 15.5
		Eye arrival latency (s)			Eye leaving latency (s)		
Movement	Event	*p*	Baseline	Transfer Learning	*p*	Baseline	Transfer Learning
1	Pickup	ns	3.07 ± 1.54	2.66 ± 0.74	ns	-0.73 ± 0.47	-0.65 ± 0.31
	Dropoff	ns	1.26 ± 0.35	1.19 ± 0.19	ns	-1.69 ± 0.87	-1.28 ± 0.64
2	Pickup	ns	2.42 ± 0.83	2.18 ± 0.85	ns	-1.28 ± 0.98	-0.74 ± 0.30
	Dropoff	ns	1.60 ± 0.14	1.46 ± 0.26	ns	-2.38 ± 1.17	-1.30 ± 0.45
3	Pickup	ns	4.56 ± 1.26	3.48 ± 1.52	ns	-1.91 ± 1.35	-1.38 ± 0.92
	Dropoff	ns	1.07 ± 0.22	1.01 ± 0.18	ns	-1.26 ± 0.63	-1.09 ± 0.52

5.4.4 General performance

There was no significant difference in the number of successful trials, *t*(6) = .354, *p* = .736, *d* = .134. On average, participants completed 9.6 ± 0.5 trials with the baseline control strategy and 9.4 ± 0.8 trials with the transfer learning control strategy. There was no significant difference in mental workload rating, as assessed by the NASA TLX, *t*(6) = -.211, *p* = .840, *d* = -0.080. Participants had a weighted rating of 47.0 ± 10.7 for baseline and 47.8 ± 10.8 for transfer learning (Table 5-6).

Table 5-6: General performance metrics values with pairwise comparisons of baseline and transfer learning control strategies. A p value < 0.05 was considered to be significant, p values were given for observed trends, and ns indicates a p value that was not significant. Values are given as mean ± standard deviation.

	p	Baseline	Transfer Learning
Task duration (s)	ns	28.6 ± 7.8	24.0 ± 4.9
Number of successes	ns	9.6 ± 0.5	9.4 ± 0.8
NASA TLX	ns	47.0 ± 10.7	47.8 ± 10.8

5.5 Discussion

This study aimed to investigate whether the visuomotor behaviours of myoelectric prosthesis users could be improved with a novel advanced control strategy. In general, findings from the present study demonstrated that visuomotor performance was improved to more closely resemble normative behaviour with a transfer learning control strategy compared to a baseline control strategy. Visual attention towards the hand was reduced with the advanced control strategy, as demonstrated by a significant reduction in eye latencies throughout the task and percent fixation to hand in movement 3. The advanced control strategy also demonstrated trends in which performance time was reduced and hand kinematic function was improved. These improvements were only observed when the arm was in a cross-body position that was at or above the participant's shoulder height. When the arm was oriented in this position, variations to the EMG signals recorded from the forearm likely rendered the control challenging when using the baseline controller. To address the limb position effect, an advanced control strategy that used transfer learning methods, likely remedied this issue by improving the reliability of myoelectric control in an extended arm position and thereby reduced the reliance on vison to monitor the prosthetic hand.

5.5.1 General performance metrics provide an incomplete analysis of movement behaviour

General performance metrics, including total task duration and number of successes, demonstrated no significant difference between baseline and transfer learning control strategies. This finding was in contrast to studies that demonstrated a reduction in task completion time with novel control strategies aimed at mitigating the limb position effect[114–116]. Although researchers have commonly reported completion times and success rates to assess the functional performance of myoelectric prostheses[117–119], these metrics do not provide a complete understanding of the quality of hand, wrist and arm movements, or inform about the underlying mechanisms driving these changes in overall performance[26,29]. Therefore, this rationale lends motivation for an assessment of the visuomotor performance to examine patterns of eye and hand movements during functional task performance. With GaMA, this assessment tool further affords the ability to analyze participant's behaviour in individual movements and phases to reveal the nuances of various types of movements in order to identify specific instances of the limb position effect.

5.5.2 Advanced myoelectric control outperformed baseline control

Differences between hand kinematic measures suggest that the advanced control strategy performed better than the baseline control strategy, as shown by trends towards shorter phases durations and smoother movements. Despite a non-significant difference in total task duration between control strategies, shorter durations were revealed at the phase level. Specifically, there was a trend towards shorter release times and relative release times in movement 2 with the advanced control strategy. There was a large but non-significant reduction in grasp time and a significant reduction in relative grasp time in movement 3 compared to baseline. In line with previous work, grasp and release phases were disproportionately prolonged for prosthesis users[8]. With an advanced control strategy, we have shown that these phase durations could be reduced. In addition, there were smoother movements, such as fewer unwanted wrist rotations and changes in grip aperture, as evidenced by trends towards fewer movement units in transport-release for movement 2 and reach-grasp for movement 3. Together these findings demonstrate that the advanced control strategy improved hand kinematic performance in phases where the pasta box was moved to and from the highest shelf of the pasta box task with a myoelectric prosthesis.

Differences in performance between control strategies provide evidence of the limb position effect. The baseline controller had poorer control than the advanced control strategy when the elbow was fully extended and the arm was raised at or above shoulder height. In this position, different muscle activation patterns may have contributed to these myoelectric control issues[120,121]. Teh et al.[114] previously demonstrated that positions in which the elbow was fully extended, yielded the poorest performance for both subjects with intact limbs and amputation. When the elbow is extended, the brachioradialis is activated to stabilize the arm[122,123]. As the brachioradialis is also involved in forearm pronation and supination[124], activation of this muscle may have contributed to unwanted wrist movements and an increased number of movement units, which rendered the control difficult. However, the advanced control strategy included both hand motion and arm position predictions in the model to improve the accuracy and reliability of movement predictions in multiple limb positions. Prosthetic control was therefore improved when using this controller in positions where the elbow was fully extended, effectively mitigating the limb position effect.

5.5.3 Improving myoelectric control reduced reliance on vision

We additionally demonstrate, for the first time, that improving the reliability of myoelectric control reduced the reliance on vision to monitor the prosthetic hand. With an advanced control strategy, visual fixations towards the hand were significantly reduced in movement 3, which involved cross-body reaching and transporting actions. It was likely that significant changes stemmed from a large decrease in percent fixation in transport because participants trusted that the hand would not open unexpectedly while transporting the pasta box from the pick up location to the drop off location. An increased difficulty to release objects using the baseline controller led to an inability to disengage visual attention from drop off locations, whereas with the advanced control strategy, an improved ability to release objects, most notably in movement 2, also reduced the latency for the eyes to shift away.

The unpredictability of myoelectric control draws visual attention towards the prosthesis to ensure that the hand performs as intended and cannot be alleviated even with higher skill level or traditional movement training. Bouwsema et al.[46] have shown that some experienced prosthesis users with high functional skill level had gaze behaviours that were consistent with novice users. Parr et al.[10] demonstrated that when novice prosthesis users were provided with explicit movement-based training instructions, no changes in gaze behaviour were observed over multiple training sessions, despite faster movements. Interestingly, in our cohort of novice users of myoelectric prostheses, limited training with an advanced myoelectric control revealed initial improvements in visuomotor performance. Without any additional training over multiple testing sessions, participants adopted more proficient control with transfer learning than baseline, which was able to alleviate visual attention towards the hand.

Parr et al.[61] proposed that the unreliable nature of prosthetic devices continually prevents normal sensorimotor mapping rules from developing. Typically, individuals with intact limb function rely on vision in the initial stages of motor learning, however the reliance on vision can usually be overcome as skill acquisition progresses and sensory feedback information becomes integrated into the motor control loop[90,92]. In contrast to intact limb function, which responds to reliable motor commands, there can be unreliable responses in myoelectric prostheses due to variations in EMG signals in different arm position. Moreover, prosthesis users lack the tactile and proprioceptive feedback pathways that are typically provided by the anatomical limb. By implementing a more reliable control system that takes into account multiple limb positions, we have been able to alleviate the visual demand experienced by prosthesis users, likely revealing an increased confidence in the prosthetic control.

5.5.4 Relevance of real-time functional testing with the inclusion of eye tracking

In this research, we have aimed to quantify the visuomotor behaviours of prosthesis users in response to control interventions during an experimental task that closely resembles everyday tasks. Although many studies have developed new methods to mitigate the limb position effect, the majority of these studies evaluated offline performance[100,101,125–128], while a few studies investigated the real-time effects during a simple target achievement task[114–116]. Offline classification accuracy may not be a sufficient metric, as it does not always translate to the usability of myoelectric devices[129,130]. In an attempt to close the gap between lab-based research findings and actual clinical use, we employed a functional task that was designed specifically to challenge users in multiple planes of movement, while testing the real-time performance of a novel control strategy. In doing so, we have highlighted the challenges of cross-body movements, while no other movements demonstrated any difference in visuomotor performance between control strategies. Importantly, the use of eye tracking has enabled us to further assess the usability of myoelectric prostheses. Reduced visual fixations towards the hand suggests that the mental workload was reduced[83], thus making the prosthesis more useable. Therefore, future work should consider the practicality of the experimental task and the translatability of research findings, particularly as the work relates to implementing solutions meant to overcome the challenges encountered with the physical attachment of a prosthesis. Moreover, we recommend the inclusion of eye tracking metrics in control comparison studies, as these metrics have presently been shown to be sensitive to control interventions.

5.5.5 Limitations

Firstly, the number of significant findings were limited in power. Although we observed many trends in transport-release for movement 2 and reach-grasp for movement 3, these findings likely were not significant due to a small sample size of 7 that were included in the statistical analyses. In addition, participants of this study were without limb difference and performed experimental tasks using a simulated myoelectric prosthesis. Limb loading has been shown to differ in intact limb individuals and individuals with amputation, which can be explained by anatomical differences[114]. Individuals with intact limbs have greater moments across the elbow to support the weight of the anatomical hand, resulting in different muscle activation patterns than individuals with a transradial amputation that no longer have forearm muscles crossing the wrist joint[114]. Future work should investigate whether the visuomotor behaviours of individuals with upper limb amputation would likewise be sensitive to myoelectric control interventions.

In this experimental design, participants were given the opportunity to practice using the prosthesis prior to the recorded trials, but training over multiple days was not provided. It is unknown to what extent participants were able to learn to use the prosthesis within a short amount of time. However, we postulate that the observed visuomotor behaviours may have been representative of mid-skilled prosthesis users[62]. Given a more reliable control, it is possible that with repeated testing over multiple days, participants may have been able to learn to develop a more reliable feedforward control strategy, as with normal patterns of motor learning, thereby further reducing the reliance on vision. Presently, we have only described the effects of modulating prosthetic control on improving visuomotor behaviour without considering the role of sensory feedback. However, successful object manipulation relies on both feedforward and feedback control mechanisms[3]. Notably in prosthesis use, control is not often optimal, thus sensory feedback may provide an equally important role in determining prosthesis performance[11,73,131] and may further aid in developing typical patterns of visuomotor behaviour. Therefore, future work could explore the potential benefit of combined control and feedback interventions and whether these combined effects can further improve gaze behaviour and the usability of myoelectric prostheses.

Although we have demonstrated that an advanced control strategy can alleviate the need to visually monitor the prosthesis, we did not see a corresponding improvement in participant's subjective mental workload ratings, as indicated by the NASA TLX. The objective of measuring gaze behaviour was to understand whether improvements in prosthesis control would result in more natural visuomotor behaviours and hence provide an indicator of usability. Therefore, we would have expected reductions in visual fixations towards the hand and shorter eye leaving latencies to relate to a decrease in overall workload rating, including factors such as mental demand, effort and frustration. However, the NASA TLX that was employed in the current study may not have been appropriate for this cohort of participants using a simulated prosthesis[132]. Recently, a prosthesis user-specific task load index (PROS-TLX) was developed and validated, demonstrating the relationship between visual fixations and mental workload factors[83]. Future work could consider the inclusion of the PROS-TLX to capture the user experience of upper limb prosthesis users, as it is ultimately users' satisfaction that will determine whether prosthetic devices will be well-adopted.

5.6 Conclusion

This work investigated the effect of different myoelectric control strategies on visuomotor behaviours and provided a novel contribution – that eye metrics are sensitive to control interventions. The advanced myoelectric control strategy proved to be more reliable than the baseline control strategy. As a result, a more reliable control likely increased users' confidence in the prosthesis and enabled users to visually fixate less on their prosthesis. In addition, the baseline controller highlighted the challenges with controlling a prosthesis in a fully extended cross-body arm position. The implementation of a novel control strategy, that included both arm position and movement intent predictions, essentially mitigated the control challenges associated with the limb position effect. Therefore, a more reliable prosthesis that performs as intended has the potential to reduce the visual demands associated with prosthetic use, thereby making myoelectric prostheses more useable for the users. Moreover, eye tracking served as a purposeful tool in understanding the changes in gaze behaviours of prosthesis users. Future work should thus consider the inclusion of eye tracking in future prosthesis control comparison studies.

Chapter 6: Summary of Contributions

In Chapter 3 a literature review was undertaken to provide a comprehensive overview of the existing literature on the visual behaviours of upper limb prosthesis users. The findings in this research presented a detailed understanding of how prosthesis users visually interact with their devices. Prosthesis users have a characteristic visuomotor behaviour, such that the eyes fixate more towards the hand and less towards target objects or locations, compared to intact limb individuals. Some studies have suggested that more experienced prosthesis users demonstrate patterns of eye-hand coordination that are more typical with individuals with intact arm function, however these findings have been inconsistent. Therefore, the link between gaze behaviour and prosthetic skill level remained unknown. The reviewed literature additionally demonstrated that eye tracking metrics were sensitive to sensory feedback interventions, providing evidence that advancements in prosthetics research is beneficial in alleviating the visual and cognitive demands of prosthesis users. However, there was little evidence on the impact of modulating prosthetic control factors, such as novel control strategies, on the visuomotor behaviours of prosthesis users.

In Chapter 4, the relationship between gaze behaviour and skill level was confirmed, using hand kinematics as a measure of skill. Eye gaze behaviours that were reflective of improved motor planning were associated with more efficient hand movement patterns and indicated increased prosthetic functionality. This understanding of the complex coordination between eye and hand movements of upper limb prosthesis users has the potential to guide the development of more effective prosthetic technologies that are likewise more intuitive and user-friendly solutions. More specifically, in Chapter 5, the next step was to determine whether addressing the unpredictability of myoelectric control could alleviate the demand on the visual system.

In Chapter 5, an advanced myoelectric control strategy was implemented in real-time to address the limb position effect and to provide users with a more reliable control strategy. A fully extended, raised arm position was identified as a challenging limb position in which control was unreliable. Using a novel control strategy, that included both arm position and movement intent predictions, these control challenges were mitigated. As a result, a more reliable control strategy alleviated visual monitoring of the prosthetic hand, suggesting that users had increased confidence that the prosthesis would perform as intended.

Altogether, this work has highlighted the importance of eye tracking as an evaluation tool for upper limb prosthesis users. Importantly, this thesis provided a novel contribution – that eye metrics are sensitive to control interventions. Given the research findings highlighted in this thesis, future work should consider the inclusion of eye tracking as an outcome measure when evaluating novel prosthetic interventions. This is to ensure that research work is guided towards developing more user-centered prostheses that are both functional and useable, as it is ultimately the usability that will determine the acceptance of these devices and the impact on the quality of life of prosthesis users.

References

1. Cordella F, Ciancio AL, Sacchetti R, Davalli A, Cutti AG, Guglielmelli E, et al. Literature Review on Needs of Upper Limb Prosthesis Users. Front Neurosci. 2016;10:209.

2. Bates TJ, Fergason JR, Pierrie SN. Technological Advances in Prosthesis Design and Rehabilitation Following Upper Extremity Limb Loss. Curr Rev Musculoskelet Med. 2020;13(4):485–93.

3. Hermsdörfer J, Elias Z, Cole JD, Quaney BM, Nowak DA. Preserved and Impaired Aspects of Feed-Forward Grip Force Control After Chronic Somatosensory Deafferentation. Neurorehabil Neural Repair. 2008;22(4):374–84.

4. Gordon AM, Westling G, Cole KJ, Johansson RS. Memory representations underlying motor commands used during manipulation of common and novel objects. J Neurophysiol. 1993;69(6):1789–96.

5. MacKenzie CL, Iberall T. The Grasping Hand. North Holland (Netherlands): Elsevier; 1994.

6. Wolpert DM, Ghahramani Z, Jordan MI. An Internal Model for Sensorimotor Integration. Science. 1995;269(5232):1880–2.

7. Nowak DA, Hermsdörfer J. Selective deficits of grip force control during object manipulation in patients with reduced sensibility of the grasping digits. Neurosci Res. 2003;47(1):65–72.

8. Hebert JS, Boser QA, Valevicius AM, Tanikawa H, Lavoie EB, Vette AH, et al. Quantitative Eye Gaze and Movement Differences in Visuomotor Adaptations to Varying Task Demands Among Upper-Extremity Prosthesis Users. JAMA Netw Open. 2019 ;2(9):e1911197.

9. Parr JVV, Vine SJ, Harrison NR, Wood G. Examining the Spatiotemporal Disruption to Gaze When Using a Myoelectric Prosthetic Hand. J Mot Behav. 2018;50(4):416–25.

10. Parr JVV, Vine SJ, Wilson MR, Harrison NR, Wood G. Visual attention, EEG alpha power and T7-Fz connectivity are implicated in prosthetic hand control and can be optimized through gaze training. J Neuroeng Rehabil. 2019;16(1):52.

11. Saunders I, Vijayakumar S. The role of feed-forward and feedback processes for closed-loop prosthesis control. J Neuroeng Rehabil. 2011;8(1):60.

12. Marinelli A, Boccardo N, Tessari F, Domenico DD, Caserta G, Canepa M, et al. Active upper limb prostheses: a review on current state and upcoming breakthroughs. Prog Biomed Eng. 2023;5(1):012001.

13. Geethanjali P. Myoelectric control of prosthetic hands: state-of-the-art review. Med Devices (Auckl). 2016;9:247–55.

14. Scheme E, Englehart K. Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use. J Rehabil Res Dev. 2011;48(6):643.

15. Campbell E, Phinyomark A, Scheme E. Current Trends and Confounding Factors in Myoelectric Control: Limb Position and Contraction Intensity. Sensors. 2020;20(6):1613.

16. Head JS. The effect of socket movement and electrode contact on myoelectric prosthesis control during daily living activities [Internet] [PhD thesis]. University of Salford; 2014 [cited 2023 Feb 12]. Available from: https://usir.salford.ac.uk/id/eprint/30774/

17. Young AJ, Hargrove LJ, Kuiken TA. The Effects of Electrode Size and Orientation on the Sensitivity of Myoelectric Pattern Recognition Systems to Electrode Shift. IEEE Trans Biomed Eng. 2011;58(9):2537–44.

18. Clancy EA, Morin EL, Merletti R. Sampling, noise-reduction and amplitude estimation issues in surface electromyography. J Electromyogr Kinesiol. 2002 Feb;12(1):1–16.

19. Chen Z, Min H, Wang D, Xia Z, Sun F, Fang B. A Review of Myoelectric Control for Prosthetic Hand Manipulation. Biomimetics. 2023 Jul;8(3):328.

20. Light CM, Chappell PH, Kyberd PJ. Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: normative data, reliability, and validity. Arch Phys Med Rehabil. 2002;83(6):776–83.

21. Lindner HY, Linacre JM, Norling Hermansson LM. Assessment of capacity for myoelectric control: evaluation of construct and rating scale. J Rehabil Med. 2009 May;41(6):467-74.

22. Resnik L, Adams L, Borgia M, Delikat J, Disla R, Ebner C, et al. Development and evaluation of the activities measure for upper limb amputees. Arch Phys Med Rehabil. 2013 Mar;94(3):488-494.e4.

23. Mathiowetz V, Volland G, Kashman N, Weber K. Adult norms for the Box and Block Test of manual dexterity. Am J Occup Ther. 1985 Jun;39(6):386–91.

24. Kyberd P, Hussaini A, Maillet G. Characterisation of the Clothespin Relocation Test as a functional assessment tool. J Rehabil Assist Technol Eng. 2018 Jan 1;5:2055668317750810.

25. Wang S, Janice Hsu C, Trent L, Ryan T, Kearns NT, Civillico EF, et al. Evaluation of Performance-Based Outcome Measures for the Upper Limb: A Comprehensive Narrative Review. PM R. 2018 Sep;10(9):951-962.e3.

26. Valevicius AM, Boser QA, Lavoie EB, Murgatroyd GS, Pilarski PM, Chapman CS, et al. Characterization of normative hand movements during two functional upper limb tasks. Nordez A, editor. PLoS One. 2018;13(6):e0199549.

27. Cognolato M, Atzori M, Müller H. Head-mounted eye gaze tracking devices: An overview of modern devices and recent advances. J Rehabil Assist Technol Eng. 2018;5.

28. Lavoie EB, Valevicius AM, Boser QA, Kovic O, Vette AH, Pilarski PM, et al. Using synchronized eye and motion tracking to determine high-precision eye-movement patterns during object-interaction tasks. J Vis. 2018;18(6):18.

29. Valevicius AM, Boser QA, Lavoie EB, Chapman CS, Pilarski PM, Hebert JS, et al. Characterization of normative angular joint kinematics during two functional upper limb tasks. Gait Posture. 2019 Mar;69:176–86.

30. Land M, Mennie N, Rusted J. The Roles of Vision and Eye Movements in the Control of Activities of Daily Living. Perception. 1999 Nov 1;28(11):1311–28.

31. Hayhoe M. Vision Using Routines: A Functional Account of Vision. Vis Cogn. 2000 Jan 1;7(1–3):43–64.

32. Hayhoe MM, Shrivastava A, Mruczek R, Pelz JB. Visual memory and motor planning in a natural task. J Vis. 2003 Feb;3(1):6.

33. Land MF, Hayhoe M. In what ways do eye movements contribute to everyday activities? Vision Res. 2001;41(25–26):3559–65.

34. Desanghere L, Marotta JJ. The influence of object shape and center of mass on grasp and gaze. Front Psychol. 2015;6:1537.

35. Vater C, Williams AM, Hossner EJ. What do we see out of the corner of our eye? The role of visual pivots and gaze anchors in sport. Int Rev Sport Exerc Psychol. 2020 Jan 1;13(1):81–103.

36. Morimoto CH, Mimica MRM. Eye gaze tracking techniques for interactive applications. Comput Vis Image Underst. 2005;98(1):4–24.

37. Petersch B, Dierkes K. Gaze-angle dependency of pupil-size measurements in head-mounted eye tracking. Behav Res. 2022 Apr 1;54(2):763–79.

38. Land MF. Vision, eye movements, and natural behavior. Vis Neurosci. 2009 Jan;26(1):51–62.

39. Tatler BW, Hayhoe MM, Land MF, Ballard DH. Eye guidance in natural vision: Reinterpreting salience.J Vis. 2011;11(5):5.

40. Hayhoe M, Ballard D. Eye movements in natural behavior. Trends Cogn Sci. 2005;9(4):188–94.

41. Wolf A, Ueda K. Contribution of Eye-Tracking to Study Cognitive Impairments Among Clinical Populations. Front Psychol. 2021;12:590986.

42. Cheng K, Rehani M, Hebert JS: Visuomotor Behaviour of Upper Limb Prosthesis Users: Protocol for a Scoping Review. https://era.library.ualberta.ca/items/617897a1-f035-4835-aaa8-90ba434000aa (2021). Accessed 5 Oct 2022.

43. Tricco A, Lillie E, Zarin W, O'Brien K, Colquhoun H, Levac D, et al. PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. Ann Intern Med. 2018;169(7):467-473.

44. Bayani KY, Lawson RR, Levinson L, Mitchell S, Atawala N, Otwell M, et al. Implicit development of gaze strategies support motor improvements during action encoding training of prosthesis use. Neuropsychologia. 2019;127:75–83.

45. Boser QA. Characterizing the Visuomotor Behaviour of Upper Limb Body-Powered Prosthesis Users. [Internet] [Master's thesis]. [Edmonton, Canada]: University of Alberta; 2019 [cited 2022 Aug 8]. Available from: https://era.library.ualberta.ca/items/b2931eef-1dd9-4b97-8b45-56f2a0f29501

46. Bouwsema H, Kyberd PJ, Hill W, van der Sluis CK, Bongers RM. Determining skill level in myoelectric prosthesis use with multiple outcome measures. J Rehabil Res Dev. 2012;49(9):1331-48.

47. Chadwell A, Kenney L, Granat MH, Thies S, Head J, Galpin A, et al. Upper limb activity in myoelectric prosthesis users is biased towards the intact limb and appears unrelated to goal-directed task performance. Sci Rep. 2018;8(1):11084.

48. Chadwell A, Kenney L, Thies S, Head J, Galpin A, Baker R. Addressing unpredictability may be the key to improving performance with current clinically prescribed myoelectric prostheses. Sci Rep. 2021;11(1):3300.

49. Kaspersen T. Objective Measurement of the Experience of Agency during Myoelectric Pattern Recognition based Prosthetic Limb Control using Eye-Tracking. [Internet] [Master's thesis]. [Gothenburg, Sweden]: Chalmers University of Technology; 2020 [cited 2022 Aug 8]. Available from: https://odr.chalmers.se/items/151b9594-f869-483c-91ef-aff7e08280d6

50. White MM, Zhang W, Winslow AT, Zahabi M, Zhang F, Huang H, et al. Usability Comparison of Conventional Direct Control Versus Pattern Recognition Control of Transradial Prostheses. IEEE Trans Hum Mach Syst. 2017;47(6):1146–57.

51. Zhang W, White M, Zahabi M, Winslow AT, Zhang F, Huang H, et al. Cognitive workload in conventional direct control vs. pattern recognition control of an upper-limb prosthesis. In: 2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC); 2016 Oct 9-12; Budapest, Hungary. IEEE; 2017. p. 002335–40.

52. Sobuh MM, Kenney LP, Galpin AJ, Thies SB, McLaughlin J, Kulkarni J, et al. Visuomotor behaviours when using a myoelectric prosthesis. J Neuroeng Rehabil. 2014;11(1):72.

53. Raveh E, Friedman J, Portnoy S. Evaluation of the effects of adding vibrotactile feedback to myoelectric prosthesis users on performance and visual attention in a dual-task paradigm. Clin Rehabil. 2018;32(10):1308-16.

54. Raveh E, Friedman J, Portnoy S. Visuomotor behaviors and performance in a dual-task paradigm with and without vibrotactile feedback when using a myoelectric controlled hand. Assist Technol. 2017;30(5):274–80.

55. Marasco PD, Hebert JS, Sensinger JW, Beckler DT, Thumser ZC, Shehata AW, et al. Neurorobotic fusion of prosthetic touch, kinesthesia, and movement in bionic upper limbs promotes intrinsic brain behaviors. Sci Robot. 2021;6(58):eabf3368.

56. Zahabi M, White MM, Zhang W, Winslow AT, Zhang F, Huang H, et al. Application of Cognitive Task Performance Modeling for Assessing Usability of Transradial Prostheses. IEEE Trans Hum Mach Syst. 2019;49(4):381–7.

57. Chadwell A, Kenney L, Thies S, Galpin A, Head J. The Reality of Myoelectric Prostheses: Understanding What Makes These Devices Difficult for Some Users to Control. Front Neurorobot. 2016;10:7.

58. Marshall SP. The Index of Cognitive Activity: measuring cognitive workload. In: Proceedings of the IEEE 7th Conference on Human Factors and Power Plants. 2002; Scottsdale, United States. IEEE; 2002.

59. Biddiss EA, Chau TT. Upper limb prosthesis use and abandonment: A survey of the last 25 years. Prosthet Orthot Int. 2007;31(3):236–57.

60. Sailer U, Flanagan JR, Johansson RS. Eye-Hand Coordination during Learning of a Novel Visuomotor Task. J Neurosci. 2005;25(39):8833-42.

61. Parr JVV, Wright DJ, Uiga L, Marshall B, Mohamed MO, Wood G. A scoping review of the application of motor learning principles to optimize myoelectric prosthetic hand control. Prosthet Orthot Int. 2022 Jun 1;46(3):274–81.

62. Williams HE, Chapman CS, Pilarski PM, Vette AH, Hebert JS. Myoelectric prosthesis users and non-disabled individuals wearing a simulated prosthesis exhibit similar compensatory movement strategies. J Neuroeng Rehabil. 2021;18(1):72.

63. Sinke M, Chadwell A, Smit G. State of the art of prosthesis simulators for the upper limb: A narrative review. Ann Rehabil Med. 2022 Nov 1;65(6):101635.

64. Kestner S. Defining the Relationship between Prosthetic Wrist Function and Its Use in Performing Work Tasks and Activities of Daily Living. J Prosthet Orthot. 2006 Jul;18(3):80.

65. Østlie K, Lesjø IM, Franklin RJ, Garfelt B, Skjeldal OH, Magnus P. Prosthesis use in adult acquired major upper-limb amputees: patterns of wear, prosthetic skills and the actual use of prostheses in activities of daily life. Disabil Rehabilitation Assist Technol. 2012 Nov 1;7(6):479–93.

66. Kingstone A, Smilek D, Eastwood JD. Cognitive Ethology: A new approach for studying human cognition. Br J Psychol. 2008;99(3):317–40.

67. Freedman EG. Coordination of the Eyes and Head during Visual Orienting. Exp Brain Res. 2008;190(4):369–87.

68. Niehorster DC, Cornelissen THW, Holmqvist K, Hooge ITC, Hessels RS. What to expect from your remote eye-tracker when participants are unrestrained. Behav Res. 2018 Feb 1;50(1):213–27.

69. Gregori V, Cognolato M, Saetta G, Atzori M, The MeganePro Consortium, Gijsberts A. On the Visuomotor Behavior of Amputees and Able-Bodied People During Grasping. Front Bioeng Biotechnol. 2019;7:316.

70. Schofield JS, Evans KR, Carey JP, Hebert JS. Applications of sensory feedback in motorized upper extremity prosthesis: a review. Expert Rev Med Devices. 2014;11(5):499–511.

71. Shaw EP, Rietschel JC, Hendershot BD, Pruziner AL, Wolf EJ, Dearth CL, et al. A Comparison of Mental Workload in Individuals with Transtibial and Transfemoral Lower Limb Loss during Dual-Task Walking under Varying Demand. J Int Neuropsychol Soc. 2019 Oct;25(9):985–97.

72. Markovic M, Schweisfurth MA, Engels LF, Bentz T, Wüstefeld D, Farina D, et al. The clinical relevance of advanced artificial feedback in the control of a multi-functional myoelectric prosthesis. J Neuroeng Rehabil. 2018 Dec;15(1):1–15.

73. Sensinger JW, Dosen S. A Review of Sensory Feedback in Upper-Limb Prostheses From the Perspective of Human Motor Control. Front. Neurosci. 2020;14:345.

74. Kuiken TA, Li G, Lock BA, Lipschutz RD, Miller LA, Stubblefield KA, et al. Targeted Muscle Reinnervation for Real-Time Myoelectric Control of Multifunction Artificial Arms. JAMA. 2009;301(6):619–28.

75. Hughey L, Wheaton LA. Incidental Learning and Explicit Recall in Upper Extremity Prosthesis Use: Insights Into Functional Rehabilitation Challenges. J Mot Behav. 2016;48(6):519–26.

76. Beatty J, Lucerno-Wagoner B. The pupillary system. In: Handbook of psychophysiology. 2000. p. 142–62.

77. Rozado D, Dünser A. Combining EEG with Pupillometry to Improve Cognitive Workload Detection. Computer. 2015;48(10):18–25.

78. Wilbanks BA, Aroke E, Dudding KM. Using Eye Tracking for Measuring Cognitive Workload During Clinical Simulations: Literature Review and Synthesis. Comput Inform Nurs. 2021;39(9):499–507.

79. Marchand C, De Graaf JB, Jarrassé N. Measuring mental workload in assistive wearable devices: a review. J Neuroeng Rehabil. 2021;18(1):160.

80. Schofield JS, Shell CE, Thumser ZC, Beckler DT, Nataraj R, Marasco PD. Characterization of the Sense of Agency over the Actions of Neural-machine Interface-operated Prostheses. J Vis Exp. 2019;(143).

81. Zbinden J, Lendaro E, Ortiz-Catalan M. Prosthetic embodiment: systematic review on definitions, measures, and experimental paradigms. J Neuroeng Rehabil. 2022;19(1):37.

82. Zopf R, Polito V, Moore J. Revisiting the link between body and agency: visual movement congruency enhances intentional binding but is not body-specific. Sci Rep. 2018 Jan 9;8(1):1–9.

83. Wood G, Parr J. A tool for measuring mental workload during prosthesis use: The Prosthesis Task Load Index (PROS-TLX) [Internet]. PsyArXiv; 2022. Available from: https://psyarxiv.com/k2uq5/

84. Cruz AAV, Garcia DM, Pinto CT, Cechetti SP. Spontaneous Eyeblink Activity. Ocul Surf. 2011 Jan 1;9(1):29–41.

85. Tsubota K, Hata S, Okusawa Y, Egami F, Ohtsuki T, Nakamori K. Quantitative Videographic Analysis of Blinking in Normal Subjects and Patients With Dry Eye. Arch Ophthalmol. 1996 Jun 1;114(6):715–20.

86. Andreu-Sánchez C, Martín-Pascual MÁ, Gruart A, Delgado-García JM. Looking at reality versus watching screens: Media professionalization effects on the spontaneous eyeblink rate. PLoS One. 2017 May 3;12(5):e0176030.

87. Jeannerod M. The neural and behavioural organization of goal-directed movements. New York, (US): Clarendon Press/Oxford University Press; 1988.

88. Miall RC, Reckess GZ, Imamizu H. The cerebellum coordinates eye and hand tracking movements. Nat Neurosci. 2001 Jun;4(6):638–44.

89. Fisk JD, Goodale MA. The organization of eye and limb movements during unrestricted reaching to targets in contralateral and ipsilateral visual space. Exp Brain Res. 1985;60(1):159-78.

90. Sailer U, Eggert T, Ditterich J, Straube A. Spatial and temporal aspects of eye-hand coordination across different tasks. Exp Brain Res. 2000 Sep 5;134(2):163–73.

91. Gribble PL, Everling S, Ford K, Mattar A. Hand-eye coordination for rapid pointing movements: Arm movement direction and distance are specified prior to saccade onset. Exp Brain Res. 2002 Aug;145(3):372–82.

92. Bosch TJ, Hanna T, Fercho KA, Baugh LA. Behavioral performance and visual strategies during skill acquisition using a novel tool use motor learning task. Sci Rep. 2018 Sep 13;8(1):13755.

93. Kuus TG, Dawson MR, Schoepp K, Carey JP. Development of a simulated sensory motor prosthesis: A device to research prosthetic sensory feedback using able-bodied individuals. In: Proceedings of MEC17; 2017 Aug 15-18; Fredericton, Canada. 2017. p. 120.

94. Williams HE, Chapman CS, Pilarski PM, Vette AH, Hebert JS. Gaze and Movement Assessment (GaMA): Inter-site validation of a visuomotor upper limb functional protocol. Buckingham G, editor. PLoS One. 2019 Dec;14(12):e0219333.

95. Stergiou N, Decker LM. Human movement variability, nonlinear dynamics, and pathology: Is there a connection? Hum Mov Sci. 2011 Oct;30(5):869–88.

96. Muratori LM, Lamberg EM, Quinn L, Duff SV. Applying principles of motor learning and control to upper extremity rehabilitation. J Hand Ther. 2013;26(2):94–103.

97. Sarlegna FR, Mutha PK. The influence of visual target information on the online control of movements. Vision Res. 2015 May 1;110:144–54.

98. Valevicius AM, Boser QA, Chapman CS, Pilarski PM, Vette AH, Hebert JS. Compensatory strategies of body-powered prosthesis users reveal primary reliance on trunk motion and relation to skill level. Clin Biomechan (Bristol, Avon). 2020 Feb;72:122–9.

99. Scheme E, Fougner A, Stavdahl Ø, Chan ADC, Englehart K. Examining the adverse effects of limb position on pattern recognition based myoelectric control. In: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2010 Aug 31-Sep 4; Buenos Aires, Argentina. IEEE; 2010. p. 6337–40.

100. Fougner A, Scheme E, Chan ADC, Englehart K, Stavdahl Ø. Resolving the Limb Position Effect in Myoelectric Pattern Recognition. IEEE Trans Neural Syst Rehabil Eng. 2011 Dec;19(6):644-51.

101. Betthauser JL, Hunt CL, Osborn LE, Masters MR, Lévay G, Kaliki RR, et al. Limb Position Tolerant Pattern Recognition for Myoelectric Prosthesis Control with Adaptive Sparse Representations From Extreme Learning. IEEE Trans Biomed Eng. 2018 Apr;65(4):770-8.

102. Chen L, Geng Y, Li G. Effect of upper-limb positions on motion pattern recognition using electromyography. In: 2011 4th International Congress on Image and Signal Processing (CISP); 2011 Oct 15-17; Shanghai, China. IEEE; 2011. p. 139–42.

103. Liu J, Zhang D, He J, Zhu X. Effect of dynamic change of arm position on myoelectric pattern recognition. In: 2012 IEEE International Conference on Robotics and Biomimetics (ROBIO); 2012 Dec 11-14; Guangzhou, China. IEEE. 2012. p. 1470–5.

104. Liu J, Zhang D, Sheng X, Zhu X. Quantification and solutions of arm movements effect on sEMG pattern recognition. Biomed Signal Process and Control. 2014 Sep 1;13:189–97.

105. Jiang N, Muceli S, Graimann B, Farina D. Effect of arm position on the prediction of kinematics from EMG in amputees. Med Biol Eng Comput. 2013 Feb 1;51(1):143–51.

106. Geng Y, Zhou P, Li G. Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classification in transradial amputees. J Neuroeng Rehabil. 2012 Dec;9(1):1–11.

107. Khushaba RN, Al-Timemy A, Kodagoda S, Nazarpour K. Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. Expert Syst Appl. 2016 Nov 1;61:154–61.

108. Franzke AW, Kristoffersen MB, Bongers RM, Murgia A, Pobatschnig B, Unglaube F, et al. Users' and therapists' perceptions of myoelectric multi-function upper limb prostheses with conventional and pattern recognition control. PLoS One. 2019 Aug;14(8):e0220899.

109. Williams HE, Hebert JS, Pilarski PM, Shehata AW. A Case Series in Position-Aware Myoelectric Prosthesis Control using Recurrent Convolutional Neural Network Classification with Transfer Learning. In: 2023 International Conference on Rehabilitation Robotics (ICORR); 2023 Sep 24-28; Singapore. IEEE. 2023.

110. Williams HE, Shehata AW, Cheng KY, Hebert JS, Pilarski PM. A multifaceted suite of metrics for comparative myoelectric prosthesis controller research [Internet]. bioRxiv; 2023. Available from: https://www.biorxiv.org/content/10.1101/2023.08.28.554998v1

111. Cheng KY, Rehani M, Hebert JS. A scoping review of eye tracking metrics used to assess visuomotor behaviours of upper limb prosthesis users. J Neuroeng Rehabil. 2023 Dec;20(1):1–22.

112. Hallworth BW, Shehata AW, Dawson MR, Sperle F, Connan M, Friedl W, et al. A transradial modular adaptable platform for evaluating prosthetic feedback and control strategies. In: Proceedings of MEC20; 2020 Aug 10-13; Frederiction, Canada. 2023 p. 203-6.

113. Hart SG, Staveland LE. Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. In: Advances in Psychology [Internet]. North Holland (Netherlands): Elsevier; 1988. p. 139–83.

114. Teh Y, Hargrove LJ. Understanding limb position and external load effects on real-time pattern recognition control in amputees. IEEE Trans Neural Syst Rehabil Eng. 2020 Jul;28(7):1605–13.

115. Geng Y, Samuel OW, Wei Y, Li G. Improving the Robustness of Real-Time Myoelectric Pattern Recognition against Arm Position Changes in Transradial Amputees. Biomed Res Int.. 2017 Apr;2017:e5090454.

116. Woodward RB, Hargrove LJ. Adapting myoelectric control in real-time using a virtual environment. J Neuroeng Rehabil. 2019 Jan;16:11.

117. Fougner AL, Stavdahl Ø, Kyberd PJ. System training and assessment in simultaneous proportional myoelectric prosthesis control. J Neuroeng Rehabil. 2014 Dec;11(1):1–13.

118. Amsuess S, Vujaklija I, Goebel P, Roche AD, Graimann B, Aszmann OC, et al. Context-Dependent Upper Limb Prosthesis Control for Natural and Robust Use. IEEE Trans Neural Syst Rehabil Eng. 2016 Jul;24(7):744–53.

119. Fu Q, Santello M. Improving Fine Control of Grasping Force during Hand–Object Interactions for a Soft Synergy-Inspired Myoelectric Prosthetic Hand. Front Neurorobot. 2018 Jan 10;11:71.

120. Howard JD, Hoit JD, Enoka RM, Hasan Z. Relative activation of two human elbow flexors under isometric conditions: a cautionary note concerning flexor equivalence. Exp Brain Res. 1986 Mar;62(1):199–202.

121. Jamison JC, Caldwell GE. Muscle synergies and isometric torque production: influence of supination and pronation level on elbow flexion. J Neurophysiol. 1993 Sep;70(3):947–60.

122. Boland MR, Spigelman T, Uhl TL. The Function of Brachioradialis. J Hand Surg Am. 2008 Dec;33(10):1853–9.

123. Stokes IAF, Gardner-Morse MG. Strategies used to stabilize the elbow joint challenged by inverted pendulum loading. J Biomech. 2000 Jun;33(6):737–43.

124. Lung BE, Ekblad J, Bisogno M. Anatomy, Shoulder and Upper Limb, Forearm Brachioradialis Muscle. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2023.

125. Khushaba RN, Takruri M, Miro JV, Kodagoda S. Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features. Neural Netw. 2014 Jul;55:42–58.

126. Radmand A, Scheme E, Englehart K. On the Suitability of Integrating Accelerometry Data with Electromyography Signals for Resolving the Effect of Changes in Limb Position during Dynamic Limb Movement. J Prosthet Orthot. 2014 Oct;26(4):185.

127. Teh Y, Hargrove LJ. The effects of limb position and external load on offline myoelectric pattern recognition control. In: 2020 8th IEEE RAS/EMBS International Cnference for Biomedical Robotics and Biomechatronics (BioRob); 2020 Nov 29-Dec 1; New York, USA. 2020. p. 654–9.

128. Beaulieu RJ, Masters MR, Betthauser J, Smith RJ, Kaliki R, Thakor NV, et al. Multi-position Training Improves Robustness of Pattern Recognition and Reduces Limb-Position Effect in Prosthetic Control. J Prosthet Orthot. 2017 Apr;29(2):54–62.

129. Hargrove L, Losier Y, Lock B, Englehart K, Hudgins B. A real-time pattern recognition based myoelectric control usability study implemented in a virtual environment. In: 2007 Annual

International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2007 Aug 22-26; Lyon, France. 2007. p. 4842–5.

130. Ortiz-Catalan M, Rouhani F, Branemark R, Hakansson B. Offline accuracy: A potentially misleading metric in myoelectric pattern recognition for prosthetic control. In: 2015 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2015 Aug 25-29; Milan, Italy. 2015. p. 1140-3.

131. Dosen S, Markovic M, Wille N, Henkel M, Koppe M, Ninu A, et al. Building an internal model of a myoelectric prosthesis via closed-loop control for consistent and routine grasping. Exp Brain Res. 2015 Jun;233(6):1855–65.

132. Hart SG, Field M. Nasa-Task Load Index (NASA-TLX); 20 Years Later. In: Proceedings of the Human Factors and Ergonomics Society Annual Meeting; 2006 Oct 16-20; San Francisco, USA. 2006. p. 904-8.

Appendix A: General study characteristics of the included literature

Table A-1: General study characteristics of the included literature

Reference	*Study design*	*Source of literature*	*Population*	*Number of participants*
Bouwsema et al. (2012)[46]	Cross-sectional study	Journal article	Upper limb amputation	6
Sobuh et al. (2014)[52]	Repeated-measures study (Experiment 1) Case study (Experiment 2)	Journal article	Intact arm (Experiment 1) Upper limb amputation (Experiment 2)	7 (Experiment 1) 4 (Experiment 2)
Chadwell et al. (2016)[57]	Case study	Journal article	Intact arm Upper limb amputation	1 2
Zhang et al. (2016)[51]	Cross-sectional study	Conference paper	Intact arm	20
Raveh et al. (2017)[54]	Crossover study	Journal article	Intact arm	43
White et al. (2017)[50]	Cross-sectional study	Journal article	Intact arm	20
Chadwell et al. (2018)[47]	Cross-sectional study	Journal article	Intact arm Upper limb amputation	20 20
Parr et al. (2018)[9]	Repeated-measures study	Journal article	Intact arm	21
Raveh et al. (2018)[53]	Crossover study	Journal article	Upper limb amputation	12
Bayani et al. (2019)[44]	Cross-sectional study	Journal article	Intact arm	20

Boser et al. (2019)[45]	Cross-sectional study	Thesis	Upper limb amputation	8
Hebert et al. (2019)[8]	Cross-sectional study	Journal article	Intact arm Upper limb amputation	16 8
Parr et al. (2019)[10]	Cross-sectional study (Experiment 1) Repeated-measures study (Experiment 2)	Journal article	Intact arm	20 (Experiment 1) 24 (Experiment 2)
Zahabi et al. (2019)[56]	Case study	Journal article	Upper limb amputation	1
Kaspersen et al. (2020)[49]	Cross-sectional study	Thesis	Intact arm	6
Chadwell et al. (2021)[48]	Cross-sectional study	Journal article	Upper limb amputation	20
Marasco et al. (2021)[55]	Case study	Journal article	Upper limb amputation	2

Appendix B: Participant characteristics of the included literature

Table B-1: Participant characteristics of the included literature

Reference	*Sex ratio (M:F)*	*Age**	*Level of amputation*	*Type of prosthetic device*	*Number of years using a prosthesis**	*Cause of amputation*
Bouwsema et al. (2012)[46]	3:3	36 ± 18 (19 to 59)	Transradial	Myoelectric prosthesis	3.8 ± 2.3 (1 to 7) (calculated)	Accident (3), congenital (3), illness (1)
Sobuh et al. (2014)[52]	4:3 (Experiment 1) 3:1 (Experiment 2)	36 ± 10 (26 to 48) (Experiment 1) 49 ± 10 (35 to 56) (Experiment 2)	Transradial	Myoelectric simulator prosthesis (Experiment 1) Myoelectric prosthesis (Experiment 2)	20 ± 13 (2 to 32)	Not reported
Chadwell et al. (2016)[57]	1:0 2:0	21 (44 to 45)	Transradial	Myoelectric simulator prosthesis (1) Myoelectric prosthesis (2)	(1.5 to 35)	Congenital
Zhang et al. (2016)[51]	10:10	23.5 ± 2.36	N/A	Myoelectric simulator prosthesis	N/A	N/A
Raveh et al. (2017)[54]	18:25	26 ± 6.6	N/A	Myoelectric simulator prosthesis	N/A	N/A

White et al. (2017)[50]	10:10	23.5 ± 2.36	N/A	Myoelectric simulator prosthesis	N/A	N/A
Chadwell et al. (2018)[47]	9:11 14:6	43 (23 to 61) 53 (18 to 75)	Transradial	Myoelectric prosthesis	20 (1.5 to 39)	Congenital (11), amputation (9)
Parr et al. (2018)[9]	13:8	25.3 ± 5.05	N/A	Myoelectric simulator prosthesis	N/A	N/A
Raveh et al. (2018)[53]	11:1	65 ± 13[†]	Transradial	Myoelectric prosthesis	15.5 ± 6[†§]	Not reported
Bayani et al. (2019)[44]	10:10	24.7 ± 3.39 (18 to 34)	N/A	Body-powered simulator prosthesis	N/A	N/A
Boser et al. (2019)[45]	7:1	(31 to 64)	Transradial (5) Transhumeral (3)	Body-powered prosthesis (8)	10.6 ± 4.3 (2 to 14) (calculated)	Not reported
Hebert et al. (2019)[8]	8:8 8:0	26 (18 to 43) 45 (30 to 64)	Transradial (5) Transhumeral (3)	Body-powered prosthesis (6), myoelectric prosthesis (1), hybrid hand (1)	11 ± 3.4 (4 to 14) (calculated)	Not reported
Parr et al. (2019)[10]	12:8 (Experiment 1) 12:12 (Experiment 2)	Experiment 1: 25.3 ± 5.05 Experiment 2: 24.4 ± 7.23	N/A	Myoelectric simulator prosthesis	N/A	N/A
Zahabi et al. (2019)[56]	1:0	42	Transradial	Myoelectric prosthesis	2	Accident
Kaspersen et al. (2020)[49]	3:3	26.8 ± 3.1 (23 to 32)	N/A	Myoelectric controlled virtual reality arm	N/A	N/A

Chadwell et al. (2021)[48]	14:6	53 (18 to 75)	Transradial	Myoelectric prosthesis	20 (1.5 to 39)	Congenital (11), amputation (9)
Marasco et al. (2021)[55]	1:1	(38 to 40)	Shoulder disarticulation (1) Transhumeral (1)	Myoelectric prosthesis with touch and kinesthetic feedback tactors	Not reported	Not reported

*Values are given as the mean, with or without the standard deviation, in years, with or without the range in parentheses.

†These data are given as the median with the interquartile range.

§These data are given in hours per day.

Appendix C: Context and key findings of included studies

Table C-1: Context and key findings of included studies

Reference	*Aims*	*Type of eye tracker*	*Eye metrics*	*Other outcome metrics*	*Experimental task*	*Key findings*
Bouwsema et al. (2012)[46]	1) To provide a description of prosthetic control and performance 2) To relate clinical outcomes to kinematic measures 3) To identify parameters that characterize the skill level of a prosthesis user	Head-mounted (model RK-826PCI, iScan Online, Inc; Dallas, Texas)	Number of fixations and percent fixation	End point kinematics, joint angles, grasp force control and SHAP[a]	Performed direct and indirect grasping tasks with prosthesis and object manipulation with the intact hand. Objects were solid or compressible. Participants also performed the SHAP[a].	Two types of gaze behaviours were observed: 1) Visual fixations directed towards the object at the start of the trial and maintained; 2) Visual fixations switched repeatedly between the hand and object. Participants who did not use their prosthesis frequently had a higher total number of fixations, lower percent fixation to the object and higher percent fixation to the hand than frequent myoelectric prosthesis users. SHAP[a] scores did not correlate to measures of gaze behaviour.

Sobuh et al. (2014)[52]	1) To characterize the visuomotor behaviours of participants with intact arm function learning to use a prosthesis simulator 2) To compare the visuomotor behaviours of participants with intact arm function and individuals with an upper limb amputation using a prosthesis	Head-mounted (iView X™ HED 2, SenseMotoric Instruments GmbH, Tellow, Germany)	Gaze sequence, percent fixation and number of fixations	Movement time and SHAP[a]	A carton pouring task using the anatomic or the prosthetic hand. The SHAP[a] was performed as training between testing sessions.	When using the prosthesis simulator for carton pouring, gaze was more fixated to the hand in reach and rarely fixated the glass, compared to gaze when using the anatomic hand. During manipulation, similar critical areas were focused on regardless of using the anatomic or prosthetic hand. There were significantly greater fixations and a lower SHAP[a] when using the prosthesis simulator, compared to using the anatomic hand. Training significantly improved SHAP[a] for prosthesis simulator users but had no significant effect on gaze behaviour. Percent fixations, number of fixations during reach, movement times and SHAP[a] scores were similar between subjects with normal arm function and prosthesis users. The number of fixations were higher for prosthesis users during manipulation.
Chadwell et al. (2016)[57]	1) To assess factors of the prosthesis control chain, including EMG skill and electrode reliability 2) To evaluate performance, including kinematic and gaze patterns	Head-mounted (Dikablis Professional, Ergoneers)	Number of fixations, percent fixation and percent of look-ahead fixations	Success of task completion, task duration, aperture onset delay, plateau time during reach to grasp, kinematic variability and symmetry of	Participants began by reaching and grasping for a cylinder rotating it 90°, then placing and releasing it into a tube. If over 80% of trials were successful, the same task was repeated with a smaller diameter cylinder. If less than	Prosthesis User 1 was able to look ahead to the cylinder and tube, whereas Prosthesis User 2 spent most of the time monitoring the hand and cylinder during reach to grasp. Prosthesis User 1 looked ahead of the hand 76% of the time, while Prosthesis User 2 looked at the hand for over 50% of the time.

	and myoelectric prosthesis usage			real-world arm use	80% of trials were successful, the cylinder was placed vertically into a vertical tube.	
Zhang et al. (2016)[51]	To compare the cognitive workload of individuals with intact arm function when using a myoelectric prosthesis simulator with direct control or pattern recognition control.	Remote (Facelab 5.1, Seeing Machines, Australia)	Percent change in pupil size	Number of clothespins successfully relocated	Clothespin relocation task. Participants moved as many clothespins as possible between the horizontal and vertical bars within a 2-minute trial.	The pattern recognition group had a greater task performance and lower cognitive load, as shown by a smaller increase in pupil size, than the direct control group. Task performance increased while cognitive workload decreased in later trials.
Raveh et al. (2017)[54]	To evaluate the effects of adding vibrotactile feedback on visual attention and performance of individuals with normal arm function using a myoelectric prosthesis simulator in a dual task paradigm.	Remote (GP3 Desktop eye tracker, Gazepoint, Canada)	Percent fixation to the screen	Task completion time and percentage of error in secondary task	Dual task involved using the left hand to toggle arrow keys to navigate a virtual car while grasping activities were performed with the prosthesis simulator. Dual tasks were performed with and without vibration.	Adding vibrotactile feedback had no effect on visual attention and task performance in a dual task.

White et al. (2017)[50]	To compare the usability of direct control and pattern recognition control for individuals with intact arm function using a transradial myoelectric prosthesis simulator.	Remote (Facelab 5.1, Seeing Machines, Australia)	Number of pupil size increases per second	Number of clothespins successfully relocated and learning percentage	Clothespin relocation task. Participants moved as many clothespins as possible between the horizontal and vertical bars within a 2-minute trial.	Participants that used pattern recognition had a lower cognitive workload as shown by fewer increases in pupil size, greater task performance and an improved ability to learn compared to direct control. There was also a trend for task performance to increase across trials for both groups
Chadwell et al. (2018)[47]	1) To report real-world activity of prosthesis users and participants with intact arm function 2) To investigate whether measures of kinematic and gaze behaviour during a goal-directed task correlate to measures of upper limb activity.	Head-mounted (Dikablis Professional, Ergoneers)	Percent fixation	Prosthesis wear time, balance of activity between arms, success of task completion, task duration, delay plateau, reach plateau, acceleration temporal variability	Participants began by reaching and grasping for a cylinder rotating it 90°, then placing and releasing it into a tube. If over 80% of trials were successful, the same task was repeated with a smaller diameter cylinder. If less than 80% of trials were successful, the cylinder was placed vertically into a vertical tube.	Prosthesis users relied on their anatomical side to perform daily activities whereas participants with intact arm function relied more on both dominant and non-dominant arms. There were no significant correlations between any measures of everyday use and measures of task performance.
Parr et al. (2018)[9]	To explore the spatial and temporal disruptions to eye-hand coordination during prosthetic hand use in a fine motor task.	Head-mounted (Mobile Eye XG, Applied Science Laboratories, Bedford, MA)	Percent fixation, target locking strategy and gaze shifting	Task completion time	Four coins on a board were sequentially picked up from right to left and placed in a jar located in the centre of the board. The task was first performed with the anatomic hand then the prosthetic hand.	When using the prosthetic hand, significantly greater visual attention was directed towards the hand and coin and less visual attention to other target areas, when compared to the anatomic hand. In all phases, more time was spent fixating the hand than the target when using the prosthetic hand. There was a significant delay for the eyes to

						disengage from the current target and shift to the next movement.
Raveh et al. (2018)[53]	To evaluate the effects of adding vibrotactile feedback to myoelectric prostheses on visual attention and performance in a dual task paradigm.	Remote (GP3 Desktop eye tracker, Gazepoint, Canada)	Number of fixations to the hand and percent fixation to the screen	Task completion time and percentage of error in secondary task	Dual task involved using the left hand to toggle arrow keys to navigate a virtual car while grasping activities were performed with the prosthesis. Dual tasks were performed with and without vibration.	Adding vibrotactile feedback reduced task performance time in a dual task activity performed by myoelectric prosthesis users. There was no effect of adding vibrotactile feedback on gaze behaviour.
Bayani et al. (2019)[44]	To identify gaze strategies that develop implicitly during matched and mismatched limb training during action observation	Head-mounted (Pupil Labs, binocular, Berlin, Germany)	Percent fixation	Movement time, number of errors, type of errors, peak height, peak velocity, peak lateral trunk movement, variability in lateral trunk movement and smoothness	The task involved reaching and grasping for a disc and transporting it over a barrier to be placed in an open slot. Participants watched an instruction video performed either by an actor with a body-powered prosthesis (matched) or with the anatomic limb (mismatched). After watching the video, participants performed the task with the prosthetic hand.	In the mismatched group, gaze fixations were directed towards the start and endpoints of the action, whereas for the matched group, gaze was focussed on the path of the prosthesis and the shoulders. With matched action observation, the allocation of gaze shifted from the start and end locations towards monitoring the trajectory of the prosthesis across trials. There was a progressive improvement in motor control in the matched group.

Boser et al. (2019)[45]	To characterize the visuomotor behaviour of transradial and transhumeral body-powered prosthesis users	Head-mounted (Dikablis Professional, Ergoneers)	Percent fixation, target locking strategy, number of fixations and eye latencies	Task completion time, hand distance travelled, hand trajectory variability, number of movement units, peak hand velocity, percent to peak hand velocity, percent to peak hand deceleration, percent to peak grip aperture	A cup transfer task involved moving two cups sequentially across a partition to two target locations then returning the cups to their starting locations. A pasta task involved moving a pasta box from a starting location on the side of the body to a centre shelf, then around a barrier to a second higher shelf, then to its starting location.	Transradial body-powered prosthesis users had longer task completion times, increased fixations to their prosthetic hand during reach and transport phases, and movements that were not as smooth compared to individuals with normal arm function. Look-ahead fixations to the drop-off target were within a normative range. Transhumeral body-powered prosthesis users had similar movements as transradial body-powered prosthesis users, however increased fixations to the hand in transport prevented the ability to look ahead to the drop-off target. In the cup transfer task, there were longer fixations to the terminal device during reach than the pasta task.
Hebert et al. (2019)[8]	To determine whether different tasks performed by prosthesis users would result in different visuomotor behaviours.	Head-mounted (Dikablis Professional, Ergoneers)	Percent fixation and eye latencies	Movement time and upper body range of motion	A cup transfer task involved moving two cups sequentially across a partition to two target locations then returning the cups to their starting locations. A pasta task involved moving a pasta box from a starting location on the side of the body to a centre shelf, then around a barrier to a second higher shelf,	The cup transfer task required more visual attention to the hand than the pasta task during reach and transport phases, likely due to the risk of spilling the contents of the cup. In both tasks, users had prolonged eye latencies and less fixation on the current target compared to a normative group.

					then to its starting location.	
Parr et al. (2019)[10]	1) To explore the spatial and temporal disruptions to eye-hand coordination during prosthetic hand use in a fine motor task. 2) To explore the efficacy of a novel gaze training intervention on prosthetic hand skill learning and retention compared to movement training.	Head-mounted (Mobile Eye XG, Applied Science Laboratories, Bedford, MA)	Target locking strategy and gaze shifting	Task completion time, number of errors, alpha power and high alpha connectivity	Experiment 1: picking up a jar filled with water over a barrier to a location on the other side of the board. The task was performed with the anatomic hand first followed by the prosthetic hand. Experiment 2: Four coins on a board were sequentially picked up from right to left and placed in a jar located in the centre of the board. A tea making task involved placing a mug on a place mat, adding and then stirring contents with a spoon.	With the prosthetic hand, participants focused significantly more on the hand and had a time delay to disengage visual attention in all phases of the jar task. There was also a global decrease in alpha power, indicating increased cortical activation and mental effort. Gaze training increased fixations to the target and speed of gaze shifts, reduced performance time, and improved neural efficiency compared to movement training. These improvements were transferred to a more complex tea-making task. Target locking strategy and faster gaze shifting were significant predictors of T7-Fz connectivity (indicates less conscious control) at retention and delayed retention with gaze training.
Zahabi et al. (2019)[56]	To assess the validity of using a cognitive model to assess the mental workload of upper limb prosthesis use under direct control and pattern recognition control.	Remote (Facelab 5.1, Seeing Machines, Australia)	Pupil size	Task completion time and number of clothespins successfully relocated	A single subject performed the clothespin relocation task with two different control modes on two separate days. A cognitive performance model was then constructed to compare	Significantly more clothespins were moved with pattern recognition compared to direct control. Using pattern recognition also resulted in a smaller pupil size, indicating lower cognitive load. The cognitive model indicated that there were fewer cognitive and motor operators with pattern recognition than direct

					the demands of using different control modes.	control and no difference in the number of perceptual operators. The model underestimated task completion times.
Kaspersen et al. (2020)[49]	To evaluate the feasibility of using an eye tracker to quantify the sense of agency towards a virtual limb controlled using myoelectric pattern recognition.	Head-mounted (Tobii Pro Glasses 2, Tobii AB, Stockholm, Sweden)	Duration of fixations and number of fixations	Reaction time	Four onscreen virtual reality arms were controlled using myoelectric control. Different levels of noise were introduced to randomly reclassify movements to 3 of the 4 virtual arms, making them less controllable. Random arms would flash red at two random time points during each trial and participants were instructed to press a key when they detected a red flash.	Two types of gaze behaviours were observed. Participants either fixated on the centre of the screen and used peripheral vision to detect red flashes, or they moved around to fixate on each quadrant. Significantly more time was spent fixating on the most controllable virtual arm, however noise level did not affect the time taken to react to a red flash. Results suggest that visual attention is directed to the virtual arm that provides the best experience of agency to the participant.
Chadwell et al. (2021)[48]	To establish the relative impact of control factors (signal acquisition, signal generation and device response) on user functionality (task performance, kinematics and gaze behaviour) and	Head-mounted (Dikablis Professional, Ergoneers)	Percent fixation and number of fixations	EMG signal, reaction time, number of undesired activations, electromechanical delay, number of successes, task completion time, reach aperture	Participants began by reaching and grasping for a cylinder rotating it 90°, then placing and releasing it into a tube. If over 80% of trials were successful, the same task was repeated with a smaller diameter cylinder. If less than 80% of trials were	A higher number of unwanted EMG activations was significantly correlated to lower success rate, longer task duration, higher temporal kinematic variability, increased fixations to the hand, decreased fixations to grasp critical areas during reach to grasp and increased gaze switches. Longer electromechanical delay was significantly correlated to shorter

	everyday prosthesis usage			plateau, movement variability, prosthesis wear time and balance of activity between arms	successful, the cylinder was placed vertically into a vertical tube.	task duration, shorter length of aperture plateau, decreased fixations to the hand during transport, increased fixations to location critical areas during transport, fewer gaze switches and longer prosthesis wear time.
Marasco et al. (2021)[55]	To quantify the performance of individuals who received targeted sensory and motor reinnnervation using metrics such as visual attention, cognitive demand, fine motor dexterity and ownership.	Head-mounted (Pupil Labs, binocular, Berlin, Germany)	Percent fixation	Prosthesis Efficiency and Profitability, Dynamic Prosthesis Incorporation, Grasping Relative Index of Performance, Adaptation rate	A cup transfer task involved moving two cups sequentially across a partition to two target locations then returning the cups to their starting locations. A pasta task involved moving a pasta box from a starting location on the side of the body to a centre shelf, then around a barrier to a second higher shelf, then to its starting location.	Providing touch and kinesthetic feedback to prosthesis users with targeted sensory and motor reinnervation reduced fixations to the hand in reach and transport phases, and increased fixations to the next target location. Overall, the integration of bidirectional control allowed users to adopt more natural behaviours.

[a] Southampton Hand Assessment Procedure

Appendix D: Simulated Prosthesis Training Protocol

The goal of this training is to first, provide participants with a conceptual understanding of the technologies used in this research and thus to create a shared vocabulary between participant and researcher. Secondly, it allows for participants to practice using pattern recognition while receiving verbal feedback prior to performing the recorded tasks.

1. Explain to the participant that a controller training routine is required to learn the muscle signals of the individual, which will then be used to control the prosthetic hand.
2. Play the instruction video demonstrating each hand gesture (wrist flexion, extension, pronation, and supination) that is performed in each arm position (arm at side, elbow bent at 45°, arm out at shoulder height, and arm at 45° above shoulder height).
3. Have participants demonstrate wrist flexion/extension and forearm pronation/supination with their non-dominant hand.
4. Explain that while their hand is in the brace, they won't be able to move their wrist. Instead, they will perform isometric contractions, where the joint does not move when the muscles are contracted.
5. Ensure that the correct muscle contractions are being performed by holding the participant's hand statically while they perform isometric contractions.
    a. Ask the participant to flex their wrist. Restrict the participant's movement and ensure that they are pushing with the palmar side of their hand.
    b. Ask the participant to extend their wrist. Restrict the participant's movement and ensure that they are pushing with the dorsal side of their hand.
    c. Ask the participant to turn their palm up for supination. Restrict the participant's movement and ensure that they are pushing with the palm on the ulnar side.
    d. Ask the participant to turn their palm down for pronation. Restrict the participant's movement and ensure that they are pushing with the palm on the radial side.
6. Instruct the participant to make each movement as distinct as possible when training the controller. The same strength of muscle contractions performed during training are later used to control the prosthetic hand.
7. Ensure that the thumb is not involved in these contractions, especially extension, and remind participants to keep their thumb in a neutral position.

While the controller is being trained (2-3 min), briefly explain how the simulated prosthesis is controlled and used to perform tasks.

1. The bypass prosthesis is controlled using pattern recognition, so the same pattern of muscle signals produced to train the controller will be recognized and translated to functional hand movements.
    a. Wrist flexion will translate to hand close.
    b. Wrist extension will translate to hand open.
    c. Forearm supination will translate to wrist rotation, i.e. palm up.
    d. Forearm pronation will translate to wrist rotation, i.e. palm down.
2. There are a series of electrodes in the Myo band that record electrical signals from muscle activity to control each movement of the prosthesis.
3. Consistent, moderate contractions like those performed during the training routine should be reproduced when using the prosthesis as these same muscle signals are what will allow for control of the prosthesis.
4. The robotic hand has 2 degrees of freedom, i.e. there are two axes of rotation or two joints that can be moved – hand open/close and wrist rotation.
5. Movements can only be performed one at a time so contractions need to be done sequentially.

Start by training the participant to use one degree of freedom. Turn on the torque for hand open/close.

1. Remind the participant that wrist flexion will close the hand and wrist extension will open the hand.
2. Start by instructing the participant to flex and extend their wrist and observe that the correct movements are achieved.
3. Once the participant understands how to control opening/closing of the hand and full range of motion is successfully achieved, ask them to close the hand halfway, then fully.
4. Ask the participant to then open the hand halfway, then fully.
5. Repeat 2-3x until successful
6. Next, instruct the participant to close the hand as slow as possible.

7. Then instruct the participant to open the hand as slow as possible.
8. Repeat 2-3x until successful.
9. Next, instruct the participant to close the hand as fast as possible.
10. Then instruct the participant to open the hand as fast as possible.
11. Repeat 2-3x until successful.
12. Note that the control has a fixed speed, but this exercise allows participants to focus on controlling grip aperture in small increments.
13. Inform the participant that some movements that are being asked of them will be easier to perform than others but to try their best to follow the given instructions.
14. Once the participant has demonstrated full control of the one degree of freedom, they can then practice with a functional task – shape sorting.
15. Place the shape sorting task on the side table.
16. Instruct participants to pick up each object (1 through 4) and place them into the corresponding wells (Fig D-2a).
17. Remove the objects from the wells and reset them on the starting platform
18. Have participants repeat the same shape sorting task.
19. Next, place the starting platform on the raised shelf on the centre cart (Fig D-2b). Remove objects from wells and reset them on the starting platform.
20. Have participants repeat shape sorting task 2x from the raised shelf.

Figure D-1: (a) Each object is picked up and placed into the corresponding well; (b) objects are then picked up from a shelf on the centre cart and placed into the corresponding well.

Take a 2-minute break. Continue with training only one degree of freedom (wrist rotation). Turn off torque for hand open/close, turn on torque for wrist rotation.

1. Remind the participant that turning the palm up will rotate the wrist clockwise and turning the palm down will rotate the wrist counterclockwise.

2. Start by instructing the participant to supinate and pronate their forearm and observe that the correct movements are achieved.
3. Once the participant understands how to control wrist rotation and full range of motion is successfully achieved, ask them to rotate the wrist clockwise halfway, then fully.
4. Ask the participant to then rotate the wrist counterclockwise halfway, then fully.
5. Repeat 2-3x until successful.
6. Next, instruct the participant to rotate the wrist clockwise as slow as possible.
7. Then instruct the participant to rotate the wrist counterclockwise as slow as possible.
8. Repeat 2-3x until successful.
9. Next, instruct the participant to rotate the wrist clockwise as fast as possible.
10. Then instruct the participant to rotate the wrist counterclockiwise as fast as possible.
11. Repeat 2-3x until successful.
12. Note that the transfer learning controller has a fixed speed, but this exercise allows participants to focus on controlling wrist rotation in small increments.
13. Inform the participant that some movements that are being asked of them will be easier to perform than others but to try their best to follow the given instructions.
14. Once the participant has demonstrated full control of this degree of freedom, they can then practice with a functional task – cup pouring.
15. Set up 2 cups on the centre table with a ball in one cup.
16. Participants will have to pour the ball from one cup to the other using wrist rotation while opening/closing of the hand is controlled by a researcher.
17. Have the participant pour the ball from one cup to another.
18. Repeat until 4 successful trials are completed.
19. Then move one cup to the raised shelf on the centre cart.
20. Have the participant repeat the same cup pouring task at the raised shelf.

21. Repeat until 4 successful trials are completed.

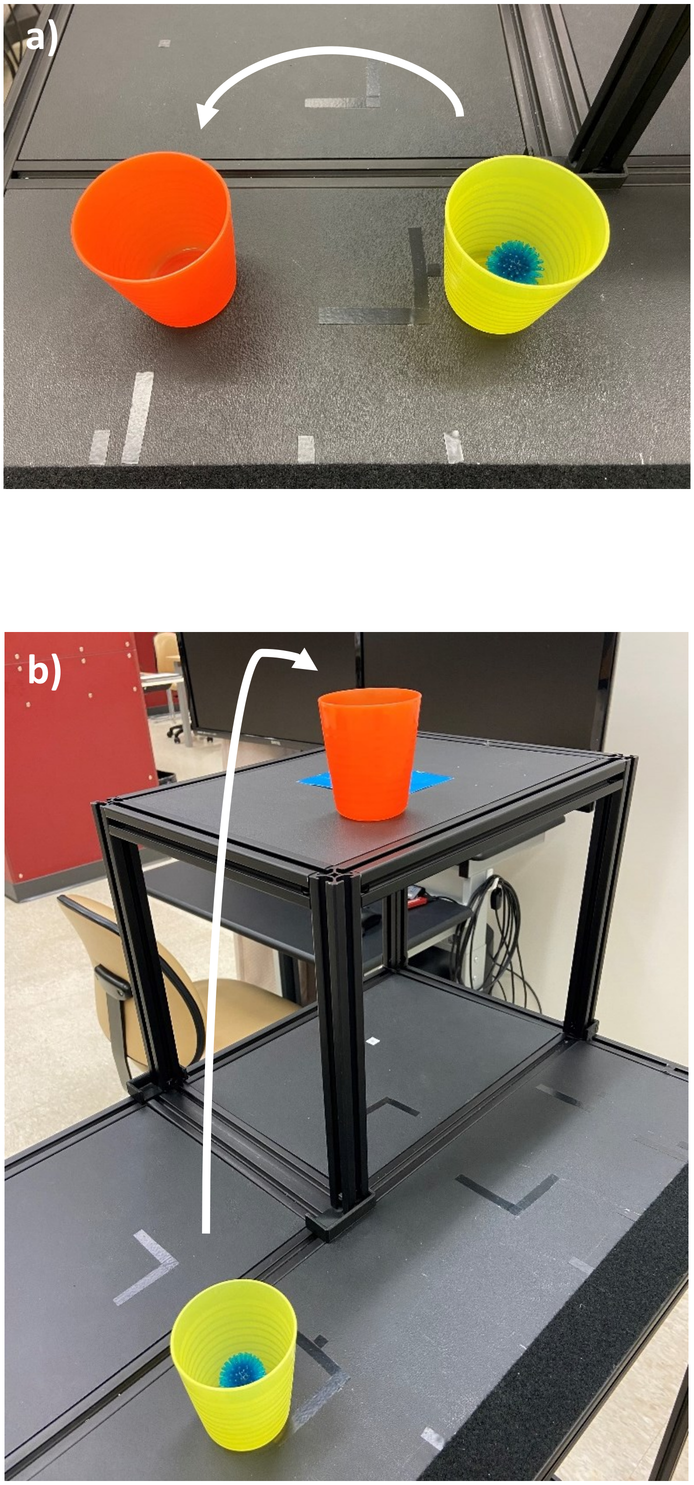


Figure D-2: (a) The ball is poured between cups; (b) the ball is then poured between a cup on the centre cart and the raised shelf.

Take a 2-minute break. This next stage will incorporate both degrees of freedom: hand open/close and wrist rotation. Participants will repeat previously performed shape sorting and cup pouring tasks with full control of the prosthetic hand, as well as 3 additional tasks. Turn on torque for all degrees of freedom.

1. Remind the participant that flexion is hand close, extension is hand open, palm up and palm down are wrist rotation in the corresponding direction.
2. Have the participant move through each movement (hand open/close, wrist rotation) until the full range of motion for all movements are successfully achieved.
3. Shape sorting task
   a. Perform at side table only (not on raised shelf).
   b. Instruct participants to pick up each object (1 through 4) and place them into the corresponding wells.
4. Cup pouring task
   a. Perform at centre table only (not on raised shelf).
   b. Have the participant pour the ball from one cup to another.
   c. Repeat for 4 successful trials.
5. Picking up balls task
   a. Disperse 4 balls at various locations on the centre table (i.e. on shelf, under shelf, different location on centre table).
   b. Place an empty cup on the shelf.
   c. Instruct the participant to pick up each ball one at a time and place them into the cup located in the centre of the shelf.

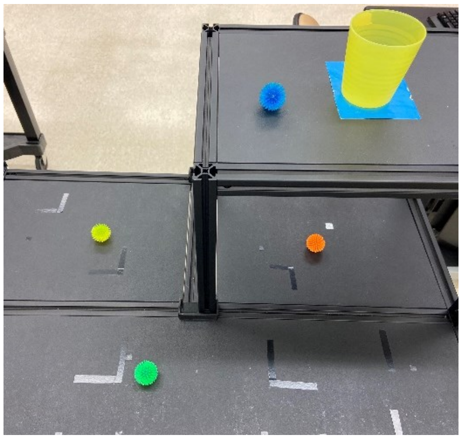


Figure D-3: Balls are picked up and placed into the cup.

6. Nesting cups task
    a. Place the small red cup next to the shelf
    b. Place the medium green cup under the shelf
    c. Place the large green cup on the shelf
    d. Instruct the participant to place the small cup into the medium cup, then place the nested cups into the large cup

Figure D-4: The small cup is placed into the medium cup, then both cups are placed into the large cup.

7. Rotating letters task
    a. Place the ‘H’ block and ‘W’ block on the centre table
    b. Instruct the participant to pick up and rotate the blocks, then place them on the shelf such that the ‘H’ block becomes an ‘I’ and the ‘W’ becomes an ‘E’
    c. Next, place the ‘I’ block and ‘E’ block on the raised shelf
    d. Instruct the participant to pick up and rotate the blocks, then place them on the centre table such that the ‘I’ block becomes an ‘H’ and the ‘E’ block becomes a ‘W’

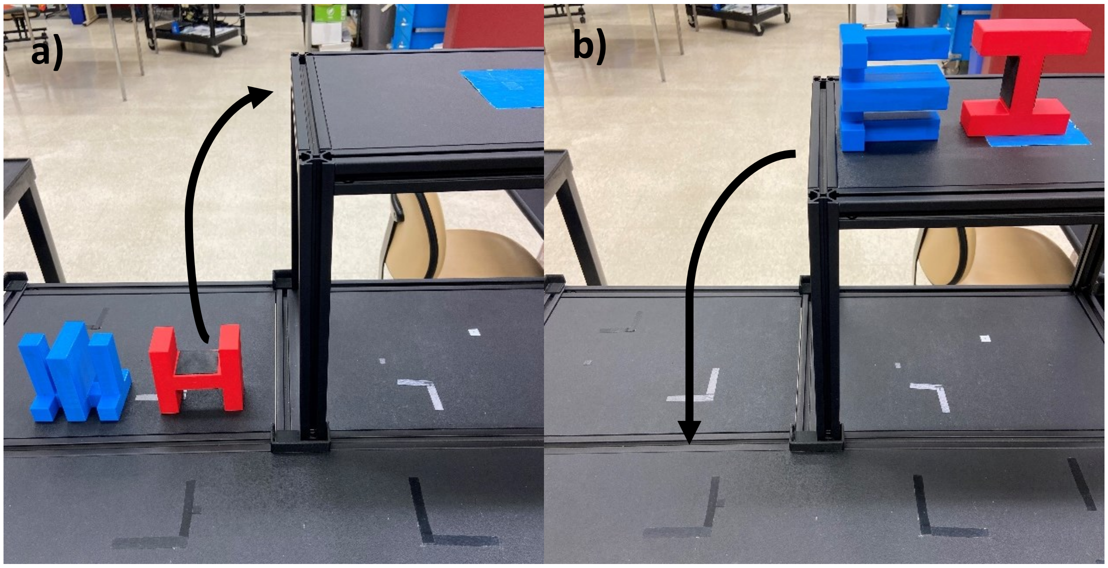


Figure D-5: (a) Letter blocks are rotated and placed on the higher shelf. (b) From the shelf, letters are then rotated again and placed on the centre table.

Reminders and tips:

- Note that participants will have greater difficulty with control when 2 degrees of freedom are introduced
- Suggest returning to a neutral/rest position if unintended movements persist as fatigue can influence signal generation
- Remind participants to produce moderate, consistent contractions like those used when training the controller
    - Producing stronger contractions that differ from training will not improve control
    - Remember that flexion is hand close, extension is hand open, palm up is clockwise wrist rotation and palm down is counterclockwise wrist rotation
- Have participants verbalize their intended movement if they are having difficulties
- Have participants mirror movements with their non-dominant hand
- Ensure that participants are not trying to produce one movement that requires sequential contractions
    - Remind them that movements can only be performed one at a time and that these contractions need to be done sequentially
- Tips for flexion/extension: relax fingers and perform movements at the wrist only
- Tips for supination: abduct and push down with the pinky finger

Appendix E: Gaze Calibration

In order to construct the gaze vector, two gaze calibrations (stationary and sweep) were performed. While standing, the participant was instructed to maintain fixated on a motion capture marker attached to the tip of a gaze calibration wand (Fig E-1) as the experimenter moved the wand around the task area. These gaze calibrations were collected after the eye tracker and motion capture set-ups were complete, and before the first and after the last pasta box task trials.

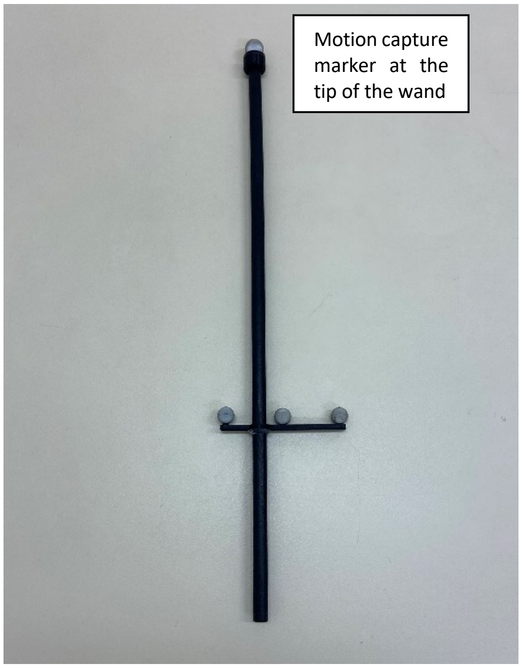


Figure E-1: Gaze calibration wand

Stationary gaze calibration

For the stationary gaze calibration, the calibration wand was held directly in front of the participant. Participants were instructed to perform the following head movements while they kept their gaze fixated on the tip of the wand. Participants should move their head until they are just about to lose sight of the marker.

1. Tilt the head up.
2. Tilt the head down.
3. Turn the head to the right.

4. Turn the head to the left.
5. Rotate the head in clockwise circles, starting with small circles that gradually get bigger.
6. Rotate the head in counterclockwise circles, starting with small circles that gradually get bigger.

Sweep gaze calibration

For the sweep gaze calibration, the experimenter stood directly in front of the participant and moved the calibration wand in large S-shaped sweeping motions that covered the task area, as shown in Fig E-2. The experimenter followed the sequence of movements as described below.

1. Start by holding the tip of the calibration wand at the home position for 2 seconds.
2. Perform four large S-shape sweeping movements from left to right from the top of the task space, parallel to the participant's frontal plane (Fig E-2a).
3. Move the tip of the calibration wand to the home positon for 1 second.
4. Perform four large S-shape sweeping movements moving up and down in the task space, parallel to the participant's frontal plane (Fig E-2b).
5. Move the tip of the calibration wand to the home positon for 1 second.
6. Perform four large S-shape sweeping movements moving back and forth along the depth of the cart at a height approximately 4 inches above the cart (Fig E-2c).
7. Return the tip of the calibration wand to the home position for 2 seconds.

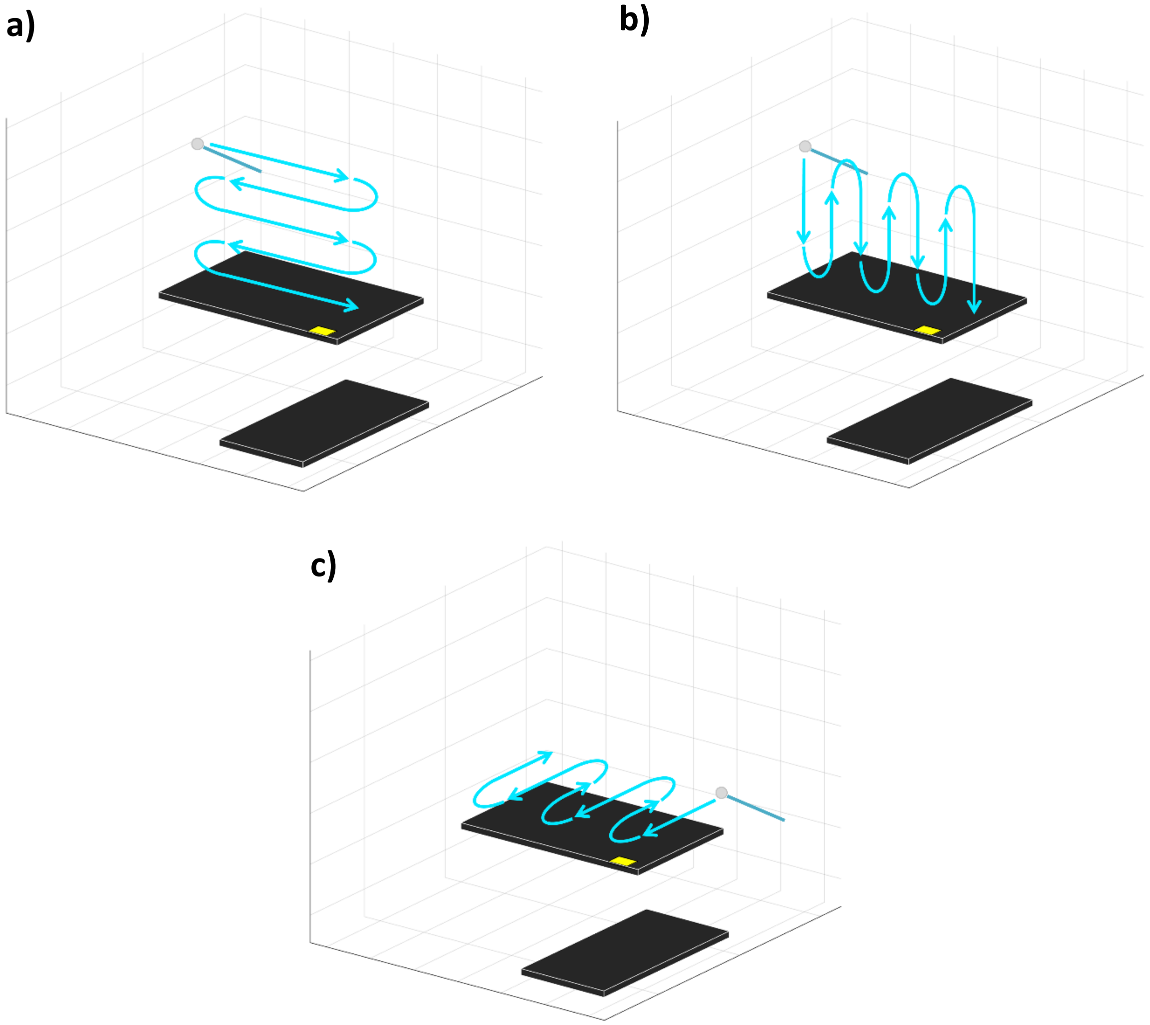


Figure E-2: Sweep gaze calibration routine: (a) left-to-right wand movements, (b) up-and-down wand movements, and (c) front-to-back wand movements, from Boser[45] used with permission.

Appendix F: Statistical Analysis of Within-Subject Comparison of Control Strategies

To investigate the within-subject differences between control strategies, a series of repeated measures analyses of variance (RMANOVA) and pairwise comparisons were conducted for each outcome measure. For each measure that was analyzed, the design of the RMANOVA was dependent on the number of movement subsets. Number of fixations to current, percent fixation to current, phase duration, and relative duration followed a three-way RMANOVA design in which strategy was a factor with two levels (baseline and transfer learning), movement was a factor with 3 levels (movement 1, movement 2 and movement 3), and movement subset was a factor with four levels (reach, grasp, transport and release). Number of fixations to hand, percent fixation to hand, eye arrival latency, eye leaving latency, peak hand velocity, hand trajectory variability, and number of movement units also followed a three-way RMANOVA design. However, movement subset was a factor with two levels (reach and transport, pick up and drop off, or reach-grasp and transport-release). Grip aperture plateau followed a two-way RMANOVA design, as this measure was only recorded for the reach-grasp segment. A summary of the RMANOVA designs are outlined in Table F-1. In addition, paired t-tests were performed to analyze the difference in total task duration, number of successes, and NASA TLX weighted rating between control strategies.

Table F-1: RMANOVA design with movement subsets for each outcome measure

		Eye metrics						Hand metrics				Duration	
		Number of fixations to current	Number of fixations to hand	Percent fixation to current	Percent fixation to hand	Eye arrival latency	Eye leaving latency	Peak hand velocity	Hand trajectory variability	Number of movement units	Grip aperture plateau	Phase duration	Relative duration
Movement Subset	Reach	X	X	X	X							X	X
	Grasp	X		X								X	X
	Transport	X	X	X	X							X	X
	Release	X		X								X	X
	Pick up					X	X						
	Drop off					X	X						
	Reach-Grasp							X	X	X	X		
	Transport-Release							X	X	X			
RMANOVA design (Strategy x Movement x Movement Subset)		2x3x4	2x3x2	2x3x4	2x3x2	2x3x2	2x3x2	2x3x2	2x3x2	2x3x2	2x3	2x3x4	2x3x4

Significant interaction effects or main effects were followed up with additional RMANOVAs or pairwise comparisons. Only significant effects involving strategy were further investigated, as the primary focus was to determine whether different strategies had an effect on visuomotor performance. If the assumption of sphericity was violated, the Greenhouse-Geisser correction was used for the interpretation of results. Interaction effects or main effects were considered to be significant if the *p* value was less than 0.05 or if the Greenhouse-Geisser corrected *p* value was less than 0.05. Pairwise comparisons were considered to be significant if the Bonferroni corrected *p* value was less than 0.05.

If a three-way RMANOVA indicated a significant three-way interaction between strategy, movement and movement subset, then follow-up two-way RMANOVAs were performed for each level of movement or movement subset. Significant two-way interaction effects were followed up with pairwise comparisons between control strategies. If a three-way RMANOVA did not indicate a significant three-way interaction, then two-way interactions between strategy and movement or movement subset were investigated. If these interaction effects were significant, pairwise comparisons between control strategies were carried out, indicating a significant difference in the outcome measure when collapsed across one factor. If no three-way or two-way interaction effects involving group were found, the main effect of strategy was investigated, followed up with pairwise comparisons between the two control strategies. Details of the three-way RMANOVA procedure are summarized in Fig F-1.

For outcome measure where a two-way RMANOVA was initially performed, significant interaction effects or main effects were followed up with pairwise comparisons between control strategies.

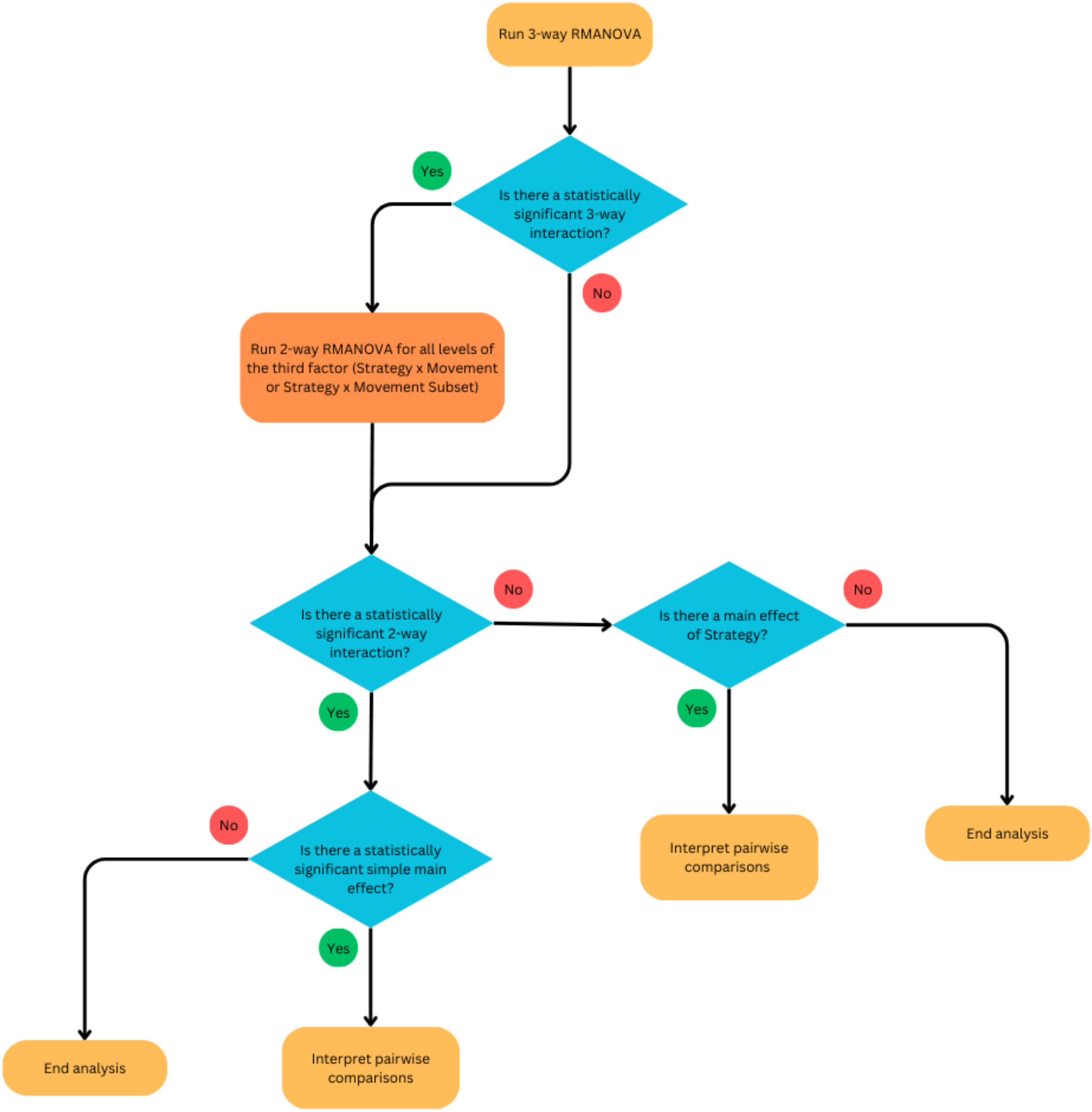


Figure F-1: Three-way RMANOVA procedure