# Investigating motor skill in closed-loop myoelectric hand prostheses

*Through speed-accuracy trade-offs*

Mamidanna, Pranav

*DOI (link to publication from Publisher):*
10.54337/aau561808227

*Publication date:*
2023

*Document Version*
Publisher's PDF, also known as Version of record

# INVESTIGATING MOTOR SKILL IN CLOSED-LOOP MYOELECTRIC HAND PROSTHESES

THROUGH SPEED-ACCURACY TRADE-OFFS

BY
PRANAV MAMIDANNA

DISSERTATION SUBMITTED 2023

AALBORG UNIVERSITY
DENMARK

# INVESTIGATING MOTOR SKILL IN CLOSED-LOOP MYOELECTRIC HAND PROSTHESES

## THROUGH SPEED-ACCURACY TRADE-OFFS

by

PRANAV MAMIDANNA

AALBORG UNIVERSITY
DENMARK

DISSERTATION SUBMITTED 2023

| | |
|---|---|
| Dissertation submitted: | June 2023 |
| PhD supervisor: | Professor Strahinja Dosen,<br>Aalborg University |
| Assistant PhD supervisor: | Associate Prof. Jakob L. Dideriksen,<br>Aalborg University |
| PhD committee: | Associate Professor Sabata Gervasio (chair)<br>Aalborg University, Denmark<br>Professor Silvestro Micera<br>École Polytechnique Fédérale de Lausanne, Switzerland<br>Professor Jacqueline S. Hebert<br>University of Alberta, Canada |
| PhD Series: | Faculty of Medicine, Aalborg University |
| Department: | Department of Health Science and Technology |

ISSN (online): 2246-1302
ISBN (online): 978-87-7573-683-6

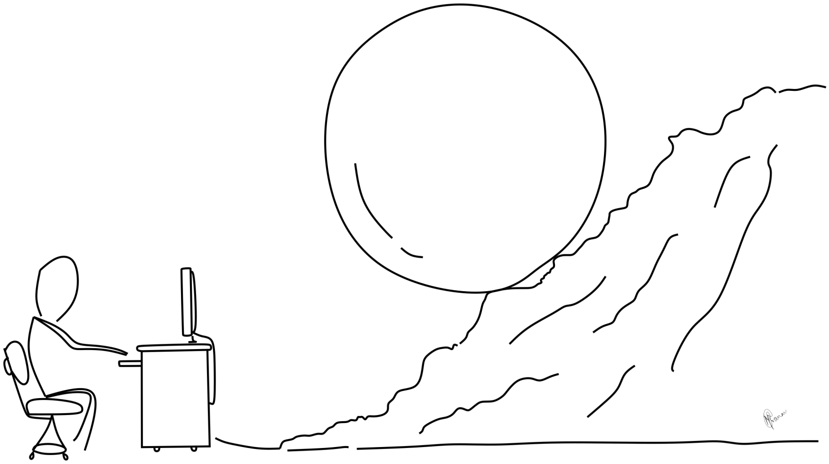
Published by:
Aalborg University Press
Kroghstræde 3
DK – 9220 Aalborg Ø
Phone: +45 99407140
aauf@forlag.aau.dk
forlag.aau.dk



Printed in Denmark by Stibo Complete, 2023

# CV

Pranav Mamidanna was born in Hyderabad, India. He obtained a bachelor's degree in chemical engineering from the Jawaharlal Nehru Technological University, Hyderabad in 2014. He then moved to Scandinavia to pursue a master's degree in applied and engineering mathematics at NTNU, Trondheim, Norway, and KTH, Stockholm, Sweden, graduating with a thesis on optimizing neural source extraction algorithms for calcium imaging data, in 2017. After a brief research stint at the Max Planck Institute for Intelligent Systems in Tübingen, Germany, working on neural network models of proprioception, he moved to Aalborg, Denmark, for his doctoral studies. During his PhD, he focused on developing and evaluating interfaces for myoelectric hand prostheses using concepts from the theory of human motor control.



# ENGLISH SUMMARY

Myoelectric hand prostheses aim to restore lost functionalities and improve the quality of life for individuals with upper-limb differences. User-prosthesis interfaces play a vital role in this technology. The most sophisticated interfaces translate user intentions into prosthesis movements and provide feedback on the prosthesis state, enabling closed-loop bidirectional interactions. Acquiring skilled prosthesis use involves learning how to activate residual muscles effectively and is determined by the interfaces used. Therefore, evaluating and monitoring user skill, and designing interfaces to facilitate it, is critical to the pursuit of a functional restoration of the lost hand.

Despite the growing efforts in designing closed-loop interfaces, evaluating how they facilitate the acquisition of skilled prosthesis usage and, moreover, how different interfaces compare in this respect remains unclear. While previous studies investigated learning effects and the underlying control processes in user-prosthesis interaction, they have either explored a subset of what constitutes prosthesis skill or used specialized experimental setups that may not be widely accessible. Specifically, skilled behavior is characterized by accurately and precisely executing movements, even at faster speeds – an aspect that has so far not been investigated.

In this thesis, we leveraged the phenomenon of speed-accuracy tradeoffs (SAF) – the scientific equivalent of 'haste makes waste' – and developed an experimental framework to evaluate and understand how two different closed-loop user-prosthesis interfaces affect user skill in the context of prosthesis grasp-force control. We investigated how speed accuracy requirements at the level of task influenced participants' control policies, how the SAF afforded by each interface differed and how it evolved across days. Towards this end, we measured how the accuracy of force control varied with execution speeds and proposed novel behavioral outcomes that analyze the control policies of users and measure how variable and smooth the user-generated commands were.

Notably, by characterizing the interfaces across a range of speeds and accuracies, we found that while interfaces could offer asymptotically similar performance (i.e., at the fastest speeds and highest accuracies), the tradeoffs they enable could be significantly different. Therefore, when evaluating competing interfaces, measuring the SAF provides a better

characterization of the interfaces than current methods. Further, we validated the utility and relevance of analyzing user-generated myoelectric commands to infer and monitor behavioral markers of skill. Finally, we developed parametric models of the SAF and proposed model-based methods to monitor user skill.

Taken together, we have developed an experimental framework that can be used to determine the performance characteristics afforded by different interfaces, understand user behavior, and rigorously monitor user skill. We believe that it is a valuable addition to existing methods that enable us to carefully investigate motor skill in myoelectric hand prosthesis and develop interfaces and learning protocols that optimally facilitate it.

# DANSK RESUME

*Undersøgelse af motoriske færdigheder i tovejs myoelektriske håndproteser Gennem afvejning af hastighed og nøjagtighed*

Myoelektriske håndproteser har til formål at genskabe tabte funktioner og forbedre livskvaliteten for personer med handicap i overekstremiteterne. Bruger-protese-grænseflader spiller en afgørende rolle i denne teknologi. De mest sofistikerede interfaces oversætter brugerens intentioner til protesens bevægelser og giver feedback om protesens tilstand, hvilket muliggør closed-loop tovejsinteraktioner. For at blive dygtig til at bruge protesen skal man lære at aktivere de resterende muskler effektivt, og det afhænger af de interfaces, der bruges. Derfor er det vigtigt at evaluere og overvåge brugerens færdigheder og designe grænseflader, der gør det lettere, hvis man vil genskabe den mistede hånds funktion.

På trods af den voksende indsats for at designe closed-loop interfaces, er det stadig uklart, hvordan de letter tilegnelsen af færdigheder i protesebrug, og hvordan forskellige interfaces sammenlignes i denne henseende. Mens tidligere studier har undersøgt læringseffekter og de underliggende kontrolprocesser i interaktionen mellem bruger og protese, har de enten udforsket en delmængde af, hvad der udgør protesekompetence, eller brugt specialiserede forsøgsopstillinger, som måske ikke er bredt tilgængelige. Specifikt er dygtig adfærd kendetegnet ved nøjagtig og præcis udførelse af bevægelser, selv ved hurtigere hastigheder - et aspekt, der indtil videre ikke er blevet undersøgt.

I denne afhandling har vi udnyttet fænomenet speed-accuracy tradeoffs (SAF) - den videnskabelige ækvivalent til "hastværk gør mester" - og udviklet en eksperimentel ramme til at evaluere og forstå, hvordan to forskellige closed-loop bruger-protese-grænseflader påvirker brugerens færdigheder i forbindelse med protesens grebskraftkontrol. Vi undersøgte, hvordan den SAF, som hvert interface gav, var forskellig, og hvordan den udviklede sig over flere dage. Til det formål målte vi, hvordan nøjagtigheden af kraftkontrollen varierede med udførelseshastigheden, og foreslog nye adfærdsmæssige resultater, der analyserer brugernes kontrolpolitikker og måler, hvor variable og jævne de brugergenererede kommandoer var.

Ved at karakterisere grænsefladerne på tværs af en række hastigheder og nøjagtigheder fandt vi, at selvom grænsefladerne kunne tilbyde asymptotisk

lignende ydeevne (dvs. ved de hurtigste hastigheder og højeste nøjagtigheder), kunne de afvejninger, de muliggør, være væsentligt forskellige. Når man evaluerer konkurrerende grænseflader, giver måling af SAF derfor en bedre karakterisering af grænsefladerne end de nuværende metoder. Desuden validerede vi nytten og relevansen af at analysere brugergenererede myoelektriske kommandoer for at udlede og overvåge adfærdsmæssige markører for færdigheder. Endelig har vi udviklet parametriske modeller af SAF og foreslået en modelbaseret metode til at monitorere brugerfærdigheder.

Samlet set har vi udviklet en eksperimentel ramme, der kan bruges til at bestemme de præstationsegenskaber, som forskellige grænseflader giver, forstå brugeradfærd og nøje overvåge brugerfærdigheder. Vi mener, at det er en værdifuld tilføjelse til eksisterende metoder, der gør os i stand til omhyggeligt at undersøge motoriske færdigheder i myoelektriske håndproteser og udvikle grænseflader og rehabiliteringsprotokoller, der letter det optimalt.

# ACKNOWLEDGEMENTS

These past four years in Aalborg have been some of the most intellectually challenging and rewarding ones of my life. I owe a tremendous debt of gratitude to the people I have had the privilege of meeting and working with here, as they have shaped me both as a researcher and as a person.

First and foremost, a sincere thanks to my supervisor, Professor Strahinja Dosen. Always beaming with positive energy, you have been a constant source of inspiration to me! I am immensely grateful for the intellectual freedom you granted me, allowing me to pursue my own ideas while providing invaluable guidance and direction when I needed it most. Your insistence on thinking critically and writing clearly has been instrumental in my growth as a researcher. I could not have asked for a more supportive mentor!

I would also like to extend thanks to my co-supervisor Associate Professor Jakob Diderksen, for all your support and guidance. Your insights have played a crucial role in shaping my research and broadening my perspective. A special thanks to Associate Professor Patrik Telleus for inspiring discussions on the challenges of translational and inter-disciplinary science and for expanding my understanding of the research process.

To my dear friends Shima, Jack, Lisha, and Gai, words cannot express how much your companionship has meant to me. Throughout the ups and downs of not just a PhD but a pandemic-stricken one, you have been there to save my sanity. Thanks for all the lovely movie nights, incredible food, and cocktails, and for making all my bus rides to the city absolutely worth it!

A huge thanks to all the members of the lab, Romain, Luis, Fabri, Naja, Martin, Sabina, Mauri, Miguel, and Prithvi, and ‘CNAP friends’ Felipe, Daniel, Caro, and Marco, for all the coffee room chats, Jomfru nights, and for creating a wonderful working environment.

To my family, Amma, and Akka, my pillars of strength! Thanks for all the love and support :’)

Last but not least, thanks to all those who kindly participated in my experiments and made this thesis possible!

# TABLE OF CONTENTS

# CHAPTER 1. INTRODUCTION

As is customary in the field of bionic-hand research, we begin this thesis in awe of the human hand. With a sophisticated anatomy and a complex sensorimotor system that allow its numerous muscles to work in harmony, the human hands produce precise and intricate movements. This enables us to perform actions ranging from seemingly simple ones, such as picking up a cup of coffee, to those reserved for virtuoso violinists.

The loss of a hand is, therefore, debilitating, restricting one's ability to perform daily activities and engage in various social interactions. As a result, individuals with upper-limb differences face significant challenges that affect their quality of life and psychosocial well-being and require extensive physical rehabilitation and care.

Throughout history, people have sought ways to compensate for this loss by developing prosthetic attachments ranging from purely cosmetic to hook-like gripping devices that are body-powered and highly advanced bionic hands (Thurston, 2007; Zuo & Olson, 2014). This pursuit of a bionic hand continues to captivate and challenge scientists, engineers, and designers alike, not just to restore and replace but reimagine the very form and function of human hands.

## 1.1. MYOELECTRIC HAND PROSTHESES AND INTERFACES

The current state-of-the-art in bionic hands is characterized by dexterous mechatronic devices driven by the user's intentions. These 'myoelectric' prostheses record electromyography (EMG) signals from the user's residual limb and estimate the movement intention behind the recorded signal. This estimation is then translated into the corresponding movements of the prosthesis.

What sets these devices apart from traditional robotic systems is the central role of the interface between the user and the prosthesis. While conventional robotic control relies on well-defined cost functions that take advantage of high-precision sensing systems to move, the success of myoelectric prostheses hinges on the seamless integration of the user's intentions and the device's actions.

The earliest myoelectric control interfaces, developed in the 1940s and 50s, used two-state amplitude modulation to drive the opening and closing of a prosthetic hook (for a brief historical perspective, see Parker et al., 2006). Stated simply, the amplitude of the EMG signal recorded from a single electrode was translated into on/off commands, depending on whether the amplitude was higher or lower than a set threshold. Then emerged multistate control, amplitude-modulation (or proportional control), and subsequently pattern recognition- and machine learning-based controllers, which used various algorithms to map EMG signals into intended movements (Zecca et al., 2002; E. Scheme & Englehart, 2011; Shehata et al., 2021).

While breakthroughs in design and mechanics have allowed these bionic hands to mimic natural hand movements more closely than ever before (Catalano et al., 2014; Laffranchi et al., 2020; Piazza et al., 2019), and advancements in EMG acquisition continue to improve the quality and resolution of the recorded signals (Merletti & Farina, 2016; Holobar & Farina, 2021), the precision and fluidity of control have yet to reach the same level of advancement (Salminger et al., 2020).

Consequently, prosthesis abandonment rates have been reported to be high. While many factors have been linked to the rejection or abandonment of prostheses, such as comfort (related to the weight of the prosthetic hand and the socket that it is mounted on), cost, aesthetics, and perceived need for a prosthesis (Millstein et al., 1986; E. A. Biddiss & Chau, 2007; Kyberd & Hill, 2011; Østlie et al., 2012), here we focus on functional factors. Several studies report a lack of intuitiveness of the interface, reliance on visual feedback, and instabilities in control as contributing factors to prosthesis rejection (E. Biddiss et al., 2007; E. A. Biddiss & Chau, 2007; Burger & Marincek, 1994; Engdahl et al., 2015; Salminger et al., 2020).

A particularly appealing and effective solution to address these drawbacks has been the inclusion of feedback in the system (Bensmaia et al., 2020; Jabban et al., 2022).

## 1.2. THE PROMISE OF CLOSED-LOOP INTERFACES

Biological control is closed-loop control. Dexterous hand movements are

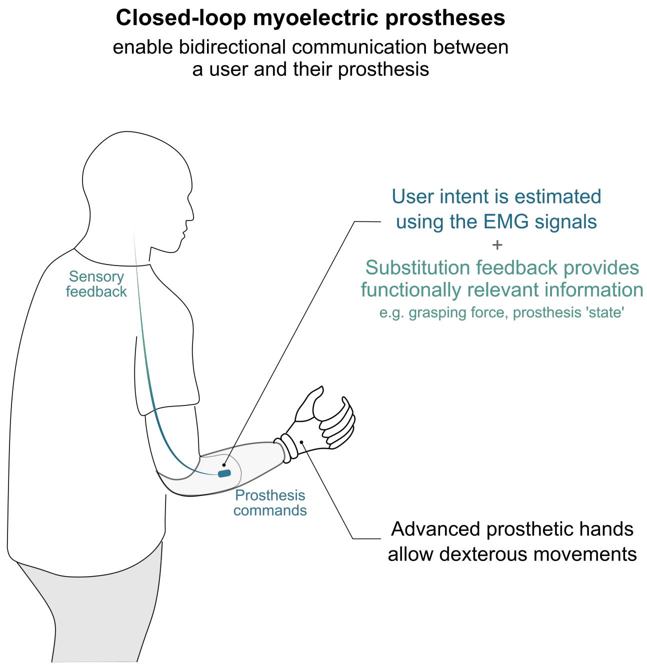



Figure 1.1: The anatomy of closed-loop myoelectric prostheses.

constantly informed and even driven by the sensory feedback we receive through vision, touch, and proprioception. Closed-loop interfaces, which combine myoelectric control with some form of supplementary sensory feedback, seek to restore some aspects of feedback, e.g., perception of grasp strength, textural properties of objects, slippage etc. (Figure 1.1). Notably, these interfaces have been driven by user needs, and consequently, have been shown to provide both functional and psychosocial benefits (Jabban et al., 2022).

Several approaches have been proposed to provide supplementary sensory feedback, ranging from invasive electrical stimulation of the brain using chronically implanted electrodes to non-invasive electrical or mechanical stimulation of the skin using wearable haptic systems (Flesher et al., 2021; D'Anna et al., 2019; Markovic et al., 2018c; for a recent review see Bensmaia et al., 2020). The main driving principle behind the invasive methods has been biomimicry, to provide sensations as close as possible to those available to the intact hand, while non-invasive methods have been predominantly driven by sensory substitution principles.

This thesis concerns itself with sensory substitution feedback, which involves conveying information that would typically be perceived by the missing limb through an intact sensory modality, such as through tactile vibrations or auditory cues, e.g., grasp force communicated as the amplitude of a vibration motor placed on the skin. Such feedback has been shown to enhance the user's control over their prosthetic device and facilitate a more intuitive and effective use of the prosthesis. Several studies have shown that electro- or vibrotactile stimulation improved the control of hand aperture, grasp force, joint position, and object properties (for a thorough discussion, see Antfolk et al., 2013; Schofield et al., 2014; Svensson et al., 2017; Dideriksen & Dosen, 2021).

Further, based on theories of sensorimotor control, Cipriani et al., (2014) demonstrated that discrete event-based feedback, i.e., communicating the moment of object contact and release, improved manipulation performance and reduced object slippage (Clemente et al., 2016; Aboseria et al., 2018). Dosen et al., (2015) demonstrated that EMG biofeedback, i.e., to deliver user’s own myoelectric commands as feedback, improved grasp force control, conferred stronger internal models, and enabled better adaptation to control disturbances (Dosen et al., 2015b; Dosen et al., 2017; Tchimino et al., 2022). Finally, multi-variable feedback methods that simultaneously inform the user of the aperture, rotation, and force (Garenfeld et al., 2020, 2023) are being developed to convey as much information to the user as possible, while maintaining interpretability.

Despite these promising results, there have also been studies that cast a shadow on the utility of sensory substitution feedback. For example, Saunders & Vijayakumar (2011), report how such feedback may be beneficial only when there is uncertainty in feedforward control. Similarly, Markovic et al., (2018a) report that advanced substitution feedback provided a functional advantage only during ‘complex tasks’ (also see Markovic et al., 2018b, Chatterjee et al., 2008; Cipriani et al., 2008; for a recent review on the promise and perils of feedback, see Jabban et al., 2022). Moreover, clinical utility through large-scale studies is yet to be shown.

As a consequence, there are currently only a few prosthetic hands which include an option for feedback, including the evolution line of hands from Vincent Systems GmBH, the LUKE arm from Mobius Bionics Inc., and the Ability hand from Psyonic.

## 1.3. EVALUATING AND UNDERSTANDING CLOSED-LOOP USER-PROSTHESIS INTERACTION

Closed-loop user-prosthesis interaction is a complex, multi-faceted phenomenon, and therefore, determining whether a specific interface (or a part of it, such as feedback) enhances functionality for the end user is a difficult question. While task performance is an important indicator, it is far from complete. To understand the role of feedback in user-prosthesis interaction and to reconcile the apparently contradictory findings in literature, Sensinger & Dosen, (2020) propose that it is critical to look at this phenomenon through the framework of motor control and motor learning (Wolpert & Ghahramani, 2000; Krakauer, 2006; Kitago & Krakauer, 2013; Shadmehr & Krakauer, 2008).

### 1.3.1. MOTOR CONTROL AND MOTOR LEARNING IN THE CONTEXT OF HAND LOSS

In a nutshell, the theory of motor control explains that our brain solves three kinds of problems to move the body from a given state to a desired goal state. These three problems or processes are called system identification, state estimation and optimal control (Shadmehr & Krakauer, 2008). System identification involves predicting sensory consequences of intended movements (also called motor commands). State estimation generates an internal representation of the state of the body and the world by combining the predictions of the system identification process and actual sensory feedback. Optimal control then generates the optimal motor commands given the current state of the body and the desired goal state. The generality and explanatory power of this framework had a tremendous impact on understanding how humans move in both health and disease and has guided research and practice of recovery and rehabilitation in motor disorders (Kitago & Krakauer, 2013; Krakauer & Carmichael, 2022).

Applying this framework to the context of hand loss and user-prosthesis interaction, we readily observe that all three processes are severely disrupted. State estimation becomes heavily reliant on alternative sensory inputs, such as visual cues and other forms of 'incidental feedback' not originally intended for controlling hand movements. And predicting sensory consequences of prosthesis movements and generating optimal commands (alternatively called internal models) needs to be learned anew.

The learning processes that determine how an amputee gains functional use of the prosthetic hand can be understood as a product of motor adaptation and skill learning. Motor adaptation is the process by which the motor system responds to perturbations – both internal bodily changes and environmentally imposed ones. Skill learning, on the other hand, involves the acquisition and retention of new movement patterns and achieving ever higher levels of performance (Krakauer, 2006; Kitago & Krakauer, 2013).

As an amputee recovers from a limb loss and adjusts to their prosthesis, the motor system first needs to learn the properties of the prosthesis to predict how it responds to motor commands. At the same time, it needs to learn how to interpret the supplementary sensory information being provided (in the case of closed-loop interfaces) and include it in state estimation. Finally, the motor system must become more skilled at controlling the prosthesis, a long process thought to correspond to learning a new optimal control policy and getting increasingly more accurate and faster at implementing it.

Importantly, feedback, whether it is error-based such as arising from task performance or sensory feedback supplemented through external stimulation, plays a key role in enabling the above-mentioned processes to occur. Specifically, supplementary feedback enables the formation and retention of stronger internal models, and aids state estimation, thereby supporting motor control processes. At the same time, it plays a role in facilitating and accelerating motor learning processes to achieve skilled prosthesis usage.

### 1.3.2. EXISTING APPROACHES AND METRICS TO INVESTIGATE MOTOR CONTROL AND LEARNING

Using the theoretical framework laid out above, either explicitly or implicitly, several studies have argued for evaluating and understanding the utility of feedback, or closed-loop interfaces, in a way that sheds light on how they affect users' motor control and learning processes. Consequently, several methods and metrics were proposed to investigate user-prosthesis interaction, focused on quantifying various aspects of control, including quality and efficiency of the executed movements, reliability of control, user confidence, and so on, while also focusing on task-level performance. It is through this holistic approach that we can start to comprehend the utility of sensory substitution feedback.

The first step in trying to understand the motor control aspects of user-prosthesis interaction is to look at visuomotor behavioral markers such as end-point kinematics (e.g., trajectory, speed, and efficiency of reaching movements), joint kinematics (e.g., range of motion and coordination between different joints), and visual gaze (e.g., where, and how long users look at the prosthesis or task at hand) (Kitago & Krakauer, 2013; de los Reyes-Guzmán et al., 2014; Alt Murphy & Häger, 2015). These metrics indicate the quality of prosthesis users' movements and provide insights into how it differs from able-bodied individuals. For instance, end-point kinematics can reveal the precision and smoothness of the user's movements, while joint kinematics can indicate how effectively they are utilizing their residual limb and prosthesis. Visual gaze can help measure the extent to which users rely on vision to monitor their prosthetic movements, reflecting users' trust in their prosthesis' movements and consequently investigate if providing supplementary feedback reduces this dependence on vision.

Towards this end, Bouwsema et al., (2012, 2014), demonstrated how performance and behavioral metrics that quantify multiple aspects of 'skilled' behavior such as speed, accuracy, and economy (in terms of end-point kinematics, and visual attention), recorded using motion capture and eye tracking, could be incorporated into rehabilitation practice. In a similar vein, the Gaze and Movement Assessment (GaMA) protocol was developed to quantify compensatory body movements and visual gaze behavior, along with rigorous validation and normative data captured in able-bodied individuals (Williams et al., 2019; Valevicius et al., 2018; Hebert et al., 2019). Using this protocol, Marasco et al., (2021) demonstrated that integrating touch and kinesthetic sensory feedback through sensory reinnervation led to more naturalistic prosthetic use. However, sensory substitution feedback has not been tested using such advanced methods yet.

As alluded to previously, developing internal models of the prosthesis is a necessary component of gaining control ability. To this end, several groups have investigated the role of supplementary feedback in enabling the formation and retention of better internal models. Notably, Shehata, et al., (2018a, b, c) have developed a framework to evaluate internal model strength by measuring trial-by-trial adaptation to user generated errors and just noticeable differences in control disturbances. They demonstrated that supplementary feedback resulted in improved performance and movement efficiency in prosthesis control. Dosen et al., 2015 investigated the benefits of supplementary feedback in developing and maintaining an internal model of prosthesis grasp force control and demonstrated that supplementary force feedback was essential in maintaining an internal model of prosthesis force control (also see Gillespie et al., 2010; Saunders & Vijayakumar, 2011; Johnson et al., 2017; Hahne et al., 2017). Further, Gholinezhad et al., 2021; Risso et al., 2019 and others used psychophysics-based approaches to quantify how substitution feedback is integrated into state estimation.

All these studies, therefore, provide different ways to understand and reason about what aspects of the sensorimotor user-prosthesis interaction is affected by a particular intervention (such as a new feedback interface or a control algorithm), and by extension, how to evaluate if a particular interface improves functionality for the user. Particularly, measures concerning just-noticeable differences in sensorimotor disturbances, internal model strength etc. provide insight into low-level motor control aspects. Kinematic analysis of visuomotor behavior enable an intermediate-level analysis of variables that are directly related to task success but are the result of multiple underlying control processes, and finally, gross performance in the task informs about overall ability.

### 1.3.3. SKILL ACQUISITION AND SPEED-ACCURACY TRADEOFFS

Learning to use a myoelectric (closed-loop) interface as explained earlier involves learning to implement arbitrary, new, movement patterns, such as activating flexor muscles to close a prosthetic hand (i.e., learning a new optimal control policy), and executing it faster and better (i.e., improved ‘motor acuity’, see Krakauer et al., 2019; Du et al., 2022). This process of skill acquisition takes place over weeks and months (Schofield et al., 2020; Osborn et al., 2021; Butkus, 2022). However, the ways in which an interface (or practice or familiarity with an interface) affects this process, has been under-explored (Figure 1.2).

Motor skill and its acquisition have typically been gauged using two distinct parameters: a task performance metric, such as accuracy, and the speed or duration of task execution. This approach often conflates skill and accuracy, where improved accuracy is inferred to mean enhanced skill. However, genuine skill improvement can only be inferred when both accuracy and speed improve simultaneously. If these parameters develop in opposite directions, e.g., if accuracy improves at the cost of speed, it becomes challenging to discern whether the improved accuracy is due to better skill or merely slower execution. Measuring a speed-accuracy tradeoff ‘function’ (SAF), i.e., how accuracy varies with speed, has therefore been proposed as the preferred metric to quantify skill, as it encapsulates both measures (Reis

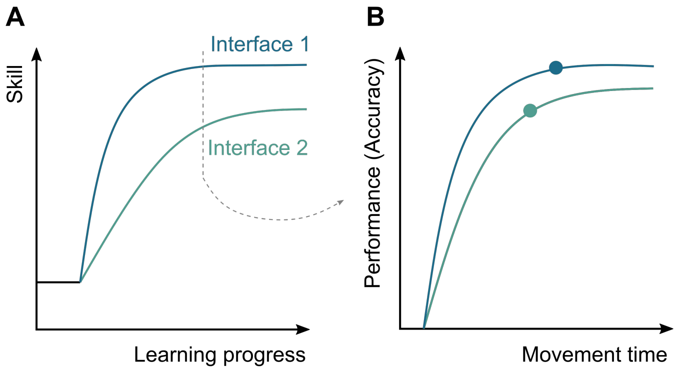



Figure 1.2: Motor skill acquisition in user-prosthesis interaction is determined by the interfaces. (**A**) Concept diagram indicates how one interface may facilitate faster and better skill acquisition than another. (**B**) The skill afforded by both interfaces in panel A, during a particular time point in the learning process, as measured by a speed-accuracy tradeoff function (SAF). Notice that by simply measuring the performance at a single speed, it becomes impossible to figure out if the better performance due to interface 1 is due to better overall skill ('better' SAF) or merely due to slower execution speed.

et al., 2009; Shmuelof et al., 2012, 2014). Empirically measuring the SAF also enables rigorous kinematic analysis of underlying behavior, which can be used to understand the control policies developed by the users and to quantify motor acuity.

Therefore, we believe that studying motor skill acquisition and motor acuity through SAF will lead to complementary and holistic understanding of learning and control processes in user-prosthesis interaction, and consequently equip us to comprehensively characterize the role of supplementary feedback. In addition to existing measures that enable us to understand low-level control processes, and intermediate-level visuomotor behaviors, measuring SAF adds a dimension, specifically that of execution speed, to rigorously characterize skill at the gross performance level and motor acuity that enables said skill at the intermediate-level.

## 1.4. OUTLINING THE RESEARCH: SCOPE AND OBJECTIVES

This section outlines the scope of research presented and discussed in this thesis, with the larger goal of developing ever better closed-loop user-prosthesis interfaces that bridge the gap between bionic and natural hand control.

### 1.4.1. SCOPE

This thesis will focus on evaluation and understanding of non-invasive, sensory substitution feedback based closed-loop interfaces for transradial myoelectric prostheses, with a particular emphasis on the role of feedback in this setting. We further limit our attention to quantifying the functional improvements made possible with these interfaces, as opposed to the equally (if not more) important psychosocial benefits of feedback. We focus on non-invasive myoelectric prostheses, since despite being in the nascent stages of technological advancement and accessibility – particularly in developing countries – they still account for the majority of devices in use today. Sensory substitution feedback offers a practical and convenient choice in providing users with vital information about their prosthesis and its interactions with the environment. Therefore, we believe that creating an understanding of these interfaces is an important goal.

Further, we will focus on the problem of grasp force control, arguably the primary function of hand prostheses. Force control represents a classic instance where supplementary feedback is thought to be beneficial, and consequently has received a lot of attention (see Chapter 2). And importantly, fine force control has been shown to be one of the more difficult skills to obtain with current interfaces (Bouwsema et al., 2012, 2014; Butkus, 2022). While the learning processes involved in other tasks, e.g., hand pre-shaping (or grasp selection), might be different from grasp force control, we believe that the methodology we develop here is not constrained by the task at hand.

### 1.4.2. OBJECTIVES

Facilitating and monitoring skill acquisition is fundamental in enabling amputees to use their prosthesis proficiently. Therefore, creating interfaces to facilitate this process, and tools to evaluate it is the central concern of this thesis.

Operating under the constraints laid out in Chapter 1.4.1, we aim to understand skill acquisition in prosthesis force control, and the role of different supplementary feedback interfaces in enabling it. Here, we operationally define skill acquisition as learning a new optimal control policy, i.e., a control policy that generates optimal motor commands to move the prosthesis from a given state to a desired state using the available system identification and state estimation resources, and gaining acuity in executing it, by reducing variability at the level of motor execution, even at faster speeds.

Specifically, we will address the following two broad research questions:

---

***Q1.*** *How do different closed-loop interfaces facilitate skill acquisition and how is it affected by training?*

---

The skill level in user-prosthesis interaction depends on the user's ability to utilize a specific interface. Consequently, different interfaces naturally vary in the skill they facilitate. Here, we make a crucial distinction between performance and skill, where the latter can only be understood as a combination of performance (accuracy) and execution speed. While interface- and learning-induced changes in performance have been investigated before, we argue that it only informs a part of the overall process of skill acquisition. For example, it is unknown if performance differences caused by interfaces exist at all execution speeds, or if differences between interfaces manifest only at some speeds. Similarly, it is unknown how training affects performance across different execution speeds.

At a more fundamental level, behavioral differences and motor acuity enabled by different interfaces has not been studied before. To study this, we develop a method to empirically measure speed-accuracy tradeoffs enabled by different interfaces, borrowing from studies in human motor control of point-to-point movements. Together with performance changes related to execution speed, we will investigate how underlying behavior is affected by these interfaces. This leads to the second broad research question:

---

***Q2.*** *What are the relevant behavioral markers of control policies and motor acuity in user-prosthesis interaction?*

---

Characterizing and quantifying user behavior is significant for several reasons, as also outlined in Chapter 1.3.2. For instance, such ‘behavioral markers’ can enable us to understand the control policies adopted by users, allowing us to identify undesirable behaviors, such as suboptimal strategies of completing a task. Importantly, control policies are affected not just by the interface at hand, but the speed and accuracy demands imposed by tasks or situations. Therefore, evaluating and understanding control policies can enable us to monitor high-level user behavior and curate interventions through further instruction. Further, identifying behavioral changes over time gives us a sense of the effect of repeated practice on how a user responds to their prosthesis. Changes in these metrics provide a quantitative measure of the effect of different interfaces on user behavior and not just performance. Finally, identifying interface effects and desirable motor behaviors can together be used to inform the design of new interfaces. However, such a detailed analysis of user behavior is lacking in prosthesis control, and specifically closed-loop control.

To this end, we propose analyzing the properties of user-generated myoelectric commands is appropriate. We believe that it is a suitable surrogate for more resource intensive measures of end-point kinematics (such as through motion capture) and offers valuable insights into users’ control.

In summary, we aim to investigate skill acquisition in user-prosthesis interaction by empirically measuring the effects of interfaces and learning on speed-accuracy tradeoffs and the underlying control policies and motor acuity. We believe that this also enables us to better understand the role of feedback in user-prosthesis interaction.

## 1.5. ORGANIZATION OF THE THESIS

To achieve the above goals, we conducted three experimental studies, which resulted in the following three manuscripts –

> **Study 1:** Mamidanna, P., Dideriksen, J.L. and Dosen, S., 2021.
> The impact of objective functions on control policies in closed-loop control of grasping force with a myoelectric prosthesis.
> Journal of Neural Engineering, 18(5), p.056036.

Here, we investigated how to measure the relevant behavioral markers of control policies in force control (***Q2***), and how speed and accuracy demands at the task level influenced these policies.

> **Study 2:** Mamidanna, P., Dideriksen, J.L. and Dosen, S., 2022.
> Estimating Speed-accuracy tradeoffs to evaluate and understand closed-loop prosthesis interfaces.
> Journal of Neural Engineering 19(5) p.056012.

Next, we studied how different interfaces affect skill acquisition through SAF (***Q1***) and develop metrics to quantify it, in terms of both control policies and acuity of user generated motor commands (***Q2***).

> **Study 3:** Mamidanna, P.*, Gholinezhad, S.*, Farina, D., Dideriksen, J.L. and Dosen, S.
> Measuring and monitoring skill-learning in closed-loop myoelectric prostheses using speed-accuracy tradeoffs.
> *Equal contribution, manuscript under preparation.

Finally, we quantified learning induced changes in the SAF at both the level of task performance, and underlying behavior to understand how skill acquisition is facilitated by closed-loop interfaces (***Q1***).

In the subsequent chapters, we summarize the central contributions of the three studies with respect to previous research and reinterpret them with the broader objectives presented through the research questions ***Q1*** and ***Q2***. In Chapter 2, we outline relevant background and state of the art in non-invasive substitution feedback based closed-loop interfaces for prosthesis force control. Then, we present the major methodological choices which run across the three studies and their implications in Chapter 3. Chapter 4 provides a summary of the main outcomes from each of the studies and their importance, while Chapter 5 provides an outlook of the contributions of this thesis and its limitations, as well as discuss potential future work that it engenders.

# CHAPTER 2. BACKGROUND AND STATE OF THE ART

## 2.1. SENSORY SUBSTITUTION FEEDBACK

Grasping is arguably the primary function of hands, enabling us to apply "functionally effective forces" to manipulate objects (C. L. MacKenzie & Iberall, 1994). Both anticipatory (feedforward) and reactive (feedback) processes are required for successful object manipulation (Hermsdörfer et al., 2008). Recognizing this, several sensory substitution-based feedback interfaces have been developed to facilitate better grasp force control in myoelectric hand prostheses.

Broadly, there are three major components to these feedback interfaces – (1) the information to be fed back to the user, (2) the encoding scheme, which converts the sensed information into an encoded stimulus, and (3) the stimulus delivery system which delivers this information to the user.

The most common feedback delivery systems have used vibro- or electro-tactile stimulation or auditory signals to deliver feedback. Vibrotactile feedback is delivered through mechanical vibration of the skin using tactors, whereas electrotactile stimulation is delivered by stimulating afferent nerve endings within the skin through a local electrical current. The amplitude, frequency, pulse duration, shape, and duty cycle etc. of both the delivery systems can be varied, together with the number of tactors or electrodes, to deliver rich tactile sensations to the residual limb or other strategically selected areas of the skin. Similarly, auditory signals can be designed to provide a detailed yet intuitive feedback to be exploited by users.

While practicalities of the interface are affected by the delivery system, it is the information and encoding scheme that determine their success, enabling users to interpret and include the provided feedback into their motor control processes. Several different variables have been tested to be fed back, starting with the most obvious – grasp force, either recorded at the fingers or approximated by the motor load within the prosthesis, implemented at least as far back as 1925 (see Childress, (1980) for a historical review). Other common choices include prosthesis aperture, closing velocity, and contact events (reviewed comprehensively in Antfolk et al., 2013; Schofield et al., 2014; Svensson et al., 2017).

More recently, Dosen et al., (2015a) introduced a novel interface where they provided participants' own myoelectric commands as feedback. Participants used a proportional control scheme where the amplitude of the EMG is mapped linearly to the prosthesis velocity, which in turn (linearly) determined the force that will be generated. Given such a control interface, they observed that transmitting the EMG amplitude itself as feedback facilitated better force control than when recorded force was transmitted as feedback. Interestingly, in effect, participants received not just an efference copy of their outgoing motor commands as feedback, but an approximation of the true sensory feedback (re-afference), by virtue of the coupling between EMG, prosthesis velocity, and force. Subsequently, EMG Feedback has been shown to facilitate better force control in functional settings even in the presence of control disturbances (Schweisfurth et al., 2016; Tchimino et al., 2022).

In this thesis, we further explore how feedback interfaces based on these two information streams (myoelectric command vs prosthesis force) enable participants to acquire skilled force control. We believe these represent two well-established force feedback interfaces and therefore provide the right point of comparison for a detailed analysis of the skill each of them afford.

## 2.2. EVALUATING PROSTHESIS FORCE CONTROL

Given the plentiful options for designing feedback (and by extension, closed-loop) interfaces, evaluation of their effectiveness plays a crucial role in reducing the design space and optimizing interfaces. While standardized clinical tasks such as the box-and-blocks, clothespin relocation, and the Southampton Hand Assessment Procedure (SHAP) exist, they do not explicitly require participants to apply "economical" forces, and therefore do not provide a useful testbed to evaluate force control.

Therefore, several tasks and paradigms have been introduced in the literature to evaluate prosthesis force control and the effect of interfaces on it. A popular paradigm has been that of force-matching, where participants are asked to apply a prespecified force on an object of interest (Chatterjee et al., 2008; Dosen et al., 2015a; Witteveen et al., 2015; Schweisfurth et al., 2016 and so on). Others have designed implicit versions of force-matching, by exposing participants to objects of different sizes and weights and measuring applied forces in presence and absence of supplementary feedback (Pylatiuk et al., 2006; Cipriani et al., 2008; Kim & Colgate, 2012; Thumser et al., 2018). Further, in the context of delicate objects, Clemente et al., (2016) developed the instrumented virtual eggs task, Markovic et al., (2018a) used a cup stacking task and Tyler, (2016) used a cherry picking task, a non-exhaustive list at best.

Most of these studies focused on performance (some measure of task-related accuracy) with and without feedback, and as mentioned in Chapter 1.3.2., noticed that despite the overall positive effect of the supplementary feedback, there are instances where visual feedback, users' expertise, or simplicity of tasks implies that substitution feedback is not necessary for high performance (Sensinger & Dosen, 2020). However, even when focusing on functional benefits of feedback alone, quantifying performance is not enough, and evaluating its role in the motor control and learning processes of users is important.

Towards this end, Shehata et al., (2018b) and Engels et al., (2019) studied how different interfaces affected force control using the instrumented virtual eggs task, where the primary objective is to grasp and lift the virtual egg without exceeding a certain force. They evaluated the strength of the internal model developed, just noticeable differences in externally imposed control disturbances, and trial-by-trial adaptation rate to comprehensively characterize the internal models developed by participants using different feedback interfaces (auditory biofeedback, discrete event-based feedback, and their combinations).

On the motor learning front, Bouwsema and colleagues in a series of experiments (Bouwsema et al., 2010, 2012, 2014) investigated learning related changes in performance and kinematics of reaching, opening and closing of the prosthesis, and object compression – the surrogate for fine force control, recorded using motion capture. Consequently, they delineated the timescales of learning for the various phases of a reach and grasp movement and informed how to structure practice towards developing an evidence-based rehabilitation program and facilitating user learning. However, these studies only evaluated open-loop control, i.e., without supplementary feedback.

## 2.3. MOTOR SKILL AND ITS CONSTITUENTS

While the methods detailed above enable one to quantify task-level performance and certain aspects of motor control and learning processes in user-prosthesis interaction, as outlined in Chapter 1.3.3, we believe that the study of skill acquisition, adds complementary understanding.

Motor skill has been notoriously hard to define, given the complexity and scope of such an inquiry (Christensen, 2019; Krakauer et al., 2019; Krakauer & Carmichael, 2022). In the broadest sense, motor skill is an acquired capability to successfully achieve a motor goal (Du et al., 2022). And skilled behavior is characterized by an ability to consistently select the appropriate action (action selection) and execute the action precisely (action execution). Applied to a batter (in cricket), such a definition can enable us to understand why expertise is often attributed to the ability to select the right shot as well as precisely execute it.

In the context of grasp force control, skilled behavior correspondingly involves selecting the right force to apply and execute the movement. Accordingly, in this thesis we focus on action (motor) execution. At the level of motor execution, skill is characterized by the ability to execute movements accurately and precisely, even when moving quicky (Du et al., 2022; Shmuelof et al., 2012). This ability can be quantified using measures of task success (performance) and movement kinematics, which emphasize speed and accuracy at the level of performance and smoothness and stereotypy of the underlying movements. To this end, measuring the speed-accuracy tradeoff has been proposed as the preferred method to analyze all the above aspects of motor execution.

### 2.3.1. FITTS' LAW

In his seminal experiments, Fitts noticed that when he asked participants to move a pen between two goal regions on a piece of paper, the movement durations grew logarithmically with the distance between the targets (Fitts, 1954; Fitts & Peterson, 1964). This relationship was also modulated by the size of goal regions, and the weight of the pen they used. In other words, he noticed that there exists a tradeoff between movement speed and the accuracy demands (i.e., difficulty) of a task.

In the information theoretic formulation that followed, Fitts introduced the idea that in carrying out goal-directed point-to-point movements (such as moving our hands, or a computer cursor, from a given location to a goal location), information is transmitted through the human (musculoskeletal) channel. The difficulty of the movement can be measured as bits, and the channel throughput is measured in bits/s. A higher throughput thereby implies better efficiency of the human motor system in performing the task or a human-computer interface in enabling it.

Its widespread applicability and empirical validation across a range of tasks, input devices, and user populations led to its recognition as a 'law' in human-computer interaction (I. S. MacKenzie, 1992). The methodology of using a cursor-pointing type task, where goal locations are specified by target amplitude and target widths, to measure the throughput became a standard for evaluating different pointer-like interfaces. It subsequently had a tremendous impact on interface design (I. S. MacKenzie, 1992; Soukoreff & MacKenzie, 2004) and has been a common framework for evaluating online myocontrol using 1-d to 3-d cursor pointing tasks (Fimbel et al., 2006; Wurth & Hargrove, 2013; E. J. Scheme & Englehart, 2013; Borish et al., 2018, 2020).

Notably, Thumser et al., 2018 proposed an innovative method to determine speed-accuracy tradeoffs involved in grasping of everyday objects (termed Grasping Relative Index of Performance test, GRIP), by measuring 'intrinsic' (as opposed to extrinsic, specified difficulties manipulated by target amplitude and width) isometric forces that participants applied by grasping a force transducer upon seeing an object on the screen. By measuring both the intrinsic precision of force production and the throughput, they proposed to describe and compare the grasping ability afforded by different grasping devices, or between patient populations.

While Fitts' law measures an important aspect of skill – the relationship between movement difficulty and movement time, the movement times so measured are from an asymptotic (near-perfect) task success regime, i.e., the mean reaching errors are negligible. That is, while it provides a predictive model for mean reach time to almost always reach a target of specified difficulty successfully, it cannot predict the accuracy when reaching the target at a faster speed. Indeed, by asking participants to reach a target "as fast and as accurate as possible", and making sure that the mean reaching error is close to zero, the participants' own speed-accuracy tradeoff which dictates execution is sidelined.

Therefore, the experimental and theoretical formalisms of Fitts' law do not provide the best testbed for investigating motor execution, where the focus is on how execution, mainly modulated by speed, affects task performance.

### 2.3.2. SPEED-ACCURACY TRADEOFFS AND MOTOR ACUITY

In this thesis, we will apply a more general framework to analyze speed-accuracy tradeoffs. Broadly, it consists of an experimental paradigm which imposes time constraints on execution to control for speed, as opposed to the spatial constraints specified in Fitts type tasks. Multiple execution speeds are imposed to measure how performance changes across speeds. Consequently, true skill acquisition is inferred a systematic change in the SAF driven by learning. As also mentioned in Chapter 1.3.3, this eliminates the ambiguity when we have just two pairs of (speed, accuracy) measurements where both dimensions don’t change in the same direction – the two pairs could come from different points on the same SAF (where skill remains the same), or indeed from two different SAFs (where skill has changed).

Reis et al., (2009) developed this framework to analyze changes in skill during repeated practice of a sequential visual isometric pinch task and investigated the effect of transcranial direct current stimulation over primary motor cortex in acquisition and retention of skill, in terms of a change in the SAF. Shmuelof et al., (2012, 2014) extended the framework and characterized the changes at the level of motor execution in an arc pointing task and coined the term ‘motor acuity’ to denote the learning induced reduction in trial-by-trial variability, across all speeds, in the cursor trajectories traced by participants. In addition, they noticed that there were small changes in the mean trajectory across days, as well as the trajectory smoothness thereby establishing behavioral markers of skill.

While the studies from Bouwsema and colleagues (Bouwsema et al., 2010, 2014) proposed to study skill as a combination of performance and visuomotor behavior, they measured the task performance at a single speed by asking participants to execute their movements as quickly and as accurately as possible. Similarly, while Shehata and colleagues (Shehata et al., 2018b and Engels et al., 2019) investigate low-level motor control processes and some intermediate behavior-level aspects, these have also not investigated how skill manifests as a change in the speed-accuracy tradeoffs and the behavioral changes that subserve it.

Importantly, the present thesis builds on previous work and (1) investigates closed-loop interfaces, and (2) skill acquisition enabled by them, which has not been investigated before. Moreover, we investigate (3) motor acuity at the level of myoelectric commands, as a surrogate to motion tracking based end-point kinematic analysis, but is easier to measure. The latter aspect has recently been investigated in (A. W. Franzke et al., 2021; A. W. Franzke, 2023), who measured EMG feature space characteristics and how repeatability and separability of user generated myoelectric commands associated with real-time performance and found that EMG-amplitude related features better correlated with performance. However, these studies investigated the characteristics of multi-channel EMG time-domain features which were then fed to a linear-discriminant analysis classifier for gesture classification, a class of movements that is arguably different from proportional control using isometric contractions.

# CHAPTER 3. METHODS

In this chapter, we describe the salient details of the methodology used throughout the three studies and discuss some of the implications of these choices.

## 3.1. EQUIPMENT

Figure 3.1 shows the typical experimental setup used across the studies, with slight modifications in Study 1.

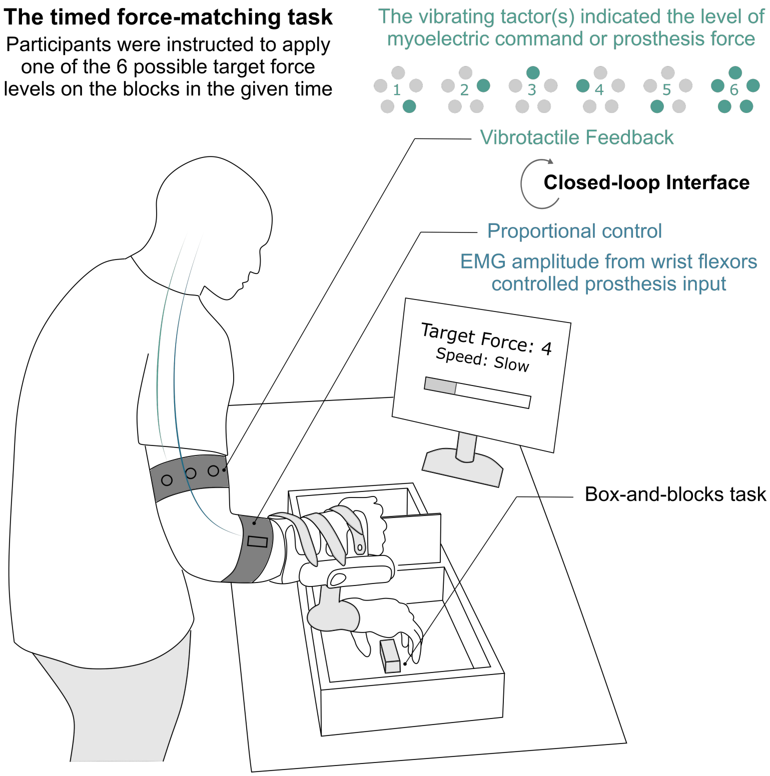



Figure 3.1: Investigating motor skill in prosthesis force control. Modified with permission from Mamidanna et al., (2022).

### The closed-loop user-prosthesis system

Participants donned the Michelangelo prosthesis (OttoBock GmBH[1]) through a custom printed bypass socket. A wrist immobilization splint sat within the bypass socket such that participants could perform isometric wrist contractions. The prosthesis was capable of both grasping and wrist rotation, where the former could be achieved in two configurations – palmar and lateral grasp. Here, we only focused on palmar grasping, and did not use the other degrees of freedom.

Two dry EMG electrodes (13E200, OttoBock GmBH[2]) were placed on the wrist flexor and extensor muscle by palpitating, visually observing the muscle contraction, and ensuring that the EMG signal is of sufficient amplitude. In case the signal amplitude was considered low, the gain of the electrode was increased accordingly. Analog EMG signals were amplified, rectified, and filtered, using a low-pass filter with a 3 Hz cutoff, by the electrodes. This processed linear envelope was acquired through the controller attached to the Michelangelo prosthesis at 100 Hz and was used as the input signal to the control interface (see below).

Five C-2 tactors (EAI Inc[3]) were used to provide vibrotactile feedback to the users. They were placed around a cross section of the upper arm and held in place using a band. The placement of the tactors was chosen such that participants could feel the vibration of each individual tactor distinctly, and care was taken to ensure there were no unpleasant sensations.

The entire closed-loop control system was designed in MATLAB Simulink, using the open-source testbench developed by Dosen et al., (2015c), and ran at 100 Hz on a Lenovo P52 workstation laptop.

### The box-and-blocks task

In Studies 2 and 3, participants performed a modified box-and-blocks task where the objective was to transport objects from one side of the box to the other, but with additional requirements concerning force produced on the object and the speed at which they performed the task. On the other hand, in Study 1, the box-and-blocks task was not involved, and instead participants were seated and performed a force-matching task where the prosthesis was

[1] https://www.ottobock.com/de-de/product/8E500

[2] https://shop.ottobock.us/c/Electrode/p/13E200~550

[3] https://eaiinfo.com/product/c2/

affixed to a table in front of the participants.

In all the studies, participants were shown task instructions and were provided performance related feedback on a computer screen placed at comfortable viewing angle and distance.

## 3.2. THE CONTROL AND FEEDBACK INTERFACES

Designing (closed loop) prosthesis interfaces for force control depends critically on how user's EMG signal is mapped to the prosthesis inputs, and the dynamics of the prosthesis which determines the generated force on the object given a certain input. In the subsequent sections, we will outline our choice of the EMG-to-prosthesis input mapping (the control interface) and how the relevant feedback variable – either self-generated myoelectric command (in the EMG Feedback interface) or prosthesis force (in the Force Feedback interface) – is conveyed to the user.

Towards this end, we first characterized the input-output behavior of the Michelangelo prosthesis. To actuate the opening and closing of the palmar grasp, two independent input commands could be communicated to the prosthesis' internal motor drivers. The input command for closing drives the closing speed of the prosthesis, such that it results in a decreasing aperture before object contact and increasing force after object contact. Similarly, the command for opening drives an increase in aperture with an instantaneous drop in force. The minimum and maximum magnitudes for these commands are set by the manufacturer. For convenience, we will refer to these as prosthesis inputs. Based on our characterization of the prosthesis' force behavior (described below), we proceeded to design the interfaces.

Here, we designed discretized interfaces, where the participants were only ever exposed to 6 discrete 'levels' of prosthesis force. That is, from the point of view of the participants, the prosthesis could apply 6 different levels of forces on objects, and this could be modulated using their muscle contractions. Notably, it is only the output (force) behavior that is discretized, while participants could still continuously modulate the prosthesis inputs. Such a discretized interface is appealing since it is quite simple to understand and intuitive to use. In our own experiments, we found that participants almost immediately understood how their muscle contractions affected the different force levels afforded by the interface.

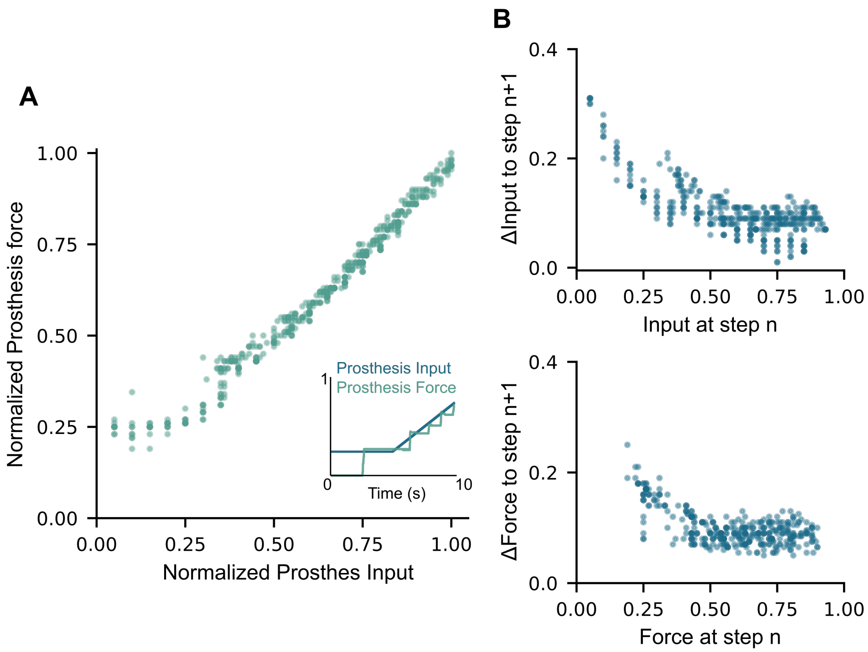



Figure 3.2: Characterizing the prosthesis input-output relationship. (**A**) Input to prosthesis was varied using a ramp profile, with 17 initial input magnitudes and 3 slopes, and the corresponding force was recorded (inset); notice the step-like behavior. Normalized inputs and forces for each recorded step is plotted. (**B**) Change in prosthesis input to cause the next step, and the corresponding change in force at the next step is plotted relative to the input-outputs at 'current' step.

### Characterizing the prosthesis input - force relationship

Figure 3.2 shows empirically measured prosthesis behavior. The gearing mechanisms, and non-backdrivability of force, where users can only up-regulate the force applied on an object, a feature that enables users to relax their muscles once the force is applied, leads to a step-like force behavior in most commercial prostheses. To characterize this behavior, we performed several trials where starting from the prosthesis at a fully open position, we varied the prosthesis closing inputs as a ramp, consisting of a 5 s constant input followed by a 5 s ramp (Figure 3.2A, inset). During the constant input, the prosthesis aperture decreased until its fingers contacted with itself, resulting in an initial grasp force. Thereafter, increases in the input caused an increase in the force. Here, we chose 17 initial input magnitudes (0.05 – 0.85x maximum input), and 3 slopes (corresponding an increase of 0.03, 0.05, and 0.07 per second) with 3 repetitions per each combination (a total

| Level | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| **Myoelectric command** | 0.025 | 0.1 | 0.27 | 0.47 | 0.69 | 0.95 | 1 |
| **Prosthesis input** | 0 | 0.25 | 0.42 | 0.59 | 0.76 | 0.9 | 1 |
| **Force** | 0.05 | 0.31 | 0.45 | 0.58 | 0.73 | 0.9 | 1 |

Table 3.1: the myoelectric command, prosthesis input and force 'level' boundaries for the discretized interface.

of 3 x 17 x 3 = 153 trials) and recorded the magnitudes of the input and force at the initial time point of each force step.

Our observations revealed that, for constant slope profiles, once the object contact was established, the force increased in steps of approximately 10% of the maximum force, on average. Similarly, the increase in closing input required to induce this change was nearly 10% of the prosthesis's maximum input. Consequently, we discerned a linear relationship between the force and inputs of the prosthesis when the force exceeded 30% of the maximum force. In order to apply forces below this threshold, a bell-shaped input profile that allows the fingers to decelerate before contacting the object is required. However, forces in this range were hard to reproduce with the Michelangelo prosthesis.

Given that the initial 30% of the force range was harder to reproducibly reach, and that 90 percentile of force steps were of the magnitude corresponding to 15% of the maximum force, we decided to design an interface with 6 discrete levels that can be reproducibly reached by the prosthesis. For convenience, both these variables can be considered to lie on a normalized scale (range of [0, 1]), where the maximum values are determined by the maximum input and force of the prosthesis, set by the manufacturer. Then, the boundaries of the discrete levels are given in Table 3.1, such that if an input (colloquially, closing speed) in the range of a particular input level, say level 4, is applied (or maintained) as input to the prosthesis, then a force corresponding to level 4 is applied on the object.

### Piecewise-linear direct proportional control

We then designed a control interface based on the acquired EMG envelope, and further processed it using a 2$^{nd}$ order Butter-worth low pass filter with a cutoff of 0.5 Hz to improve the responsiveness and further smooth the signal (following the results of Tchimino et al., (2021)). This processed EMG envelope is called the myoelectric command or amplitude. The myoelectric command captured using the electrode placed on the wrist flexors was used to close the prosthesis, while the command from the extensors was used to open it.

The most common force control interface is that of proportional control, where the user's muscle contraction strength (as detected by the amplitude of the EMG signal) is mapped linearly to the prosthesis speed (Fougner et al., 2012). This creates an intuitive interface, since grasping objects with a greater force requires a stronger muscle contraction. However, since myoelectric signals are characterized with variability that increases with the contraction strength, we designed a piece-wise linear map between the myoelectric command and prosthesis closing input such that the levels corresponding to higher contraction strengths are wider. To control hand opening, which in our tasks did not require fine modulation, we used a simple on-off control.

For notational convenience, the myoelectric command can also be converted to a normalized scale. The minimum and maximum corresponded to 0% and 50% of the amplitude at maximum voluntary contraction (MVC) respectively. The MVC was calculated at the beginning of each experimental session, by asking participants to maximally contract their wrist flexors and extensors. This was repeated 3 times to obtain an average MVC amplitude for the flexor and extensor commands separately.

Once normalized, the boundaries of the levels for the flexor command correspond to those shown in Table 3.1. Thereby, a contraction strength corresponding to a particular level of the myoelectric command causes a closing input of the same level, as described by the piece-wise linear map. On the other hand, for the extensor command, the participants needed to reach 0.4 on the normalized scale (20% MVC) to trigger prosthesis opening.

**Discretized feedback interface**

Finally, we designed the feedback interface using a spatial encoding scheme as shown in Figure 3.1, where the activation of a tactor indicated the level of the feedback variable. As explained before, we designed two interfaces, which only differed in the information that was delivered back to the participant – the level of either the myoelectric command (EMG Feedback interface), or the prosthesis force (Force Feedback). The spatial encoding scheme was chosen since it is a very simple and intuitive scheme to learn, and often took less than 5 minutes for participants to fully understand.

Since only the level of the variable was to be fed back, each of the five tactors vibrated at the same frequency – 200 Hz, and a gain that the participants felt was comfortable. The first five levels were indicated by activating one tactor per level (in a fixed order, posterior to anterior), while the sixth level was conveyed by activating all tactors simultaneously.

Thereby, when using the EMG Feedback interface, participants received feedback about the level of the myoelectric command, as soon as they started to contract their muscle (above 0.025 on the normalized scale). Therefore, if a participant wished to apply a force level of 3, they could use the feedback to gradually modulate their muscle contraction from level 0 to 3, and dwell in level 3 to affect the desired force on the object. In other words, this information could be used to predictively modulate their muscle contraction to reach the desired level of force. On the other hand, when using the Force Feedback interface, they received the force level as feedback as soon as the prosthesis established contact with the object. That is, until object contact, the participants had to rely on their own internal models of the prosthesis, (residual) proprioception, and incidental visual and auditory feedback, to modulate the myoelectric command.

## 3.3. A TIMED FORCE-MATCHING TASK

Given the interfaces above, participants performed force-matching tasks in all the three studies. In effect, their objective was to reach the target force, specified as one of the 6 possible levels (in fact, only levels 3, 4, and 5 were used in the experiments) using the closed-loop interface. In Study 1, this was performed while participants were seated and prosthesis fixed to a table, while in studies 2 and 3, they donned the prosthesis and performed the box-and-blocks task, during which they were required to apply the specified force on the blocks before transporting them.

In addition, during studies 2 and 3, participants were required to adhere to time constraints, which allowed us to measure the speed-accuracy tradeoff. Here, we used a time-band methodology for this purpose (Wickelgren, 1977). In such a 'timed' force matching task, the minimum and maximum time to complete the task was specified and shown to the participants using a bar on the screen. A red bar appeared as soon as participants started a particular trial (produce a myoelectric command larger than 0.025) and turned green once the minimum time to task completion was reached. They were instructed to reach the target force while the bar was green. Once the maximum time was reached, the bar disappeared, and they could no longer modulate the prosthesis closing inputs.

In effect, each trial proceeded as follows: the force and speed target levels were displayed to on the screen, and a cue signal (a beep sound) was provided to indicate that the participant was allowed to start performing the trial. They then contracted their wrist flexors to close the prosthesis and grasp the object, while receiving supplementary vibrotactile feedback. Once the desired force level or greater was applied, or maximum time was reached, the participants transported object, and released it by opening the prosthesis.

# CHAPTER 4. SUMMARY OF FINDINGS

In this chapter, we present the key takeaways associated with each of three studies conducted as part of this thesis (see Chapter 1.4.2) and (re-)interpret the results within the broader framework of motor learning and control. In essence, Study 1 investigated how to quantify and understand the control policies developed by participants for prosthesis force control. Subsequently, Study 2 and 3 focused on empirically measuring skill acquisition and how it is affected by interfaces and practice, by employing speed-accuracy tradeoffs to rigorously quantify performance and motor acuity.

Taken together, in Studies 1 and 2 we developed metrics and methods to investigate the control policies and motor acuity of participants, in line with ***Q2***, while throughout the three studies we investigated two different closed-loop interfaces to understand how each interface facilitated skill acquisition, laying a blueprint for future studies in pursuit of ***Q1***.

## 4.1. IMPACT OF TASK OBJECTIVES ON CONTROL POLICIES

As outlined in Chapter 1.3, skill acquisition involves the development of new control policies, and internal models that support it. While substitution feedback has been shown to facilitate the development and maintenance of internal models (Dosen et al., 2015; Shehata et al., 2018a,b), the control policies enabled by it have not been explicitly investigated before. We believe it is important to quantify and understand the control policies developed by users so that interventions can be curated to develop specific control policies or facilitate learning of better internal models.

Concretely, here, we developed simple metrics to investigate the control policies developed by participants, specifically concerning the extent to which substitution feedback was included, under varying speed and accuracy requirements demanded by the task. We identified how feedforward and feedback policies emerged in a task-dependent manner and the performance they enabled.

### Varying task instructions to probe control policies

Seventeen able-bodied participants used a proportional control scheme and

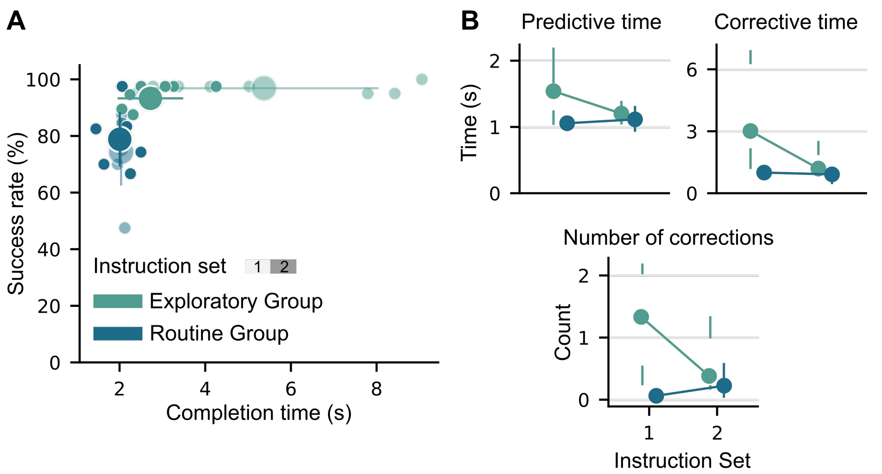



Figure 4.1: Summary of experimental results, Study 1. (**A**) Performance of individual participants (small circles) and group averages (large circles) shows that only exploratory group were successful across the two instruction sets. Horizontal or vertical lines indicate standard deviation of observed completion times or success rates respectively, only the most informative is plotted. (**B**) Quartile plots (circle indicates median, lines indicated lower and upper quartiles) of time spent predictively and correctively (based on Force Feedback) modulating myoelectric commands, and the number of resulting force corrections enables us to understand the degree to which feedback was incorporated into participants' control policies. Exploratory group demonstrated flexibility in this aspect, by incorporating feedback to different extents, depending on task objectives.

discretized Force Feedback, as explained in Chapter 3.2, to perform a force matching task with additional speed and accuracy requirements provided through verbal instructions.

The participants were divided into two groups, called the exploratory and routine groups. For the first 90 trials, participants in the exploratory group were instructed to maximize accuracy (trial success) without paying any attention to speed. On the other hand, the routine group was asked to maximize accuracy but with an imposed time restriction by which they could not send control commands to the prosthesis 1s after object contact. After completing 90 trials in this manner, the exploratory group was asked to improve on their speed without sacrificing the accuracy for the next 90 trials, whereas the routine group was asked to keep maximizing success without sacrificing on the speed.

In this way, participants in the routine group were first forced to develop a feedforward policy through error-based adaptation across trials, whereas the exploratory group were not incentivized to develop any particular policy, only the one that maximizes task success. Upon altering the instructions, we aimed to find out which group were able to quickly modify their policies and successfully execute the task at a different speed.

**Behavioral markers of feedforward and feedback control policies**

Figure 4.1A shows how the performance of participants in both groups varied based on the instructions. Notably, success rates of the exploratory group remained high throughout, despite the large difference in the completion time between the two instruction sets. On the other hand, the routine group did not gain performance even after the enforced time restriction was lifted.

We then determined three metrics (1) predictive time – time to object contact, (2) corrective time – time after object contact to trial end, and (3) number of force corrections, to gain insights into the control policies implemented by the participants and how these were shaped by instructions (Figure 4.1B). We reasoned that since Force Feedback would be available to the participants only after object contact, the period before and after this event most clearly indicate how participants included feedback into their actions.

Further, we computed the number of force corrections to evaluate participants' dependence on feedback to reach the target force, by counting the number of 'plateaus' in the force readings of each trial (similar to Shehata et al., 2018b). To distinguish whether the plateau was caused due to an intended corrective command from the participant or due to the discrete nature of the prosthesis itself (see Chapter 3.1), we verified if they co-occurred with an inflection point in the input commands of the participants (data not shown). We found that force plateaus longer than 250ms tended to coincide with intended corrective actions. Therefore, we defined the number of force corrections as the number of force plateaus longer than 250ms.

Using these metrics, we were able to conclude that participants in the exploratory group initially developed a predominantly feedback policy (see corrective time and number of corrections in Figure 4.1B). The routine group, as expected, developed a feedforward policy, perhaps using the 1 s of feedback to adapt their actions on the next trial.

Interestingly, when the instructions were altered, the exploratory group could dramatically improve their speed (as much as to closely resemble the routine group, see predictive and corrective time) without sacrificing accuracy. Moreover, together with the low number of corrections, it is apparent that they were also able to learn a strong internal model to execute a feedforward policy. On the other hand, the routine group could not change their control policies to incorporate more feedback.

### Online modulation vs adaptation across trials

Put differently, we examined two extreme strategies of using Force Feedback – to use it continuously for online modulation of motor commands vs across trials to develop a feedforward policy (akin to adaptation). We found that participants who initially used the former strategy consistently performed better, and also developed a more flexible policy that they could modify for faster speeds. While the latter, that corresponds to a purely repetitive error-based learning strategy, proved to be too rigid that participants could not successfully change when required.

We believe that these results underscore the value of instruction in facilitating learning (Krakauer & Carmichael, 2022), especially when substitution feedback is involved, and inform how to design rehabilitation protocols. While we tested unguided exploration through our instructions, it would be interesting to consider guided exploration of the feedback, such as through coaching. The metrics developed here can be used to design such protocols, both at clinical and at-home levels, to guide users, and indeed, have been used to gain insights into the control policies developed by users in the remainder of this thesis.

In summary, we proposed simple metrics to evaluate the control policies exhibited by users in a prosthesis force control task. We found that Force Feedback was flexibly included in exploratory group’s control policies, enabling them to switch between feedback driven and feedforward policies when required, while routine group developed a rigid feedforward policy that limited their performance. Therefore, while supplementary feedback can be critical in enabling acquisition of new control policies, facilitating such a development depends on creating the right environment for learning, for example through instruction.

## 4.2. SPEED-ACCURACY TRADEOFFS TO EVALUATE INTERFACES

At the intersection (or rather, the union) of the research questions of interest, in Study 2 we investigated how skill is affected by the interface available to the user, by measuring the SAF each interface affords and acuity of the underlying motor (here, myoelectric) commands.

Comparing interfaces is an important practical question, given the availability of several interfaces in the literature, even if we just consider the various feedback interfaces for force control (e.g., see Chapter 2 and tables provided in Sensinger & Dosen, 2020; Antfolk et al., 2013). While studies introducing a new (feedback) interface compare the proposed interface to a baseline, systematic comparisons between interfaces are rather few (e.g., Engels et al., 2019). In addition, interfaces are commonly evaluated at a single speed resulting in an average success and average completion time measure; and as explained in Chapter 1.3.3, if the two measures differ in opposite directions, it is infeasible to determine which interface affords better skill.

Here, we investigated the skill (control policies, SAF, and motor acuity) afforded by two interfaces – Force and EMG Feedback, as outlined in Chapter 2.1 and 3.2, to determine how they differed and what that implies for evaluating interfaces.

### Investigating interfaces through the timed force-matching task

Ten able-bodied participants and an individual with a limb difference took part in a 2-session cross-over experiment with a 1-week washout period. Each participant donned the Michelangelo prosthesis using a bypass socket and performed the timed force-matching task using the box-and-blocks setup. The closed-loop user-prosthesis interface they used consisted of proportional control, while the discretized feedback communicated through vibrotactile stimulation was either based on participants' own EMG commands (EMG Feedback) or the force recorded by the prosthesis (Force Feedback). The order in which they were exposed to the interfaces was counter balanced.

The timed force-matching task was repeated at 3 speeds, namely Fast (0 – 2 s), Medium (2 – 4 s) and Slow (4 – 8 s). To help participants maintain the speed, a visual bar indicating time elapsed was shown on a screen.

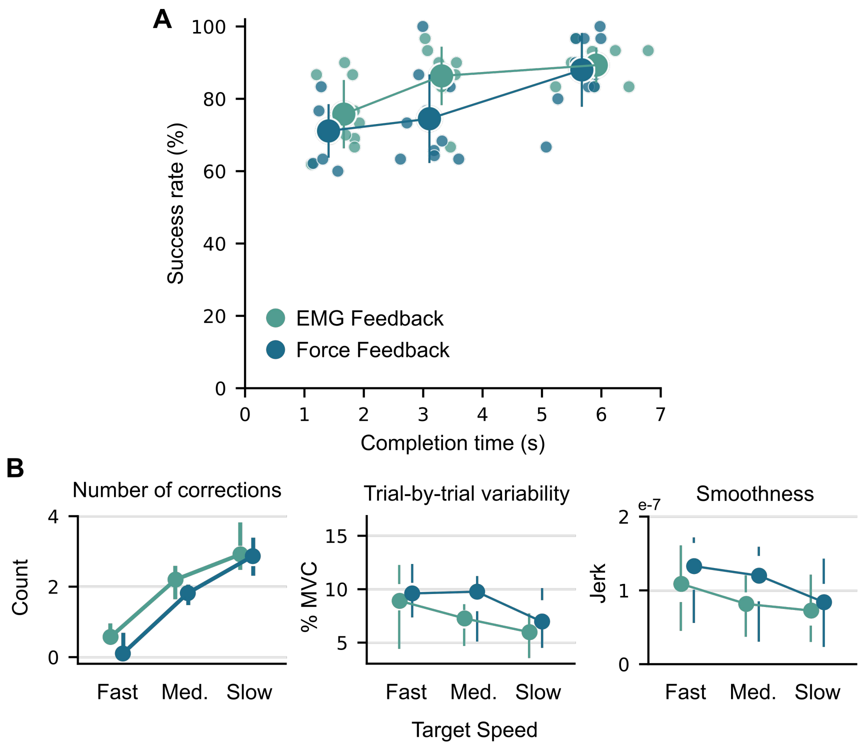



Figure 4.2: Summary of experimental results, Study 2. (**A**) Speed-accuracy tradeoffs of individual participants (small circles) and group means (large circles) demonstrate the execution-speed-specific effects of interfaces on user skill. (**B**) Quartile plots showing number of corrections, and repeatability and smoothness of myoelectric commands indicate that EMG Feedback enabled participants to build a successful control policy at all speeds and obtain higher motor acuity in executing it.

### Interface-specific effects on participants' speed-accuracy tradeoffs

First, we observed that all participants exhibited a wide range of success rates with execution speed being a crucial factor in how accurate they were (see Figure 4.2A). Success rate monotonically increased with speed, at both the population and individual levels, indicating the effectiveness of the timed force-matching task employed to measure SAFs.

Interestingly, while the SAFs were significantly affected by the interface that participants used, the difference between interfaces originated in the Medium speed condition alone. This demonstrates that the effect of execution speed on performance is interface specific, where different interfaces may enable better or worse performance at different speeds.

### Kinematic measures of motor acuity and interface-specific effects

In addition to measuring the SAF, we investigated motor acuity of the participants through (1) smoothness and (2) trial-by-trial variability of the myoelectric commands, and (3) analysed the number of corrections to investigate the control policies developed by them (see Figure 4.2B). Reduced execution variability and improved movement smoothness are a defining feature of skilled behavior (Sternad, 2018; Krakauer et al., 2019; Du et al., 2022). The former indicates motor acuity – the ability to perform the same action repeatedly and is computed using a point-wise standard deviation of time-normalized myoelectric commands. The latter, movement smoothness, has been proposed as a fundamental characteristic feature of well-trained motor behavior (Balasubramanian et al., 2015) and is here measured using the normalized integrated squared jerk. While studies that investigated motor acuity before considered end-point trajectories (e.g., cursor coordinates in Shmuelof et al., 2012), here we investigated myoelectric commands, since they are (1) easiest to measure, and available throughout a trial (e.g., unlike aperture, which is uninformative after object contact, except for highly pliable objects), and (2) the variable which is directly under the control of participants.

Both feedback interfaces were successfully and flexibly included in participants' control policies as indicated by the number of corrections. Next, we verified that observed changes in motor acuity were in agreement with performance changes, thereby establishing the validity of investigating myoelectric commands. Interestingly, execution level metrics also showed that EMG Feedback enabled smoother and less variable trajectories indicating it enabled participants to converge on a solution that they could repeatedly execute.

### EMG Feedback enabled better skill overall

While previous studies that compared EMG Feedback with other feedback interfaces (see Chapter 2.1) have shown that such an online biofeedback-based interface improves performance, here we empirically evaluated the SAF it affords participants. The SAF showed that EMG Feedback allows a tradeoff such that participants could rapidly make performance gains in the 2 – 4 s range, a common range of movement times observed in prosthesis force-matching tasks. These performance gains are enabled by better motor acuity in terms of lower trajectory variability and smoothness. Overall, this shows the effectiveness of EMG Feedback in promoting several aspects of skilled behavior.

### SAFs to evaluate (closed-loop) interfaces

A key takeaway from the current study is its implications for evaluating interfaces. Evaluating how competing interfaces enable skill is a pressing concern, given the rapid development of new interfaces. However, such a comparison is rather difficult, given that the interfaces may be tested using incomparable setups and metrics. Here, we showed that this maybe further complicated if the interfaces are tested at a single “comfortable speed”, as is commonplace. For example, here we showed that comparing the two interfaces only at the Fast or Slow conditions would result in an incorrect inference that the interfaces enable similar performance. Therefore, we propose that measuring SAFs is a better evaluation criterion.

In summary, we established that the EMG Feedback interface afforded better force control across execution speeds, but this difference primarily manifested in the Medium speed condition. In addition, we proposed metrics to evaluate motor acuity by analyzing the properties of user-generated myoelectric commands and verified that these were indeed in agreement with performance level metrics. Taken together, we argue that evaluation of interfaces must take execution speed related effects into consideration and measuring the SAF (such as through the methodology we developed here) provides a holistic view of user skill, in terms of both performance and behavior.

## 4.3. SPEED-ACCURACY TRADEOFFS TO MEASURE AND MONITOR USER SKILL

Equipped with methods to analyze motor skill acquisition at both performance and behavioral levels, in Study 3 we sought to understand how this process was affected by repeated practice.

Monitoring how users acquire and retain a skill is important to ensure positive training outcomes and long-term behavior. However, research on learning-induced changes in user-prosthesis interaction remains scarce (with some notable exceptions in Dijk et al., 2016; Strbac et al., 2017; Kristoffersen et al., 2019). Bouwsema et al., (2014) were one of the first to

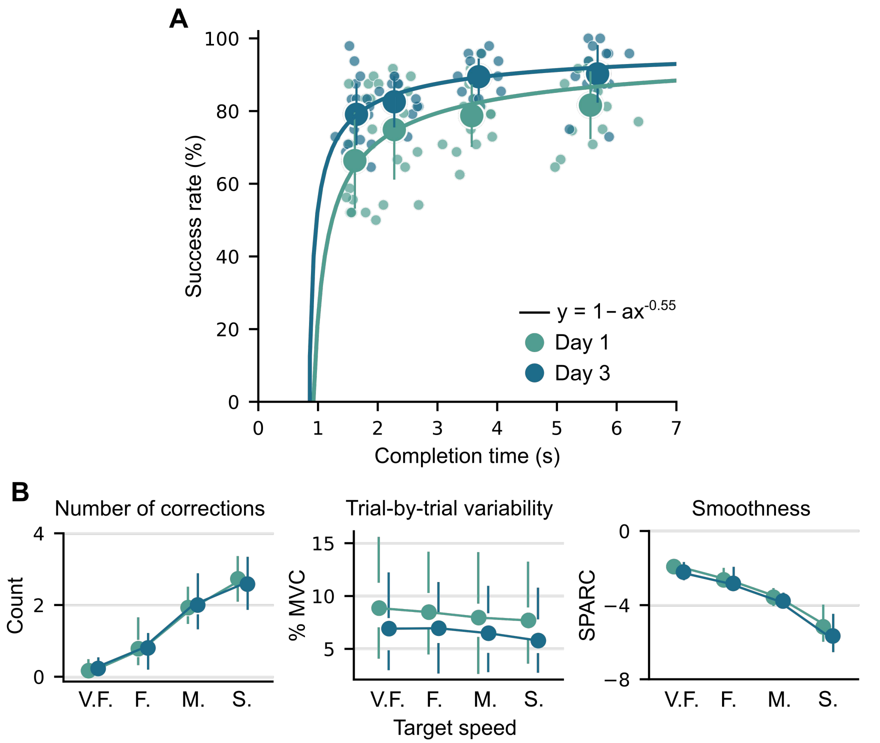



Figure 4.3: Summary of experimental and modeling results, Study 3. (**A**) Speed-accuracy tradeoffs of individual participants (small circles) and mean across participants (large circles) is shown. Improvements were not significantly different between the 4 tested speeds. Solid lines indicate the simplified power-law model fit to pooled participant data. (**B**) Quartile plots of the number of corrections, trial-by trial variability and smoothness quantify the changes in motor acuity across days. (Note: V.F, F., M., S., stand for Very Fast, Fast, Medium, and Slow, respectively).

focus on user training and found that performance and coordination improved with time but saturated within three sessions, while training on up to 3 different tasks. They noticed that grasp force control took longer to learn than gross coordination and suggest that clinical practice focus specifically on training grasp force control. Here, we investigated learning related changes, not just in performance at a single speed but in the SAF, across three days as participants used EMG Feedback. Given that EMG feedback promotes predictive modulation of myoelectric commands and enables faster grasping (Schweisfurth et al., 2016), we expected the highest gains in performance to occur at the faster speeds.

Additionally, we built a 2-parameter power-law model of the SAF, such that changes in the parameters of the model could be monitored over time to understand the changes in skill. Since a change in skill can be inferred by a change in the SAF, it follows that monitoring the parameters that describe the SAF allows one to monitor skill. Moreover, previous studies (Reis et al., 2009; Guiard et al., 2011; Guiard & Rioul, 2015) observed that this model could be further simplified to a single-parameter model that can be conveniently used to infer changes in the SAF. We therefore investigated if this would hold true in prosthesis force control as well, and if such a simplified model could be used to circumvent measuring SAF.

### Timed force-matching across multiple sessions

Sixteen able-bodied participants and an individual with a limb difference (who also participated in Study 2) took part in a 3-session experiment, with at least 1 day and at most 2 days gap between each session. Similar to Study 2, participants were instructed to perform the timed force-matching task using the box-and-blocks setup. However, participants only used the proportional control + EMG Feedback interface. The timed force-matching task was repeated at 4 speeds to better capture the speed-accuracy tradeoff (i.e., one additional speed compared to Study 2).

### Performance improvements were identical across speeds

First, we observed that much like in Study 2, participants displayed a wide range of performance that monotonically improved across execution speeds, in other words, a SAF (see Figure 4.3A). Moreover, this SAF improved across days. Interestingly, improvement across all speeds was similar, indicating that the shape of the SAF curve remained similar across days, a phenomenon also observed in studies which investigated SAF in natural movements (Reis et al., 2009; Shmuelof et al., 2012, 2014).

### Motor acuity and control policies across days

We observed that the number of force corrections remained similar across days, indicating that participants largely executed the same control policies they acquired on Day 1 (Figure 4.3B, left), and therefore any improvements in motor acuity can be inferred as practice effects on execution. Mirroring the performance results, we observed that trial-by-trial variability of EMG commands improved across the three days (Figure 4.3B, middle), thereby lending more evidence to the validity of analyzing changes in myoelectric commands.

However, we observed that the smoothness of the commands slightly decreased across the days (Figure 4.3B, right). We believe that this may be due to the discretized nature of the task and the interface, where participants could learn to “navigate” the discrete levels of force using feedback (see Chapter 3). Under this assumption, it makes sense that over time participants learn a better start-stop behavior, where participants increase their muscle contraction to go from one level to the next, thereby making “less smooth” trajectories, but nevertheless a successful and repeatable strategy. Analogously, we can explain results from Study 2, where Force Feedback led to worse smoothness than EMG Feedback, in that Force Feedback only enables corrective actions, where participants need to wait longer to receive feedback regarding changes to recorded force, thereby making the trajectory even less smooth.

Therefore, while smoothness of movements is a routinely employed marker of skilled behavior, the discretized nature of our task and interface could have favored behavior that led to jerkier movements. While EMG Feedback enabled participants to partly compensate for the jerkiness by providing a predictive signal, Force Feedback necessitated longer pauses to confirm force changes and thereby jerkier movements. An interesting future study would be to investigate how a continuous feedback interface (e.g., amplitude modulated EMG feedback) would affect smoothness.

**A power-law model of SAF**

To quantify changes in the SAF, we fit a two-parameter power-law model, $y = ax^b$, where y denotes average success rate across trials, and x denotes the average completion time. We found that this model was able to capture the observed SAF data quite well across days, at the population level (model fit shown in Figure 4.3A, solid lines, average $R^2$ of 0.86). However, the data at the individual participant level were too variable for meaningful fits (average $R^2$ of 0.38), therefore, we only focused on the population-level model fits.

In line with previous experimental studies of motor skill and human-computer interaction, we observed that the power-law model can be simplified to a one-parameter model where the exponent was kept constant (Reis et al., 2009; Guiard et al., 2011), while changes in skill were reflected by changes in the scaling factor $a$. We found that by fixing the exponent at -0.55, there was no change in the average $R^2$ across days.

**Skill inference through a simplified SAF model**

So far in the thesis, we have focused on explicitly measuring the SAF to both measure and monitor skill. However, given that changes in skill can be inferred by changes in the parameters of the SAF model, and since we have shown that it is only the intercept that informs about skill, we proposed a method, based on Reis et al., (2009), to infer skill changes from trials where execution speed was not controlled (such as in the SAF experiment), but where participants could execute the movements at a single self-chosen comfortable speed. This would eliminate the need for repeated execution of the same task at different speeds but would come at the expense of rigorously quantifying skill and acuity.

Through a case-study involving a single amputee, we measured the SAF through the timed force matching task and additionally asked the participant to perform a separate block of 64 trials at a comfortable speed. The SAF showed that the performance across days barely improved (+2.6% improvement in success rate across speeds). The single-speed trials on the other hand showed that the performance improved (89% to 96%) but at the expense of speed (1.95 s vs 2.96 s), thereby making skill inference infeasible, since the improved success could be explained as facilitated by a slower execution speed.

Then, we estimated the scaling factor using the single-speed trials and found that the estimated $a$ decreased between the days, indicating an improvement in skill. Therefore, while skill inference through a simplified SAF model (given an interface for which the exponent had been predetermined) offers a way to measure skill, as opposed to performance and speed separately, we believe that measuring the SAF and associated motor acuity together is substantially more informative. Moreover, since it has only been investigated in a single amputee participant with a high level of skill, the method needs to be validated in a larger pool of participants.

In summary, we found that SAF improved across the three days, with similar improvements across movement speeds. Motor acuity, in terms of the variability of myoelectric commands, also improved across the days and mirrored the performance improvements. We then built a power-law model of the SAF that could be used to infer skill improvements across days, without the need for measuring a SAF, and discussed the implications of such a method. Taken together, we believe that measuring and monitoring skill through SAFs and the corresponding changes in motor acuity provides a detailed overview of user performance and behavior.

# CHAPTER 5. DISCUSSION

Closed-loop myoelectric hand prostheses are a remarkable technology, that aim to reliably carry out user intended movements and provide users a sense of their prosthesis through supplementary feedback, thereby narrowing the divide between natural and bionic hand control. Effective use of these devices critically relies on facilitating and monitoring how users acquire skilled usage of them.

In this thesis, we aimed to address two broad questions concerning the effect of closed-loop interfaces on skill acquisition and the ways to quantify it. Accordingly, we developed a framework to evaluate the skill afforded by an interface in prosthesis force control by measuring speed-accuracy tradeoffs, acuity of user generated myoelectric commands, and the resulting control policies. Using this framework, we quantified the effects of two closed-loop interfaces on skill acquisition, validating its utility and laying a blueprint for future investigations.

## 5.1. OUTLOOK

### Skill vs performance: the utility of speed-accuracy tradeoffs

An important advancement put forward in this thesis is quantifying and understanding the dissociation between skill and performance in prosthesis force control. We demonstrated that measuring skill through speed-accuracy tradeoffs is both theoretically appealing to study the motor learning processes in user-prosthesis interaction and has practical implications in comparing between interfaces and monitoring learning outcomes over time.

Measuring SAFs gives us a comprehensive overview of the performance characteristics afforded by interfaces. Such a detailed characterization can aid in meta-analytic comparison of interfaces, and for the development of user-specific approaches (Jabban et al., 2022; Jones et al., 2022), where user priorities (such as reliable accuracy vs speed) can be satisfied when choosing an interface. In a similar vein, monitoring user skill using SAFs enables us to rigorously ensure training positive outcomes.

### Estimating motor acuity by investigating EMG commands

Investigating motor acuity is appealing since it opens a window into intermediate execution level variables that are directly controlled by the brain to achieve better task performance. Therefore, analyzing motor acuity is key to understanding how different interfaces are integrated into users' motor control processes, and to monitor learning behavior.

Here, we demonstrated that myoelectric commands provide a natural avenue for such an analysis, and that a reduction in their variability consistently indicated user skill. Therefore, they are a suitable surrogate to e.g., quantifying end-point kinematics of movements through motion tracking. Consequently, investigating the motor acuity afforded by two different interfaces – EMG vs Force Feedback, through variability and smoothness of commands, and the acquired control policies, enabled us to explain why EMG Feedback enabled better performance.

### EMG vs Force Feedback: the role of (feedback) interfaces

Another key outcome of the thesis is the comprehensive characterization of two closed-loop interfaces that use the same control algorithm, that of direct proportional control, but differ in the feedback variable provided to the user – discretized EMG biofeedback vs prosthesis force. Overall, we found that EMG Feedback enabled better feedback policies, which consequently led to lower variability in commands and higher performance. Interestingly, this difference originated in only one of the three tested execution speeds, demonstrating the intricacies involved in understanding how different (feedback) interfaces enable skill acquisition.

Interfaces are at the heart of prosthetic technologies and play a crucial role in determining users' skill and their journey towards acquiring it. We argue that the framework we developed here is a valuable addition to existing methods that enable us to carefully evaluate and understand this process, and to develop interfaces that optimally facilitate it.

## 5.2. LIMITATIONS

Here we consider some of the limitations of the key conclusions listed above. Firstly, despite the generality of the SAF in terms of applicability to any task to investigate motor execution of said task, one limitation is that it may be time consuming. Specifically, SAF demands that multiple speeds be tested and each with enough trials to ensure validity. This therefore places limitations on the applicability of SAF outside the lab, which we believe is an important use case for determining a SAF – namely for skill monitoring. Future work on model-based skill monitoring may help alleviate this issue, as we demonstrated in Study 3.

Methodologically, one facet of measuring the SAF that we have not fully explored is the number of execution speeds to evaluate it, which so far remains a free hyperparameter. While SAF in natural movements have been determined at anywhere between 3 to 10 speeds (Reis et al., 2009; Guiard et al., 2011; Shmuelof et al., 2012), here we observed that evaluating a single extra speed (from Study 2 to 3) led to small performance drops (averaged across speeds) indicating an increased learning burden to arrive at a control policy that they could then focus on executing reliably. Further, for modelling-based efforts, it becomes crucial to specify the number of speeds – since this naturally affects the estimated parameter values. Therefore, future work needs to inform about the effects of this hyperparameter more systematically. In a similar vein, a key limitation to Study 3 is the lack of validation of the proposed simplified skill inference method. While we have discussed the utility of such a method in Chapter 4.3, it remains to be shown if estimating the model parameter using a single speed is enough, or perhaps two?

Here, we investigated how interfaces affected prosthesis force control, and chose a force-matching (i.e., reaching a particular force) paradigm that has shown high construct validity across several studies. However, force control also involves other aspects such as the ability to adaptively modulate forces under a changing environment, e.g., when grasping an object whose weight was initially misjudged, which we have not investigated here. Further, we used a simple proportional control scheme to control prosthesis closing speed, to reflect the most commonly available control interface. Therefore, while EMG Feedback indeed enabled a better SAF and consistently lowered trial-by-trial variability compared to Force Feedback, it remains to be seen how more complex control interfaces, such as through multichannel regression, will affect the role of feedback.

Finally, we acknowledge a lack of rigorous validation of the proposed methods in an amputee population. However, the case studies in a single individual with a limb difference indicated that both performance and behavioral outcomes closely matched their able-bodied counterparts, providing preliminary evidence of the validity. Moreover, the simplicity of the interfaces we used implies that the results obtained from the able-bodied population should generalize to individuals with a limb difference.

## 5.3. FUTURE WORK

While understanding the role of feedback interfaces has been a consistent goal in the thesis, we have not yet evaluated the open-loop baseline, where users only have access to incidental feedback, using SAFs. We believe it is critical to establish this baseline, especially given open-loop interfaces are current state-of-the-art in commercial prostheses, and it as yet unknown how execution speed is impacted in this case.

A natural extension of our work involves evaluating SAF in more complex tasks, such as those that involve combined wrist rotation and grasping. Simultaneous control of multiple degrees of freedom remains an open challenge, and the framework developed here could be used to understand which movements impose stronger tradeoffs, and whether SAF of the sum can be understood from the parts. This would involve, e.g., identifying the range of movement times that are meaningful to study the SAF, and developing new metrics to understand control policies, since the number of corrections exclusively deals with force control.

At a broader level, we see two exciting opportunities to develop on and apply the methods proposed in this thesis:

**Benchmarking interfaces**

In the current landscape of user-prosthesis interfaces, we are faced with a wealth of fragmented knowledge and a lack of systematic comparisons between the available interfaces. This fragmentation arises from the diversity of tasks and the range of outcome measures that are reported, making side-by-side comparisons challenging. We believe that the true potential of user-prosthesis interfaces lies in the possibility for manufacturers, prosthetists, or even users to customize control schemes to suit their unique needs. Future research efforts should therefore prioritize benchmarking interfaces on a set of tasks that can reproducibly be setup and analyzed. We believe that characterizing the SAF across such a set of tasks is a necessary step towards this end.

### Monitoring user skill and experience

Recent increases in opportunities to log EMG data and make it available for research purposes opens up exciting possibilities for research on real-world skill acquisition (e.g., the 5 billion lines of at-home data from CoApt[4]). We believe that the methods we introduced in this thesis, to investigate motor acuity of myoelectric commands, and for skill inference through SAF models, can be further developed to study user behavior at a scale that was so far impossible.

[4] “*CTRL-Shift-Data: The fundamental change in myoelectric controls research and development.*” Perspective talk by Blair Lock, CoApt Inc., at the Myoelectric Controls Symposium, MEC22, August 2022, Canada.

# REFERENCES


Aboseria, M., Clemente, F., Engels, L. F., & Cipriani, C. (2018). Discrete Vibro-Tactile Feedback Prevents Object Slippage in Hand Prostheses More Intuitively Than Other Modalities. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *26*(8), 1577–1584. https://doi.org/10.1109/TNSRE.2018.2851617

Alt Murphy, M., & Häger, C. K. (2015). Kinematic analysis of the upper extremity after stroke – how far have we reached and what have we grasped? *Physical Therapy Reviews*, *20*(3), 137–155. https://doi.org/10.1179/1743288X15Y.0000000002

Antfolk, C., D'Alonzo, M., Rosén, B., Lundborg, G., Sebelius, F., & Cipriani, C. (2013). Sensory feedback in upper limb prosthetics. *Expert Review of Medical Devices*, *10*(1), 45–54. https://doi.org/10.1586/erd.12.68

Balasubramanian, S., Melendez-Calderon, A., Roby-Brami, A., & Burdet, E. (2015). On the analysis of movement smoothness. *Journal of NeuroEngineering and Rehabilitation*, *12*, 112. https://doi.org/10.1186/s12984-015-0090-9

Bensmaia, S. J., Tyler, D. J., & Micera, S. (2020). Restoration of sensory information via bionic hands. *Nature Biomedical Engineering*, 1–13. https://doi.org/10.1038/s41551-020-00630-8

Biddiss, E. A., & Chau, T. T. (2007). Upper limb prosthesis use and abandonment: A survey of the last 25 years. *Prosthetics and Orthotics International*, *31*(3), 236–257. https://doi.org/10.1080/03093640600994581

Biddiss, E., Beaton, D., & Chau, T. (2007). Consumer design priorities for upper limb prosthetics. *Disability and Rehabilitation: Assistive Technology*, *2*(6), 346–357. https://doi.org/10.1080/17483100701714733

Borish, C. N., Bertucco, M., & Sanger, T. D. (2020). Effect of target distance on controllability for myocontrol. *International Journal of Human-Computer Studies*, *140*, 102432. https://doi.org/10.1016/j.ijhcs.2020.102432

Borish, C. N., Feinman, A., Bertucco, M., Ramsy, N. G., & Sanger, T. D. (2018). Comparison of speed-accuracy tradeoff between linear and nonlinear filtering algorithms for myocontrol. *Journal of Neurophysiology*, *119*(6), 2030–2035. https://doi.org/10.1152/jn.00188.2017

Bouwsema, H., Kyberd, P. J., Hill, W., van der Sluis, C. K., & Bongers, R. M. (2012). Determining skill level in myoelectric prosthesis use with multiple outcome measures. *Journal of Rehabilitation Research & Development*, *49*(9), 1331–1347. https://doi.org/10.1682/JRRD.2011.09.0179

Bouwsema, H., van der Sluis, C. K., & Bongers, R. M. (2010). Learning to Control Opening and Closing a Myoelectric Hand. *Archives of Physical Medicine and Rehabilitation*, *91*(9), 1442–1446. https://doi.org/10.1016/j.apmr.2010.06.025

Bouwsema, H., van der Sluis, C. K., & Bongers, R. M. (2014). Changes in performance over time while learning to use a myoelectric prosthesis. *Journal of NeuroEngineering and Rehabilitation*, *11*(1), 16. https://doi.org/10.1186/1743-0003-11-16

Burger, H., & Marincek, C. (1994). Upper limb prosthetic use in Slovenia. *Prosthetics and Orthotics International*, *18*(1), 25–33. https://doi.org/10.3109/03093649409164667

Butkus, J. (2022). Upper Extremity Prosthetic Rehabilitation: A 20 day plan of therapy, education and coaching. *Myoelectric Controls and Upper Limb Prosthetics Symposium*, 14–16.

Catalano, M. G., Grioli, G., Farnioli, E., Serio, A., Piazza, C., & Bicchi, A. (2014). Adaptive synergies for the design and control of the Pisa/IIT SoftHand. *The International Journal of Robotics Research*, *33*(5), 768–782. https://doi.org/10.1177/0278364913518998

Chatterjee, A., Chaubey, P., Martin, J., & Thakor, N. (2008). Testing a Prosthetic Haptic Feedback Simulator With an Interactive Force Matching Task. *JPO: Journal of Prosthetics and Orthotics*, *20*(2), 27. https://doi.org/10.1097/01.JPO.0000311041.61628.be

Childress, D. S. (1980). Closed-loop control in prosthetic systems: Historical perspective. *Annals of Biomedical Engineering*, *8*(4–6), 293–303. https://doi.org/10.1007/BF02363433

Christensen, W. (2019). Skilled action. *Philosophy Compass*, *14*(11), e12631. https://doi.org/10.1111/phc3.12631

Cipriani, C., Segil, J. L., Clemente, F., ff. Weir, R. F., & Edin, B. (2014). Humans can integrate feedback of discrete events in their sensorimotor control of a robotic hand. *Experimental Brain Research*, *232*(11), 3421–3429. https://doi.org/10.1007/s00221-014-4024-8

Cipriani, C., Zaccone, F., Micera, S., & Carrozza, M. C. (2008). On the Shared Control of an EMG-Controlled Prosthetic Hand: Analysis of User–Prosthesis Interaction. *IEEE Transactions on Robotics*, *24*(1), 170–184. https://doi.org/10.1109/TRO.2007.910708

Clemente, F., D'Alonzo, M., Controzzi, M., Edin, B. B., & Cipriani, C. (2016). Non-Invasive, Temporally Discrete Feedback of Object Contact and Release Improves Grasp Control of Closed-Loop Myoelectric Transradial Prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *24*(12), 1314–1322. https://doi.org/10.1109/TNSRE.2015.2500586

D'Anna, E., Valle, G., Mazzoni, A., Strauss, I., Iberite, F., Patton, J., Petrini, F. M., Raspopovic, S., Granata, G., Di Iorio, R., Controzzi, M., Cipriani, C., Stieglitz, T., Rossini, P. M., & Micera, S. (2019). A closed-loop hand prosthesis with simultaneous intraneural tactile and position feedback. *Science Robotics*, *4*(27), eaau8892. https://doi.org/10.1126/scirobotics.aau8892

de los Reyes-Guzmán, A., Dimbwadyo-Terrer, I., Trincado-Alonso, F., Monasterio-Huelin, F., Torricelli, D., & Gil-Agudo, A. (2014). Quantitative assessment based on kinematic measures of functional impairments during upper extremity movements: A review. *Clinical Biomechanics (Bristol, Avon)*, *29*(7), 719–727. https://doi.org/10.1016/j.clinbiomech.2014.06.013

Dideriksen, J., & Dosen, S. (2021). Chapter 5 - Supplementary feedback for upper-limb prostheses using noninvasive stimulation: Methods, encoding, estimation-prediction processes, and assessment. In B. Güçlü (Ed.), *Somatosensory Feedback for Neuroprosthetics* (pp. 179–206). Academic Press. https://doi.org/10.1016/B978-0-12-822828-9.00019-8

Dijk, L. van, Sluis, C. K. van der, Dijk, H. W. van, & Bongers, R. M. (2016). Learning an EMG Controlled Game: Task-Specific Adaptations and Transfer. *PLOS ONE*, *11*(8), e0160817. https://doi.org/10.1371/journal.pone.0160817

Dosen, S., Markovic, M., Hartmann, C., & Farina, D. (2015). Sensory Feedback in Prosthetics: A Standardized Test Bench for Closed-Loop Control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *23*(2), 267–276. https://doi.org/10.1109/TNSRE.2014.2371238

Dosen, S., Markovic, M., Somer, K., Graimann, B., & Farina, D. (2015). EMG Biofeedback for online predictive control of grasping force in a myoelectric prosthesis. *Journal of NeuroEngineering and Rehabilitation*, *12*(1), 55. https://doi.org/10.1186/s12984-015-0047-z

Dosen, S., Markovic, M., Strbac, M., Belic, M., Kojic, V., Bijelic, G., Keller, T., & Farina, D. (2017). Multichannel Electrotactile Feedback With Spatial and Mixed Coding for Closed-Loop Control of Grasping Force in Hand Prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(3), 183–195. https://doi.org/10.1109/TNSRE.2016.2550864

Dosen, S., Markovic, M., Wille, N., Henkel, M., Koppe, M., Ninu, A., Frömmel, C., & Farina, D. (2015). Building an internal model of a myoelectric prosthesis via closed-loop control for consistent and routine grasping. *Experimental Brain Research*, *233*(6), 1855–1865. https://doi.org/10.1007/s00221-015-4257-1

Du, Y., Krakauer, J. W., & Haith, A. M. (2022). The relationship between habits and motor skills in humans. *Trends in Cognitive Sciences*, *26*(5), 371–387. https://doi.org/10.1016/j.tics.2022.02.002

Engdahl, S. M., Christie, B. P., Kelly, B., Davis, A., Chestek, C. A., & Gates,

D. H. (2015). Surveying the interest of individuals with upper limb loss in novel prosthetic control techniques. *Journal of NeuroEngineering and Rehabilitation*, *12*. https://doi.org/10.1186/s12984-015-0044-2

Engels, L. F., Shehata, A. W., Scheme, E. J., Sensinger, J. W., & Cipriani, C. (2019). When Less Is More – Discrete Tactile Feedback Dominates Continuous Audio Biofeedback in the Integrated Percept While Controlling a Myoelectric Prosthetic Hand. *Frontiers in Neuroscience*, *13*, 578. https://doi.org/10.3389/fnins.2019.00578

Fimbel, E. J., Lemay, M., & Arguin, M. (2006). Speed–accuracy trade-offs in myocontrol. *Human Movement Science*, *25*(2), 165–180. https://doi.org/10.1016/j.humov.2005.12.001

Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology*, *47*, 381–391. https://doi.org/10.1037/h0055392

Fitts, P. M., & Peterson, J. R. (1964). Information capacity of discrete motor responses. *Journal of Experimental Psychology*, *67*, 103–112. https://doi.org/10.1037/h0045689

Flesher, S. N., Downey, J. E., Weiss, J. M., Hughes, C. L., Herrera, A. J., Tyler-Kabara, E. C., Boninger, M. L., Collinger, J. L., & Gaunt, R. A. (2021). A brain-computer interface that evokes tactile sensations improves robotic arm control. *Science*, *372*(6544), 831–836. https://doi.org/10.1126/science.abd0380

Fougner, A., Stavdahl, O., Kyberd, P. J., Losier, Y. G., & Parker, P. A. (2012). Control of Upper Limb Prostheses: Terminology and Proportional Myoelectric Control—A Review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *20*(5), 663–677. https://doi.org/10.1109/TNSRE.2012.2196711

Franzke, A. (2023). *Machine-learning myoelectric prosthesis control: Towards the advancement of assessing functional use and control skill* [Thesis fully internal (DIV), University of Groningen]. https://doi.org/10.33612/diss.663805052

Franzke, A. W., Kristoffersen, M. B., Jayaram, V., van der Sluis, C. K., Murgia, A., & Bongers, R. M. (2021). Exploring the Relationship Between EMG Feature Space Characteristics and Control Performance in Machine Learning Myoelectric Control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *29*, 21–30. https://doi.org/10.1109/TNSRE.2020.3029873

Garenfeld, M. A., Mortensen, C. K., Strbac, M., Dideriksen, J. L., & Dosen, S. (2020). Amplitude versus spatially modulated electrotactile feedback for myoelectric control of two degrees of freedom. *Journal of Neural Engineering*, *17*(4), 046034. https://doi.org/10.1088/1741-2552/aba4fd

Garenfeld, M. A., Strbac, M., Jorgovanovic, N., Dideriksen, J. L., & Dosen, S.

(2023). Closed-Loop Control of a Multifunctional Myoelectric Prosthesis With Full-State Anatomically Congruent Electrotactile Feedback. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *31*, 2090–2100. https://doi.org/10.1109/TNSRE.2023.3267273

Gholinezhad, S., Dosen, S., & Dideriksen, J. (2021). Electrotactile feedback outweighs natural feedback in sensory integration during control of grasp force. *Journal of Neural Engineering*. https://doi.org/10.1088/1741-2552/ac1fce

Gillespie, R. B., Contreras-Vidal, J. L., Shewokis, P. A., O'Malley, M. K., Brown, J. D., Agashe, H., Gentili, R., & Davis, A. (2010). Toward improved sensorimotor integration and learning using upper-limb prosthetic devices. *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, *2010*, 5077–5080. https://doi.org/10.1109/IEMBS.2010.5626206

Guiard, Y., Olafsdottir, H. B., & Perrault, S. T. (2011). Fitt's law as an explicit time/error trade-off. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1619–1628. https://doi.org/10.1145/1978942.1979179

Guiard, Y., & Rioul, O. (2015). A mathematical description of the speed/accuracy trade-off of aimed movement. *Proceedings of the 2015 British HCI Conference*, 91–100. https://doi.org/10.1145/2783446.2783574

Hahne, J. M., Markovic, M., & Farina, D. (2017). User adaptation in Myoelectric Man-Machine Interfaces. *Scientific Reports*, *7*(1), 4437. https://doi.org/10.1038/s41598-017-04255-x

Hebert, J. S., Boser, Q. A., Valevicius, A. M., Tanikawa, H., Lavoie, E. B., Vette, A. H., Pilarski, P. M., & Chapman, C. S. (2019). Quantitative Eye Gaze and Movement Differences in Visuomotor Adaptations to Varying Task Demands Among Upper-Extremity Prosthesis Users. *JAMA Network Open*, *2*(9), e1911197. https://doi.org/10.1001/jamanetworkopen.2019.11197

Hermsdörfer, J., Elias, Z., Cole, J. D., Quaney, B. M., & Nowak, D. A. (2008). Preserved and impaired aspects of feed-forward grip force control after chronic somatosensory deafferentation. *Neurorehabilitation and Neural Repair*, *22*(4), 374–384. https://doi.org/10.1177/1545968307311103

Holobar, A., & Farina, D. (2021). Noninvasive Neural Interfacing With Wearable Muscle Sensors: Combining Convolutive Blind Source Separation Methods and Deep Learning Techniques for Neural Decoding. *IEEE Signal Processing Magazine*, *38*(4), 103–118. https://doi.org/10.1109/MSP.2021.3057051

Jabban, L., Dupan, S., Zhang, D., Ainsworth, B., Nazarpour, K., & Metcalfe,

B. W. (2022). Sensory Feedback for Upper-Limb Prostheses: Opportunities and Barriers. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *30*, 738–747. https://doi.org/10.1109/TNSRE.2022.3159186

Johnson, R. E., Kording, K. P., Hargrove, L. J., & Sensinger, J. W. (2017). Adaptation to random and systematic errors: Comparison of amputee and non-amputee control interfaces with varying levels of process noise. *PLOS ONE*, *12*(3), e0170473. https://doi.org/10.1371/journal.pone.0170473

Jones, H., Webb, L., Dyson, M., & Nazarpour, K. (2022). Towards User-Centred Prosthetics Research Beyond the Laboratory. *Frontiers in Neuroscience*, 458.

Kim, K., & Colgate, J. E. (2012). Haptic Feedback Enhances Grip Force Control of sEMG-Controlled Prosthetic Hands in Targeted Reinnervation Amputees. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *20*(6), 798–805. https://doi.org/10.1109/TNSRE.2012.2206080

Kitago, T., & Krakauer, J. W. (2013). Motor learning principles for neurorehabilitation. In *Handbook of Clinical Neurology* (Vol. 110, pp. 93–103). Elsevier. https://doi.org/10.1016/B978-0-444-52901-5.00008-3

Krakauer, J. W. (2006). Motor learning: Its relevance to stroke recovery and neurorehabilitation: *Current Opinion in Neurology*, *19*(1), 84–90. https://doi.org/10.1097/01.wco.0000200544.29915.cc

Krakauer, J. W., & Carmichael, S. T. (2022). *Broken Movement: The Neurobiology of Motor Recovery after Stroke*. MIT Press.

Krakauer, J. W., Hadjiosif, A. M., Xu, J., Wong, A. L., & Haith, A. M. (2019). Motor Learning. In R. Terjung (Ed.), *Comprehensive Physiology* (1st ed., pp. 613–663). Wiley. https://doi.org/10.1002/cphy.c170043

Kristoffersen, M. B., Franzke, A. W., van der Sluis, C. K., Murgia, A., & Bongers, R. M. (2019). The Effect of Feedback During Training Sessions on Learning Pattern-Recognition-Based Prosthesis Control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(10), 2087–2096. https://doi.org/10.1109/TNSRE.2019.2929917

Kyberd, P. J., & Hill, W. (2011). Survey of upper limb prosthesis users in Sweden, the United Kingdom and Canada. *Prosthetics and Orthotics International*, *35*(2), 234–241. https://doi.org/10.1177/0309364611409099

Laffranchi, M., Boccardo, N., Traverso, S., Lombardi, L., Canepa, M., Lince, A., Semprini, M., Saglia, J. A., Naceri, A., Sacchetti, R., Gruppioni, E., & De Michieli, L. (2020). The Hannes hand prosthesis replicates the key biological properties of the human hand. *Science Robotics*, *5*(46), eabb0467. https://doi.org/10.1126/scirobotics.abb0467

MacKenzie, C. L., & Iberall, T. (1994). *The grasping hand* (pp. xvii, 482). North-Holland/Elsevier Science Publishers.

MacKenzie, I. S. (1992). Fitts' Law as a Research and Design Tool in Human-Computer Interaction. *Human–Computer Interaction*, *7*(1), 91–139. https://doi.org/10.1207/s15327051hci0701_3

Marasco, P. D., Hebert, J. S., Sensinger, J. W., Beckler, D. T., Thumser, Z. C., Shehata, A. W., Williams, H. E., & Wilson, K. R. (2021). Neurorobotic fusion of prosthetic touch, kinesthesia, and movement in bionic upper limbs promotes intrinsic brain behaviors. *Science Robotics*, *6*(58), eabf3368. https://doi.org/10.1126/scirobotics.abf3368

Markovic, M., Schweisfurth, M. A., Engels, L. F., Bentz, T., Wüstefeld, D., Farina, D., & Dosen, S. (2018). The clinical relevance of advanced artificial feedback in the control of a multi-functional myoelectric prosthesis. *Journal of NeuroEngineering and Rehabilitation*, *15*. https://doi.org/10.1186/s12984-018-0371-1

Markovic, M., Schweisfurth, M. A., Engels, L. F., Farina, D., & Dosen, S. (2018). Myocontrol is closed-loop control: Incidental feedback is sufficient for scaling the prosthesis force in routine grasping. *Journal of NeuroEngineering and Rehabilitation*, *15*(1), 81. https://doi.org/10.1186/s12984-018-0422-7

Merletti, R., & Farina, D. (Eds.). (2016). *Surface electromyography: Physiology, engineering and applications*. IEEE Press ; Wiley.

Millstein, S. G., Heger, H., & Hunter, G. A. (1986). Prosthetic use in adult upper limb amputees: A comparison of the body powered and electrically powered prostheses. *Prosthetics and Orthotics International*, *10*(1), 27–34. https://doi.org/10.3109/03093648609103076

Osborn, L. E., Moran, C., Johannes, M., Sutton, E., Wormley, J., Dohopolski, C., Nordstrom, M., Butkus, J., Chi, A., Pasquina, P., Cohen, A., Wester, B., Fifer, M. S., & Armiger, R. S. (2021). Extended home use of an advanced osseointegrated prosthetic arm improves function, performance, and control efficiency. *Journal of Neural Engineering*. https://doi.org/10.1088/1741-2552/abe20d

Østlie, K., Lesjø, I. M., Franklin, R. J., Garfelt, B., Skjeldal, O. H., & Magnus, P. (2012). Prosthesis rejection in acquired major upper-limb amputees: A population-based survey. *Disability and Rehabilitation. Assistive Technology*, *7*(4), 294–303. https://doi.org/10.3109/17483107.2011.635405

Parker, P., Englehart, K., & Hudgins, B. (2006). Myoelectric signal processing for control of powered limb prostheses. *Journal of Electromyography and Kinesiology*, *16*(6), 541–548. https://doi.org/10.1016/j.jelekin.2006.08.006

Piazza, C., Grioli, G., Catalano, M. G., & Bicchi, A. (2019). A Century of

Robotic Hands. *Annual Review of Control, Robotics, and Autonomous Systems*, *2*(1), 1–32. https://doi.org/10.1146/annurev-control-060117-105003

Pylatiuk, C., Kargov, A., & Schulz, S. (2006). Design and Evaluation of a Low-Cost Force Feedback System for Myoelectric Prosthetic Hands. *JPO: Journal of Prosthetics and Orthotics*, *18*(2), 57.

Reis, J., Schambra, H. M., Cohen, L. G., Buch, E. R., Fritsch, B., Zarahn, E., Celnik, P. A., & Krakauer, J. W. (2009). Noninvasive cortical stimulation enhances motor skill acquisition over multiple days through an effect on consolidation. *Proceedings of the National Academy of Sciences*, *106*(5), 1590–1595. https://doi.org/10.1073/pnas.0805413106

Risso, G., Valle, G., Iberite, F., Strauss, I., Stieglitz, T., Controzzi, M., Clemente, F., Granata, G., Rossini, P. M., Micera, S., & Baud-Bovy, G. (2019). Optimal integration of intraneural somatosensory feedback with visual information: A single-case study. *Scientific Reports*, *9*(1), Article 1. https://doi.org/10.1038/s41598-019-43815-1

Salminger, S., Stino, H., Pichler, L. H., Gstoettner, C., Sturma, A., Mayer, J. A., Szivak, M., & Aszmann, O. C. (2020). Current rates of prosthetic usage in upper-limb amputees – have innovations had an impact on device acceptance? *Disability and Rehabilitation*, 1–12. https://doi.org/10.1080/09638288.2020.1866684

Saunders, I., & Vijayakumar, S. (2011). The role of feed-forward and feedback processes for closed-loop prosthesis control. *Journal of NeuroEngineering and Rehabilitation*, *8*(1), 60. https://doi.org/10.1186/1743-0003-8-60

Scheme, E., & Englehart, K. (2011). Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use. *The Journal of Rehabilitation Research and Development*, *48*(6), 643. https://doi.org/10.1682/JRRD.2010.09.0177

Scheme, E. J., & Englehart, K. B. (2013). Validation of a Selective Ensemble-Based Classification Scheme for Myoelectric Control Using a Three-Dimensional Fitts' Law Test. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *21*(4), 616–623. https://doi.org/10.1109/TNSRE.2012.2226189

Schofield, J. S., Evans, K. R., Carey, J. P., & Hebert, J. S. (2014). Applications of sensory feedback in motorized upper extremity prosthesis: A review. *Expert Review of Medical Devices*, *11*(5), 499–511. https://doi.org/10.1586/17434440.2014.929496

Schofield, J. S., Shell, C. E., Beckler, D. T., Thumser, Z. C., & Marasco, P. D. (2020). Long-Term Home-Use of Sensory-Motor-Integrated Bidirectional Bionic Prosthetic Arms Promotes Functional, Perceptual, and Cognitive Changes. *Frontiers in Neuroscience*, *14*.

https://doi.org/10.3389/fnins.2020.00120

Schweisfurth, M. A., Markovic, M., Dosen, S., Teich, F., Graimann, B., & Farina, D. (2016). Electrotactile EMG feedback improves the control of prosthesis grasping force. *Journal of Neural Engineering*, *13*(5), 056010. https://doi.org/10.1088/1741-2560/13/5/056010

Sensinger, J. W., & Dosen, S. (2020). A Review of Sensory Feedback in Upper-Limb Prostheses From the Perspective of Human Motor Control. *Frontiers in Neuroscience*, *14*, 345. https://doi.org/10.3389/fnins.2020.00345

Shadmehr, R., & Krakauer, J. W. (2008). A computational neuroanatomy for motor control. *Experimental Brain Research. Experimentelle Hirnforschung. Experimentation Cerebrale*, *185*(3), 359–381. https://doi.org/10.1007/s00221-008-1280-5

Shehata, A. W., Engels, L. F., Controzzi, M., Cipriani, C., Scheme, E. J., & Sensinger, J. W. (2018). Improving internal model strength and performance of prosthetic hands using augmented feedback. *Journal of NeuroEngineering and Rehabilitation*, *15*(1), 70. https://doi.org/10.1186/s12984-018-0417-4

Shehata, A. W., Scheme, E. J., & Sensinger, J. W. (2018a). Audible Feedback Improves Internal Model Strength and Performance of Myoelectric Prosthesis Control. *Scientific Reports*, *8*(1), 8541. https://doi.org/10.1038/s41598-018-26810-w

Shehata, A. W., Scheme, E. J., & Sensinger, J. W. (2018b). Evaluating Internal Model Strength and Performance of Myoelectric Prosthesis Control Strategies. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *26*(5), 1046–1055. https://doi.org/10.1109/TNSRE.2018.2826981

Shehata, A. W., Williams, H. E., Hebert, J. S., & Pillarski, P. M. (2021). Machine Learning for the Control of Prosthetic Arms: Using Electromyographic Signals for Improved Performance. *IEEE Signal Processing Magazine*, *38*(4), 46–53. https://doi.org/10.1109/MSP.2021.3075931

Shmuelof, L., Krakauer, J. W., & Mazzoni, P. (2012). How is a motor skill learned? Change and invariance at the levels of task success and trajectory control. *Journal of Neurophysiology*, *108*(2), 578–594. https://doi.org/10.1152/jn.00856.2011

Shmuelof, L., Yang, J., Caffo, B., Mazzoni, P., & Krakauer, J. W. (2014). The neural correlates of learned motor acuity. *Journal of Neurophysiology*, *112*(4), 971–980. https://doi.org/10.1152/jn.00897.2013

Soukoreff, R. W., & MacKenzie, I. S. (2004). Towards a standard for pointing device evaluation, perspectives on 27 years of Fitts' law research in HCI. *International Journal of Human-Computer Studies*, *61*(6), 751–789. https://doi.org/10.1016/j.ijhcs.2004.09.001

Sternad, D. (2018). It's not (only) the mean that matters: Variability, noise and exploration in skill learning. *Current Opinion in Behavioral Sciences*, *20*, 183–195. https://doi.org/10.1016/j.cobeha.2018.01.004

Strbac, M., Isakovic, M., Belic, M., Popovic, I., Simanic, I., Farina, D., Keller, T., & Dosen, S. (2017). Short- and Long-Term Learning of Feedforward Control of a Myoelectric Prosthesis with Sensory Feedback by Amputees. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *25*(11), 2133–2145. https://doi.org/10.1109/TNSRE.2017.2712287

Svensson, P., Wijk, U., Björkman, A., & Antfolk, C. (2017). A review of invasive and non-invasive sensory feedback in upper limb prostheses. *Expert Review of Medical Devices*, *14*(6), 439–447. https://doi.org/10.1080/17434440.2017.1332989

Tchimino, J., Dideriksen, J. L., & Dosen, S. (2022). EMG feedback outperforms force feedback in the presence of prosthesis control disturbance. *Frontiers in Neuroscience*, *16*. https://www.frontiersin.org/articles/10.3389/fnins.2022.952288

Tchimino, J., Markovic, M., Dideriksen, J. L., & Dosen, S. (2021). The effect of calibration parameters on the control of a myoelectric hand prosthesis using EMG feedback. *Journal of Neural Engineering*, *18*(4), 046091. https://doi.org/10.1088/1741-2552/ac07be

Thumser, Z. C., Slifkin, A. B., Beckler, D. T., & Marasco, P. D. (2018). Fitts' Law in the Control of Isometric Grip Force With Naturalistic Targets. *Frontiers in Psychology*, *9*, 560. https://doi.org/10.3389/fpsyg.2018.00560

Thurston, A. J. (2007). Pare and prosthetics: The early history of artificial limbs. *ANZ Journal of Surgery*, *77*(12), 1114–1119. https://doi.org/10.1111/j.1445-2197.2007.04330.x

Tyler, D. J. (2016). Restoring the human touch: Prosthetics imbued with haptics give their wearers fine motor control and a sense of connection. *IEEE Spectrum*, *53*(5), 28–33. https://doi.org/10.1109/MSPEC.2016.7459116

Valevicius, A. M., Boser, Q. A., Lavoie, E. B., Murgatroyd, G. S., Pilarski, P. M., Chapman, C. S., Vette, A. H., & Hebert, J. S. (2018). Characterization of normative hand movements during two functional upper limb tasks. *PLOS ONE*, *13*(6), e0199549. https://doi.org/10.1371/journal.pone.0199549

Wickelgren, W. A. (1977). Speed-accuracy tradeoff and information processing dynamics. *Acta Psychologica*, *41*(1), 67–85. https://doi.org/10.1016/0001-6918(77)90012-9

Williams, H. E., Chapman, C. S., Pilarski, P. M., Vette, A. H., & Hebert, J. S. (2019). Gaze and Movement Assessment (GaMA): Inter-site validation of a visuomotor upper limb functional protocol. *PLOS*

*ONE*, *14*(12), e0219333. https://doi.org/10.1371/journal.pone.0219333

Witteveen, H. J., Rietman, H. S., & Veltink, P. H. (2015). Vibrotactile grasping force and hand aperture feedback for myoelectric forearm prosthesis users. *Prosthetics and Orthotics International*, *39*(3), 204. https://doi.org/10.1177/0309364614522260

Wolpert, D. M., & Ghahramani, Z. (2000). Computational principles of movement neuroscience. *Nature Neuroscience*, *3*(11), Article 11. https://doi.org/10.1038/81497

Wurth, S. M., & Hargrove, L. J. (2013). Real-time comparison of conventional direct control and pattern recognition myoelectric control in a two-dimensional Fitts' law style test. *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 3630–3633. https://doi.org/10.1109/EMBC.2013.6610329

Zecca, M., Micera, S., Carrozza, M. C., & Dario, P. (2002). Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal. *Critical Reviews™ in Biomedical Engineering*, *30*(4–6). https://doi.org/10.1615/CritRevBiomedEng.v30.i456.80

Zuo, K. J., & Olson, J. L. (2014). The evolution of functional hand replacement: From iron prostheses to hand transplantation. *Plastic Surgery*, *22*(1), 44–51. https://doi.org/10.1177/229255031402200111

ISSN (online): 2246-1302
ISBN (online): 978-87-7573-683-6

AALBORG UNIVERSITY PRESS