Interaction-Driven Approaches for Efficient and Autonomous Calibration of Myoelectric Controllers

Interaktionsbasierte Ansätze für eine effiziente und autonome Kalibrierung von myoelektrischen Steuerungssystemen

Der Technischen Fakultät
der Friedrich-Alexander-Universität
Erlangen-Nürnberg

zur
Erlangung des Doktorgrades Dr.-Ing.

vorgelegt von
Andrea Gigli, M.Sc.

Als Dissertation genehmigt
von der Technischen Fakultät
der Friedrich-Alexander-Universität Erlangen-Nürnberg

Tag der mündlichen Prüfung:	05.07.2024
Gutachter:	Prof. Dr. Claudio Castellini
Gutachterin:	Prof. Dr. Cristina Piazza

Abstract

Dexterous myoelectric prostheses of the hand and wrist typically use machine learning to translate muscle activations into motor commands. Their performance relies on the quality of the training data, posing challenges to the effectiveness of the calibration process. The lack of immediate quality assessment during standard data acquisition renders the need for additional data only apparent after the acquisition is complete. Additionally, accurate labeling of the training data for supervised learning relies on the user's ability to deliver precise muscle contractions, which necessitates professional supervision during preprosthetic signal assessment and training.

These challenges may be addressed through novel calibration protocols that leverage continuous interaction between the user and the myocontrol system. The research initially focused on the inefficiency of existing multi-arm-position data acquisition protocols, which do not allow an instantaneous evaluation of model quality in different arm configurations. An interactive protocol was elaborated that combined real-time incremental model building with a feedback mechanism to direct users to acquire data in underperforming arm configurations. In subsequent work, the need for labeled training data was circumvented altogether by devising a novel unsupervised calibration paradigm, driven by an interaction protocol where the user and system synergistically identify muscle contractions suitable as myocontrol inputs. This was achieved by having the user practice an abstract motor mapping between adaptively extracted muscle synergies and arbitrarily associated prosthetic functions. An initial version of this method focused on the simultaneous learning of multiple functions, whereas a successive version enabled users to learn the prosthetic functions progressively.

The studies highlighted that interactive procedures for myoelectric data acquisition and labeling increase the efficacy of supervised model calibration, holding practical relevance for prosthetic control and warranting further investigation in a broader range of myocontrol applications. Additionally, the potential of unsupervised calibration methods for myocontrol was demonstrated, especially in enabling users with varied residual motor abilities to engage quickly and autonomously with myocontrol systems, and to concurrently explore or even expand their muscle capabilities. Ultimately, this work presented a shift in perspective toward greater user involvement in myocontrol model calibration, contributing to more personalized and accessible myoelectric control.

Zusammenfassung

Multifunktionale myoelektrische Hand- und Handgelenksprothesen verwenden in der Regel maschinelles Lernen, um Muskelaktivierungen in motorische Befehle umzusetzen. Ihre Richtigkeit hängt von der Qualität der Trainingsdaten ab, was auch die Effektivität des Kalibrierungsprozesses beeinflussen kann. Da mit der Standardmethode zur Datenerfassung keine unmittelbare Qualitätsbewertung möglich ist, wird der Bedarf an zusätzlichen Daten erst nach beendeter Erfassung deutlich. Darüber hinaus hängt die genaue Kennzeichnung der Trainingsdaten für das überwachte Lernen von der Fähigkeit des Anwenders ab, akkurate Muskelkontraktionen durchzuführen. Dies erfordert eine professionelle Überwachung der Signalbewertung und des Trainings zur Vorbereitung auf die Prothesennutzung.

Diese Herausforderungen können mit neuartigen Kalibrierungsprotokollen adressiert werden, die eine kontinuierliche Interaktion zwischen dem Benutzer und dem Myokontrollsystem ermöglichen. Dafür evaluierte diese Arbeit zunächst die Ineffizienz bestehender Protokolle bei der Datenerfassung in verschiedenen Armkonfigurationen, die keine unmittelbare Bewertung der Modellqualität in diesen Armkonfigurationen ermöglichen. Es wurde ein interaktives Protokoll entwickelt, das die inkrementelle Modellerstellung in Echtzeit mit einem Feedback-Mechanismus kombinierte, um den Benutzer direkt aufzufordern mehr Daten in eingeschränkt funktionierenden Armkonfigurationen aufzunehmen. In weiteren Arbeiten wurde ein neuartiges unbeaufsichtigtes Kalibrierungsparadigma entwickelt, das durch ein Interaktionsprotokoll ermöglicht, dass der Benutzer und das System synergetisch Muskelkontraktionen identifizieren, die als Input für die Myokontrolle geeignet sind. Dadurch wird der Bedarf an klassifizierten Trainingsdaten umgangen. Stattdessen übt der Benutzer ein abstraktes motorisches Mapping zwischen adaptiv extrahierten Muskelsynergien und willkürlich zugeordneten Prothesenfunktionen. Eine erste Version dieser Methode zielte auf das gleichzeitige Erlernen verschiedener Prothesenfunktionen ab, während eine spätere Version den Benutzern ein schrittweises Erlernen der Funktionen ermöglichte.

Die Studien haben gezeigt, dass interaktive Methoden zur Erfassung und Kennzeichnung myoelektrischer Daten die Effizienz der überwachten Modellkalibrierung erhöhen. Dies ist für die Prothesensteuerung von praktischer Bedeutung und rechtfertigt weitere Untersuchungen in einem breiteren Spektrum von Myokontrollanwendungen. Darüber

hinaus wurde das Potenzial unbeaufsichtigter Kalibrierungsmethoden für die Myokontrolle aufgezeigt, insbesondere um Nutzern mit unterschiedlichen motorischen Restfähigkeiten die Möglichkeit zu geben, schnell und autonom mit Myokontrollsystemen zu arbeiten und dabei ihre Muskelfähigkeiten zu erkunden oder sogar zu erweitern. Damit stellt diese Arbeit einen Perspektivwechsel hin zu einer stärkeren Einbeziehung der Nutzer in die Kalibrierung von Myokontrollmodellen dar und trägt so zu einer personalisierten und leichter zugänglichen myoelektrischen Steuerung bei.

Acknowledgments

This dissertation reflects professional collaborations and personal encounters during my time at the Institute of Robotics and Mechatronics of the German Aerospace Center. I would like to thank Claudio Castellini for supervising my research and always valuing my ideas. I am beyond grateful to Arjan Gijsberts for inspiring my work both as a mentor and a friend. I sincerely appreciate Freek Stulp's essential guidance in making major professional decisions. My thanks are extended to Markus Nowak for helping me shape this dissertation through extensive and engaging discussions. Acknowledgments are also due to Ivan Vujaklija for his very insightful input and availability. I am honored to have shared this journey with my colleagues Marek, Donato, Harsimran, and others at DLR and IROB Lab, who have enriched my work with diverse perspectives, ideas, and experiences. Special thanks go to Annika and Mathilde for brightening my working days and reliably helping me with matters of all sorts. I am most grateful to Ben for providing unwavering motivation, support, and stability to my life over these years. Finally, I am thankful to my dear parents, family, and friends for their unconditional affection and encouragement.

List of Publications

Core publications

This dissertation is supported by findings from the following peer-reviewed core publications. For clarity of exposition within this document, the core publications are cited using an alphanumeric system that employs the letter "p" followed by a sequence number. Additionally, these works are occasionally referenced by their abbreviated titles.

Publication 1: "Merits of Dynamic Data Acquisition"

[p1] **Andrea Gigli**, Arjan Gijsberts, and Claudio Castellini. "The Merits of Dynamic Data Acquisition for Realistic Myocontrol." In: *Frontiers in Bioengineering and Biotechnology* 8 (April 2020), pp. 1–20.

Publication 2: "Feedback-aided Dynamic Data Acquisition"

[p2] **Andrea Gigli**, Donato Brusamento, Roberto Meattini, Claudio Melchiorri and Claudio Castellini. "Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand." In: *Journal of Neural Engineering* 17.5 (2020), p. 056047.

Publication 3: "Coadaptive Unsupervised Myocontrol"

[p3] **Andrea Gigli**, Arjan Gijsberts, and Claudio Castellini. "Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping." In: *2022 IEEE International Conference on Rehabilitation Robotics.* Rotterdam, 2022, pp. 1–6.

Publication 4: "Progressive and Coadaptive Unsupervised Myocontrol"

[p4] **Andrea Gigli**, Arjan Gijsberts, Markus Nowak, Ivan Vujaklija and Claudio Castellini. "Progressive Unsupervised Myocontrol of Myoelectric Upper Limbs." In: *Journal of Neural Engineering* 20.6 (2023), p. 066016.

Further publications

The author has also contributed to additional publications that further support the research discussed in this dissertation.

[1] **Andrea Gigli**, Arjan Gijsberts, and Claudio Castellini. "Natural Myocontrol in a Realistic Setting: a Comparison Between Static and Dynamic Data Acquisition." In: *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*. 2019, pp. 1061–1066.

[2] Donato Brusamento, **Andrea Gigli**, Roberto Meattini, Claudio Melchiorri and Claudio Castellini. "Closed-Loop Acquisition of Training Data Improves Myocontrol of a Prosthetic Hand." In: *Converging Clinical and Engineering Research on Neurorehabilitation IV (ICNR 2020)*. Springer International Publishing, 2022, pp. 421–425.

Contents

List of Figures

Glossary

ADL activity of daily living. 8, 34–36, 45, 46, 58

DoF degree of freedom. 8, 20, 21, 27, 28

EMG electromyography. 11–13

HD-sEMG high-dimensional surface electromyography. 12, 19, 21

IML interactive machine learning. 29, 30

KRR kernel ridge regression. 21, 22

LD limb differences. 41–43, 45, 48, 49, 51, 53–55, 58, 59

ND non-disabled. 41–43, 45, 46, 48–51, 53–55, 58

NMF nonnegative matrix factorization. 16–18, 28, 38, 41, 52, 53, 57, 58

PCA principal component analysis. 16

PUM progressive unsupervised myocontrol. 53–55

RFF random Fourier features. 22, 34, 36, 39

RMS root mean square. 15, 21

RR ridge regression. 21, 22, 34, 36, 39

sEMG surface electromyography. 7, 8, 12–21, 24, 26–28, 34, 36, 39, 41, 55, 56, 58, 63

SP simultaneous and proportional. 20, 21, 26, 27, 53

TAC target achievement control. 32, 39, 41, 43, 45, 47, 50, 53, 54

Chapter 1

Introduction

Dexterous myoelectric prostheses for the hand and wrist can significantly improve the daily lives of people with limb differences by restoring motor functions and aiding activities of daily living [3, 4, 5]. These devices not only facilitate essential personal care but also specialized tasks pertinent to vocational or recreational activities, thereby promoting personal independence. In addition, prosthetic devices are shown to enhance the user's self-esteem and sense of worth by reducing the perceived social stigma surrounding limb absence and increasing the person's engagement in social and professional environments. Importantly, the societal integration supported by prosthetic limb use is anticipated to provide socio-economic gains that benefit not only the individual but society as a whole.

1.1 Myocontrol of Prosthetic Upper Limbs

To take full advantage of myoelectric hand and wrist prostheses, their control must be as natural and intuitive as possible [6, 7, 8]. Users should be enabled to control the prosthesis through muscle activations that are both comfortable to generate and easy to mentally associate with the intended prosthetic functions. The control system should modulate the degree of activation of a prosthetic function proportional to the intensity of the corresponding muscle contraction and to coordinate the activation of multiple functions simultaneously. Achieving this requires defining myoelectric control models capable of inferring motor intents embedded within complex muscle coactivation patterns and associating them with the activation of related prosthetic functions. Supervised machine learning algorithms are commonly employed to define such myocontrol models due to their ability to capture complex relationships between muscle activity and motor intents from training datasets of labeled muscle data [9, 10].

The **calibration of machine learning-based myocontrol models** involves the acquisition of user-specific training muscle signals for each desired motor function, the subsequent learning of the model, and the evaluation of its performance [11]. This process can be repeated until satisfactory intent detection is achieved. Although supervised calibration approaches have become standard practice in both academic and commercial settings, they still face **challenges** related to the efficiency of data acquisition and the reliance on the user's ability to provide consistent training signals, among other factors.

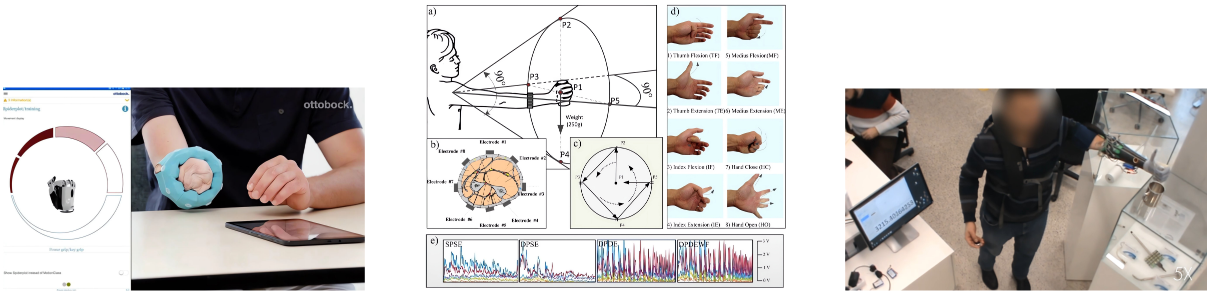
1.2 Challenges of Myocontrol Model Calibration

A core challenge in calibrating myocontrol models is the acquisition and labeling of training data from subjects with limb differences. During data acquisition, subjects must produce specific muscle activations that correspond to the desired myocontrol functions to establish the ground truth for model training. However, **generating accurate training muscle signals on demand can be difficult** for subjects with limb differences, who may lack visual and proprioceptive feedback from a healthy limb [12, 13, 14]. Therefore, before calibrating the model, it is often necessary to assess the user's existing motor skills and then train the user to generate stable, distinctive, and repeatable muscle signals. These steps, collectively referred to as preprosthetic user training, require direct guidance from healthcare professionals and are performed in specialized clinical settings [13]. Such requirements may delay or limit the user's initial engagement with the myocontrol system, which could complicate the subsequent acceptance of the prosthesis [15, 16]. Figure 1.1 illustrates aspects of the preprosthetic user training process.

(a) (b) (c)

Figure 1.1: Preprosthetic assessment and signal training of users with limb differences in preparation for myocontrol model calibration and use. These procedures include *(a)* palpation to assess muscle activity, *(b)* mirroring exercises to develop motor skills, and *(c)* biofeedback techniques for refined muscle signal control. Each step is actively guided or supervised by healthcare professionals. Screenshots from an instructional video by Ottobock [17], timestamps 2:28, 2:48, and 4:37, ©Ottobock 2019.

Another challenge relates to the open-loop design of standard protocols for the acquisition of labeled training data. Users typically follow preset acquisition routines prompted by visual cues to generate training muscle contractions [18, 19], but they receive no simultaneous feedback on the quality of the generated signals. The **absence of immediate feedback during training data acquisition** delays the evaluation of the model's performance until the end of the calibration process, after the model has been trained. Should this delayed assessment indicate that additional training data is required, the data acquisition would need to be repeated, reducing the overall efficiency of the calibration process [11]. This issue is especially evident in calibration procedures that are designed to improve the model's robustness to specific confounding factors by capturing the effect of such confounding factors in the training data. For example, to counter prediction inaccuracies induced by variation of the arm position, users may be required to execute training gestures at various arm configurations. The absence of immediate feedback during this data acquisition phase represents a missed opportunity, as it could guide the user to elicit the confounding factor in a manner that is more conducive to increasing the model's robustness. Figure 1.2 depicts data acquisition procedures used in commercial or state-of-the-art systems, as well as the evaluation of myocontrol model performance conducted during real-time myocontrol tasks.



(a) (b) (c)

Figure 1.2: Acquisition and labeling of training data for machine learning-based myocontrol models and subsequent evaluation of model quality during prosthetic control. *(a)* Training data acquisition using MyoPlus, a commercially available myocontrol system based on pattern recognition; screenshot from an instructional video by Ottobock [19], timestamp 14:42, ©2022 Ottobock. *(b)* Schematic representation of a state-of-the-art training data acquisition protocol designed to capture the variability of the myoelectric signal due to confounding factors such as limb position, contraction intensity, and weight of the grasped object; reprinted from Yang et al. [20], ©2017 Elsevier. *(c)* Despite using advanced data acquisition protocols to anticipate and counteract the effects of confounding factors, model instabilities may still surface during realistic prosthetic control, suggesting the need for further calibration. In this example, a failed attempt to grasp a cup on a high shelf reveals possible model instability related to the limb position effect; adapted from Meattini et al. [21], ©2019 Meattini et al.

1.3 Contributions

This dissertation explores the role of user-system interaction in addressing the challenges associated with the calibration of machine learning-based myocontrol models for myoelectric hands. Foundational to this exploration is recognizing that interaction is a core component of myoelectric control since the user inherently participates in the control loop [11, 22, 23]. On one side, the control system interprets the user's muscle signals and activates the corresponding prosthetic functions, which provide implicit visual feedback on the control quality. Recent myocontrol systems even use interactive machine learning methods to incrementally refine the model while interacting with the user [11, 22]. On the other side, the user may operate real-time adjustments of their control inputs based on the received feedback [23, 24] and even permanently adapt their control strategy to balance performance and workload [11, 25].

This synergy between the user's cognitive agency and the system's adaptive capabilities highlights the potential to leverage interaction not just for real-time control adjustments but also for addressing certain challenges in the calibration of myocontrol models. Therefore, this thesis posits that **a structured user-system interaction can enhance the calibration process**, offering **two main contributions** to this end.

The first contribution addresses the aforementioned inefficiency of traditional supervised calibration approaches that acquire and label training data using open-loop acquisition protocols. Specific focus is given to standard multi-arm-position data acquisition protocols, designed to enhance the robustness of myocontrol models to variations of the limb position. The idea is to aid the user in generating more useful training data by conducting the data acquisition interactively, thereby reducing the need for repeated calibration cycles.

Two supporting publications jointly contribute toward defining an efficient interactive multi-arm-position data acquisition procedure. The study in Gigli et al. [p1] provides a preliminary comparison of static and dynamic variants of open-loop multi-arm-position acquisition within a realistic prosthetic setup. The purpose of this comparison is to initially assess which method offers greater practical advantages for prosthetic control and thus holds the most promise for interactive redesign. Such preliminary investigation is necessary because a direct comparison between the two variants is not available in the current literature. Supported by the practical advantages of dynamic data acquisition, the work in Gigli et al. [p2] proposes and validates an **interactive version of dynamic multi-arm-position acquisition**. This approach integrates a novel interaction protocol in which the model is built in real-time through incremental updates and immediate feedback on the inference quality is used to guide the user to target underperforming arm configurations with more training data.

The second contribution of this dissertation focuses on the development of **coadaptive unsupervised calibration methods**. Instead of utilizing labeled training data, these methods construct the myocontrol model incrementally through a user-driven interaction protocol. Unlike supervised calibration approaches that require the user to produce predefined muscle contractions for accurate data acquisition and labeling, these methods are designed to adapt to the user's existing motor abilities. Consequently, these approaches aim at eliminating the need for professionally supervised preprosthetic user training, enabling a more direct and autonomous engagement with the myocontrol system.

The publication Gigli et al. [p3] introduces an unsupervised calibration approach where the user and the myocontrol system coadaptively identify distinctive control inputs based on muscle synergies. Throughout this process, an abstract motor mapping is established by arbitrarily associating a predefined set of prosthetic functions with the activation of an equivalent number of distinctive and adaptively extracted muscle synergies. Concurrently, the user is challenged to learn to control all the prosthetic functions by identifying and refining the muscle synergies detected by the system. This coadaptive process eliminates the need for preliminary signal training, as the user and system synergistically learn to generate or recognize distinctive control signals. However, this method still requires a prior assessment of the user's motor skills to determine the number of controllable prosthetic functions. This limitation is addressed in Gigli et al. [p4], where a refined version of the unsupervised calibration method allows the user to start learning a single function and gradually unlock additional functions when desired. By adopting a progressive approach to learning prosthetic functions instead of learning them all at once, this method implicitly aligns the complexity of the control model to the user's existing motor skills and supports the potential development of those skills during practice.

1.4 Structure of the Work

The structure of this dissertation is organized as follows. **Chapter 2** provides an overview of methodologies for myoelectric control of upper limb prostheses, with a focus on supervised and unsupervised calibration approaches. **Chapter 3** summarizes the aim, methodology, and results of the studies in the supporting publications, which can be found in full format in the **Appendix**. The outcomes, significance, and limitations of these studies are discussed in **Chapter 4**. Finally, a brief recapitulation of the key findings of this work is offered in **Chapter 5**.

Chapter 2

Background and State of the Art

2.1 Upper-Limb Prosthetics

2.1.1 Social Aspects of Limb Difference

People coping with limb differences, whether congenital or acquired, encounter extensive challenges that affect their societal participation and psychological health [26]. These differences hinder the performance of daily activities, impacting their autonomy and potentially limiting opportunities in work and leisure [5]. Additionally, they often adopt compensatory behaviors using unaffected limbs or other body parts, which can result in further physical strain and health issues [27].

Individuals with limb differences often experience challenges to their self-esteem and emotional well-being [28]. Those with acquired limb loss may struggle with accepting changes in body image, with effects on their emotional life [28]. Psychiatric disorders may also arise, including anxiety and depression [28, 29]. In severe cases, these psychological effects can lead to permanent changes in personality and lifestyle[4].

The socio-economic impact of limb difference is also significant. While global statistics on limb differences are not readily available, estimates for the United States of America indicate that the number of people with upper limb loss is expected to double by 2050, primarily due to an aging population and the rising prevalence of diabetes and vascular diseases [5, 30]. Correspondingly, the estimated costs associated with upper-limb differences are extensive, considering the required medical procedures, postoperative care, psychological support, and social security measures needed to compensate for partial societal exclusion [31].

2.1.2 Prosthetic Upper Limbs

Prosthetic upper limbs play a crucial role in improving the lives of people with limb differences, offering both cosmetic and functional benefits [4, 32]. Simple cosmetic prostheses are found to boost self-confidence, aiding in social reintegration after limb loss [4]. Meanwhile, functional and active prostheses allow individuals to regain independence in daily and work-related activities [3, 33]. These prostheses vary depending on the limb difference they address, movable parts, restored features, and control mechanisms.

Upper limb differences are classified based on location, ranging from the shoulder level to the hand [3]. This classification includes transradial limb differences, the primary focus of this thesis. These differences can be congenital, involving joint structure or limb length anomalies, or acquired through amputation. Prostheses for these differences are divided into passive, which are either cosmetic or functional, and active, which are further classified as body-powered or electric.

Passive Prostheses

Passive prosthetic limbs are defined by their lack of actively movable components [8]. These include static prostheses with no movable parts and adjustable prostheses whose parts can be locked in different configurations for specific tasks. These prostheses serve either aesthetic purposes, restoring limb appearance to mitigate societal stigma Kristjansdottir et al. [4], or functional purposes, such as protecting the residual limb, aiding balance, or facilitating specific tasks like using cutlery or playing instruments [8, 34, 35]. Their benefits include being cost-effective, lightweight, and requiring low maintenance [8].

Body and Electrically-Powered Active Prostheses

Active prostheses are designed with components that can be intentionally moved by the user [3]. In body-powered prostheses, these movable parts are mechanically linked to sound body parts and are operated through the user's physical movements. Conversely, electrically powered prostheses employ motors to control specific prosthetic joints.

Body-powered prostheses consist of a harness, movable parts mounted on rigid limb segments, and a cable connecting them [3]. Standard designs include an active hook or elbow controlled by shoulder movements [36], offering indirect proprioceptive feedback of the gripping force [37]. They are advantageous for their light weight, durability, and affordability [3]. These prostheses are light, durable, and cost-effective but may impose physical strain, have a limited operational range, and require regular maintenance due to cable wear and tear [3].

Electrically powered prostheses function by interpreting the user's motor intent from the muscle activity in the residual limb and using electric motors to actuate the movable mechanical parts. These devices commonly use surface electromyography (sEMG) to non-invasively measure neuroelectric signals amplified by muscle contractions. For this reason, these devices are interchangeably referred to as electric or myoelectric prostheses. section 2.2 and subsection 2.3.1 will provide further details on sEMG signal etiology and measurement, as well as on alternative input methods for myoelectric prostheses under academic research.

Myoelectric prosthesis designs cater to restoring varied motor functions, featuring different levels of anthropomorphism, a varied number of active degrees of freedom (DoFs), and sometimes hybrid designs with passive DoFs. The range of active hand prostheses extends from simple motorized hooks to complex polyarticulated anthropomorphic hands [3, 8]. An active DoF indicates a set of moving parts designed to move together for a specific motor function [26]. For example, a prosthetic finger typically includes multiple joints controlled by a single motor, accounting for one active DoF. Similarly, if a group of fingers of a prosthetic hand are mechanically coupled to move together, they also account for one active DoF. Commercially available prosthetic hands currently include both fully-actuated solutions, which have dedicated motors for every finger, and under-actuated ones, where groups of fingers are constrained to move together [8]. The overview by Marinelli et al. [8] provides an overview of commercially available hand prostheses and research prototypes. Commercially available myoelectric prosthetic wrists offer 1-DoF control over flexion-extension or prono-supination movements [3, 38], while a range of active prosthetic elbows and one 2-DoFs active shoulder are available for users with more proximal limb differences [8]. Besides the sensory and actuation elements, the design of the socket and shaft is also relevant [3, 39] to ensure a secure and comfortable fit, to house the necessary components, and to balance the weight of the contralateral limb [3].

Control strategies for myoelectric prostheses differ based on the device's complexity. For example, simple mechanical grippers may be directly operated through the activity of antagonistic muscle pairs, while polyarticulated hands necessitate advanced myocontrol models for intent detection from multichannel sEMG measurements. For individuals with proximal limb differences, advanced control techniques may also be complemented by invasive surgical procedures like targeted muscle reinnervation [40] and regenerative peripheral nerve interfaces [41], aiming to improve the resolution of the measured muscle signal. Section 2.5 provides a detailed overview of the control schemes used for myoelectric prostheses.

Myoelectric prostheses provide higher grip forces and a more extensive functional range than body-powered devices. By restoring multiple motor functions, they may support the user in a greater variety of activities of daily living (ADLs). However, these prostheses have higher initial and maintenance costs, require extensive user training, and their reliability can be compromised by disturbances in muscle signal measurements [3, 13, 42, 43].

2.1.3 User Needs

Despite significant technological advancements in the past few decades, the acceptance of upper-limb prostheses remains problematic [8], primarily due to discomfort and lack of functionality [44, 45]. A recent survey by Salminger et al. [44] reported average rejection rates of approximately 45 % for active upper limb prostheses, with myoelectric devices accounting for approximately 90 % of the rejections.

The acceptance of prosthetic limbs depends on satisfying diverse user needs, spanning device design, functionality, and ancillary care services [8]. Design enhancements regard increased comfort of the socket, decreased weight, as well as improved cost-effectiveness and durability of the components. From a functional perspective, users seek more biomimetic designs and grasping behaviors, more precise control over strength generation, and intuitive control of an increased number of functions [6, 8]. Concurrently, increased control reliability of multi-functional myoelectric hands is a critical focus, demanding machine learning methods that effectively handle the variability of the myoelectric signals for robust motor intent detection [5, 8]. Additionally, tactile restoration solutions are sought to reduce visual reliance and favor the prosthesis' embodiment.

Comprehensive user care, including early rehabilitation and training programs, is essential for the acceptance of prosthetic devices [13, 27, 46]. This is underscored by the desire for better preprosthetic user training and support reported by around 40 % of prosthesis abandoners [47]. Interactive and engaging training methods, such as serious games, are increasingly deployed to encourage intuitive and autonomous engagement with myoelectric technologies. These methods enhance initial user confidence and competence with the myoelectric system and support the role of healthcare professionals, who must guide users in understanding the prosthesis' benefits and integrating them into daily activities [8].

2.2 Anatomy and Physiology of Muscle Signals

The human muscular system, essential for maintaining posture and enabling body and organ movements, is divided into involuntary and voluntary muscles [48]. Involuntary muscles, such as cardiac and smooth muscles, autonomously control vital functions like blood circulation and peristalsis. Voluntary, or skeletal, muscles can instead be consciously contracted to facilitate body movements and are of interest for myoelectric control applications.

2.2.1 Anatomy of Skeletal Muscles and Motor Units

Skeletal muscles are composed of bundles of muscle cells, or fibers. These fibers contain bundles of elongated protein filaments divided into repeating units called sarcomeres, responsible for muscle contraction [48, 49]. Muscle fibers have specialized cell membranes, called sarcolemmas, that can generate and conduct electrical impulses in a similar way to the membrane of a neuron. Each muscle fiber is innervated by a motor neuron originating in the spinal cord at a specialized site called neuromuscular junction [48]. Each motor neuron controls a group of muscle fibers, forming a motor unit [49, 50]. The size of a motor unit reflects the number of muscle fibers controlled and influences the amount of force it can generate [51]. Motor units are characterized by properties of the innervated muscle fibers, such as size, location, and fatigability, as well as properties of the motor neuron, like its firing frequency [48].

2.2.2 Muscle Contractions

Muscle contractions are initiated by electrical signals representing movement intentions in the brain's motor cortex [49]. These signals are transmitted to the spinal cord via corticospinal neurons, then relayed to appropriate motor neurons through interneurons [52], and finally directed to the muscle fibers of the corresponding motor units [49]. The action potential at the neuromuscular junction triggers neurotransmitter release, causing the depolarization of the muscle fiber's membrane. The generated action potential travels along the surface of the muscle fiber and causes the sarcomeres within the muscle fiber to contract, resulting in the exertion of forces on the connected tendons and bones. Isotonic contractions lead to joint movements by shortening muscles, while isometric contractions stabilize joints without changing muscle length. The muscle fiber relaxes again when the action potential terminates.

The strength, precision, and endurance of muscle movements are governed by the process of motor unit recruitment [49, 50, 53]. The nervous system selectively activates motor units based on the intended force and speed of contraction. For low-force movements, the nervous system recruits motor units that are slower, smaller, less susceptible to fatigue, and typically found in the outer layers of a muscle [49, 50, 54]. As the required force or speed increases, motor units that are larger, faster, more prone to fatigue, and located in the innermost muscle layers are progressively activated. When the number of available motor units is insufficient to further increase the contraction intensity, the rates of the already recruited motor units may be further increased, a phenomenon known as rate coding [49, 50]. Motor units tend to deactivate in the reverse order once the movement is complete [50]. This recruitment strategy enables precise control of muscle force, optimizing energy efficiency and fatigue resistance.

2.2.3 Physiology of Muscle Synergies

Executing complex tasks, such as grasping an object, involves the coordinated activation of multiple muscles. Nevertheless, humans execute these tasks without consciously controlling the activity of each individual muscle. This capacity hints at the existence of mechanisms within the motor system that simplify movement control, referred to as muscle synergies [55, 56]. A muscle synergy represents a group of motor units, innervating different muscles, that are activated together to achieve a specific movement or task [55]. In this sense, muscle synergies can be thought of as modules of motor control [57]. This coordination mechanism reduces complex control of individual motor units to the modulation of fewer coordinated muscle activation patterns.

The physiological implementation of muscle synergies occurs within the spinal cord, where networks of premotor interneurons coordinate the activation of motor neurons in response to high-level cortical motor commands [52, 56]. Muscle synergies may evolve over time in response to physical development, training, practicing new skills, or recovering from injury [56, 58, 59]. This adaptability is due to the inherent plasticity of synergy-encoding interneuron networks in the spinal cord and may also involve modulation of synaptic inputs by neurons within the supraspinal system [52, 58]. The origin of muscle synergies is a topic of ongoing research. Some theories suggest a neural origin, where the nervous system organizes motor units into synergies for control efficiency [55, 60], while others propose that they emerge from biomechanical or task-related constraints [55, 61].

2.3 Measuring the Muscle Signals

2.3.1 Surface Electromyography (sEMG)

Electric prostheses are primarily controlled by the activity of skeletal muscles in the residual limb, which reflects the user's motor intent and the desired force of the movement [8]. Electromyography (EMG) is a method to measure the electrical activity of the muscles during contraction and is broadly employed in prosthetic applications [8, 49]. The relevance of this method lies in the direct measurement of the electrical activity that drives muscle contractions, and not in the detection of indirect effects, such as changes in the muscle shape or vibrations from muscle bulking [8, 53, 62]. Under normative conditions, moreover, the amplitude of the myoelectric signal corresponds proportionally to the intensity of muscle contractions because stronger contractions are obtained by recruiting more motor units and increasing the firing rate of already active ones [50, 62, 63]. Therefore, the EMG can be used to control prosthetic actuators proportionally to the muscle contraction intensity [8].

EMG generation and measurement

The myoelectric signal originating from a contracting muscle corresponds to the aggregated action potentials generated by its fibers [49, 64, 65]. As a muscle is commanded to contract, multiple motor units are recruited, each inducing almost simultaneous action potentials in its innervated muscle fibers. The cumulative action potential generated by a motor unit, referred to as motor unit action potential, is an amplified version of the stimulus provided by the motor neuron and manifests as an electric field that can be detected by nearby electrodes [65, 66]. After further electronic amplification, such estimation constitutes the raw EMG signal [65].

Invasive or non-invasive measurements of myoelectric activity can be performed using intramuscular EMG or sEMG, respectively. While intramuscular EMG offers reduced noise and better muscle selectivity, sEMG is most commonly used in prosthetics due to its greater comfort.

The measurement of SEMG presents challenges related to noise and electrical interference, especially crosstalk from adjacent muscles. To reduce signal interference in sEMG, various electrode configurations like monopolar, single-differential, and double-differential are used [66]. The monopolar configuration, with one active electrode on the muscle and a reference electrode on an electrically neutral site, amplifies voltage differences but can be prone to crosstalk. The single-differential or bipolar configuration uses two active electrodes along the muscle plus a reference electrode at an electrically neutral site. This arrangement amplifies the signal differences between the two active electrodes, reducing crosstalk from adjacent muscles. The double-differential configuration aligns three active electrodes along the muscle and one reference electrode at a neutral site, further localizing muscle activity by comparing signal differences. Finally, high-dimensional surface electromyography (HD-sEMG) systems use a dense grid of active electrodes and a reference electrode located at a neutral site. This allows myoelectric measurements with high spatial resolution, enabling detailed analysis of muscle activity and even the identification of individual motor unit action potentials. The works of Campanini et al. [66] and Rubin [67] provide detailed information on both non-invasive and invasive EMG setups.

In addition to electrode configuration and placement, other critical parameters for sEMG measurement systems include their number of electrodes, sampling rate, and resolution [65]. The number of electrodes affects the specificity of muscle activity detection. The sampling rate is crucial to capture the range of muscle activity frequencies, with most systems designed between 1 kHz and 2 kHz. Lastly, the resolution of the analog-to-digital converter embedded in the measurement system is also relevant, with clinical devices usually featuring resolutions above 12 bits to limit the quantization error.

In all supporting publications of this research, myoelectric measurements were performed using a Myo Armband by Thalmic Labs [68]. This device features eight sEMG sensors operating at 200 Hz with an 8-bit resolution. Despite its inferior features compared to other sEMG systems for clinical use, this device was chosen for its wireless design and cost-effectiveness, which render it particularly suitable for academic prototyping.

SEMG preprocessing

Several preprocessing steps are typically necessary to effectively analyze raw sEMG signals [8, 65]. International guidelines set by SENIAM [69] and CEDE [70] aim at ensuring procedural consistency of these steps. Bandpass filtering, typically within the 20-500 Hz range, is performed to eliminate possible low-frequency mechanical artifacts caused by electrode movements or high-frequency environmental interferences [65]. Notch filters at 50 Hz or 60 Hz may be employed to eliminate power line interference. DC offset correction is applied to the signal for battery-powered systems to eliminate any constant bias.

In order to infer motion intents from a continuous stream of sEMG data, the filtered signal is segmented into discrete windows capturing quasi-stationary muscle activity [65, 71]. Window size and relative overlap vary with the application requirements, but a window length of approximately 200 ms and time increments around 25 ms usually provide a reasonable balance between capturing sufficient information in each window and ensuring low processing times [72].

2.3.2 Alternative Muscle Activity Measurements

While EMG is currently the sole input modality used in commercial myoelectric prostheses, various alternative modalities are explored in research [8]. These are often combined with sEMG to enhance user intent recognition and prosthetic control. Alternative non-invasive modalities like force myography and mechanomyography measure physical properties derived from muscle contractions. The first assesses volumetric changes in the muscle structure using force sensors wrapped around the arm, while the second detects skin surface vibrations caused by muscle fiber contractions. Both modalities, however, are sensitive to external forces and motion artifacts, challenging their integration into prosthetic sockets. Sonomyography and electrical impedance tomography monitor muscle cross-sectional distribution changes in the residual limb non-invasively. The former estimates the muscle structure using ultrasound, and the latter applies weak electrical currents through skin electrodes to map internal structures based on impedance variations. Although these approaches provide a detailed estimate of muscle activity, they have limitations in terms of limited time resolution and sensitivity to sensor displacements. Peripheral neural interfaces, consisting of electrodes implanted in muscles or nerves, provide high-precision measurements but are less used for prosthetic control due to their invasiveness. Finally, inertial sensors, cameras, and physical buttons can be used to detect contextual information that is not directly related to the muscle activity, such as the user's posture, environmental characteristics, and user intents.

2.4 Feature Extraction from sEMG Signals

Interpreting motor intents from sEMG recordings presents intrinsic challenges due to the stochastic generation and nonstationary properties of the myoelectric signal [63, 73]. Addressing these complexities necessitates extracting dedicated features from the myoelectric signal to condense relevant information and mitigate confounding factors for effective data analysis and inference [10, 59]. This section outlines the confounding factors affecting the analysis of sEMG signals and explores commonly used engineered or projection-based features, as well as feature learning methods. The reader is referred to the works of Oskoei et al. [10], Ison et al. [59], McManus et al. [65], and Phinyomark et al. [74] for a comprehensive description of existing features for myocontrol.

2.4.1 Confounding Factors in sEMG Analysis

The sEMG is regarded as a nonstationary signal as its statistical characteristics may change over time due to measurement artifacts or physiological processes underlying muscle control [42, 43].

Measurement artifacts in the sEMG can result from sensor shifts, changes in the skin conductivity, and electromagnetic interference [65, 66]. Sensor shifts often result from donning and doffing a prosthesis, changing the established statistical relationships between the sEMG measurements from different channels and compromising the control of the prosthesis [42]. Crosstalk from neighboring muscles and electrical interference from external sources similarly affect the sEMG signal and complicate the detection of motor intention [66].

Among the physiological processes underlying muscle control, limb movements notably influence the myoelectric signal [42, 43]. Reaching and holding different arm configurations inherently require varying levels of baseline muscle activity for moving the arm and stabilizing it against gravity. This baseline activity overlaps with the muscle activity directly related to executing specific hand or wrist movements, which complicates the identification of the user's intended hand gestures from the myoelectric signals. Additionally, limb movements alter muscle shapes and lengths, impacting the relationship between myoelectric activity and generated force. This phenomenon, known as "limb position effect", represents a significant practical challenge in prosthetic control.

Modulation of the contraction intensity also affects the sEMG characteristics, as muscle recruitment and code rating mechanisms alter the relationship between the signal's amplitude and the force generated at different contraction intensity regimes. During prolonged motor tasks, muscle fatigue may reduce the action potential propagation speed along muscle fibers, resulting in shifts in the signal spectrum and average amplitude [42]. Furthermore, the user's adaptation to a myocontrol system through practice plays a complex role in this context. While individuals develop more refined motor skills through practice, enhancing myocontrol system performance, this adaptation also causes shifts in the statistical distribution of the measured signals [42]. Additionally, anatomical differences and diverse muscle recruitment strategies among individuals present considerable challenges in transferring myocontrol models between users [42].

2.4.2 Engineered Features

Engineered features for myoelectric signals capture specific characteristics in the time, frequency, or time-frequency domains [59, 65]. Time-domain features reflect the intensity and duration of muscle contractions and are extracted directly from windowed sEMG measurements [59, 65]. Two standard time-domain features are the root mean square (RMS) and the mean absolute value, which, despite theoretical differences, are used interchangeably to estimate the intensity of muscle contraction during defined time windows [10, 65, 75]. The envelope of the myoelectric signal, representing its amplitude evolution, can be computed by applying these features over a sliding window and adjusting the window size for a balance between smoothness and time resolution [65]. An alternative, non-windowed envelope computation involves concatenating full-wave rectification and low-pass filtering. Variations of the sEMG amplitude are most often characterized by the feature set proposed by Hudgins et al. [76], which is sometimes integrated with autoregressive coefficients to capture the signal's nonstationary characteristics [59, 77].

Frequency-domain features provide insights into the power distribution changes in the myoelectric signal, reflecting potential physiological changes in muscle control mechanisms [10, 65]. These are commonly applied to detect the onset of muscle fatigue, corresponding to shifts in the mean and median frequencies of the power spectrum.

Time-frequency features, obtained through techniques such as the wavelet transform, characterize the evolution of the myoelectric signal's frequency over time [10, 59]. While more computationally demanding than time or frequency-domain features, these descriptors help model dynamic modulations of the muscle contraction intensity.

The feature choice depends on the application and the specifics of the sEMG measurement setup, like its sampling rate [74]. For the analysis of myoelectric signals or offline evaluations of machine learning-based myocontrol approaches, complementary features are often combined, even from different domains [74]. On the other hand, applications involving motor learning or real-time myocontrol typically use simpler amplitude features like RMS for a more intuitive correlation between muscle activation intensity and controlled prosthetic function [59].

2.4.3 Projection-Based Features and Identification of Muscle Synergies

Projection-based features integrate information from multichannel sEMG data to highlight physiological or task-driven muscle coactivations [59]. By leveraging information redundancy across multiple channels, this combined representation counters the effects of confounding factors inherent in single-channel sEMG. Projection-based features are commonly derived through dimensionality reduction techniques that transform high-dimensional data into a lower-dimensional "latent" space while aiming to preserve essential information [59, 77, 78]. Latent dimensions, or "components", are computed to capture relevant relationships between the original dimensions that are conveyed by the input data. The projected coordinates of the data samples in the latent space, also referred to as "coefficients", describe the sample in terms of these relationships and thus serve as their feature representation.

Different dimensionality reduction algorithms highlight specific relationships in data and can be used for applications including noise reduction and muscle synergy estimation. Nonnegative matrix factorization (NMF) expresses data as a combination of nonnegative components, modeling additive processes seen in muscle activities [59]. This property makes NMF a prominent choice for estimating physiological muscle synergies from sEMG data [55, 79]. The characteristics and practical uses of NMF in this domain are elaborated further in section 2.4.3. Principal component analysis (PCA) identifies primary variance directions in the data, aiding in noise and collinearity reduction, but its components do not provide a physiological interpretation of underlying muscle synergies [59, 78, 79]. Factor analysis reveals latent variables based on correlations between the input dimensions, often giving a more accurate muscle synergy interpretation than PCA [79]. Independent component analysis decomposes data into statistically independent components relating to distinct motor commands, reducing sEMG crosstalk and aiding in the identification of subject-independent muscle coactivation patterns [59]. Autoencoders capture nonlinear relationships between sEMG channels, making them particularly useful for modeling the activity of antagonistic muscle pairs [59], but their latent dimensions hardly reflect physiological muscle synergies [59, 79]. The comparative performance of these algorithms in estimating physiological muscle synergies has been evaluated by multiple studies [79, 80, 81, 82]. While the specific outcomes are influenced by sEMG setup or noise levels, NMF consistently emerges as a preferred choice.

Nonnegative matrix factorization in SEMG analysis

NMF is a dimensionality reduction technique used in myoelectric signal analysis to extract features from multichannel EMG data that reflect the underlying patterns of physiological muscle synergies [55, 59, 79, 82]. This method expresses nonnegative multidimensional data as a linear nonnegative combination of nonnegative components [83]. When applied to multichannel sEMG recordings, the method identifies components that represent characteristic activation patterns of the sEMG channels and computes the relative contribution of those components to each data sample as a set of dedicated coefficients. This factorization principle imitates the structure and function of physiological muscle synergies, wherein complex movements are realized by modulating available time-invariant muscle coordination patterns [55, 84]. Consequently, NMF is employed in sEMG analysis to estimate the muscle synergies underlying multichannel recordings [55, 59]. The coefficients derived for each sample, corresponding to its projection in the latent synergy space, serve as a compact feature representation. Additionally, since these coefficients quantify the contribution of each estimated muscle synergy to the overall measured muscle activity, they may align with physiological high-level motor commands. Utilizing these coefficients as control inputs in myoelectric systems can potentially enhance motor learning by leveraging already established motor coordination schemes [85].

In practice, NMF approximates a nonnegative data matrix with the product of a components matrix and a coefficients matrix, both of which are also nonnegative [55, 56, 83]. The rank of these matrices corresponds to the number of components desired for the factorization and is usually lower than the original data dimension, making NMF suitable for dimensionality reduction purposes. For sEMG analysis based on NMF, the rows of the data matrix typically contain the envelopes of each channel's measurement, the columns of the components matrix define bases in a transformed latent space, and the columns in the coefficients matrix hold each sample's latent representation. [85, 86, 87]. Essentially, the components and coefficients matrices' columns correspond to the estimated muscle synergies and their activation levels, used to reconstruct observed muscle activity.

The NMF factorization problem does not admit a closed-form solution, necessitating the use of iterative optimization methods [83, 86, 88]. One commonly used method is multiplicative updates, a form of alternating gradient descent that preserves the nonnegativity of the optimized matrices throughout the optimization. Among the complications of this method are the potential convergence to suboptimal solutions depending on the parameter initialization and the "zero-locking" phenomenon, whereby parameters may become unresponsive to the update process if they reach a zero value [89]. Although several heuristics exist to mitigate this zero-locking issue, their effectiveness varies with the NMF formulation. Additionally, identifying the optimal factorization solution is complicated because NMF allows multiple valid matrix combinations to approximate the original data [83, 88].

NMF variants used in sEMG analysis aim to resemble physiological muscle synergies and meet application-specific requirements [88]. Regularized NMF formulations are used to capture the inherent sparsity in the temporal coordination of muscle synergies [90, 91, 92]. Lin et al. [91] employed L1-regularized NMF to minimize myocontrol synergies' temporal overlap. However, this sparsity enforcement artificially inflated component norms, reducing physiological plausibility. This problem remained unaddressed until one of the supporting publications of this thesis integrated an L1 regularization for coefficients' sparsity with an L2 regularization to control the components' norm [p3].

Incremental NMF methods are designed for situations where periodic updates of the factorization model are required, but full model retraining is unfeasible due to computational or memory constraints [p3, 87, 93]. These methods encode historical information into fixed-sized matrices, which are then used in combination with new data to inform model updates. This is relevant for myocontrol, where the myoelectric activity characteristics may vary due to changes in control strategy, fatigue, or measurement noise, and where memory constraints prevent explicit storage of historical data required for model retraining [42]. The integration of incremental NMF variants in myoelectric control applications has only been recently observed, namely in a study by Yeung et al. [85] and in one of the supporting publications of this thesis [p3].

Sequential NMF solutions are used to progressively increase the number of identified components while retaining the existing ones [94]. This could be useful in the context of prosthetic control, as the user's motor development during prolonged myocontrol sessions has been shown to lead to the progressive emergence of novel muscle synergies [55, 58, 95]. Typical sequential NMF solutions retrain the model on all the historical data with an increased count of components, using the previously trained model for initialization. However, storing historical data in real myoelectric control scenarios is often impractical. This issue has been first addressed in the supporting publication Gigli et al. [p4] by integrating the progressive addition of components within an incremental framework.

While the operating principles of NMF align with aspects of physiological muscle coordination, the physiological plausibility of the estimated synergies must be evaluated carefully [82]. The factorization's results could conflate natural physiological phenomena underlying the analyzed myographic recording and mathematical artifacts. Factors influencing the results include the number, placement, and quality of the sEMG electrodes, measurement noise, choice of NMF variant, and hyperparameters [79, 96]. In particular, a misalignment between the chosen number of NMF components and the actual number of elicited muscle synergies could lead to estimating synergies that are either combinations or fractions of real ones [55, 79]. Synergy validation methods include using synthetic sEMG data or assessing consistency among various factorization algorithms on the same real dataset [82].

2.4.4 Feature Learning

Feature learning has gained interest as an alternative to traditional feature engineering in several fields, including myoelectric control [97]. This method leverages deep learning algorithms to automatically extract feature sets tailored to solving specific learning tasks. Different neural network architectures are used to capture various types of relationships in the data. Multilayer perceptrons capture instantaneous nonlinear relationships in multichannel sEMG, convolutional neural networks handle spatial hierarchies found in HD-sEMG, and recurrent neural networks model time relationships within myographic recordings. While studies comparing engineered and learned features in myoelectric control show varied outcomes, both techniques demonstrate similar effectiveness in realistic settings [97, 98]. Challenges in implementing deep learning for prosthetic control include limited computational resources in prosthetic devices and the need for extensive human-elicited datasets [97].

2.5 Myoelectric Control Schemes

Myoelectric control involves mapping myoelectric activity to specific kinematic or kinetic outputs, such as the position or speed of a virtual cursor or the motor functions of a prosthesis [8, 18]. In this work, the term "prosthetic functions" is broadly used to refer to the actions that a prosthesis can perform, such as executing hand gestures or moving individual joints. The motor mapping implemented by a myocontrol model can be either biomimetic, aligning muscle activity with natural limb movements, or abstract, mapping muscle activity to physiologically unrelated movements [59, 99].

2.5.1 Criteria for Characterizing Myocontrol Schemes

Myoelectric control strategies differ in the number and type of functions they implement [18].

Early myoelectric prostheses were restricted to single functions, such as hand opening or closing [8, 18], whereas more advanced models allow controlling multiple functions. Multiple functions can be controlled either through sequential switching or through simultaneous modulation based on muscle coactivation patterns.

The function activation in myoelectric control schemes is categorized as either on-off or proportional [18]. The on-off method activates the function when the myoelectric signal amplitude crosses a predetermined threshold. In contrast, proportional control allows the degree of function activation to vary with the intensity of muscle contractions. Prosthetic limbs are controlled proportionally by regulating joint positions or velocities based on the myoelectric signal's amplitude [18, 100]. Recent studies have indicated that the intuitiveness and effectiveness of position or velocity control in myoelectric prostheses depend on the specific biomechanical joint being controlled, as the neural representations of the human hand and arm are different in terms of position and velocity [101]. For prosthetic hands, position control is usually considered more intuitive, as the controlled joints return to a neutral position in the absence of muscle contractions, but it is also considered more physically demanding, as it requires sustaining muscle contractions for the entire duration of a task [102, 103].

2.5.2 Direct Myocontrol

Dual-site direct control is the most widely adopted control methodology in clinical settings for myoelectric upper limbs [8, 104]. In this setup, myoelectric data is measured from a pair of antagonistic muscles using two electrodes and is used to control the movement of a single function in opposing directions, typically in a proportional way. Commercial prosthetic systems often combine direct control with sequential function-switching mechanisms based on muscle co-contractions.

2.5.3 Simultaneous and Proportional (SP) Myocontrol

Advanced myocontrol systems use multichannel sEMG measurements to enable simultaneous and proportional (SP) control across multiple functions [8, 18]. These systems translate muscle coactivation patterns into distinct functions, enabling users to control several functions simultaneously by adjusting their muscle activity. One approach is to learn a biomimetic relationship between specific functions and the muscle activations a user naturally associates with them [8, 76, 97, 105]. This is achieved using supervised machine learning algorithms like classification or regression, which are applied to sEMG data labeled with desired outcomes. Alternatively, some systems implement abstract motor mappings by identifying unique muscle patterns or synergies that are available to the user and utilizing them to control arbitrary prosthetic functions [99, 106, 107]. An overview of the supervised and unsupervised methods used in myoelectric control is given in section 2.6 and section 2.7.

2.6 Supervised Machine Learning for SP Myocontrol

The machine learning algorithm utilized to learn a myocontrol model depends on the nature of the output variable. Classification algorithms are used for gesture recognition tasks with discrete outcomes, while regression approaches are utilized for graded control over the movement of the prosthesis DoFs [8, 9, 18]. Both types of problems can be approached using statistical or deep learning algorithms [108].

Various classification algorithms like linear discriminant analysis, support vector machines, or k-nearest neighbors, have been employed for gesture classification tasks [8, 43, 109]. The linear discriminant analysis classifier combined with the Hudgins feature set is a common choice in clinical and commercial settings, balancing accuracy, efficiency, and adaptability [8, 109]. Deep learning classifiers based on convolutional neural networks effectively capture spatial relationships between HD-sEMG channels, while recurrent neural networks can identify multiresolution temporal patterns [110]. In order to achieve robust SP control based on classification, several postprocessing steps are typically undertaken, including smoothing predictions through majority vote and scaling gesture activation based on sEMG signal magnitude [8, 111]. Additionally, simultaneous control of multiple prosthetic functions is feasible by modulating the activation of the predicted classes according to the corresponding prediction confidence level [112].

Regression algorithms in prosthetics estimate the activation of the device's active DoFs proportionally to the muscle input [109, 113]. Simultaneous control of multiple DoFs can be realized through regression methods supporting multiple output variables or by combining multiple single-output regressors in parallel [114]. Besides natively enabling SP control, these approaches also can interpolate or extrapolate beyond the training data, thereby allowing prostheses users to control combinations of trained DoFs without explicitly training on those combinations [105]. Finally, the continuous motor mappings offered by regression models have been found to foster a more robust understanding of the model and a better compensation of the prediction instabilities during real-time myocontrol [24]. Unlike classification methods, which can yield abrupt switches in predicted gestures due to noise and nonstationarities in the muscle signal, regression approaches deliver smoother and more predictable responses [25].

The most commonly adopted regression approaches for myocontrol are least squares and its regularized variants, such as ridge regression (RR), in combination with features engineered to capture nonlinearities that fit specific use cases [9, 102, 115]. These features range from RMS envelopes [113], to nonlinearly-transformed envelopes simplifying the relationship between contraction intensity and controlled variables [105], to spectral descriptors capturing invariant characteristics of the input signal across different contraction intensity regimes [116]. Both least squares and RR enable incremental model updates that do not require explicitly storing historical data. In incremental RR, historical data is encoded in fixed-size matrices, specifically an inverse covariance matrix and a vector representing the cumulative product between input features and corresponding outputs, which are used to inform model updates [117, 118]. This approach maintains consistent space complexity, as matrix size depends on data dimensionality rather than the number of samples. It also enhances computational efficiency, requiring only simple rank-1 updates to the inverse covariance matrix instead of complex matrix inversions for complete retraining. A detailed description of RR, its incremental formulation, and their properties can be found in the works of González et al. [118] and Gijsberts et al. [117].

In addition to using nonlinear features, nonlinear regression models can be desirable in specific myocontrol setups and applications, for example, when only a limited number of sensors are available [105, 109, 115]. Kernel-based methods like kernel ridge regression (KRR) address this by modeling nonlinear input-output relationships without explicit feature extraction [119]. These methods base their inference on the similarity between new samples and the training data, determined through kernel functions. Kernel functions calculate a similarity value between sample pairs corresponding to the inner product between their projections into a high-dimensional feature space. This operation allows modeling nonlinear relationships between the original dimensions without the computational overhead of operating the data transformation and is commonly referred to as "kernel trick". While KRR can model complex nonlinear data relationships, its formulation does not allow for incremental updates [120], and its complexity increases with the number of training samples.

An approximation of KRR that reduces computational complexity and enables incrementality can be achieved using random Fourier features (RFF) [121]. The RFF-based approach maps data to an approximated version of the kernel-induced feature space and then solves linear regression in this space. The kernel mapping is approximated as the concatenation of a finite number of sinusoids whose frequencies and phases are randomly sampled from specific probability distributions [120, 121]. This version of RR with RFF enables nonlinear regression while retaining the benefits of incrementality and the constant time and space complexity of RR [117]. Several studies have verified the effectiveness of RR with RFF for a variety of myocontrol applications, including offline finger force estimation, prosthetic control, and robotic teleoperation [p1, p2, p3, 117]. Additionally, this method is used as a supervised myocontrol approach in three of the supporting papers of this dissertation [p1], Gigli et al. [p2] and Gigli et al. [p3].

Recent investigations into deep learning-based regression methods for myocontrol reveal mixed results. While some studies show superior offline performance [122], real-time application comparisons with traditional techniques have found no significant differences [115, 123].

The choice of regression algorithm in myocontrol varies by application. In offline tests, Gijsberts et al. [117] found KRR and its RFF-based incremental variant more accurate than linear RR for mapping muscle contractions to fingertip forces. Similarly, Hahne et al. [105] showed nonlinear KRR outperforming linear models, including RR, in wrist flexion modeling. However, the same study also noted that linearizing features could align RR's performance with those of nonlinear methods. Nevertheless, there is a consensus in the myocontrol community that offline test results may not accurately predict real-time myocontrol effectiveness. This is primarily because such tests fail to account for the user's ability to adapt to and compensate for real-time inaccuracies in myocontrol models [23]. In fact, studies such as the one by Jiang et al. [23] show that potential differences in offline performance between linear and nonlinear myocontrol models tend to decrease or disappear in online settings.

2.6.1 Challenges of Accurate Training Data Labeling

The calibration of myocontrol model based on machine learning relies on correctly labeled training data [78]. Inaccurate labeling affects the model's performance as it impairs the understanding of the statistical relationships within the training dataset. The acquisition and labeling of training data for myocontrol applications pose challenges as they depend on the user's ability to consistently deliver appropriate control signals [13, 124]. This involves the user generating stable, distinguishable, and repeatable muscle contractions corresponding to target motor intents. The ability to generate these contractions is influenced by the characteristics of the limb difference, individual experience, and the myocontrol task. Persons with limb differences might struggle to produce muscle contractions coherent with desired movements due to impaired visual or proprioceptive feedback and reduced motor control of the affected limb.

People with limb differences, particularly those unfamiliar with myoelectric control, often undergo specific preparatory procedures before they can effectively participate in the data acquisition for myoelectric control model calibration [13, 15]. These procedures focus on identifying which muscles in the residual limb can be engaged and enhancing the quality of the corresponding muscle signals. These processes are sometimes referred to as preprosthetic signal assessment and training [13], and this terminology will be adopted throughout the dissertation for clarity. These activities form part of a larger preprosthetic user training process [13, 15, 124], which includes rehabilitation, preparation for myocontrol, and familiarization with the prosthesis.

In preprosthetic signal assessment, residual muscle contractions are assessed by manual palpation, and control sites are then determined using Myotester devices [13, 14, 17]. Subsequent signal training includes exercises to enhance the stability, distinctiveness, and reliability of the elicited myoelectric activity [13, 15]. These exercises typically involve evoking phantom limb movements, either mirroring external visual stimuli or coordinating with movements of the unaffected limb. They may also involve isolating the activity of targeted muscles, aided by visual biofeedback of the corresponding myoelectric signal. Recent developments in serious gaming aim to increase user engagement during the preprosthetic phase by incorporating signal training into computer games, although their effectiveness compared to traditional methods is still showing inconsistent results [124, 125]. Preprosthetic user training typically necessitates direct supervision and coaching from healthcare professionals, which poses logistical challenges related to the availability of medical professionals and the accessibility of specialized rehabilitation facilities. These challenges can delay the initial engagement with the myocontrol system, which is believed to be fundamental for improving the functional use of prosthetic limbs and enhancing their long-term acceptance [15].

After ensuring that users can elicit the necessary muscle activity, myoelectric training data can be acquired and labeled using purposely designed acquisition protocols. Contralateral data acquisition involves measuring the muscle activity from the affected limb while capturing the intended gesture from the unaffected limb [126]. Alternatively, the user may execute phantom limb movements with the affected limb following a visual reference that is simultaneously used to label the measured muscle data [118, 126]. Training data for classification problems is usually collected by performing the desired gestures at a stable contraction intensity level. For regression problems, capturing dynamic modulation of the muscle contraction intensity in the training data can be beneficial, but labeling can be challenging due to synchronization issues between myoelectric signal and reference stimulus [105, 126]. An alternative approach for regression models involves training with steady-state contractions at different contraction intensities and leveraging the model's ability to interpolate and extrapolate from discrete data points [126].

2.6.2 Challenges Related to the Data Distribution Shift

The sequential nature of sEMG signals poses a challenge to myoelectric control, as it contravenes the assumption that data samples are independent and identically distributed, which is critical for many machine learning methods [42, 43, 127, 128]. Multichannel sEMG recordings exhibit temporal and spatial correlations due to neural drive and muscle coordination, countering the assumption of data sample independence and potentially leading to modeling inaccuracies. Strategies to address this involve extracting features from contiguous time windows and recognizing relationships across sEMG channels [129]. As detailed in subsection 2.3.1, various factors like measurement artifacts and physiological or functional characteristics of the musculoskeletal system may cause changes in the statistical properties of sEMG signals over time [42, 43]. Such changes can be detrimental in machine learning applications as they cause the characteristics of new inputs to diverge from those of the training data, increasing the inaccuracy, variability, and uncertainty of model inference. This issue is referred to as "domain shift" or "concept drift" [42]. Several approaches are used to counteract the domain shift in myocontrol depending on the specific confounding factors. One approach consists of developing robust features and models [42], another involves capturing as much of the data variability as possible in the training dataset [42], and a different one employs periodic model recalibration or updates to maintain performance levels in changing conditions [130].

Robust learning algorithms for myoelectric control involve specific data transformations, feature design, and algorithmic strategies [42, 108]. Data transformations may address muscle fatigue by normalizing myoelectric signal amplitude and median frequency [42, 131]. Certain frequency-domain features show greater invariance to limb position and contraction intensity variations while still being responsive to force modulation in proportional control [132, 133]. Sparsity-inducing algorithms can help identify feature subspaces resilient to limb position changes [43, 134]. The limb and contraction intensity effects are sometimes also tackled using cascaded combinations of learning models specialized on distinct levels of the confounding factor [42, 108].

Approaches based on data abundance have gained prominence in pattern recognition-based myoelectric control because they can be easily adapted and used to multiple use cases [42]. These methods integrate the effects of confounding factors directly into the training data by eliciting those factors in a structured manner during the acquisition routine. Consequently, the learning algorithm can account for broader data variability, and the resulting model is more likely to generalize inference effectively when confronted with unfamiliar inputs. For example, the limb position effect in myoelectric hand control is most commonly mitigated by capturing muscle data for the desired hand or wrist gestures in different arm configurations [42, 43]. While static multi-arm-position acquisition methods involve repeating data acquisition with the arm held in specific configurations [135, 136, 137, 138, 139, 140], dynamic methodologies capture data as the arm moves through the peripersonal space [20, 141, 142, 143]. In the broader context of this work, it is important to note that although dynamic acquisition is theoretically more efficient than static acquisition, previous assessments of their comparative performance have yielded inconsistent results. This aspect has been further investigated in the first supporting publication of our work [p1].

Robust algorithms and data abundance strategies may not always sufficiently address the challenges of domain shifts in myoelectric control. The complexity and unpredictability of certain confounding factors may necessitate periodic recalibration or updating of the control model [22, 117, 130, 144, 145, 146]. Such recalibration or updates of the myocontrol model are intended to complement robust models or data abundance approaches, and are currently integrated into commercial myocontrol systems [147, 148]. User-initiated full recalibrations effectively compensate for performance degradation of the myocontrol model [145, 149] but can be time-consuming and disruptive to prosthetic operation [6, 150]. Incremental machine learning algorithms present a more efficient alternative by updating the model with a limited amount of newly available data, enhancing computational efficiency and scalability without the need for full retraining [117, 144, 151]. Supervised incremental updates employ newly labeled data for specific prosthetic functions showing diminished performance. The data is acquired either through a reduced version of the data acquisition protocol or by deriving labels for the historical data implicitly from the myocontrol task [22, 117, 143, 152]. Conversely, unsupervised adaptation methods use pseudo-labeling based on the model's historical predictions in combination with heuristics like majority voting or confidence-based sample selection [42, 130, 153, 154, 155, 156, 157]. Although unsupervised methods offer the advantage of continuous and user-independent model adaptation, they tend to be less robust in maintaining consistent performance compared to supervised updating methods [130].

As discussed, data abundance and supervised incremental updates are fundamental in addressing domain shifts in myoelectric control. Since both strategies relate to the acquisition and labeling of training data, the effectiveness and efficiency of the data acquisition process appear to have practical relevance for realistic prosthetic control. A limitation of standard data acquisition protocols is their open-loop nature, where users perform predefined routines without real-time feedback on the quality of the generated training data for the model [11, 22]. This often leads to a protracted calibration process, as the model's performance and the need for additional training data only become apparent post-training. Multiple iterations of data acquisition, model update, and performance evaluations may thus be required. The work of Hahne et al. [22] initially proposed a shift toward more closed-loop data acquisition protocols. By updating the myocontrol model in real-time during online tasks using automatically labeled data, this approach enables the system to quickly compensate for domain shift and the user to immediately respond to model changes. Despite its advances, this method has been observed to restrict the user's involvement to the sole operation of the myoelectric interface, without enabling them to consciously identify and produce training muscle contractions that would be most beneficial for the model performance [156]. A closed-loop data acquisition approach promoting active user involvement was introduced in one of this thesis' supporting publications [p2].

2.7 Toward Unsupervised SP Myocontrol

Unsupervised methods for SP myocontrol focus on calibrating or updating the control system without using labeled training data. These methods shape the control model to the user's existing motor skills, aiming to eliminate the need for structured data acquisition protocols and prior signal assessment and training. Furthermore, if reliable updates of the unsupervised model are achieved, the amount of training data available can be significantly increased without burdening the user.

2.7.1 Abstract Decoding

Abstract decoding, or postural control, is an unsupervised myoelectric control method that establishes arbitrary connections between sEMG channels and prosthetic functions [99, 107, 158]. The myocontrol model is defined by an expert to utilize the user's pre-existing motor skills as control inputs and leverage the user's ability to learn the resulting abstract motor mapping through practice. Rather than utilizing machine learning methods to learn biomimetic motor mappings from labeled training data, this approach emphasizes the user's motor learning. This method extends the principles of direct myocontrol to multichannel sEMG inputs. Each channel's activity proportionally controls a designated function, allowing users to command multiple functions simultaneously by activating various channels [99, 159].

Research on motor learning indicates that, with sufficient practice, humans can master arbitrarily complex abstract motor mappings, retain them over periods of nonuse, and generalize the involved motor skill to different tasks [59, 160, 161, 162, 163, 164]. This holds for both individuals with and without limb differences [165]. Notably, a recent study demonstrated that both biomimetic and abstract motor mappings result in equivalent myocontrol performance provided the users are allowed sufficient familiarization time [166]. A downside of abstract decoding is its sensitivity to electrode displacement and other measurement issues due to the one-to-one mapping between sEMG sensors and controlled functions [167]. To counter this, some researchers proposed using muscle synergies as control inputs for abstract mappings as they are less prone to electrode-specific disturbances [59, 168]. This approach was validated for both the control of virtual myoelectric interfaces and prosthetic hands [159, 160].

Despite reducing training and data labeling needs, abstract decoding still necessitates expert supervision for motor skills evaluation and precise sEMG sensor placement [165, 169]. The necessity to tailor this approach to an individual's physiology raises questions about its scalability across diverse users and its impact on the broader accessibility of myocontrol.

2.7.2 Unsupervised Machine Learning for SP Myocontrol

Recent efforts to calibrate biomimetic motor models without explicitly labeled training data involve using muscle synergies as control inputs alongside tailored data acquisition protocols. These protocols variably constrain the range of training muscle contractions, aligning them with the intended prosthetic functions. By biasing the training data in this manner, unsupervised muscle synergy estimation algorithms are influenced to reflect functionally relevant muscle coactivation patterns, thereby facilitating a later manual definition of biomimetic motor mapping. Due to the combination of supervised elements, such as task-specific acquisition designs and manual establishment of the motor mapping, and unsupervised elements, like the derivation of control signals from unlabeled myoelectric data, these calibration methods are often referred to as "semi-unsupervised".

This paradigm was first introduced by Jiang et al. [84] for training SP models to predict wrist forces. They devised a DoF-wise calibration procedure in which independent factorization models are obtained from the unlabeled myoelectric activity of distinct wrist DoFs. These models are then combined to enable the factorization of myoelectric activity into a linear combination of non-overlapping, DoF-specific muscle synergies. The process is semi-unsupervised as it does not require explicit data labeling but does rely on users performing designated movements on demand. Later evaluation showed the comparative effectiveness of this method for real-time myoelectric control compared to existing supervised calibration [170].

Kim et al. [171] and Yang et al. [172] utilized an NMF variant aimed at extracting task-related muscle synergies without the necessity to train multiple movement-specific NMF models. This was achieved by directly linking myoelectric samples to corresponding wrist movements within the NMF formulation. Despite this advancement, their approach still relied on the established DoF-wise data acquisition process. Lin et al. [91] later proposed a regularized NMF variant that concurrently simplified both the model training and the acquisition of unsupervised training data. This enforces the extraction of synergies with minimal temporal overlap, allowing for a more flexible data acquisition where users can activate and even coactivate target DoFs in any sequence. However, this process still includes an element of supervision, as users are asked not to move undesired DoFs. This approach demonstrated superior performance to supervised methods in Fitts' law-style tests with non-disabled subjects.

Yeung et al. [85] recently developed an adaptive version of the regularized NMF variant used in [91]. This was designed to update the factorization model during operation while discounting historical information, ensuring compensation of changes in muscle synergies due to both sEMG nonstationarities and the user's adaptation to the control task. Their system incorporated an automated trigger for model updates, which activates when increased coactivation of antagonistic muscle synergies is detected, signaling performance degradation. Although this approach supported unsupervised model updates during use, the semi-unsupervised calibration procedure of [91] was necessary to initially set up the factorization model and establish a biomimetic motor mapping.

Although the presented calibration methods reduce the need for meticulous data labeling, they maintain limitations tied to constraints in the data acquisition protocol, such as limiting calibration movements to specific DoFs [85]. This protocol assumes that users have sufficient motor control to distinguish between gestures, which may not initially be the case for people with limited motor skills due to limb differences. Therefore, these methods may necessitate a preliminary evaluation and training of the user's motor skills, typically overseen by a medical professional. In addition, limiting the exploration of the user's muscle space during calibration may preclude the detection of muscle activations that are more suitable for myocontrol by being more prominent or easier to elicit. These issues have been first addressed in two of the supporting publications, which proposed fully unsupervised calibration paradigms leveraging user-prosthesis interaction and abstract motor mappings based on adaptive muscle synergies [p3, p4].

2.8 Interaction in Myoelectric Control

Interaction is a process in which two entities influence or react to each other by exchanging interpretable information, possibly to achieve a common goal [173, 174]. An interaction is mediated by an interface, which provides a protocol that regulates the type of information exchanged and its effects on the agents. Interaction protocols can be designed to leverage entities' agency and cognition, resulting in interactions of varying complexity. For example, entities may react to feedback, influence each other, or even mutually adapt their behavior to achieve a shared goal.

The control of myoelectric prostheses involves a continuous interaction between the user and the myocontrol system [11, 175]. The user generates and adjusts muscle signals in real-time to compensate for system inaccuracies and also adapts their motor control strategy to optimize task execution, efficiency, and comfort. In response, the control system interprets myoelectric inputs to actuate the prosthesis or to update the myocontrol model while also providing implicit visual feedback or explicit feedback through different modalities. The myoelectric interface includes an interaction protocol regulating the information exchange and defining the user and system's behavior, biosensors for capturing the user's motor intention, and potentially a dedicated feedback system [8].

The research community increasingly acknowledges the potential of enhancing myoelectric control through user-prosthesis interaction [8, 11, 175]. Central to this is understanding the interaction dynamics and the adaptive behaviors of both the user and the control system [102, 176], which includes aspects of user adaptation, interactive machine learning (IML), and coadaptation [8, 102].

2.8.1 User Learning

Humans improve their performance in motor tasks by adapting to external feedback [11, 42, 177]. When practicing myocontrol, users make cognitive, perceptual, and motor adaptations necessary to master the required motor mapping [59]. By forming an internal model of the myocontrol system, they learn to adjust their muscle inputs to compensate for potential prediction inaccuracies in real-time [24]. Concurrently, they may develop and refine motor skills for more effective and efficient muscle coordination [58, 164]. This usually yields increased separability, consistency, and repeatability of myoelectric signals, as well as the potential formation of new muscle synergies through merging and fractionation of existing ones [42, 58, 177].

As described in subsection 2.6.2, such specialization of muscle activity can lead to shifts in the statistical characteristics of the myoelectric inputs, requiring regular model updates to retain the model's inference quality [11, 42]. While worsened inference in response to user adaptation is observed in offline evaluations [25, 42, 178], this appears to be offset by the improved user abilities in online settings [23]. Indeed, studies usually report exponential improvements in online performance during the initial stages of using a myoelectric interface [160, 177].

2.8.2 Interactive Machine Learning

The human-in-the-loop characteristic of myoelectric control offers a considerable advantage for calibrating and maintaining the control model [174]. Since the user may be engaged to provide additional data and evaluate the model during operations, IML techniques are often used to continuously refine the control model interactively and incrementally [144, 179]. These methods enable both the user and the system to initiate model updates interactively during prosthetic operation, aiming to counteract performance degradation or expand the functional range of the prosthesis [180]. These updates involve the acquisition and integration of novel training data in the model and are designed to minimize the disruption of regular prosthetic use by focusing only on the prosthetic functions of interest. Incremental learning algorithms are utilized to conduct the updating process effectively without necessitating full model retraining on accumulated historical data [8, 181]. This capability allows for scaling the computational and memory requirements with growing amounts of training data. Addressing data distribution shifts through incremental updates is currently a standard approach in the field, as discussed in subsection 2.6.2. Since human input can be unpredictable and varied, the design of IML-based myocontrol methods must account for such variability, provide clear feedback guidance, and promote user engagement.

The IML framework does not differentiate between supervised and unsupervised algorithms, yet most interactive myoelectric control methods engage users in providing labeled training data for model updates [22, 117, 146, 182, 183, 184]. The extent to which existing methods for unsupervised domain adaptation in myocontrol qualify as interactive is debatable, as they derive training samples from the data stream without the conscious involvement of the user [130, 153, 154, 155, 185].

Although IML methods are commonly utilized in myocontrol applications to enable on-demand model updates, only a few studies have investigated the integration of interactivity within the corresponding data acquisition routines. Hahne et al. [22] and Woodward et al. [143] designed myocontrol systems where model updates are conducted incrementally and in real-time while the user operates the system, labeling the incoming stream of myoelectric data through protocol-specific heuristics. As noted by Szymaniak et al. [156], these procedures for data acquisition and model update do qualify as interactive because they offer simultaneous implicit feedback on the model evolution, but they lack dedicated interaction protocols that encourage users to actively support the updating process with useful training data.

2.8.3 Coadaptation

Coadaptation denotes an interaction dynamic where entities adapt their behaviors and reciprocally influence their learning processes to fulfill a shared objective [8, 11, 22, 175].

This is evident in some real-time myocontrol applications, designed for the user and system to synergistically define and refine the control model [8, 11, 22, 175]. Marinelli et al. [8] describe this process as the user and system "agreeing" on the optimal input signals to generate and how to best interpret those signals. Successful coadaptation depends on the design of interfaces with clear bidirectional feedback, which directly affects the user's adaptation speed [173]. Additionally, aligning the system's adaptation rate with the user's abilities is also fundamental for stable coadaptation [176, 186, 187].

An early example of a coadaptive system for myoelectric control was introduced by Hahne et al. [22]. This system aimed to speed up the calibration of myocontrol models by combining real-time data acquisition with model training. It enabled performing target-reaching tasks using a virtual cursor while concurrently updating the model based on the user's performance. When a user had difficulty reaching a target within a set time, the system automatically updated the model using the recorded muscle signals labeled with the current target value. The authors discussed the coadaptive quality of this method, noting that said model updates not only accounted for confounding factors in the myoelectric signal but also promptly integrated changes resulting from user adaptation into the system. However, Szymaniak et al. [156] observed that, while this updating mechanism was indeed coadaptive, it lacked active user involvement besides operating the myoelectric interface, as the model adaptation occurred without the user's conscious input during the system's use.

Recently, Yeung et al. [85] explored coadaptation in an unsupervised context. Their myocontrol system autonomously adjusted to shifts in data distributions, with the user concurrently adapting their control signals in response to model changes, aiming for precise myocontrol. A distinguishing feature of their method is its applicability to realistic prosthetic control applications, as it eliminates the need for training labels, which other approaches could only elicit from their specific experimental contexts. However, the argument of Szymaniak et al. [156] regarding the user's limited involvement in shaping a joint control strategy still applies to this method. This highlights an area for potential enhancement in future coadaptive systems, emphasizing the value of more active user engagement and participation.

To the author's knowledge, myocontrol strategies in which the user not only adapts to model changes but also intentionally influences model adaptation have not yet been presented in the literature. The first investigations into such strategies are found in two of the supporting publications, where a coadaptive interaction protocol is employed to calibrate myoelectric control models in an unsupervised manner [p3, p4].

2.9 Performance Evaluation and Metrics

This section outlines methodologies used to assess the performance of different myocontrol applications [188, 189].

Novel machine learning models for motor intent detection are usually tested offline [9], using public datasets of labeled muscle recordings [97, 190, 191]. Gesture recognition models are evaluated based on prediction accuracy and similar metrics [6, 9]. The effectiveness of regression models is determined by goodness-of-fit measures such as normalized prediction errors or the R^2 coefficient [9, 192]. The performance of unsupervised factorization models is measured by the accuracy of their data reconstruction, assessed using normalized errors or variance explained [56].

While offline evaluations are informative for initial tests, they do not always correlate with online system performance due to real-time user adjustments [23, 24, 151, 193, 194, 195]. Thus, online performance assessments have become standard practice [7]. Early assessments of new myocontrol systems often involve controlling virtual actuators [196]. Tests like target achievement control (TAC), involving virtual hand movements [197], and Fitt's law-style tasks with virtual cursor movements [198], are common. Performance is measured by the number of successfully attained targets and the corresponding movement quality, which depends on how quickly and precisely the target is reached [198]. Descriptors such as "gross" and "fine" are sometimes used to distinguish between initial movements towards the target and subsequent adjustments [199].

Standardized functional assessment protocols are typically used for real prosthetic systems, simulating daily activities and various operational challenges [189, 196]. Some protocols, like the Box-and-blocks [200] and the Clothespin relocation [201] tests, feature simplified tasks that capture fundamental functional requirements of many daily activities. Others, such as the Southampton Hand Assessment Procedure (SHAP) [202] and the Assessment of Capacity for Myoelectric Control (ACMC) [203], include a wider variety of realistic tasks to be evaluated by trained raters. Though primarily aimed at individuals with limb differences, these protocols can also be administered to non-disabled subjects as a preliminary testing stage. In such cases, the prosthetic device is mounted on an unaffected limb using orthotic splints for the hand and wrist [1, 183, 204]. Using such splints restricts hand movements and promotes isometric muscle contractions, which is found to resemble the muscle activity observed in individuals with limb absence [205].

Long-term prosthesis use in home settings is evaluated through routine assessments, prosthesis usage, perceived control quality, usability, engagement, and sense of embodiment [8, 206, 207, 208]. Feedback on prosthetic care costs and the effectiveness of rehabilitation services also informs system validation [188].

Chapter 3

Summary of the Publications

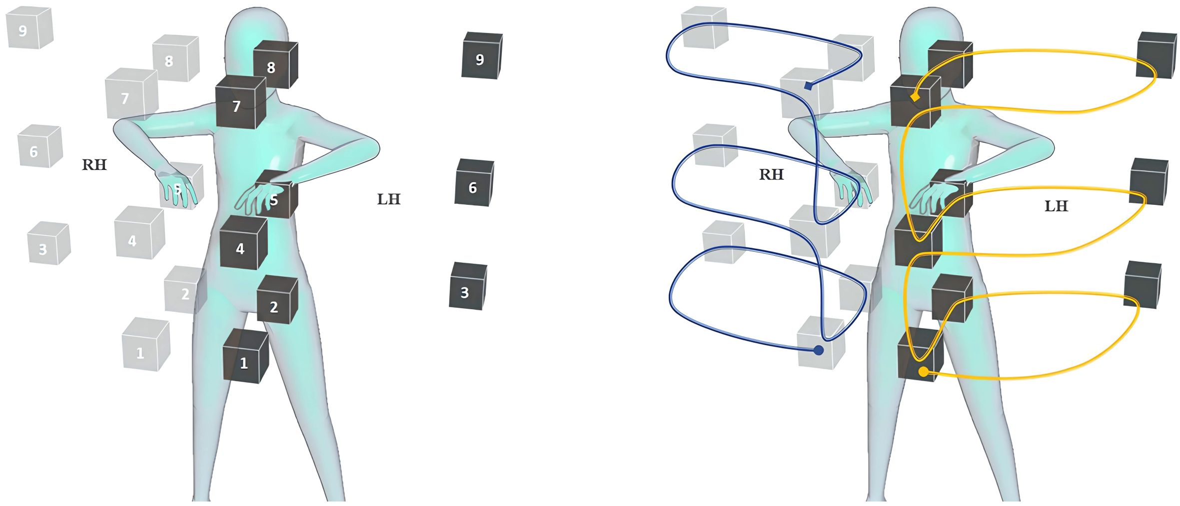
This section briefly summarizes the aim, motivation, methodology, and principal outcomes of the supporting publications [p1, p2, p3, p4], which are included in full text in the Appendix.

3.1 Publication 1: Merits of Dynamic Data Acquisition

Title: The Merits of Dynamic Data Acquisition for Realistic Myocontrol [p1]
Authors: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini
Published in: Frontiers in Bioengineering and Biotechnology 8 (April 2020), pp. 1–20.
Contribution of the thesis' author: The author of this dissertation conceived the original idea for the study. He then led the design and execution of the experiment, the data analysis, and the manuscript drafting in collaboration with the coauthors.

Aim and Motivation

The objective of this study was to compare two multi-arm-position data acquisition procedures, namely a static and a dynamic variant, depicted in Figure 3.1. These approaches are often used to increase the robustness of hand gesture recognition models to changes in the arm position. Such changes pose a challenge for the myocontrol of prosthetic hands because they introduce variability in the muscle signal that does not pertain to hand control. In order to enable the myocontrol model to capture this variability, training data for desired prosthetic functions is collected either by holding the arm statically in various configurations or by moving the arm across the reachable space. Although both these static and dynamic variants have proven promising in enhancing myocontrol, a direct comparison to ascertain their effectiveness was absent in the literature. In the broader scope of this dissertation, conducting this comparison served as a preliminary step to determine which approach held greater potential for myoelectric control and deserved consideration for further interactive redesign.



(a)

(b)

Figure 3.1: Multi-arm-position data acquisition methods to offset limb position effects in myoelectric hand control. *(a)* In static variants, myoelectric training data for the desired functions of the prosthetic hand is acquired in multiple hand configurations. *(b)* In dynamic variants, training data is recorded while moving the arm in the peripersonal space. Reprinted from Gigli et al. [p1], ©2020 Gigli et al.

Methods

The two data acquisition protocols were compared in a user study in which the resulting myocontrol models were used for realistic prosthetic control. Fourteen non-disabled subjects engaged in controlling a bimanual prosthetic system that included two commercially available armbands for multichannel surface electromyography (sEMG) measurements worn around the forearm and two prosthetic hands mounted on orthotic splints of the hand and wrist. The static acquisition protocol involved multiple arm configurations obtained by combining different arm positions and two different forearm orientations, while the dynamic acquisition was performed by moving the arm along a trajectory that interpolated these configurations. The collected data was employed to train myocontrol models for simultaneous and proportional control of three prosthetic functions, namely, a power grasp, a pointing gesture with the index finger, and a resting hand gesture. These models were learned using a nonlinear regression algorithm, specifically a variant of ridge regression (RR) that incorporates random Fourier features (RFF) for nonlinearity. The testing protocol entailed realistic and bimanual activities of daily living (ADLs). The performance evaluation included subjective aspects, such as the perceived workload during data acquisition and the controllability of the model, as well as objective criteria, such as the time required to complete each myocontrol task. Finally, an offline analysis was performed using partitions of the previously collected training data to examine whether there was a discrepancy between the offline and online grasp prediction performance of the two acquisition protocols.

Results

Static and dynamic data acquisition protocols yielded comparable myocontrol performances during bimanual ADLs, with similar perceived controllability of the prosthetic hands and task completion times. However, the reported physical effort during data acquisition was significantly lower in the dynamic case, which was also confirmed by the considerably shorter break intervals taken by the users. These results indicated that dynamic data acquisition is practically advantageous for calibrating myocontrol systems robust to the limb position effect, as it provides equivalent performance, lower physical effort, and faster completion compared to static multi-arm-position protocols. Despite these online performance similarities, offline analysis showed a notable difference. Models trained with dynamic data predicted the intended hand configurations significantly more accurately when tested with static data than in the reverse scenario, indicating stronger generalization capabilities in offline settings. The discrepancy between online and offline outcomes, likely due to users compensating for the myocontrol model's inaccuracies in real-time, further confirmed the importance of evaluating myoelectric prosthetic systems under realistic conditions.

3.2 Publication 2: Feedback-Aided Dynamic Data Acquisition

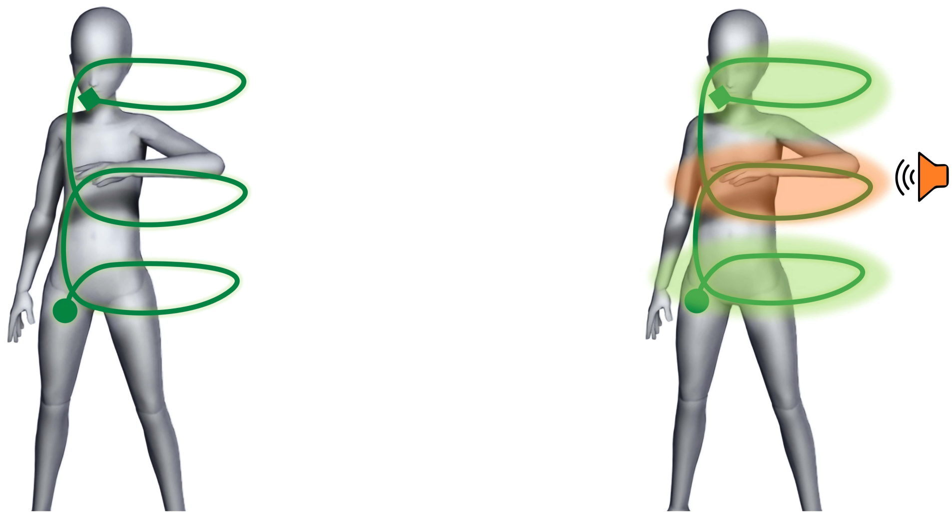
Title: Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand [p2]
Authors: Andrea Gigli, Donato Brusamento, Roberto Meattini, Claudio Melchiorri, and Claudio Castellini
Published in: Journal of Neural Engineering, 17.5 (2020), p. 056047.
Contribution of the thesis' author: The author of this dissertation conceived the original idea for the study in collaboration with CC, led the design and execution of the experiment, handled the data analysis, and oversaw the drafting of the manuscript. DB and RM contributed to the study design, with DB further aiding in the execution of the experiment. All authors contributed to the redaction of the manuscript.

Aim and Motivation

The publication aimed to improve the efficiency of protocols for the supervised calibration of myocontrol models for prosthetic hands by introducing an interactive data acquisition process. This approach was designed to encourage the user to generate muscle signals most useful for training the model, potentially decreasing the requirement for numerous calibration cycles. The investigation originated from recognizing that while certain open-loop strategies attempt to account for the muscle signal variability determined by external confounding factors, anticipating and capturing the effects of these factors is challenging. This challenge is evident in dynamic multi-arm-position data acquisition routines where it is difficult to determine a priori which arm positions might cause significant variability in the muscle signals. In response, the study investigated a feedback-aided acquisition protocol in which the system identifies difficult arm configurations in real-time and immediately signals the user to acquire more training data for those configurations.

Methods

The study explored the efficacy of conducting dynamic multi-arm-position data acquisition interactively, specifically by integrating an instantaneous feedback mechanism to guide users in generating more useful training data. Two feedback-aided acquisition variants were developed, extending the open-loop dynamic multi-arm-position strategy from previous work Gigli et al. [p1], and were subsequently compared to this conventional method. In both feedback-aided versions, the myocontrol model is built incrementally and in real-time during the data acquisition, utilizing the continuous stream of muscle data labeled with corresponding target hand gestures. This is achieved through a variant of the RR algorithm enhanced with RFF, which enables both nonlinear modeling and efficient learning. Simultaneously, the model's capacity to interpret motor intent from incoming training data is assessed and used to produce acoustic feedback proportional to the prediction error. Following an established interaction protocol, this feedback directs the user to focus on acquiring more training data in the arm configurations where the model prediction is less precise. Figure 3.2 compares standard dynamic data acquisition to an interactive, feedback-aided variant. One of the feedback-aided variants additionally incorporates a sample selection mechanism designed to reduce the number of incremental model updates required to calibrate the model. The experimental setup included eighteen non-disabled participants, fitted with a realistic prosthetic system comprising an armband for multichannel sEMG measurement worn around the forearm and a prosthetic hand mounted on an orthotic splint of the hand and wrist. All participants engaged in random order with the feedback-aided acquisition strategies and the non-interactive baseline, testing the resulting myocontrol models in realistic ADLs. The performance evaluation centered on the task completion speed and the user-reported controllability of the system.



(a) (b)

Figure 3.2: Two variants of dynamic multi-arm-position data acquisition. *(a)* Non-interactive variant where myoelectric training data for target hand functions is acquired while moving the arm along a set trajectory. *(b)* Interactive variant where the same movement routine is complemented by instantaneous acoustic feedback of the model performance to prompt the acquisition of additional training data in critical arm configurations. Adapted from Gigli et al. [p2], ©2020 IOP Publishing.

Results

The study confirmed the potential of closed-loop data acquisition to enhance the calibration of myocontrol models for prosthetic hands. The use of feedback-aided acquisition improved the experienced controllability of the myocontrol system and significantly accelerated the execution of task sequences compared to the standard acquisition method. Since the assigned tasks involved controlling the prosthesis in various limb configurations, the results suggested that the interactive dynamic data acquisition effectively increased the model's robustness to the limb position effect. On the other hand, the feedback-aided acquisition with sample selection demonstrated varied outcomes, aligning with the feedback-aided version for certain participants and with standard data acquisition for others, suggesting the necessity to further fine-tune the sample selection criterion.

3.3 Publication 3: Coadaptive Unsupervised Myocontrol

Title: Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping [p3]

Authors: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini

Published in: 2022 International Conference on Rehabilitation Robotics (ICORR), Rotterdam, 2022, pp. 1–6.

Contribution of the thesis' author: The author of this dissertation conceptualized the original idea with ArG, designed and developed the unsupervised calibration approach, designed and conducted the experiment, analyzed the results, and drafted the manuscript. ArG further contributed to the experiment design and manuscript writing. CC was involved in the experiment design and manuscript writing.

Aim and Motivation

This research aimed to eliminate the need for labeled muscle data for calibrating myocontrol models based on machine learning, transitioning towards an unsupervised calibration protocol. This protocol was aimed at enabling users with different motor skills to calibrate the control model through an autonomous interactive process that bypassed data labeling. The motivation came from the challenges faced by individuals with limb differences, who may encounter difficulties with traditional data acquisition and labeling methods, in which precise and repeatable training muscle signals must be elicited. This can be complex if the limb difference affects the motor control of the affected limb. For this reason, conventional supervised calibration approaches preliminarily assess the number of distinct muscle activations a user can generate to delineate the set of controllable prosthetic functions for the myocontrol model. Then, a signal training phase is undertaken to refine the user's muscle contractions to enable appropriate data acquisition and labeling. Both these steps require supervision and guidance by medical professionals, thus conditioning the initial engagement with the myocontrol system on the availability of these professionals and the accessibility of clinical facilities.

Methods

This study introduced and tested a novel unsupervised myocontrol paradigm for prosthetic hands where the model is calibrated through an interactive and coadaptive procedure between the user and the system. During this procedure, the user is tasked with learning to control a predefined set of prosthetic functions by interacting with the system, under the premise that there is not a biomimetic association between those functions and the muscle contractions used to control them. The calibration sequence initiates as the user interacts with a randomly initialized myocontrol model, employing visual feedback to discern which muscle activations correspond to specific prosthetic functions. Concurrently, the control system factorizes the muscle input into a set of muscle synergies with minimal time overlap, equal in number to the controlled functions. This is achieved through a novel adaptive variant sparse nonnegative matrix factorization (NMF). These synergies are arbitrarily and univocally mapped to the prosthetic functions, and their activations are employed to control those functions simultaneously and proportionally. This interactive process defines a coadaptive dynamic in which the user learns to generate increasingly distinctive myocontrol inputs and the system simultaneously improves its ability to discriminate these inputs. In addition, the calibration process also helps the user to familiarize themselves with the abstract motor mapping and the myocontrol action defined by the system. A schematic representation of this calibration approach is provided in Figure 3.3. Overall, the proposed approach eliminates the need for preliminary signal training and allows the user to autonomously identify and refine appropriate control signals while calibrating the model.

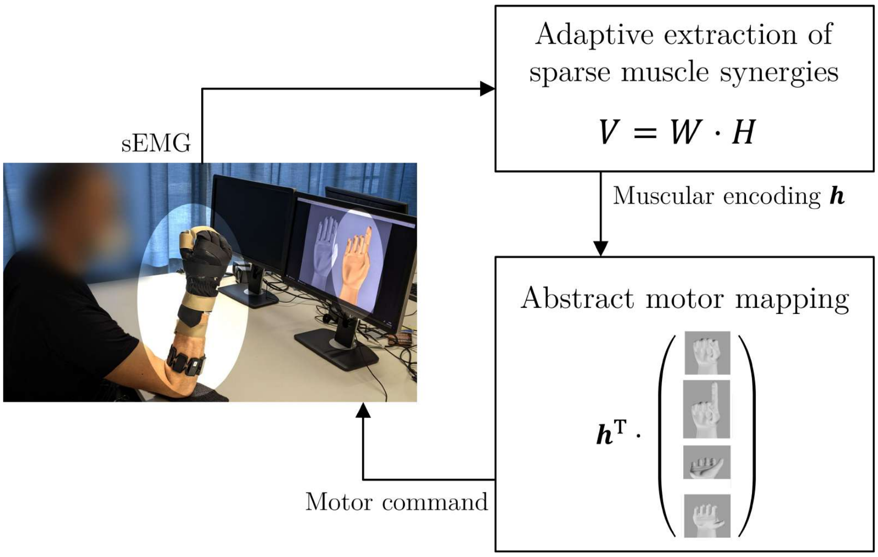


Figure 3.3: Overview of the proposed unsupervised myocontrol method. The model calibration involves an interactive process where the myocontrol system extracts salient muscle synergies from unlabeled myoelectric data and uses their activations to control arbitrarily associated functions of the prosthetic hand, while the user concurrently learns the resulting abstract motor mapping. Reprinted from Gigli et al. [p3], ©2022 IEEE.

The experiment involved eight non-disabled participants who controlled a virtual hand on a display with their forearm muscle activity, captured by a commercial armband for multichannel sEMG measurement. The myocontrol system was set to control four myocontrol functions corresponding to hand and wrist gestures. The effectiveness of the unsupervised calibration was compared with that of a state-of-the-art supervised calibration baseline. The baseline calibration approach utilized a nonlinear regression algorithm, specifically a RR with RFF, to learn a biomimetic motor mapping described in a dataset of labeled muscle data. A series of target achievement control (TAC) tests evaluated how quickly and accurately participants could control the four prosthetic functions simultaneously and proportionally. Participants self-assessed the workload associated with each calibration approach and the controllability of the resultant myocontrol model via a questionnaire. Real-time myocontrol performance was also evaluated through metrics typical of Fitts' law assessments, including task success rate, completion time, and path efficiency.

Results

The online myocontrol performance observed for both the unsupervised and supervised paradigms was largely similar in terms of success rate and completion time while controlling each prosthetic function individually. However, for more complex tasks requiring simultaneous control of multiple functions, the unsupervised paradigm's linearity offered some advantage over the supervised approach, although both paradigms saw a drop in success rates compared to the simpler tasks. The execution quality of successful tasks, measured in terms of path efficiency and mean error in target, seemed marginally superior in the unsupervised paradigm, although this result lacked statistical significance. Meanwhile, controlling the unsupervised model was considered more mentally demanding, likely due to non-disabled participants having limited experience with non-biomimetic motor mappings. Participants also perceived the unsupervised calibration process itself as more mentally challenging compared to performing a standard labeled data acquisition routine. This outcome could be attributed to participants utilizing their already-established motor skills to easily complete the labeled data acquisition instead of having to learn an unfamiliar abstract motor mapping.

3.4 Publication 4: Progressive and Coadaptive Unsupervised Myocontrol

Title: Progressive Unsupervised Control of Myoelectric Upper Limbs [p4]
Authors: Andrea Gigli, Arjan Gijsberts, Markus Nowak, Ivan Vujaklija, and Claudio Castellini
Published in: Journal of Neural Engineering, 20.6 (2023), p. 066016.
Contribution of the thesis' author: The author of this dissertation conceived the original idea, designed the progressive unsupervised calibration approach, conducted the experiment, analyzed the results, and drafted the manuscript. ArG additionally contributed to refining the design of the incremental factorization algorithm. All coauthors participated in the experiment design and manuscript revision.

Aim and Motivation

The primary goal of this study was to refine the unsupervised calibration method from previous work [p3] to create a myocontrol approach that dynamically adjusted the number of controlled prosthetic functions to users with different and evolving motor control abilities. The existing unsupervised calibration approach required predetermining the number of controllable functions because the underlying muscle synergy factorization model could only estimate a fixed number of synergies. This could represent a practical limitation for myoelectric control, as it imposed a preliminary supervised assessment of the user's motor abilities and disregarded the potential emergence of new motor skills over time. Inspired by the natural development of motor skills during motor learning tasks, the idea was to develop a calibration method that allowed a gradual increase in the number of controlled functions depending on the user's current motor performance level.

Methods

The study proposed a progressive version of the previous unsupervised calibration paradigm [p3], in which the user could increase the number of controlled prosthetic functions over time instead of learning multiple functions simultaneously. The same model-building mechanism was used, where the user and the system cooperatively refine an abstract motor mapping that is based on adaptively extracted muscle synergies. In this case, however, the user begins by learning a single function and, upon mastering it, can request an additional function to be unlocked. Accordingly, the system increases the number of estimated muscle synergies at runtime without disrupting the existing ones through a purposely designed variant of sparse NMF that is both incremental and sequential. The formulation of the factorization algorithm was also enhanced to further promote the sparsity and stability of the estimated synergies. Figure 3.4 summarizes this calibration paradigm.

A multi-session user study was conducted to evaluate the effectiveness and usability of the proposed progressive coadaptive unsupervised calibration paradigm and compare it to the previous non-progressive calibration method [p3]. Ten non-disabled (ND) participants and two individuals with limb differences (LD) participated in the study. Half of the ND participants and the subjects with LD tested the novel calibration approach, while the rest tested the non-progressive baseline. The experimental setup included a commercial armband for multichannel sEMG measurements worn around the forearm, and an orthotic splint for the hand and wrist to enforce isometric contractions in ND participants. The participants completed five test sessions over a period of 2 weeks, with a minimum interval of 24 hours between two consecutive sessions and an interval of around 1 week between the last two sessions. Each experimental session included an unsupervised calibration phase, which began with a randomly initialized model in the first session and the latest trained model in the subsequent sessions. After calibration, participants could customize the learned abstract motor mapping to their liking. This phase was followed by two versions of TAC tests, one with visual feedback from the controlled hand and the other without it. The standard TAC test was used to measure the user's ability to pro-

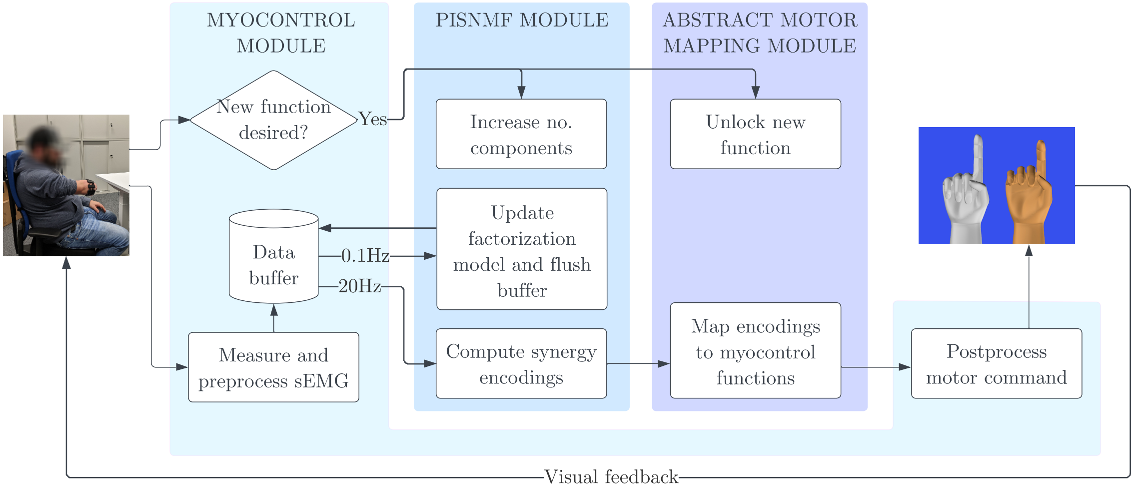


Figure 3.4: Schematic overview of the progressive unsupervised calibration method. The model calibration is based on an interactive process in which the myocontrol system implements an abstract motor mapping based on adaptively extracted muscle synergies while the user is tasked with learning this mapping. This approach allows the user to gradually increase the number of controlled prosthetic functions as they master the existing ones without having to retrain the synergy factorization model. Reprinted from Gigli et al. [p4], ©2023 Gigli et al.

portionally and simultaneously control the learned prosthetic functions, while the variant without visual feedback was used to assess the internalization of the learned motor control skills. The retention of myocontrol skills was assessed in both the short and long term by initiating the third and fifth experimental sessions with real-time myocontrol testing before performing the coadaptation phase. The performance evaluation involved a comparison of workload differences between the progressive and non-progressive calibration approaches, as well as analyzing online myocontrol performance based on task success rate, completion time, and metrics reflecting the quality of movement within each task.

Results

The experimental results allowed the evaluation of the progressive unsupervised myocontrol paradigm, focusing on individuals with LD and using the ND participants as a baseline. LD participants learned to control three out of four possible functions during the experiment, with one participant remarkably discovering one new muscle synergy during the progressive calibration process. In contrast, the ND participants already mastered all four functions at the beginning of the experiment. The workload related to performing the progressive unsupervised calibration remained consistently high for subjects with limb differences, indicating an ongoing adaptation process throughout the experiment, while it decreased significantly for the non-disabled participants over the experimental sessions. In TAC tests with visual feedback, the two groups achieved comparable completion times by the end of the experiment, although LD participants exhibited lower movement quality. On the other hand, in tests without visual feedback, LD participants performed consistently worse over the entire experiment. While LD subjects exhibited varied retention trends, the ND group consistently showed a performance drop after a prolonged period of non-practice that was quickly recovered by updating the model through a brief system calibration. Finally, ND participants reported an equivalent workload for both the progressive and non-progressive calibration protocols, and they also achieved comparable myocontrol performance with both methods.

Chapter 4

Discussion of the Contributions

The studies in this thesis have investigated interaction-based approaches to enhance the calibration process of myoelectric control models. Their results contribute to overcoming two practical challenges in the field. The supporting publications Gigli et al. [p1] and Gigli et al. [p2] collectively improve the efficiency of specific methods for the acquisition and labeling of myoelectric training data by promoting a more active involvement of the user. The research in Gigli et al. [p3] and Gigli et al. [p4], instead, circumvents the reliance of traditional calibration approaches on labeled training data by proposing novel unsupervised myocontrol paradigms based on a coadaptive interaction between user and myocontrol system. This chapter details the individual and collective achievements of the included publications, places them in the context of the existing literature, and explores their implications for myoelectric control. In addition, common limitations and possible directions for future research are discussed.

4.1 Interaction for Effective Training Data Acquisition

The performance of supervised model calibration protocols depends on the quality of the labeled training data employed. In myocontrol applications, training data is usually acquired through open-loop procedures where the user follows predetermined routines without real-time feedback on data quality. These approaches can result in the acquisition of redundant or lacking training sets, requiring multiple calibration cycles to obtain a satisfactory model [42, 117]. This issue is evident in multi-arm-position acquisition methods used to increase the robustness of myocontrol models for hand gesture prediction against limb position variations. Because anticipating underperforming arm configurations is challenging due to inherent physiological variations among individuals, multiple iterations of this data acquisition process are often necessary [134, 143].

It is hypothesized that the efficiency of multi-arm-position data acquisition could be enhanced by integrating a real-time feedback mechanism on the quality of the training data. Gigli et al. [p1] presented a preliminary comparison of a static and a dynamic version of multi-arm-position acquisition in realistic prosthetic control settings. This step was necessary because, although dynamic methods are expected to be more efficient [43, 141], a direct comparison with static methods could not be found in the existing literature. After establishing the merits of dynamic data acquisition, Gigli et al. [p2] extended this method with an interaction protocol that utilizes real-time feedback to assist the user in acquiring further training data in the arm configurations that are found to be most challenging for the model.

4.1.1 Merits of Dynamic Data Acquisition

The publication [p1] provided the first direct comparison between dynamic and static multi-arm-position data acquisition protocols for countering the limb position effect in realistic myocontrol. This investigation served as a preliminary step to determine which acquisition strategy was more effective before extending it with a dedicated interaction protocol. Our review of previous studies revealed mixed results in the comparisons among single-position, static multi-arm-position, and dynamic multi-arm-position data acquisition protocols. These performance discrepancies appear to relate to the experimental design used. For example, in offline movement recognition tasks, multi-arm-position acquisition consistently outperformed single-arm-position acquisition, regardless of whether the former was conducted statically [135, 140] or dynamically [20, 141, 209]. For online myocontrol tasks, the reported performances were instead contradictory, with multi-arm-position acquisition significantly improving target achievement control (TAC) performance compared to single-arm-position data acquisition in some studies [143] but not in others [140]. Interestingly, the study by Hwang et al. [140] found that static multi-arm-position outperformed single-arm-position acquisition in offline evaluations but not in online ones, even with the same experimental setup. Finally, although dynamic acquisition is often recommended for its supposed efficiency and efficacy, a direct comparison between static and dynamic multi-arm-position acquisition could not be found for online myocontrol applications.

In our work, the two methods were compared based on their respective workloads and the performance of the resulting myocontrol models. Myocontrol performance was assessed by functional tests based on bimanual activities of daily living (ADLs) performed with a bimanual prosthesis. Although only non-disabled (ND) participants could be recruited, efforts were made to reflect the conditions of people with limb differences (LD) by restricting the participants' muscle activity with orthotic splints and mounting the prostheses onto these splints [205].

Our study revealed no significant differences in online myocontrol performance between models trained with dynamic or static multi-arm-position data acquisition methods. This result deviates from the general expectation that dynamic acquisition should yield better myocontrol performance in ADLs by capturing functional arm movements in the training data. A different outcome, however, was obtained for offline motor intent recognition tests conducted on subsets of the training data. Models trained on dynamic data showed better offline performance on static muscle data than vice versa. This apparent contradiction, where dynamic data acquisition enhances offline performance but not online performance, mirrors the previously discussed inconsistency reported by Hwang et al. [140], highlighting how the user's active participation in the control loop compensates for the reduced variety of training data collected through static acquisition methods [24]. Such discrepancy further emphasizes the need for testing protocols that represent the challenges of realistic prosthetic control.

While both data acquisition methods had similar online performance, the dynamic approach showed distinct benefits. Not only was it designed to be more time-efficient, but it also proved less exhausting for the participants. These benefits were reflected in the users' reports of reduced physical effort and in the significantly shorter rest breaks taken during dynamic acquisition compared to the static method. Such benefits position dynamic data acquisition as a preferable choice in realistic prosthetic control applications to calibrate myocontrol models that are robust to limb position effects.

4.1.2 Feedback-Aided Dynamic Data Acquisition

Although dynamic data acquisition allows for effective calibration of prosthetic hands across multiple arm configurations, it still operates within the limits of open-loop acquisition methods. This process aims to cover different arm configurations in an approximately uniform way, even though some configurations may affect muscle activity more than others, requiring additional training data. Since the model's evaluation only occurs after training, potential deficiencies in the training data may not become apparent until after data acquisition has ended, often leading to multiple iterations of the data acquisition process.

In order to address this limitation, two closed-loop versions of dynamic multi-arm-position data acquisition were proposed in Gigli et al. [p2]. These included an interaction protocol where the user is assisted by an acoustic signal to evaluate model performance in real-time and actively target underperforming arm configurations with more training data. This process was complemented by a simultaneous creation of the myocontrol model through a series of incremental model updates. One of the proposed data acquisition variants also included a sample selection protocol to focus the updates only on the most significant training samples. Both feedback-aided variants were compared to a standard open-loop dynamic data acquisition procedure by engaging ND individuals in ADLs using a prosthetic hand.

Our study showed that using feedback during data acquisition enables the definition of myocontrol models with greater robustness to the limb position effect. This improvement was reflected in significantly faster task completion and higher user-reported controllability compared to traditional data acquisition. These results confirmed the effectiveness of closed-loop data acquisition, which was also emphasized in previous research.

The potential of closed-loop model calibration in myoelectric control was first investigated in the study of Hahne et al. [22]. Their approach allowed the myocontrol model to be updated in real-time during target achievement control tasks. If a task was not completed within a specified time interval, the system triggered instantaneous and incremental model updates using the current target as a pseudo-label for the incoming muscle signals. This improved the online myocontrol performance compared to unadapted models. The authors discussed that enabling instantaneous model updates during system operation resulted in a coadaptive interaction, as the user was implicitly induced to adjust their control strategy in response to the model's evolution. As noted by Szymaniak et al. [156], however, it is arguable that the user's active involvement in the model calibration was limited to just operating the interface. There was no prescriptive interaction protocol to guide users in intentionally adjusting their behavior to support the calibration process. In contrast, the acquisition protocol proposed in our study not only informs the user of prediction errors but also actively supports them in discerning and producing data samples that are most useful for improving the model's robustness.

The closed-loop calibration approach proposed by Hahne et al. [22] has also been adopted in other works. Woodward et al. [143] integrated it into a virtual reality environment to evaluate how well the real-time model updating mechanism could accommodate previously untrained arm postures during online TAC tests. Yeung et al. [184] extended the adaptive model updating mechanism by introducing a directional forgetting strategy that minimized unintended model distortions in regions of the input space not directly targeted by each specific update. It should be noted, however, that both these works exhibited the same limitations in user involvement discussed previously.

While the proposed feedback-aided strategy proved advantageous in our experiments, its variant with sample selection showed mixed results. Performance was similar to the feedback-aided strategy for half of the participants and comparable to the open-loop baseline for the remaining half. This implies that the sample selection criterion may have been too stringent for the low-performing participants. Although reducing the number of training samples is beneficial for prosthetic systems with limited computational capabilities [130], determining an optimal sample selection criterion across various setups is challenging and necessitates further investigation.

Reflecting on how this research could translate to practical applications, it seems evident that implementing a feedback-aided dynamic data acquisition routine into existing prosthetic systems is simple. This integration only requires basic hardware enhancements, such as adding a speaker or vibratory actuators. Moreover, the existing feedback mechanism could be further developed into more sophisticated tools for data acquisition. By combining the collected information on prediction inaccuracy with inertial arm tracking, a visualization of arm configurations with suboptimal prediction accuracy could be created and integrated into software applications used to coordinate the data acquisition process. In general, the proposed feedback-aided dynamic acquisition appears beneficial for all myocontrol applications where robustness to limb position effects is desired, including the operation of computer interfaces, virtual reality rehabilitation systems, and hand exoskeletons [43, 210, 211].

Our feedback-aided acquisition paradigm may also be used to compensate for other confounding factors, such as variations in myoelectric signal properties across different contraction intensity regimes [43]. However, it is important to note that the proposed feedback mechanism was developed assuming that only a single confounding factor would be present during data acquisition. In our study, limb position variations were considered the primary confounding factor, and the acoustic feedback was directly related to model imprecisions pertaining to this parameter. The feedback interpretation would be more difficult if several factors were present simultaneously. This difficulty could be further aggravated if the muscle signals were also affected by noise or unanticipated confounding factors during data acquisition.

The feedback interpretation also depends on the user's residual level of motor control. This is because our calibration approach assumes that the user can generate muscle contractions consistent with the target hand gestures and that model instabilities are thus only due to confounding factors. If the generated muscle signals are unstable, this may contribute to prediction errors caused by the primary confounding factor and affect the feedback clarity. While ND individuals can effortlessly generate and maintain the muscle contractions corresponding to specific hand motor intents while moving the arm, this is more challenging for people with LD. Therefore, similarly to other supervised myocontrol model calibration approaches, the proposed data acquisition method requires users with LD to undergo preliminary signal assessment and training under professional supervision.

4.1.3 Overview of the First Contribution

The supporting publications Gigli et al. [p1] and Gigli et al. [p2] demonstrated that the calibration of myocontrol models based on supervised machine learning could be rendered more efficient and effective through more active user participation. Potential for improvement was identified in open-loop multi-arm-position training data acquisition routines, commonly employed to mitigate the limb position effect. It was hypothesized that real-time guidance on the relevance of training data derived from different arm configurations could increase the robustness of the model and thus reduce the need for recurrent recalibrations. A preliminary experimental study demonstrated the practical benefits of collecting data while actively moving the arm. Then, an interactive version of dynamic data acquisition was developed where the user is guided and assisted in finding arm configurations that require additional training data. The effectiveness of this strategy was confirmed in realistic prosthetic control tests.

By improving the calibration efficacy, the discussed interactive data acquisition aims to reduce the frequency of further model recalibrations. However, it is important to clarify that periodic recalibrations remain essential for practical myocontrol. This is because factors like muscle fatigue and user adaptation lead to gradual domain shifts that are difficult to anticipate and elicit during the initial data acquisition. Therefore, the approach is intended to complement periodic model updates rather than replace them.

A shared limitation of both supporting studies is that only ND participants could be recruited. Despite this limitation, certain speculations are possible on how the obtained results could extend to the population of individuals with LD. The advantages resulting from the inherently shorter duration of the dynamic acquisition procedure are expected to remain the same for the different user groups. Although the physical workload of the data acquisition may vary depending on the weight of the residual limb and the person's functional abilities, the dynamic approach is likely less demanding. This is primarily because the residual limb does not need to be held steady in potentially uncomfortable positions for extended time intervals.

Like other supervised myocontrol approaches, the methodologies presented here depend on the user's ability to generate reliable muscle signals, often requiring individuals with LD to undergo preliminary signal training exercises. This requirement becomes even more critical with feedback-aided data acquisition, as inconsistent muscle inputs may not only compromise the quality of the training dataset but also bias the feedback interpretation. While it can be speculated that people with LD could learn to use feedback-aided data acquisition as proficiently as their ND counterparts after appropriate training, direct verification of this speculation remains necessary.

4.2 Interaction for Unsupervised Model Calibration

The second contribution of this thesis was to explore the potential of user-system interaction for unsupervised myocontrol model calibration. This paradigm circumvents intrinsic challenges of supervised calibration deriving from its reliance on accurately labeled training data. For successful data labeling, the user must execute muscle contractions that precisely correspond to the intended target gestures. This can be challenging for individuals with limited motor control due to limb differences, imposing the necessity for preliminary assessment and training of their residual muscle activity under the guidance of medical professionals. This requirement restricts users' initial autonomy in operating the myoelectric system and poses logistical challenges for those residing far from specialized clinics.

The supporting publication Gigli et al. [p3] presented a calibration method that circumvents the need for labeled training data. This is based on a synergistic interaction between the user and system where the former is induced to generate distinctive muscle patterns and the latter to factorize unlabeled myoelectric data into suitable myocontrol inputs. While this method eliminates the need to perform signal training before the initial calibration of the model, it still requires a preliminary supervised assessment of the user's motor skills to set the number of prosthetic functions of the system accordingly. Therefore, Gigli et al. [p4] further refined the method to enable the user to autonomously vary the number of controlled prosthetic functions during operations. This rendered the initial assessment of user capabilities no longer necessary, resulting in a fully autonomous and user-centered calibration of the myocontrol system.

4.2.1 Coadaptive Unsupervised Myocontrol

Gigli et al. [p3] introduced an unsupervised model calibration paradigm based on continuous and autonomous interaction between the user and the myocontrol system. The interaction protocol was designed to induce a coadaptive dynamic where both entities synergistically identify and refine muscle inputs suitable for myocontrol. The user is encouraged to adjust their muscle contractions to align with an evolving abstract motor mapping while the system adaptively identifies salient muscle synergies and uses them to control arbitrarily associated prosthetic functions.

Our approach was compared to a traditional calibration procedure that uses supervised machine learning to learn a biomimetic motor mapping. This unsupervised approach performed equivalently to the supervised baseline when ND participants were engaged in a series of TAC tests. This indicates that the proposed interaction protocol effectively induced the user and system to coadapt, resulting in a synergistic identification of muscle contractions suitable for myocontrol. The participants' proficiency also suggested that such myocontrol inputs corresponded to physiologically viable muscle coactivation patterns, although a formal analysis of the physiological plausibility of the muscle synergies with our newly proposed adaptive factorization algorithm was not provided.

While performing similarly to the supervised baseline, it is arguable that our unsupervised calibration procedure provides several advantages related to using salient muscle synergies instead of predefined muscle inputs and adopting abstract motor mappings. The user is encouraged to freely explore their muscle capacities during the data acquisition, potentially discovering and using muscle contractions that are more distinguishable and easy to generate than biomimetic ones. Moreover, since myoelectric inputs are extracted adaptively, the user may gradually refine their muscle contractions during the calibration, thereby bypassing the need for preliminary signal training under the supervision of an expert.

Despite the observed performance equivalence between our unsupervised approach and the supervised baseline, participants reported higher mental workload during the calibration and control phases of the former. This was motivated by the ND participants having to familiarize themselves with an abstract motor mapping in the unsupervised case while being already accustomed to the biomimetic mapping implemented by the supervised method. It is arguable, however, that the gap in mental workload could decrease or even disappear for individuals with LD, especially those with limited residual motor control. Regardless of the subject demographics, this evaluation highlighted the importance of reducing the complexity of the motor mapping when possible. This observation informed the design of the following investigation, where users were allowed to customize abstract motor mappings as desired after the model calibration.

To the author's knowledge, the work discussed here was the first to achieve a fully unsupervised myocontrol system calibration. It is important to note that the term "unsupervised" refers here to carrying out the model calibration without labeled training data and without obtaining task-related information about the training data through dedicated heuristics. This term, however, finds a broader interpretation in the myocontrol literature. Several calibration routines have been proposed to learn biomimetic motor mappings with only minimal supervision and have been referred to as "unsupervised" or "semi-unsupervised" [84, 85, 91, 170, 171]. These approaches derive control signals by extracting task-specific muscle synergies from unlabeled data using unsupervised factorization algorithms. To condition the factorization process to estimate task-specific muscle synergies, they restrain the range of phantom movements allowed during the acquisition process to the targeted prosthetic functions. A biomimetic mapping is then obtained by manually matching each extracted synergy with the prosthetic function that is most likely related to it. This constrained calibration assumes that the user can selectively elicit specific phantom movements, which often requires preliminary signal training. The interested reader is referred to subsection 2.7.2 for a more detailed presentation of these works.

Approaches for unsupervised domain adaptation are also sometimes referred to as "unsupervised myocontrol" in the literature [155]. These techniques learn the myocontrol model in a supervised way, then use the model's runtime predictions to automatically assign pseudo-labels to historical muscle data, and update the model with such newly labeled data using supervised algorithms [130, 154, 155]. More details on these strategies can be found in subsection 2.6.2. In contrast, our methodology updates the control model during the calibration process using unlabeled data, aiming to identify muscle synergies with minimal temporal overlap for optimal use as myocontrol control inputs.

The research of Yeung et al. [85] combined the semi-unsupervised calibration method described previously with a mechanism for continuous unsupervised domain adaptation during real-time myocontrol. After a non-interactive and semi-unsupervised initial calibration of the control model, their system enabled closed-loop unsupervised model updates during online myocontrol tasks. These updates dynamically adjusted the control inputs, based on salient muscle synergies, to compensate for shifts in muscle characteristics due to confounding factors or the user's adaptation. Their adaptive nonnegative matrix factorization (NMF) formulation appeared remarkably similar to the formulation presented in our work [p3] despite being developed independently and concurrently. This parallel remarks the growing interest within the research community in advancing adaptive myocontrol methods that minimize the necessity for supervision. The formal differences between the two factorization methods lay in emphasizing the estimated synergies' temporal independence or stability. The most distinguishing aspect of our approach, however, was employing the adaptive factorization algorithm throughout the calibration phase, enabling a coadaptive definition of the control model.

The term "coadaptation" also finds broad interpretation in the literature. While several myocontrol techniques that leverage interactive machine learning can lead to coadaptation between the user and the system, this coadaptation often emerges as a byproduct rather than a deliberately deployed mechanism. For example, works such as Hahne et al. [22] recognized user-system coadaptation during the operation of adaptive myocontrol systems but did not systematically leverage it to improve the control quality. Specifically, they recognized a coadaptive dynamic in the user adapting to the system's incremental changes during myocontrol operations, but they did not engage the user in consciously adjusting their control strategy to optimize the model updating process [156]. A similar coadaptive dynamic could be observed in the previously discussed system of Yeung et al. [85], where real-time model updates were performed without the user's active involvement but implicitly caused the user to adapt to changes in the system's behavior. In contrast to prior works, our methodology emphasizes the user's active role in coadaptation. The user drives the coadaptive dynamic by intentionally exploring their control signals, using the myoelectric interface as a means for this exploration rather than just a platform to complete myocontrol tasks.

While the presented methodology eliminates the necessity for preliminary supervised signal training, it still requires a preliminary assessment of the user's motor skills before they can engage with the myocontrol system. Such an assessment focuses on determining the number of independent muscle signals the user can generate with their residual limb. The obtained information is used to calibrate the factorization model so that the number of extracted muscle synergies is consistent with the user's identifiable motor skills. Another limitation pertaining to the muscle synergy estimation process is that the utilized adaptive NMF variant does not allow changing the number of extracted muscle synergies during operation. This does not accommodate the possible development of new motor skills that the user may exhibit while practicing with the myocontrol system.

4.2.2 Progressive and Coadaptive Unsupervised Myocontrol

The presented coadaptive unsupervised calibration paradigm [p3] has been extended in Gigli et al. [p4] to allow for a gradual increase in the number of controlled functions during operation. This extension, referred to as progressive unsupervised myocontrol (PUM), enables the user to start the calibration process with only one function and to introduce more functions upon mastering the previous ones. By implicitly adapting to the number of muscle control signals available to the user, this approach aimed to eliminate both preliminary skill assessment and signal training requirements. In addition to this dedicated interaction protocol, the paradigm also introduced a sequential variant of adaptive sparse NMF, which allows increasing the number of factorized components over time while promoting the continuity of preexisting components without explicitly storing the historical data. A multisession user study validated the PUM paradigm in terms of achieved myocontrol performance, motor skill learning and retention, and workload compared to a non-progressive unsupervised calibration counterpart, adapted from Gigli et al. [p3]. Individuals with and without LD controlled a virtual hand on a screen to conduct the unsupervised calibration and to complete TAC tests with or without visual feedback.

The experiment results validated the effectiveness of PUM in enabling users to learn myocontrol functions in a progressive manner. By the last session of the experiment, participants with LD matched the success rates of ND participants using the progressively calibrated model, even though they mastered one function less. In this comparison, the performance of ND participants served as a best-case scenario because their preexisting motor skills and limb proprioception were expected to give them an inherent advantage in myoelectric control. All subjects achieved satisfactory success rates in basic actions, consistently with other methods of simultaneous and proportional (SP) control, both unsupervised [p3, 85] and supervised [143, 212, 213]. Conversely, success rates for combined actions were worse than those of other existing methods [212, 213], possibly due to different experimental designs. Yet, the experiment in Gigli et al. [p3], which used the same experimental design, showed similarly low performance on combined actions for both a non-progressive version of unsupervised calibration and a state-of-the-art supervised calibration method. In addition, both PUM and its non-progressive counterpart yielded comparable myocontrol performance. Both algorithms showed similar performance retention after a one-week break, suggesting that the calibration approach did not significantly affect recall and recovery of learned motor skills. However, it should be noted that this comparison was based only on ND participants, as both participants with

LD were assigned the non-progressive algorithm.

Evidence from the experiment suggests that the proposed PUM method not only aligned the myocontrol model with the user's developing motor skills but also promoted such development. One subject with congenital limb difference expanded their motor skill repertoire by gaining control over a previously unexplored muscle synergy while practicing with the system. This was particularly remarkable considering that the subject had lived their entire life without this motor skill due to their congenital condition. This outcome was arguably related to the progressive nature of the PUM approach. By introducing a single function at a time, the method allows for a focused and gradual exploration of the user's muscle abilities, challenging them to identify new muscle signals without overwhelming them with the task difficulty. In line with the principles of the Challenge Point Framework [214], this strategy arguably enhances the efficiency of motor skill learning. In comparison, calibration methods where users are confronted with learning multiple functions at once may complicate the motor learning process.

The idea, implemented by the progressive calibration method, of building the myocontrol model by progressively introducing and learning new myocontrol functions finds a foundation in the principles of motor learning. It is observed that during human development or when practicing new motor skills, the motor control system may alter the structure of existing muscle synergies [215], fraction or merge them [58], and even form new ones [216, 217]. Specifically, the development of new muscle synergies in the upper limbs is also observed during the operation of myoelectric interfaces [216]. Additionally, the idea of gradually increasing the number of myocontrol functions during prosthetic control has also been illustrated in recent work by Nowak et al. [218]. There, a supervised myocontrol model was progressively recalibrated with more prosthetic functions as the user gained proficiency with the available ones.

While the PUM paradigm showed considerable potential, it was observed that participants with LD needed more time to perform progressive model calibration, that is, to identify and learn the required motor skills. Specifically, they were unable to master the final myocontrol function within the five experimental sessions, in contrast to most ND participants who had learned all functions already during the initial session. In the TAC tests, the success rates of people with LD only reached those of ND participants by the final session. Furthermore, people with LD exhibited prolonged task completion times and diminished movement quality. Their pronounced reliance on visual feedback during myocontrol, shown by their lower performance in target-reaching tests without visual feedback, indicated lower skill internalization. Finally, unlike ND subjects, their self-reported workload did not decrease across all sessions, signaling a sustained learning effort. These observations hinted at further potential skill enhancements with extended system practice. Notably, existing studies corroborate this lengthy learning process for individuals with LD. For instance, a study by Nowak et al. [218] demonstrated that even under professional supervision, a subject with a limb difference took seven sessions to learn a third myocontrol function and as many as eighteen sessions to master a fourth.

The study faced a limitation due to recruitment constraints, which resulted in a small cohort of only two participants with LD. This limited sample size prevented drawing statistically significant conclusions regarding the efficacy of the progressive unsupervised myocontrol method. Furthermore, the absence of a direct comparison between PUM and its non-progressive counterpart in subjects with LD left uncertainties about the potential of PUM to distribute the learning workload more efficiently. It was anticipated that PUM would reduce the initial mental workload compared to learning multiple functions simultaneously. However, the reported workload was similar for both calibration strategies. This unexpected result could be attributed to the ND participants leveraging their existing muscle synergies to easily master all myocontrol functions. Therefore, further research is warranted on larger samples of individuals with LD. This could strengthen the validity of performance outcomes achieved with PUM and provide more precise insights into its capacity to manage and distribute the learning workload compared to non-progressive calibration variants.

In addition to its primary role in the unsupervised calibration of myocontrol models, the proposed visualization of the synergistic activity of residual muscles can be useful whenever an autonomous exploration of one's own muscle space is desired. Although our visualization strategy was initially developed for unsupervised myocontrol to bypass conventional preprosthetic signal assessment and training, it may surprisingly also prove effective in allowing the user to perform these steps autonomously in preparation for supervised model calibration. Conventional signal training methods use biofeedback from surface electromyography (sEMG) sensors targeting specific muscles, which require healthcare professionals to precisely locate control sites through direct muscle palpation and myotesting [13, 14, 17]. In contrast, our synergy-based biofeedback provides an intuitively interpretable visualization of the higher-level motor commands encoded within coordinated measurements of non-specifically placed sEMG sensors. Such a biofeedback method could enable prospective prosthesis users to undergo preprosthetic training routines autonomously in their home environment before fitting a prosthesis. Encouraging a prolonged and self-directed exploration of one's muscle abilities could facilitate the subsequent supervised calibration process and thus improve initial engagement with the prosthesis.

The discussed biofeedback mechanism may also hold the potential for assisting individuals with severe motor impairments to control assistive platforms using myoelectric interfaces. In some cases of traumatic injury, neuromuscular disease, or neurodegenerative conditions, the ability to elicit observable muscle contractions may be significantly reduced, yet some residual myoelectric activity often remains measurable [219]. Traditional preprosthetic user training methodologies may not be effective in these situations because they usually rely on visible muscle contractions to identify control sites [13, 14, 17]. One approach to identifying control sites could involve having the user interact with a myoelectric interface, providing biofeedback from a dense array of sensors uniformly placed over areas with potential residual myoelectric activity. This approach, however, can be complex if the muscle activity is weak or unreliable, leading to low signal-to-noise ratios in individual channels. In such cases of weak muscle activity, our biofeedback method may offer more reliable detection of motor intents as it focuses on the coordinated activation of multiple channels, which is collectively more noise-resistant than individual channel measurements. Importantly, our method is designed for real-time use, enabling the user not only to identify but also to reinforce emerging motor commands while interacting with the myocontrol interface.

The visualization of the muscles' synergistic activity also presents a significant prospect for aiding the rehabilitation of motor functions in individuals with specific neurological motor impairments, such as stroke survivors. By interacting with the myocontrol system, individuals can practice and reinforce existing muscle synergies, as well as support the recovery of impacted functions. Notably, the ability of this system to track the number of recovered muscle synergies may serve as a physiological indicator for the rehabilitation progress [220, 221].

The biofeedback system could also be integrated into consumer-oriented myoelectric interfaces within wearable devices such as smartwatches. Some of these devices already incorporate gesture recognition sensors to enhance user interaction with computer systems [222], while others are planning to incorporate similar technologies [223]. Given the technological constraints on these devices' dimensions and power consumption, the complexity of the sEMG setup may be limited, allowing only a small number of sensors and a limited sampling frequency. The discussed biofeedback could be utilized to simplify gesture detection tasks from such constrained measurement setups by determining the most distinguishable muscle activation prior to calibrating the intent detection model.

However, further refinements to the system are warranted for a broader deployment of the autonomous muscle space exploration mechanism in home or commercial settings. Simplifying the user interface is necessary to ensure users can easily set up and manage the system settings without supervision. Moreover, it is crucial to develop automated heuristics to address potential instabilities of the adaptive factorization algorithm, such as zero-locking phenomena.

4.2.3 Overview of the Second Contribution

The supporting publications Gigli et al. [p3] and Gigli et al. [p4] introduced and validated a novel calibration paradigm for myocontrol models that eliminate the need for labeled training data. The model is built through a user-driven interaction in which the user and system mutually adapt toward a synergistic control strategy. This process accommodates users with different motor skills and prior experience in prosthetic control. Unlike in conventional supervised calibration, the user is not expected to produce precise and consistent muscle control signals from the beginning, and instead, they are enabled to define and refine their motor control strategy gradually. Consequently, this approach eliminates the conventional requirements of preliminary skill assessment and extensive signal training, which typically require assistance from healthcare professionals. This, in turn, alleviates the problems associated with the availability of experts and the accessibility of rehabilitation clinics.

The unsupervised calibration paradigm was first introduced in Gigli et al. [p3]. This calibration approach involved the development of a new incremental variant of NMF, an abstract motor mapping based on muscle synergies, and a dedicated interaction protocol. The interactive process involves simultaneous learning of multiple prosthetic functions, whose number is determined to reflect the user's existing motor skills as determined by prior professional assessment. The approach does not require preliminary signal training, as it relies on the user's ability to improve their control strategy autonomously during the calibration process. This methodology was further advanced in Gigli et al. [p4] by allowing users to learn the myocontrol functions progressively, unlocking new functions upon mastering the existing ones. This design implicitly aligns the number of controlled functions with the user's existing motor skills, thus eliminating the need for prior assessment of those skills. This structured approach also encourages the development of new motor skills by challenging the user to explore their muscle space while controlling the complexity of the task.

Our research validated the efficacy of using muscle synergies as control signals for achieving simultaneous and proportional myoelectric control, already observed by previous works [84, 160, 170, 224]. Particularly when muscle synergies are estimated with NMF, the linear relationship between the intensity of muscle contraction and the corresponding synergy activation levels facilitates proportional control. In addition, the linear and additive nature of NMF inherently eases simultaneous control, allowing the user to intuitively combine different functions. While non-linear methods might better capture complex muscle coactivation patterns [225], their potential for intuitive and proportional control compared to linear factorization methods is yet to be fully established.

The proposed calibration approach has, to some extent, overcome the traditional separation between the calibration and the use of myocontrol models by integrating the operation of the myocontrol interface into the calibration process. However, achieving the reverse is currently not possible with our system. The model calibration cannot be transparently integrated into real prosthetic operations as it relies on active and conscious participation from the user. During this process, the user must focus on generating distinctive muscle synergies that control the available prosthetic functions individually and cannot concurrently operate the prosthesis for other purposes. For example, if the user repeatedly controlled prosthetic functions in combination, the system could merge the corresponding control synergies, resulting in the inability to selectively control some of the original functions. Unlike our method, the unsupervised adaptation proposed by Yeung et al. [85] enabled continuous model updates during myocontrol use. Their method automatically adjusts the model to compensate for erroneous coactivation of antagonistic muscle synergies. However, the identification of antagonistic synergies was only possible in their study because they focused on biomimetic control of specific antagonistic functions obtained through a semi-unsupervised initial system calibration. Moreover, to the author's understanding, their method is similarly susceptible to the aforementioned potential synergy shifts due to combined activations.

While our unsupervised calibration approach is expected to mitigate confounding factors such as muscle fatigue, changes in skin impedance, or electrode shifts through regular model updates, the limb position effect may pose more significant challenges. Without knowledge of the current arm position, the unsupervised algorithm may have difficulty distinguishing intentional changes in muscle activation from unintended distributional shifts caused by arm movements. This means that a specific motor intent may have a clear synergy representation in one arm configuration but not in another, compromising stable myocontrol across different arm positions. Attempting to identify a more consistent synergy set by moving the arm during the calibration process may not be sufficiently effective. This could either yield an inadequate synergy representation or cause the factorization model to continuously change to adjust to specific arm positions. One possible approach to mitigate this problem could be to estimate muscle synergies using features of the sEMG that have some degree of invariance to the limb position effect, such as certain power spectral descriptors [42, 43, 139]. However, efforts would be required to ensure that such features meet the nonnegativity requirements of NMF.

4.3 Further Remarks

The experimental evaluation of our proposed calibration methods was designed to yield insights pertinent to the application of these methods in real-world prosthetic control scenarios. Ideally, such assessments should involve online evaluations using prosthetic devices, where individuals with LD engage in ADLs, measuring both objective performance and subjective user feedback. Given the logistical constraints and the characteristics of the tested methods, adaptations to these testing conditions were necessary. The proposed feedback-aided data acquisition protocol was examined in an experiment that closely mirrored everyday prosthetic control, engaging participants in ADLs using prosthetic hands. However, due to logistical limitations in the recruitment process, only ND people could participate in the evaluation. Despite this, thorough discussions were included regarding the relevance and applicability of these outcomes for actual prosthetic hand users. The evaluation of the progressive unsupervised calibration paradigm, instead, involved both individuals with and without LD. In this case, the methodological novelty of the approach demanded a more structured experimental setup involving the control of a virtual hand on a screen. More direct and comprehensive assessments of these methods and their developments are encouraged for future research. These should ideally involve larger groups of individuals with LD engaging in realistic prosthetic control.

The research presented in this dissertation focused on rendering the calibration of myocontrol models more user-centered, with specific advantages in terms of efficiency, adaptability, and reduced reliance on professional supervision. Importantly, this shift towards increased user autonomy during the model calibration process was intended to complement, not replace, the role of healthcare professionals in prosthetic control. Their contribution remains indispensable in other aspects of myocontrol, such as in devising customized rehabilitation and prosthetic training plans. Moreover, direct interaction with a human supervisor is paramount in promoting effective prosthetic use, establishing a positive perception of the device, and supporting its long-term acceptance [8, 226]. This synergy between user autonomy and professional guidance is fundamental in developing a comprehensive and effective approach to prosthetic control.

Chapter 5

Conclusion

The research outlined in this dissertation has demonstrated the **benefits of leveraging user-system interaction for the calibration of myocontrol models** for prosthetic hands. By devising interaction protocols that promote mutual understanding and active collaboration between the user and the system, more efficient and convenient creation of the myocontrol model could be achieved. The motivation for this research stemmed from observing that specific challenges in myocontrol model calibration could be addressed by leveraging the ability of the user and system to react, influence, and adapt to one another. The role of these abilities is recognized for the successful operation of prosthetic devices, where the user actively participates in the control loop by modulating the control signals to compensate for possible model inaccuracies. Despite this intrinsically interactive dynamic in myoelectric control, it was noted that existing calibration methods only marginally exploited this potential.

The first contribution of this work focused on **improving the efficacy of supervised calibration** of myocontrol models by investigating an interactive approach to data acquisition and labeling. This approach aimed at promoting an active role of the user during the data acquisition, particularly in identifying and generating more useful training data. This was in contrast with traditional data acquisition methods where the user generates muscle training signals following predefined routines and the model quality is evaluated only after data acquisition, often resulting in multiple iterations of the data acquisition process to obtain a model with satisfactory performance. This research specifically concentrated on acquisition protocols that improve the robustness of myocontrol models to limb position variations by acquiring training data for the desired prosthetic hand gestures in multiple arm configurations. The hypothesis was that by adapting these multi-arm-position data acquisition methods into an interactive design, users could be directed to identify the arm configurations where more data was necessary, aiming to enhance the efficiency of the data acquisition process.

A preliminary analysis was conducted in Gigli et al. [p1] to compare two main approaches for multi-arm-position data acquisition, one in which the arm is held in different arm configurations and the other in which the arm is moved across the reachable space. This study aimed to determine the most beneficial method for realistic prosthetic myocontrol before redesigning the methodology for interactive use. The results highlighted the advantages of the dynamic version, especially in terms of lower physical effort and faster execution, while providing equivalent robustness to the limb position effect. This finding informed the myocontrol field about the **practical merits of dynamic multi-arm-position data acquisition** for managing the limb position effect and motivated the subsequent investigation of an interactive redesign of the dynamic acquisition method.

An **interactive version of dynamic multi-arm-position data acquisition** was designed and assessed for realistic prosthetic control in Gigli et al. [p2]. The data acquisition featured an algorithm for real-time incremental model building and an interaction protocol where auditory feedback on prediction errors directed users to acquire more training data in challenging arm configurations. This approach **enhanced the efficacy of the data acquisition process**, improving the model's robustness to the limb position effect in prosthetic control tasks. Although further validation with individuals with limb differences remains necessary, this study highlighted the practical potential of conducting supervised myocontrol model calibration interactively. This potential might extend to myocontrol applications beyond prosthetic control, in any scenario that requires the recognition of hand gestures during unrestrained limb movements. Examples include teleoperation of robotic and assistive platforms, interaction with virtual reality, or interfacing with computer systems [227, 228, 229, 230].

Beyond investigating certain inefficiencies of supervised calibration methods, this research recognized challenges that individuals with limb differences inherently face with these methods. To accurately label training myoelectric signals, existing data acquisition methods rely on the user to elicit stable, distinctive, and repeatable muscle contractions upon request. However, this task may be difficult for individuals with limb differences due to the potential lack of visual and proprioceptive feedback from a healthy limb. These challenges have practical implications for the preparatory steps of supervised myocontrol model calibration. The user must undergo a preliminary assessment of the number of distinct muscle contractions they can generate, followed by extensive and targeted signal training to learn to generate muscle signals of appropriate quality. Both these preliminary processes require direct guidance from healthcare professionals, which can complicate the initial engagement with the myocontrol system by conditioning its use on the availability of an expert and the accessibility of clinical facilities. Therefore, this work's second contribution was exploring **unsupervised calibration methods** based on a structured interaction between the user and the myocontrol system. Instead of relying on labeled training data, these approaches enabled the user and the system to cooperatively define the myocontrol model while interacting with each other.

Gigli et al. [p3] presented a novel paradigm for unsupervised calibration of myocontrol models based on an interactive process. The myocontrol system established an abstract motor mapping between adaptively extracted salient muscle synergies and a predefined set of prosthetic functions. Unlike supervised calibration methods, the user was engaged in learning to control these functions upon a random initialization of the model. This direct interaction between the user and system, along with the adaptive characteristic of the synergy factorization algorithm, induced a **coadaptive construction of the myocontrol model**. While the system updated the model to better differentiate distinctive control signals within the muscle activity, the user concurrently attempted to generate such distinctive signals.

The proposed unsupervised paradigm was validated against a state-of-the-art supervised approach, demonstrating the capacity to produce models with equivalent performance in myoelectric control of virtual prosthetic hands. To the author's knowledge, this study was the first to demonstrate the feasibility of fully unsupervised myocontrol model calibration, which is of practical relevance to the field of myoelectric control. Besides not requiring labeled training data, this approach does not constrain the user's muscle activity during the calibration process, as it is done in other existing semi-unsupervised calibration methods to implement biomimetic motor mappings. This aspect emphasizes a practical advantage of utilizing abstract motor mappings in myoelectric control. Since the muscle control inputs are not limited to those physiologically related to the controlled prosthetic functions, the user can explore their muscle space in an unsupervised and unconstrained manner, identifying control inputs that are both distinctive and convenient to use in practice. While highlighting the benefits of abstract motor mappings, our work also reveals that enabling customization of those mappings is desirable to lessen the mental workload of the motor learning task.

Compared to standard supervised calibration, the unsupervised approach showed promise in improving the user's autonomy during the initial myocontrol system calibration. It effectively replaced the need for preliminary signal training under professional guidance, enabling users to autonomously explore their muscle space through direct interaction with the system. It should be noted, however, that while this approach reduced the need for professional supervision, it still required a preliminary supervised assessment of the user's existing motor skills in order to define the number of controllable prosthetic functions.

This coadaptive unsupervised calibration approach was further refined in Gigli et al. [p4] to enable the user to **learn myocontrol functions progressively** rather than simultaneously. The refined calibration was based on an entirely user-driven interaction protocol and on a novel adaptive synergy factorization algorithm that allowed to dynamically change the number of estimated muscle synergies without disrupting the already extracted ones. The user began the interaction by practicing with one prosthetic function and gradually requested unlocking more functions upon mastering the available ones. The results of a multi-session user study showed that the novel calibration approach enabled participants with limb differences to calibrate and use a myocontrol model without preliminary supervised assessment or training of their motor skills, and to achieve performance comparable to non-disabled individuals. Notably, the method also enabled one participant with a congenital limb difference to **expand their motor skill set** by discovering a previously unrecognized muscle synergy in a completely autonomous way.

Overall, the progressive coadaptive unsupervised calibration method emerges as a viable alternative to standard acquisition and labeling of myoelectric data. Because the method automatically detects the most appropriate myocontrol signals within the user's muscle activity, its success does not depend on the user's ability to generate precise and potentially challenging muscle contractions. In turn, this eliminates the need for supervised signal training, which is often a preparatory step for supervised calibration. This aspect reduces the financial and logistical burden associated with professional supervision for control model calibration and promotes an earlier and **more autonomous engagement with the myocontrol system**. Moreover, since an adaptive refinement of control signals is possible during the model calibration, and not only during preparatory exercises, this method may also benefit users with initially limited motor skills, allowing them to refine their control signals through autonomous direct interaction with the myoelectric system. At the same time, by enabling users to progressively increase the number of controlled prosthetic functions, the calibration process automatically aligns with the user's preexisting motor skills, eliminating the necessity for preliminary supervised assessment to estimate the number of controllable functions. This adaptability also accommodates the users' potential evolution of motor skills over time, which makes the calibration method especially useful for individuals with initially limited control of residual limbs, who may develop control over more muscle groups over time.

It was observed that the visualization of salient muscle synergies embedded in our unsupervised calibration methods may also serve as an **advanced biofeedback tool**. Unlike traditional biofeedback methods that focus on the individual activity of each surface electromyography (sEMG) channel, this visualization synthesizes information from multiple channels and does not require the placement of sensors on specific target muscles. By utilizing this visualization during the operation of a myocontrol system, the user can track the emergence of new muscle synergies and learn to activate them intentionally, thus progressively expanding their repertoire of motor skills. The developed biofeedback mechanism was discussed to find potential applications beyond unsupervised calibration of prosthetic control systems, into the broader field of human-computer interaction. It can facilitate the supervised calibration of myocontrol interfaces for prosthetic devices, assistive robotic platforms, and consumer wearable electronics. It can also be beneficial in rehabilitation settings for individuals recovering from neurological disorders. Importantly, these applications cater to a broad range of end users, including individuals with severe motor impairments, those with limb differences, as well as non-disabled ones.

The contributions outlined in this thesis describe a **perspective shift toward a more active user involvement in the myocontrol model calibration**. Recognizing the user not only as a source of data, but as a resource with advanced cognitive skills, reveals the potential for more effective calibration. Such potential is leveraged through innovative interactive calibration protocols that encourage mutual understanding and synergistic adaptation between the user and the system. This enhanced the model calibration process by enabling more effective data acquisition or broadening the accessibility of myocontrol to individuals with varied motor capacities. Importantly, it provides an avenue for users to not only refine but potentially expand their control capacities whilst establishing a model tailored to their needs.

Transitioning toward more user-centric calibration approaches reflects other recent efforts in prosthetic control to develop customized training programs, enhance system usability in daily living settings, and focus more on user satisfaction assessment. This shift also aligns with a trend in the broader fields of rehabilitative and assistive technologies toward customizing interventions, aimed at fostering a deeper connection and acceptance between the user and the system they utilize. Overall, the interaction-driven calibration approaches delineated in this work not only tackle specific technical challenges inherent to myoelectric control but also pave the way for more personalized and accessible prosthetic solutions.

References to the Supporting Publications

[p1] Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. "The Merits of Dynamic Data Acquisition for Realistic Myocontrol." In: *Frontiers in Bioengineering and Biotechnology* 8 (April 2020), pp. 1–20.

[p2] Andrea Gigli et al. "Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand." In: *Journal of Neural Engineering* 17.5 (2020), p. 056047.

[p3] Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. "Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping." In: *2022 IEEE International Conference on Rehabilitation Robotics*. Rotterdam, 2022, pp. 1–6.

[p4] Andrea Gigli et al. "Progressive Unsupervised Control of Myoelectric Upper Limbs." In: *Journal of Neural Engineering* 20.6 (2023), p. 066016.

References

[1] Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. "Natural Myocontrol in a Realistic Setting: A Comparison Between Static and Dynamic Data Acquisition." In: *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)*. 2019, pp. 1061–1066.

[2] Donato Brusamento et al. "Closed-Loop Acquisition of Training Data Improves Myocontrol of a Prosthetic Hand." In: *Converging Clinical and Engineering Research on Neurorehabilitation IV (ICNR 2020)*. Springer International Publishing, 2022, pp. 421–425.

[3] Lauren Trent et al. "A Narrative Review: Current Upper Limb Prosthetic Options and Design." In: *Disability and Rehabilitation: Assistive Technology* 15.6 (17, 2020), pp. 604–613.

[4] Freyja Kristjansdottir et al. "Social Participation in Persons With Upper Limb Amputation Receiving an Esthetic Prosthesis." In: *Journal of Hand Therapy* 33.4 (2020), pp. 520–527.

[5] Francesca Cordella et al. "Literature Review on Needs of Upper Limb Prosthesis Users." In: *Frontiers in Neuroscience* 10 (May 2016), pp. 1–14.

[6] Ziming Chen et al. "A Review of Myoelectric Control for Prosthetic Hand Manipulation." In: *Biomimetics* 8.3 (2023), p. 328.

[7] Dapeng Yang et al. "Improving the Functionality, Robustness, and Adaptability of Myoelectric Control for Dexterous Motion Restoration." In: *Experimental Brain Research* 237.2 (1, 2019), pp. 291–311.

[8] Andrea Marinelli et al. "Active Upper Limb Prostheses: A Review on Current State and Upcoming Breakthroughs." In: *Progress in Biomedical Engineering* 5.1 (1, 2023), p. 012001.

[9] Miguel Simao et al. "A Review on Electromyography Decoding and Pattern Recognition for Human-Machine Interaction." In: *IEEE Access: Practical Innovations, Open Solutions* 7 (c 2019), pp. 39564–39582.

[10] Mohammadreza Asghari Oskoei and Huosheng Hu. "Myoelectric Control Systems–a Survey." In: *Biomedical Signal Processing and Control* 2.4 (2007), pp. 275–294.

[11] Carles Igual et al. "User-Prosthesis Coadaptation." In: *Control of Prosthetic Hands: Challenges and Emerging Avenues*. IET Digital Library, 1, 2020, pp. 159–174.

[12] Julie Klarich and Inger Brueckner. "Amputee Rehabilitation and Preprosthetic Care." In: *Physical Medicine and Rehabilitation Clinics of North America* 25.1 (2014), pp. 75–91.

[13] Cathrine Widehammar, Kajsa Lidström Holmqvist, and Liselotte Hermansson. "Training for Users of Myoelectric Multigrip Hand Prostheses: A Scoping Review." In: *Prosthetics &Amp Orthotics International* 45.5 (2021), pp. 393–400.

[14] Agnes Sturma et al. "Rehabilitation of Upper Extremity Nerve Injuries Using Surface EMG Biofeedback: Protocols for Clinical Application." In: *Frontiers in Neuroscience* 12 (2018).

[15] Johnny V. V. Parr et al. "A Scoping Review of the Application of Motor Learning Principles to Optimize Myoelectric Prosthetic Hand Control." In: *Prosthetics &Amp Orthotics International* 46.3 (2021), pp. 274–281.

[16] Bart Peerdeman et al. "Myoelectric Forearm Prostheses: State of the Art From a User-Centered Perspective." In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), pp. 719–737.

[17] Ottobock. *MyoBock - Evaluation of the Myosignals Tutorial*. 11, 2019. URL: `https://www.youtube.com/watch?v=baCox0%5C_2LRU` (visited on 12/04/2023).

[18] Anders Fougner et al. "Control of Upper Limb Prostheses: Terminology and Proportional Myoelectric Control – A Review." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 20.5 (2012), pp. 663–677.

[19] Ottobock. *Myo Plus Pattern Recognition - 1. Evaluation With the Myo Cuff*. 1, 2022. URL: `https://www.youtube.com/watch?v=OhvYYnTKVRA` (visited on 12/04/2023).

[20] Dapeng Yang et al. "Dynamic Training Protocol Improves the Robustness of PR-based Myoelectric Control." In: *Biomedical Signal Processing and Control* 31 (2017), pp. 249–256.

[21] Roberto Meattini et al. "Automated Instability Detection for Interactive Myocontrol of Prosthetic Hands." In: *Frontiers in Neurorobotics* 13 (August 2019), p. 68.

[22] Janne M. Hahne et al. "Concurrent Adaptation of Human and Machine Improves Simultaneous and Proportional Myoelectric Control." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 23.4 (2015), pp. 618–627.

[23] Ning Jiang et al. "Is Accurate Mapping of EMG Signals on Kinematics Needed for Precise Online Myoelectric Control?" In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22.3 (2014), pp. 549–558.

[24] Ahmed W. Shehata, Erik J. Scheme, and Jonathon W. Sensinger. "Evaluating Internal Model Strength and Performance of Myoelectric Prosthesis Control Strategies." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 26.5 (2018), pp. 1046–1055.

[25] Janne M. Hahne, Marko Markovic, and Dario Farina. "User Adaptation in Myoelectric Man-Machine Interfaces." In: *Scientific Reports* 7.1 (2017), p. 4437.

[26] Ivan Vujaklija, Dario Farina, and Oskar Aszmann. "New Developments in Prosthetic Arm Systems." In: *Orthopedic Research and Reviews* Volume 8 (2016), pp. 31–39.

[27] Kristin Østlie et al. "Prosthesis Rejection in Acquired Major Upper-Limb Amputees: A Population-Based Survey." In: *Disability and Rehabilitation: Assistive Technology* 7.4 (1, 2012), pp. 294–303.

[28] So-Hye Jo et al. "Psychiatric Understanding and Treatment of Patients With Amputations." In: *Yeungnam University Journal of Medicine* 38.3 (31, 2021), pp. 194–201.

[29] Rhonda M Williams et al. "A Two-Year Longitudinal Study of Social Support Following Amputation." In: *Disability and Rehabilitation* 26.14 (22, 2004), pp. 862–874.

[30] Kathryn Ziegler-Graham et al. "Estimating the Prevalence of Limb Loss in the United States: 2005 to 2050." In: *Archives of Physical Medicine and Rehabilitation* 89.3 (1, 2008), pp. 422–429.

[31] Andrea B. Wanamaker, Rebecca R. Andridge, and Ajit M. W. Chaudhari. "Costs Associated With Lower- And Upper-Limb Amputation Over the First 4 Years With a Prosthesis." In: *JPO: Journal of Prosthetics and Orthotics* 32.2 (2020), p. 81.

[32] Abby Hutchison et al. "Exploring the Barriers and Facilitators to Community Reintegration for Adults Following Traumatic Upper Limb Amputation: A Mixed Methods Systematic Review." In: *Disability and Rehabilitation* 0.0 (12, 2023), pp. 1–14.

[33] Danielle H. Melton. “Physiatrist Perspective on Upper-Limb Prosthetic Options: Using Practice Guidelines to Promote Patient Education in the Selection and the Prescription Process.” In: *JPO: Journal of Prosthetics and Orthotics* 29.4 (2017), P40.

[34] Ilario Imbinto et al. “Treatment of the Partial Hand Amputation: An Engineering Perspective.” In: *IEEE Reviews in Biomedical Engineering* 9 (2016), pp. 32–48.

[35] Bartjan Maat et al. “Passive Prosthetic Hands and Tools: A Literature Review.” In: *Prosthetics and Orthotics International* 42.1 (1, 2018), pp. 66–74.

[36] Robert S. Kistenberg. “Prosthetic Choices for People With Leg and Arm Amputations.” In: *Physical Medicine and Rehabilitation Clinics of North America* 25.1 (1, 2014), pp. 93–115.

[37] Gerwin Smit et al. “Efficiency of Voluntary Opening Hand and Hook Prosthetic Devices: 24 Years of Development?” In: *Journal of Rehabilitation Research and Development* 49.4 (2012), pp. 523–534.

[38] Neil M. Bajaj, Adam J. Spiers, and Aaron M. Dollar. “State of the Art in Artificial Wrists: A Review of Prosthetic and Robotic Wrist Design.” In: *IEEE Transactions on Robotics* 35.1 (2019), pp. 261–277.

[39] Chris Lake. “The Evolution of Upper Limb Prosthetic Socket Design.” In: *JPO: Journal of Prosthetics and Orthotics* 20.3 (2008), p. 85.

[40] Federico Mereu et al. “Control Strategies and Performance Assessment of Upper-Limb TMR Prostheses: A Review.” In: *Sensors (Basel, Switzerland)* 21.6 (10, 2021), p. 1953.

[41] Philip P. Vu et al. “Long-Term Upper-Extremity Prosthetic Control Using Regenerative Peripheral Nerve Interfaces and Implanted EMG Electrodes.” In: *Journal of Neural Engineering* 20.2 (2023), p. 026039.

[42] Iris Kyranou, Sethu Vijayakumar, and Mustafa Suphi Erden. “Causes of Performance Degradation in Non-Invasive Electromyographic Pattern Recognition in Upper Limb Prostheses.” In: *Frontiers in Neurorobotics* 12 (21, 2018), p. 58.

[43] Evan Campbell, Angkoon Phinyomark, and Erik Scheme. “Current Trends and Confounding Factors in Myoelectric Control: Limb Position and Contraction Intensity.” In: *Sensors (Switzerland)* 20.6 (2020), p. 1613.

[44] Stefan Salminger et al. “Current Rates of Prosthetic Usage in Upper-Limb Amputees – Have Innovations Had an Impact on Device Acceptance?” In: *Disability and Rehabilitation* 44.14 (3, 2022), pp. 3708–3713.

[45] Elaine A. Biddiss and Tom T. Chau. "Upper Limb Prosthesis Use and Abandonment : A Survey of the Last 25 Years." In: *Prosthetics &Amp Orthotics International* 31 (September 2007), pp. 236–257.

[46] Mary M Rodgers et al. "Wearable Technologies for Active Living and Rehabilitation: Current Research Challenges and Future Opportunities." In: *Journal of Rehabilitation and Assistive Technologies Engineering* 6 (1, 2019), p. 2055668319839607.

[47] Elaine Biddiss and Tom Chau. "The Roles of Predisposing Characteristics, Established Need, and Enabling Resources on Upper Extremity Prosthesis Use and Abandonment." In: *Disability and Rehabilitation: Assistive Technology* 2.2 (2007), pp. 71–84.

[48] Joseph E. Muscolino. *Kinesiology - E-Book: Kinesiology - E-Book*. Elsevier Health Sciences, 15, 2010. 705 pp.

[49] Roberto Merletti and Dario Farina. *Surface Electromyography: Physiology, Engineering, and Applications*. John Wiley & Sons, 2, 2016. 592 pp.

[50] C. J. Heckman and Roger M. Enoka. "Motor Unit." In: *Comprehensive Physiology* 2.4 (2012), pp. 2629–2682.

[51] Eleanor Criswell. *Cram's Introduction to Surface Electromyography*. Jones & Bartlett Publishers, 16, 2010. 436 pp.

[52] Vincent C. K. Cheung and Kazuhiko Seki. "Approaches to Revealing the Neural Basis of Muscle Synergies: A Review and a Critique." In: *Journal of Neurophysiology* 125.5 (2021), pp. 1580–1597.

[53] Dario Farina et al. "Man/Machine Interface Based on the Discharge Timings of Spinal Motor Neurons After Targeted Muscle Reinnervation." In: *Nature Biomedical Engineering* 1.2 (2017), pp. 1–12.

[54] Carlo J De Luca and Paola Contessa. "Biomechanical Benefits of the Onion-Skin Motor Unit Control Scheme." In: *Journal of Biomechanics* 48.2 (21, 2015), pp. 195–203.

[55] Rajat Emanuel Singh et al. "A Systematic Review on Muscle Synergies: From Building Blocks of Motor Behavior to a Neurorehabilitation Tool." In: *Applied Bionics and Biomechanics* 2018 (2018), p. 3615368.

[56] Frederic Danion and Mark Latash. *Motor Control: Theories, Experiments, and Applications*. Oxford University Press, USA, 16, 2010.

[57] Cristiano Alessandro et al. "Muscle Synergies in Neuroscience and Robotics: From Input-Space to Task-Space Perspectives." In: *Frontiers in Computational Neuroscience* 7 (Apr 2013 2013), p. 43.

[58] Vincent C. K. Cheung et al. “Plasticity of Muscle Synergies Through Fractionation and Merging During Development and Training of Human Runners.” In: *Nature Communications* 11.1 (2020), p. 4356.

[59] Mark Ison and Panagiotis Artemiadis. “The Role of Muscle Synergies in Myoelectric Control: Trends and Challenges for Simultaneous Multifunction Control.” In: *Journal of Neural Engineering* 11.5 (2014), pp. 2880–2885.

[60] Emilio Bizzi and Vincent CK Cheung. “The Neural Origin of Muscle Synergies.” In: *Frontiers in Computational Neuroscience* 7 (2013).

[61] Friedl De Groote, Ilse Jonkers, and Jacques Duysens. “Task Constraints and Minimization of Muscle Effort Result in a Small Number of Muscle Synergies During Gait.” In: *Frontiers in Computational Neuroscience* 8 (2014).

[62] Dario Farina et al. “The Extraction of Neural Information From the Surface EMG for the Control of Upper-Limb Prostheses : Emerging Avenues and Challenges.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22 (September 2014), pp. 797–809.

[63] carlo de luca carlo. “The Use of Surface Electromyography in Biomechanics.” In: *Journal of Applied Biomechanics* (1997).

[64] R. Merletti and S. Muceli. “Tutorial. Surface EMG Detection in Space and Time: Best Practices.” In: *Journal of Electromyography and Kinesiology* 49 (1, 2019), p. 102363.

[65] Lara McManus, Giuseppe De Vito, and Madeleine M. Lowery. “Analysis and Biophysics of Surface EMG for Physiotherapists and Kinesiologists: Toward a Common Language With Rehabilitation Engineers.” In: *Frontiers in Neurology* 11 (2020).

[66] Isabella Campanini et al. “Fundamental Concepts of Bipolar and High-Density Surface EMG Understanding and Teaching for Clinical, Occupational, and Sport Applications: Origin, Detection, and Main Errors.” In: *Sensors* 22.11 (2022), p. 4150.

[67] Devon I. Rubin. “Chapter 16 - Needle Electromyography: Basic Concepts.” In: *Handbook of Clinical Neurology*. Ed. by Kerry H. Levin and Patrick Chauvel. Vol. 160. Elsevier, 1, 2019, pp. 243–256.

[68] Stefano Pizzolato et al. “Comparison of Six Electromyography Acquisition Setups on Hand Movement Classification Tasks.” In: *Plos One* 12.10 (12, 2017), e0186132.

[69] Hermie J Hermens et al. “European Recommendations for Surface ElectroMyoGraphy.” In: *Roessingh Research and Development* 8.2 (1999).

[70] Paul W. Hodges. "Editorial: Consensus for Experimental Design in Electromyography (CEDE) Project." In: *Journal of Electromyography and Kinesiology* 50 (1, 2020), p. 102343.

[71] Nawadita Parajuli et al. "Real-Time EMG Based Pattern Recognition Control for Hand Prostheses: A Review on Existing Methods, Challenges and Future Implementation." In: *Sensors (Switzerland)* 19.20 (2019), p. 4596.

[72] Lauren H. Smith et al. "Determining the Optimal Window Length for Pattern Recognition-Based Myoelectric Control: Balancing the Competing Effects of Classification Error and Controller Delay." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 19.2 (2011), pp. 186–192.

[73] Catherine Disselhorst-Klug, Thomas Schmitz-Rode, and Günter Rau. "Clinical Biomechanics Surface Electromyography and Muscle Force : Limits in sEMG – Force Relationship and New Approaches for Applications." In: *Clinical Biomechanics* 24.3 (2009), pp. 225–235.

[74] Angkoon Phinyomark, Rami N. Khushaba, and Erik Scheme. "Feature Extraction and Selection for Myoelectric Control Based on Wearable EMG Sensors." In: *Sensors (Switzerland)* 18.5 (2018), p. 1615.

[75] E. A. Clancy, E. L. Morin, and R. Merletti. "Sampling, Noise-Reduction and Amplitude Estimation Issues in Surface Electromyography." In: *Journal of Electromyography and Kinesiology: Official Journal of the International Society of Electrophysiological Kinesiology* 12.1 (2002), pp. 1–16.

[76] B. Hudgins, P. Parker, and R.N. Scott. "A New Strategy for Multifunction Myoelectric Control." In: *IEEE Transactions on Bio-Medical Engineering* 40.1 (1993), pp. 82–94.

[77] Purushothaman Geethanjali. "Myoelectric Control of Prosthetic Hands: State-of-the-Art Review." In: *Medical Devices: Evidence and Research* Volume 9 (2016), pp. 247–255.

[78] Kevin P Murphy. *Machine Learning - A Probabilistic Perspective*. MIT Press, 2012.

[79] Kunkun Zhao et al. "Evaluation of Methods for the Extraction of Spatial Muscle Synergies." In: *Frontiers in Neuroscience* 16 (2022).

[80] Mohammad Fazle Rabbi et al. "Non-Negative Matrix Factorisation Is the Most Appropriate Method for Extraction of Muscle Synergies in Walking and Running." In: *Scientific Reports* 10.1 (19, 2020), p. 8266.

[81] Ahmed Ebied et al. "Evaluation of Matrix Factorisation Approaches for Muscle Synergy Extraction." In: *Medical Engineering &Amp Physics* 57 (2018), pp. 51–60.

[82] Matthew C. Tresch, Vincent C. K. Cheung, and Andrea dAvella. "Matrix Factorization Algorithms for the Identification of Muscle Synergies: Evaluation on Simulated and Experimental Data Sets." In: *Journal of Neurophysiology* 95.4 (2006), pp. 2199–2212.

[83] Nicolas Gillis. *Nonnegative Matrix Factorization.* New York, NY: Society for Industrial and Applied Mathematics, 2020.

[84] Ning Jiang, K.B. Englehart, and P.A. Parker. "Extracting Simultaneous and Proportional Neural Control Information for Multiple-Dof Prostheses From the Surface Electromyographic Signal." In: *IEEE Transactions on Bio-Medical Engineering* 56.4 (2009), pp. 1070–1080.

[85] Dennis Yeung et al. "Co-Adaptive Control of Bionic Limbs via Unsupervised Adaptation of Muscle Synergies." In: *IEEE Transactions on Bio-Medical Engineering* 69 (Xx 2022), pp. 2581–2592.

[86] Daniel Lee and H. Sebastian Seung. "Algorithms for Non-Negative Matrix Factorization." In: *Advances in Neural Information Processing Systems*. Vol. 13. MIT Press, 2000.

[87] Sihang Dang et al. "SAR Target Recognition via Incremental Nonnegative Matrix Factorization." In: *Remote Sensing* 10.3 (2018), p. 374.

[88] Michael W. Berry et al. "Algorithms and Applications for Approximate Nonnegative Matrix Factorization." In: *Computational Statistics &Amp Data Analysis* 52.1 (2007), pp. 155–173.

[89] Chih-Jen Lin. "Projected Gradient Methods for Nonnegative Matrix Factorization." In: *Neural Computation* 19.10 (2007), pp. 2756–2779.

[90] Roberto Prevete et al. "Evidence for Sparse Synergies in Grasping Actions." In: *Scientific Reports* 8.1 (12, 2018), p. 616.

[91] Chuang Lin et al. "Robust Extraction of Basis Functions for Simultaneous and Proportional Myoelectric Control via Sparse Non-Negative Matrix Factorization." In: *Journal of Neural Engineering* 15.2 (2018), p. 026017.

[92] Patrik O Hoyer. "Non-Negative Matrix Factorization With Sparseness Constraints." In: *Journal of Machine Learning Research: JMLR* 5 (2004), pp. 1457–1469. arXiv: `cs/0408058`.

[93] Serhat S. Bucak and Bilge Gunsel. "Incremental Subspace Learning via Non-Negative Matrix Factorization." In: *Pattern Recognition* 42.5 (2009), pp. 788–797.

[94] Bin Ren et al. "Non-Negative Matrix Factorization: Robust Extraction of Extended Structures." In: *The Astrophysical Journal* 852.2 (2018), p. 104. arXiv: 1712.10317.

[95] Negin Hesam-Shariati et al. "A Longitudinal Electromyography Study of Complex Movements in Poststroke Therapy. 2: Changes in Coordinated Muscle Activation." In: *Frontiers in Neurology* 8 (2017), p. 277.

[96] Cristina Brambilla and Alessandro Scano. "The Number and Structure of Muscle Synergies Depend on the Number of Recorded Muscles: A Pilot Simulation Study With OpenSim." In: *Sensors* 22.22 (2022), p. 8584.

[97] Angkoon Phinyomark and Erik Scheme. "EMG Pattern Recognition in the Era of Big Data and Deep Learning." In: *Big Data and Cognitive Computing* 2.3 (2018), p. 21.

[98] Ali Ameri et al. "Real-Time, Simultaneous Myoelectric Control Using a Convolutional Neural Network." In: *Plos One* 13.9 (2018). Ed. by Ginestra Bianconi, e0203835.

[99] Tobias Pistohl et al. "Abstract and Proportional Myoelectric Control for Multi-Fingered Hand Prostheses." In: *Annals of Biomedical Engineering* 41.12 (2013), pp. 2687–2698.

[100] Aidan D. Roche et al. "Prosthetic Myoelectric Control Strategies: A Clinical Perspective." In: *Current Surgery Reports* 2.3 (25, 2014), p. 44.

[101] James M. Goodman et al. "Postural Representations of the Hand in the Primate Sensorimotor Cortex." In: *Neuron* 104.5 (4, 2019), 1000–1009.e7.

[102] Carles Igual et al. "Adaptive Auto-Regressive Proportional Myoelectric Control." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 27.2 (2019), pp. 314–322.

[103] Fabio Egle et al. "Preliminary Assessment of Two Simultaneous and Proportional Myocontrol Methods for 3-DoFs Prostheses Using Incremental Learning." In: *IEEE … International Conference on Rehabilitation Robotics: [Proceedings]* 2023 (2023), pp. 1–6.

[104] Linda Resnik et al. "Evaluation of EMG Pattern Recognition for Upper Limb Prosthesis Control: A Case Study in Comparison With Direct Myoelectric Control." In: *Journal of NeuroEngineering and Rehabilitation* 15.1 (15, 2018), p. 23.

[105] J. M. Hahne et al. “Linear and Nonlinear Regression Techniques for Simultaneous and Proportional Myoelectric Control.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22.2 (2014), pp. 269–279.

[106] Fabio Rizzoglio et al. “Building an Adaptive Interface via Unsupervised Tracking of Latent Manifolds.” In: *Neural Networks: The Official Journal of the International Neural Network Society* 137 (2021), pp. 174–187.

[107] Matthew Dyson, Jessica Barnes, and Kianoush Nazarpour. “Myoelectric Control With Abstract Decoders.” In: *Journal of Neural Engineering* 15.5 (1, 2018), p. 056003.

[108] Evan Campbell et al. *A Comparison of Amputee and Able-Bodied Inter-Subject Variability in Myoelectric Control.* 6, 2020. arXiv: `2003.03481[cs,eess]`.

[109] Carles Igual et al. “Myoelectric Control for Upper Limb Prostheses.” In: *Electronics* 8.11 (2019), p. 1244.

[110] Domenico Buongiorno et al. “Deep Learning for Processing Electromyographic Signals: A Taxonomy-Based Survey.” In: *Neurocomputing* 452 (2021), pp. 549–565.

[111] Alexander E. Olsson et al. “Learning Regularized Representations of Categorically Labelled Surface EMG Enables Simultaneous and Proportional Myoelectric Control.” In: *Journal of NeuroEngineering and Rehabilitation* 18.1 (15, 2021), p. 35.

[112] Max Ortiz-Catalan, Bo Håkansson, and Rickard Brånemark. “Real-Time and Simultaneous Control of Artificial Limbs Based on Pattern Recognition Algorithms.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 22.4 (2014), pp. 756–764.

[113] Janne M. Hahne et al. “Simultaneous Control of Multiple Functions of Bionic Hand Prostheses: Performance and Robustness in End Users.” In: *Science Robotics* 3.19 (2018).

[114] Hanen Borchani et al. “A Survey on Multi-Output Regression: Multi-Output Regression Survey.” In: *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 5.5 (2015), pp. 216–233.

[115] Mohammad Reza Mohebbian et al. *A Comprehensive Review of Myoelectric Prosthesis Control.* 25, 2021. arXiv: `2112.13192[cs,eess]`.

[116] Ashirbad Pradhan et al. “Linear Regression With Frequency Division Technique for Robust Simultaneous and Proportional Myoelectric Control During Medium and High Contraction-Level Variation.” In: *Biomedical Signal Processing and Control* 61 (2020), p. 101984.

[117] Arjan Gijsberts et al. "Stable Myoelectric Control of a Hand Prosthesis Using Non-Linear Incremental Learning." In: *Frontiers in Neurorobotics* 8 (Feb 2014), pp. 1–15.

[118] David Sierra González and Claudio Castellini. "A Realistic Implementation of Ultrasound Imaging as a Human-Machine Interface for Upper-Limb Amputees." In: *Frontiers in Neurorobotics* 7 (Oct 2013), pp. 1–11.

[119] John Shawe-Taylor and Nello Cristianini. *Kernel Methods for Pattern Analysis.* Cambridge: Cambridge University Press, 2004.

[120] Arjan Gijsberts and Giorgio Metta. "Incremental Learning of Robot Dynamics Using Random Features." In: *Proceedings - IEEE International Conference on Robotics and Automation.* Shanghai, China: Ieee, 2011, pp. 951–956.

[121] Ali Rahimi and Benjamin Recht. "Random Features for Large-Scale Kernel Machines." In: *Advances in Neural Information Processing Systems.* Vol. 20. Curran Associates, Inc., 2007.

[122] Dezhen Xiong et al. "Deep Learning for EMG-based Human-Machine Interaction: A Review." In: *IEEE/CAA Journal of Automatica Sinica* 8.3 (2021), pp. 512–533.

[123] Ali Ameri et al. "Regression Convolutional Neural Network for Improved Simultaneous EMG Control." In: *Journal of Neural Engineering* 16.3 (2019), p. 036015.

[124] Morten B. Kristoffersen et al. "User Training for Machine Learning Controlled Upper Limb Prostheses: A Serious Game Approach." In: *Journal of NeuroEngineering and Rehabilitation* 18.1 (12, 2021), p. 32.

[125] Cosima Prahm et al. "PlayBionic: Game-Based Interventions to Encourage Patient Engagement and Performance in Prosthetic Motor Rehabilitation." In: *Pm&r* 10.11 (2018), pp. 1252–1260.

[126] Annette Hagengruber et al. "A New Labeling Approach for Proportional Electromyographic Control." In: *Sensors* 22.4 (2022), p. 1368.

[127] Trevor Darrell et al. "Machine Learning With Interdependent and Non-Identically Distributed Data (Dagstuhl Seminar 15152)." In: (2015). In collab. with Marc Herbstritt, 38 pages.

[128] Christopher M Bishop. *Pattern Recognition and Machine Learning.* Vol. 27. Springer New York, 2006.

[129] Thomas G. Dietterich. "Machine Learning for Sequential Data: A Review." In: *Structural, Syntactic, and Statistical Pattern Recognition.* Ed. by Terry Caelli et al. Berlin, Heidelberg: Springer, 2002, pp. 15–30.

[130] Jonathon W. Sensinger, Blair A. Lock, and Todd A. Kuiken. "Adaptive Pattern Recognition of Myoelectric Signals: Exploration of Conceptual Framework and Practical Algorithms." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 17.3 (2009), pp. 270–278.

[131] E. Park and S. G. Meek. "Fatigue Compensation of the Electromyographic Signal for Prosthetic Control and Force Estimation." In: *IEEE Transactions on Bio-Medical Engineering* 40.10 (1993), pp. 1019–1023.

[132] Rami N. Khushaba et al. "Towards Limb Position Invariant Myoelectric Pattern Recognition Using Time-Dependent Spectral Features." In: *Neural Networks: The Official Journal of the International Neural Network Society* 55 (2014), pp. 42–58.

[133] Ali H. Al-Timemy et al. "Improving the Performance Against Force Variation of EMG Controlled Multifunctional Upper-Limb Prostheses for Transradial Amputees." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 24.6 (2016), pp. 650–661.

[134] Joseph L. Betthauser et al. "Limb Position Tolerant Pattern Recognition for Myoelectric Prosthesis Control With Adaptive Sparse Representations From Extreme Learning." In: *IEEE Transactions on Bio-Medical Engineering* 65.4 (2018), pp. 770–778.

[135] A Fougner et al. "Resolving the Limb Position Effect in Myoelectric." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* (2011), pp. 1–8.

[136] Liang Chen, Yanjuan Geng, and Guanglin Li. "Effect of Upper-Limb Positions on Motion Pattern Recognition Using Electromyography." In: *2011 4th International Congress on Image and Signal Processing*. 2011 4th International Congress on Image and Signal Processing. Vol. 1. 2011, pp. 139–142.

[137] Yanjuan Geng, Ping Zhou, and Guanglin Li. "Toward Attenuating the Impact of Arm Positions on Electromyography Pattern-Recognition Based Motion Classification in Transradial Amputees." In: *Journal of NeuroEngineering and Rehabilitation* 9.1 (2012), pp. 1–11.

[138] Liang Peng et al. "Combined Use of sEMG and Accelerometer in Hand Motion Classification Considering Forearm Rotation." In: *Conference Proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*. Vol. 2013. Ieee, 2013, pp. 4227–4230.

[139] Rami N. Khushaba et al. “Combined Influence of Forearm Orientation and Muscular Contraction on EMG Pattern Recognition.” In: *Expert Systems With Applications* 61 (2016), pp. 154–161.

[140] Han-Jeong Hwang, Janne Mathias Hahne, and Klaus-Robert Müller. “Real-Time Robustness Evaluation of Regression Based Myoelectric Control Against Arm Position Change and Donning/Doffing.” In: *Plos One* 12.11 (2017). Ed. by Yih-Kuen Jan, e0186318.

[141] E. Scheme, K. Biron, and K. Englehart. “Improving Myoelectric Pattern Recognition Positional Robustness Using Advanced Training Protocols.” In: *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. Ieee, 2011.

[142] Ashkan Radmand, Erik Scheme, and Kevin Englehart. “On the Suitability of Integrating Accelerometry Data With Electromyography Signals for Resolving the Effect of Changes in Limb Position During Dynamic Limb Movement.” In: *JPO: Journal of Prosthetics and Orthotics* 26.4 (2014), p. 185.

[143] Richard B. Woodward and Levi J. Hargrove. “Adapting Myoelectric Control in Real-Time Using a Virtual Environment.” In: *Journal of NeuroEngineering and Rehabilitation* 16.1 (2019).

[144] Claudio Castellini et al. “Upper-Limb Prosthetic Myocontrol: Two Recommendations.” In: *Frontiers in Neuroscience* 9 (Jan 2016), p. 496.

[145] Ann M. Simon, Blair A. Lock, and Kathy A. Stubblefield. “Patient Training for Functional Use of Pattern Recognition–controlled Prostheses.” In: *Journal of Prosthetics and Orthotics : JPO* 24.2 (2012), pp. 56–64.

[146] Daisuke Nishikawa et al. “On-Line Learning Based Electromyogram to Forearm Motion Classifier With Motor Skill Evaluation.” In: *JSME International Journal Series C* 43.4 (2000), pp. 906–915.

[147] Coapt. *Coapt Pattern Recognition*. Coapt Myo Pattern Recognition. 2023. URL: `https://coaptengineering.com/pattern-recognition` (visited on 05/17/2023).

[148] Ottobock. *MyoPlus Pattern Recognition*. 2023. URL: `https://www.ottobock.com/en-au/Prosthetics/UpperLimb%5C_MyoPlus` (visited on 05/17/2023).

[149] Blair A. Lock et al. “Prosthesis-Guided Training for Practical Use of Pattern Recognition Control of Prostheses.” In: (2011).

[150] Evan Campbell, Angkoon Phinyomark, and Erik Scheme. “Deep Cross-User Models Reduce the Training Burden in Myoelectric Control.” In: *Frontiers in Neuroscience* 15 (2021).

[151] Ning Jiang et al. “Myoelectric Control of Artificial Limbs–Is There a Need to Change Focus?” In: *IEEE Signal Processing Magazine* 29.5 (2012), pp. 152–150.

[152] Markus Nowak, Claudio Castellini, and Carlo Massironi. “Applying Radical Constructivism to Machine Learning: A Pilot Study in Assistive Robotics.” In: *Constructivist Foundations* 13.2 (2018), pp. 250–262.

[153] Xinpu Chen, Dingguo Zhang, and Xiangyang Zhu. “Application of a Self-Enhancing Classification Method to Electromyography Pattern Recognition for Multifunctional Prosthesis Control.” In: *Journal of NeuroEngineering and Rehabilitation* 10.1 (2013), pp. 1–13.

[154] Xiaolong Zhai et al. “Self-Recalibrating Surface EMG Pattern Recognition for Neuroprosthesis Control Based on Convolutional Neural Network.” In: *Frontiers in Neuroscience* 11 (Jul 2017), pp. 1–11.

[155] Ulysse Cote-Allard et al. “Unsupervised Domain Adversarial Self-Calibration for Electromyography-Based Gesture Recognition.” In: *IEEE Access: Practical Innovations, Open Solutions* 8 (2020), pp. 177941–177955.

[156] Katarzyna Szymaniak, Agamemnon Krasoulis, and Kianoush Nazarpour. “Recalibration of Myoelectric Control With Active Learning.” In: *Frontiers in Neurorobotics* 16 (2022), p. 1061201.

[157] Tianzhe Bao et al. “Toward Robust, Adaptive and Reliable Upper-Limb Motion Estimation Using Machine Learning and Deep Learning–A Survey in Myoelectric Control.” In: *IEEE Journal of Biomedical and Health Informatics* 26.8 (2022), pp. 3822–3835.

[158] Jacob L. Segil et al. “A Myoelectric Postural Control Algorithm for Persons With Transradial Amputations: A Consideration of Clinical Readiness.” In: *IEEE Robotics & Automation Magazine* 27.1 (2020), pp. 77–86.

[159] Mark Ison et al. “High-Density Electromyography and Motor Skill Learning for Robust Long-Term Control of a 7-DoF Robot Arm.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 24.4 (2016), pp. 424–433.

[160] Mark Ison and Panagiotis Artemiadis. “Proportional Myoelectric Control of Robots: Muscle Synergy Development Drives Performance Enhancement, Retainment, and Generalization.” In: *IEEE Transactions on Robotics: A Publication of the IEEE Robotics and Automation Society* 31.2 (2015), pp. 259–268.

[161] Kristine M. Mosier et al. “Remapping Hand Movements in a Novel Geometrical Environment.” In: *Journal of Neurophysiology* 94.6 (2005), pp. 4362–4372.

[162] Chris Wilson Antuvan, Mark Ison, and Panagiotis Artemiadis. "Embedded Human Control of Robots Using Myoelectric Interfaces." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22.4 (2014), pp. 820–827.

[163] Saritha M. Radhakrishnan, Stuart N. Baker, and Andrew Jackson. "Learning a Novel Myoelectric-Controlled Interface Task." In: *Journal of Neurophysiology* 100.4 (2008), pp. 2397–2408.

[164] Ferdinando A. Mussa-Ivaldi et al. "Sensory Motor Remapping of Space in Human-Machine Interfaces." In: *Progress in Brain Research* 191 (2011), pp. 45–64.

[165] Matthew Dyson et al. "Learning, Generalization, and Scalability of Abstract Myoelectric Control." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 28.7 (2020), pp. 1539–1547.

[166] Hunter R. Schone et al. "Should Bionic Limb Control Mimic the Human Body? Impact of Control Strategy on Bionic Hand Skill Learning." In: (8, 2023).

[167] Silvia Muceli, Ning Jiang, and Dario Farina. "Extracting Signals Robust to Electrode Number and Shift for Online Simultaneous and Proportional Myoelectric Control by Factorization Algorithms." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22.3 (2014), pp. 623–633.

[168] Kianoush Nazarpour, Amy Barnard, and Andrew Jackson. "Flexible Cortical Control of Task-Specific Muscle Synergies." In: *The Journal of Neuroscience* 32.36 (5, 2012), pp. 12349–12360.

[169] Matthew Dyson, Jennifer Olsen, and Kianoush Nazarpour. "A Home-Based Myoelectric Training System For Children." In: *Myoelectric Controls Symposium* (23, 2020).

[170] Ning Jiang et al. "Intuitive, Online, Simultaneous, and Proportional Myoelectric Control Over Two Degrees-of-Freedom in Upper Limb Amputees." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 22.3 (2014), pp. 501–510.

[171] Pyungkang Kim, Kyung-Soo Kim, and Soohyun Kim. "Modified Nonnegative Matrix Factorization Using the Hadamard Product to Estimate Real-Time Continuous Finger-Motion Intentions." In: *IEEE Transactions on Human-Machine Systems* 47.6 (2017), pp. 1089–1099.

[172] Dapeng Yang et al. "Simultaneous Estimation of 2-Dof Wrist Movements Based on Constrained Non-Negative Matrix Factorization and Hadamard Product." In: *Biomedical Signal Processing and Control* 56 (1, 2020), p. 101729.

[173] John J. Dudley and Per Ola Kristensson. "A Review of User Interface Design for Interactive Machine Learning." In: *ACM Transactions on Interactive Intelligent Systems* 8.2 (13, 2018), 8:1–8:37.

[174] Eduardo Mosqueira-Rey et al. "Human in the Loop Machine Learning: A State of the Art." In: *Artificial Intelligence Review* 56.4 (1, 2023), pp. 3005–3054.

[175] Michael Zbyszynski, Balandino Di Donato, and Atau Tanaka. "The Effect of Co-Adaptive Learning & Feedback in Interactive Machine Learning." In: (4, 2019).

[176] Jan Saputra Müller et al. "A Mathematical Model for the Two-Learners Problem." In: *Journal of Neural Engineering* 14.3 (2017), p. 036005.

[177] Jiayuan He et al. "User Adaptation in Long-Term, Open-Loop Myoelectric Training: Implications for EMG Pattern Recognition in Prosthesis Control." In: *Journal of Neural Engineering* 12.4 (2015), p. 046005.

[178] Hiroshi Yokoi et al. "Mutual Adaptation in a Prosthetics Application." In: *Embodied Artificial Intelligence: International Seminar, Dagstuhl Castle, Germany, July 7-11, 2003. Revised Papers*. Ed. by Fumiya Iida et al. Berlin, Heidelberg: Springer, 2004, pp. 146–159.

[179] Malcolm Ware et al. "Interactive Machine Learning: Letting Users Build Classifiers." In: *International Journal of Human-Computer Studies* 55.3 (2001), pp. 281–292.

[180] Saleema Amershi et al. "Power to the People: The Role of Humans in Interactive Machine Learning." In: *AI Magazine* 35.4 (22, 2014), pp. 105–120.

[181] Andreas Holzinger. "Interactive Machine Learning for Health Informatics: When Do We Need the Human-in-the-Loop?" In: *Brain Informatics* 3.2 (1, 2016), pp. 119–131.

[182] Marina M.-C. Vidovic et al. "Improving the Robustness of Myoelectric Pattern Recognition for Upper Limb Prostheses by Covariate Shift Adaptation." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 24.9 (2016), pp. 961–970.

[183] Ilaria Strazzulla et al. "Online Bimanual Manipulation Using Surface Electromyography and Incremental Learning." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 25.3 (2017), pp. 227–234.

[184] Dennis Yeung, Dario Farina, and Ivan Vujaklija. "Directional Forgetting for Stable Co-Adaptation in Myoelectric Control." In: *Sensors (Switzerland)* 19.9 (2019), p. 2203.

[185] Jie Liu. "Adaptive Myoelectric Pattern Recognition Toward Improved Multifunctional Prosthesis Control." In: *Medical Engineering & Physics* 37.4 (2015), pp. 424–430.

[186] Dalia De Santis. "A Framework for Optimizing Co-Adaptation in Body-Machine Interfaces." In: *Frontiers in Neurorobotics* 15 (2021).

[187] M Couraud et al. "Model and Experiments to Optimize Co-Adaptation in a Simplified Myoelectric Control System." In: *Journal of Neural Engineering* 15.2 (1, 2018), p. 026006.

[188] Linda Resnik. "Development and Testing of New Upper-Limb Prosthetic Devices: Research Designs for Usability Testing." In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), p. 697.

[189] Sophie Wang et al. "Evaluation of Performance-Based Outcome Measures for the Upper Limb: A Comprehensive Narrative Review." In: *PM & R: The Journal of Injury, Function, and Rehabilitation* 10.9 (2018), 951–962.e3.

[190] Manfredo Atzori et al. "Building the Ninapro Database: A Resource for the Biorobotics Community." In: *2012 4th IEEE RAS &Amp EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*. Rome, Italy: Ieee, 2012, pp. 1258–1265.

[191] Matteo Cognolato et al. "Gaze, Visual, Myoelectric, and Inertial Data of Grasps for Intelligent Prosthetics." In: *Scientific Data* 7.1 (2020), p. 43.

[192] Jena L. Nawfel, Kevin B. Englehart, and Erik J. Scheme. "A Multi-Variate Approach to Predicting Myoelectric Control Usability." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29 (2021), pp. 1312–1327.

[193] Blair Lock, Kevin Englehart, and Bernard Hudgins. "Real-Time Myoelectric Control in a Virtual Environment to Relate Usability vs. Accuracy." In: *Proceedings of the 2005 MES Symposium*. MyoElectric Controls/Powered Prosthetics Symposium. Fredericton, 2005.

[194] Max Ortiz-Catalan et al. "Offline Accuracy: A Potentially Misleading Metric in Myoelectric Pattern Recognition for Prosthetic Control." In: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference* 2015 (2015), pp. 1140–1143.

[195] Ivan Vujaklija et al. "Translating Research on Myoelectric Control Into Clinics–Are the Performance Assessment Methods Adequate?" In: *Frontiers in Neurorobotics* 11 (14, 2017), p. 7.

[196] Peter J. Kyberd. “Outcome Measures.” In: *Bionic Limb Reconstruction*. Ed. by Oskar C. Aszmann and Dario Farina. Cham: Springer International Publishing, 2021, pp. 57–74.

[197] Ann M. Simon et al. “Target Achievement Control Test: Evaluating Real-Time Myoelectric Pattern-Recognition Control of Multifunctional Upper-Limb Prostheses.” In: *The Journal of Rehabilitation Research and Development* 48.6 (2011), pp. 619–627.

[198] Erik J. Scheme and Englehart. “Validation of a Selective Ensemble-Based Classification Scheme for Myoelectric Control Using a Three-Dimensional Fitts’ Law Test.” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 21.4 (2013), pp. 616–623.

[199] Annette Hagengruber et al. “Electromyography for Teleoperated Tasks in Weightlessness.” In: *IEEE Transactions on Human-Machine Systems* 51.2 (2021), pp. 130–140.

[200] J. Desrosiers et al. “Validation of the Box and Block Test as a Measure of Dexterity of Elderly People: Reliability, Validity, and Norms Studies.” In: *Archives of Physical Medicine and Rehabilitation* 75.7 (1994), pp. 751–755.

[201] Peter Kyberd, Ali Hussaini, and Ghislain Maillet. “Characterisation of the Clothespin Relocation Test as a Functional Assessment Tool.” In: *Journal of Rehabilitation and Assistive Technologies Engineering* 5 (2018), p. 2055668317750810.

[202] Colin M. Light, Paul H. Chappell, and Peter J. Kyberd. “Establishing a Standardized Clinical Assessment Tool of Pathologic and Prosthetic Hand Function: Normative Data, Reliability, and Validity.” In: *Archives of Physical Medicine and Rehabilitation* 83.6 (2002), pp. 776–783.

[203] Liselotte M. Hermansson et al. “Assessment of Capacity for Myoelectric Control : A New Rasch-Built Measure of Prosthetic Hand Control.” In: *Journal of Rehabilitation Medicine* 37.3 (2005), pp. 166–71.

[204] Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. *A Bi-Manual Evaluation Setup for Upper Limb Prostheses in Real-Life Settings*. 2019.

[205] Morten B. Kristoffersen et al. “Should Hands Be Restricted When Measuring Able-Bodied Participants to Evaluate Machine Learning Controlled Prosthetic Hands?” In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering: A Publication of the IEEE Engineering in Medicine and Biology Society* 28.9 (2020), pp. 1977–1983.

[206] Alix Chadwell et al. "Technology for Monitoring Everyday Prosthesis Use: A Systematic Review." In: *Journal of NeuroEngineering and Rehabilitation* 17.1 (14, 2020), p. 93.

[207] A. Chadwell et al. "Upper Limb Activity in Myoelectric Prosthesis Users Is Biased Towards the Intact Limb and Appears Unrelated to Goal-Directed Task Performance." In: *Scientific Reports* 8.1 (2018), p. 11084.

[208] Philipp Beckerle et al. "Feel-Good Robotics: Requirements on Touch for Embodiment in Assistive Robotics." In: *Frontiers in Neurorobotics* 12 (2018).

[209] A. Radmand, E. Scheme, and K. Englehart. "A Characterization of the Effect of Limb Position on EMG Features to Guide the Development of Effective Prosthetic Control Schemes." In: *Conference Proceedings: ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*. Vol. 2014. Ieee, 2014, pp. 662–667.

[210] Yuni Teh and Levi J. Hargrove. "Understanding Limb Position and External Load Effects on Real-Time Pattern Recognition Control in Amputees." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 28.7 (2020), pp. 1605–1613.

[211] Muhammad Raza Ul Islam and Shaoping Bai. "Effective Multi-Mode Grasping Assistance Control of a Soft Hand Exoskeleton Using Force Myography." In: *Frontiers in Robotics and AI* 7 (16, 2020), p. 567491.

[212] Markus Nowak et al. "Simultaneous and proportional real-time myocontrol of up to three degrees of freedom of the wrist and hand." In: *IEEE transactions on bio-medical engineering* 70.2 (2023), pp. 459–469.

[213] Aaron J. Young et al. "A Comparison of the Real-Time Controllability of Pattern Recognition to Conventional Myoelectric Control for Discrete and Simultaneous Movements." In: *Journal of NeuroEngineering and Rehabilitation* 11.1 (10, 2014), p. 5.

[214] Mark A. Guadagnoli and Timothy D. Lee. "Challenge Point: A Framework for Conceptualizing the Effects of Various Practice Conditions in Motor Learning." In: *Journal of Motor Behavior* 36.2 (1, 2004), pp. 212–224.

[215] Sangsoo Park and Graham E. Caldwell. "Muscle Synergies Are Modified With Improved Task Performance in Skill Learning." In: *Human Movement Science* 83 (2022), p. 102946.

[216] Gang Seo et al. "Developing New Intermuscular Coordination Patterns Through an Electromyographic Signal-Guided Training in the Upper Extremity." In: *Journal of NeuroEngineering and Rehabilitation* 20.1 (1, 2023), p. 112.

[217] Seyed A. Safavynia, Gelsy Torres-Oviedo, and Lena H. Ting. "Muscle Synergies: Implications for Clinical Evaluation and Rehabilitation of Movement." In: *Topics in Spinal Cord Injury Rehabilitation* 17.1 (2011), pp. 16–24.

[218] Markus Nowak et al. "Simultaneous assessment and training of an upper-limb amputee using incremental machine-learning-based myocontrol: a single-case experimental design." In: *Journal of NeuroEngineering and Rehabilitation* 20.1 (2023), p. 39.

[219] Gustavo Balbinot et al. "Properties of the Surface Electromyogram Following Traumatic Spinal Cord Injury: A Scoping Review." In: *Journal of NeuroEngineering and Rehabilitation* 18.1 (29, 2021), p. 105.

[220] Yoon No Gregory Hong et al. "Are Muscle Synergies Useful for Stroke Rehabilitation?" In: *Current Opinion in Biomedical Engineering* 19 (1, 2021), p. 100315.

[221] Yixuan Sheng et al. "Upper Limb Motor Function Quantification in Post-Stroke Rehabilitation Using Muscle Synergy Space Model." In: *IEEE Transactions on Biomedical Engineering* 69.10 (2022), pp. 3119–3130.

[222] Wearable Devices LTD. *Muda Band: Touch Free Control for Apple Watch.* 2023. URL: `https://www.mudra-band.com/` (visited on 11/13/2023).

[223] Qi Wang et al. "Embedded Ultrasonic Transducers." U.S. pat. 20230099288a1. Apple Inc. 30, 2023.

[224] Zhicheng Teng et al. "Evaluation of Synergy-Based Hand Gesture Recognition Method Against Force Variation for Robust Myoelectric Control." In: *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 29 (2021), pp. 2345–2354.

[225] Ivan Vujaklija et al. "Online Mapping of EMG Signals Into Kinematics by Autoencoding." In: *Journal of NeuroEngineering and Rehabilitation* 15.1 (2018), pp. 1–9.

[226] Kristin Østlie et al. "Prosthesis Use in Adult Acquired Major Upper-Limb Amputees: Patterns of Wear, Prosthetic Skills and the Actual Use of Prostheses in Activities of Daily Life." In: *Disability and Rehabilitation: Assistive Technology* 7.6 (2012), pp. 479–493.

[227] Lian Cheng et al. "Recent Advances in Flexible Noninvasive Electrodes for Surface Electromyography Acquisition." In: *NPJ Flexible Electronics* 7.1 (16, 2023), pp. 1–26.

[228] P. Geethanjali. “Comparative Study of PCA in Classification of Multichannel EMG Signals.” In: *Australasian Physical & Engineering Sciences in Medicine / Supported by the Australasian College of Physical Scientists in Medicine and the Australasian Association of Physical Sciences in Medicine* 38.2 (2015), pp. 331–343.

[229] Mathilde Connan et al. “Learning to Teleoperate an Upper-Limb Assistive Humanoid Robot for Bimanual Daily-Living Tasks.” In: *Biomedical Physics &Amp Engineering Express* 8.1 (1, 2022), p. 015022.

[230] Christian Nissler et al. “VITA–an Everyday Virtual Reality Setup for Prosthetics and Upper-Limb Rehabilitation.” In: *Journal of Neural Engineering* 16.2 (1, 2019), p. 026039.

Appendix: Full Text of the Supporting Publications

A1 Merits of Dynamic Data Acquisition

Title: The Merits of Dynamic Data Acquisition for Realistic Myocontrol.
Authors: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini.
Journal: Frontiers in Bioengineering and Biotechnology.
Manuscript version: Published article.

Citation: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. "The Merits of Dynamic Data Acquisition for Realistic Myocontrol." In: *Frontiers in Bioengineering and Biotechnology* 8 (April 2020), pp. 1–20.

frontiers
in Bioengineering and Biotechnology

ORIGINAL RESEARCH
published: 30 April 2020
doi: 10.3389/fbioe.2020.00361

The Merits of Dynamic Data Acquisition for Realistic Myocontrol

Andrea Gigli[1], Arjan Gijsberts[2] and Claudio Castellini[1]*

[1] Institute of Robotics and Mechatronics, German Aerospace Center (DLR), Weßling, Germany, [2] Vandal Laboratory, Istituto Italiano di Tecnologia, Genoa, Italy

Natural myocontrol is the intuitive control of a prosthetic limb via the user's voluntary muscular activations. This type of control is usually implemented by means of pattern recognition, which uses a set of training data to create a model that can decipher these muscular activations. A consequence of this approach is that the reliability of a myocontrol system depends on how representative this training data is for all types of signal variability that may be encountered when the amputee puts the prosthesis into real use. Myoelectric signals are indeed known to vary according to the position and orientation of the limb, among other factors, which is why it has become common practice to take this variability into account by acquiring training data in multiple body postures. To shed further light on this problem, we compare two ways of collecting data: while the subjects hold their limb statically in several positions one at a time, which is the traditional way, or while they dynamically move their limb at a constant pace through those same positions. Since our interest is to investigate any differences when controlling an actual prosthetic device, we defined an evaluation protocol that consisted of a series of complex, bimanual daily-living tasks. Fourteen intact participants performed these tasks while wearing prosthetic hands mounted on splints, which were controlled via either a statically or dynamically built myocontrol model. In both cases all subjects managed to complete all tasks and participants without previous experience in myoelectric control manifested a significant learning effect; moreover, there was no significant difference in the task completion times achieved with either model. When evaluated in a simulated scenario with traditional offline performance evaluation, on the other hand, the dynamically-trained system showed significantly better accuracy. Regardless of the setting, the dynamic data acquisition was faster, less tiresome, and better accepted by the users. We conclude that dynamic data acquisition is advantageous and confirm the limited relevance of offline analyses for online myocontrol performance.

Keywords: myoelectric control, prosthetic hand, dynamic data acquisition, limb position effect, performance assessment

OPEN ACCESS

Edited by:
Ivan Vujaklija, Aalto University, Finland

Reviewed by:
Cristina Piazza, Northwestern University, United States
Sigrid Dupan, Newcastle University, United Kingdom

***Correspondence:**
Andrea Gigli
andrea.gigli@dlr.de

Specialty section:
This article was submitted to Bionics and Biomimetics, a section of the journal Frontiers in Bioengineering and Biotechnology

Received: *16 December 2019*
Accepted: *31 March 2020*
Published: *30 April 2020*

Citation:
Gigli A, Gijsberts A and Castellini C (2020) The Merits of Dynamic Data Acquisition for Realistic Myocontrol. Front. Bioeng. Biotechnol. 8:361. doi: 10.3389/fbioe.2020.00361

1. INTRODUCTION

Upper-limb prosthetics, as a branch of assistive robotics, poses a number of challenges both to robotics and control experts (Vujaklija et al., 2016). A prosthesis is the paradigmatic wearable device since it must be worn during most of the user's daily life. A symbiotic use of such a device, and eventually its embodiment, requires unobtrusive and seamless control (Beckerle et al., 2018a,b; Castellini, 2020). Despite decades of research, such control has not yet been achieved and a widely clinically accepted upper-limb prosthesis has yet to come (Castellini et al., 2014). De facto, the problem consists of several sub-problems—the socket, the sensors, the mechatronics, the appearance, etc.—each one of which must be solved at the same time. Academic solutions, not tested on end-users or at least in realistic conditions, will have little or no impact on the life of disabled users. Upper-limb prosthetics is a deeply holistic problem.

We hereby focus on the myocontrol problem, which is the smooth, multi-DoF control of an upper-limb prosthesis by a user through her voluntary muscle activity. Seamlessly providing the right control commands to a dexterous prosthetic device is an open problem: control based upon biological signals, such as surface electromyography (sEMG) (Merletti et al., 2011), still suffers from clumsiness and unreliability. Although seriously criticized (Schweitzer et al., 2018), the academic solution of choice nowadays is that of collecting labeled biological data from a user engaged in a series of exemplary tasks. This data is then utilized to build a model that maps signals to commands. By the very nature of the approach, it entails that the initial data acquisition phase (of necessarily short duration) must cover the space of all possible muscle configurations that the user will enact in the future (Castellini, 2016). Among other reasons, this is complicated by the so-called *limb position effect* (Fougner et al., 2011; Scheme et al., 2011; Peng et al., 2013), which refers to the change in signals depending on the position and orientation of the limb.

To alleviate this problem, incremental learning and tighter user/prosthesis interaction are generally being studied to improve and complete the initial dataset on demand, while users perform their activities of daily living (ADLs). On the other hand, whenever incremental learning is not used, the limb position effect has been countered by extending the initial data acquisition to include the same action (e.g., a power grasp) carried out in several different postures (Fougner et al., 2011; Geng et al., 2012; Peng et al., 2013; Betthauser et al., 2018). Although this strategy can be effective, it comes at the cost of a considerably longer and more tiresome data acquisition. There have been efforts to limit this increase in acquisition time by replacing a static posture in multiple positions with a single dynamic movement that passes through these positions. For instance, Scheme et al. (2011) have shown that a dynamic protocol not only sped up data acquisition but also improved offline recognition rates during simulated manipulation tasks (e.g., moving an object). An issue with this evaluation is that offline performance is only weakly related to online controllability (Lock et al., 2005; Jiang et al., 2014; Ortiz-Catalan et al., 2015; Hahne et al., 2017; Krasoulis et al., 2019). One of the reasons is that it fails to capture the natural corrections that prosthetic users undertake in response to myocontrol inaccuracies (Hahne et al., 2017).

Recent studies have shown increasing efforts into testing the effects of the data acquisition on realtime myocontrol. Batzianoulis et al. (2018) verified that dynamic training data collected during the reach-to-grasp phase of the prehension improved myocontrol stability during an online pick-and-place task. Similarly, Yang et al. (2017a) and Woodward and Hargrove (2019) acquired training sEMG data while moving the arm and tested the resulting myocontrol models by engaging the participants in online tests derived from, respectively, the target achievement control and the box-and-blocks tests. Both studies confirmed that the performance of myocontrol in online settings improves when the training data is acquired while changing the arm configuration rather than keeping the arm steady in one position. However, none of the studies clarified whether the improved performance was due to recording the dynamic movement of the arm or merely due to the inclusion of more arm poses. The latter study, moreover, also included multiple levels of muscle contractions in the data acquisition, making it impossible to determine the relative contribution of varying the arm position and muscular contraction. More importantly, none of the described performance assessment tests seems to reflect the complexity of everyday actions, since the target achievement control does not involve interactions with real objects, while the box-and-blocks requires performing only one stable grasp in a very limited portion of the user's reachable space. Therefore, it remains unclear if the claimed benefits materialize during complex and realistic ADLs.

In this work, we characterize the effects of the static and dynamic acquisition of training data on online myocontrol. In particular, we focus on the loss of controllability associated with variations of the limb position in *realistic daily-living settings*. We asked 14 able-bodied subjects to follow a static and a dynamic data acquisition protocol, while being fitted with two commercially available hand prostheses mounted on splints. With this equipment, and using a myocontrol model built with either statically or dynamically acquired data, they were required to perform a set of bimanual ADLs in a domestic-like laboratory setting. We intentionally employed a bilateral prosthetic setup and chose bimanual tasks to avoid the pitfall of subjects over-relying on their unaffected limb to execute the activities (Chadwell et al., 2018). Furthermore, this also ensures that our study applies equally to a teleoperation scenario.

This work extends the preliminary results we presented at a conference (Gigli et al., 2019) by including the results of a questionnaire, in which the participants evaluated the two data acquisition routines in terms of physical effort and achieved system controllability. Furthermore, we also characterize the learning effect that took place across the participants during the familiarization phase and contextualize the findings of our online experiments with those of previous studies conducted in offline settings. In the following, we thoroughly describe the experimental setup and protocol in section 2. The results of our experiment are presented in section 3. Further discussion and the conclusions are drawn in section 4.

2. MATERIALS AND METHODS

This study emphasizes the importance of a realistic online evaluation of myocontrol. For this reason, we have designed an experiment that involved subjects performing ADLs in a domestic environment, while using a pair of commercially available prosthetic hands. To compare our methodology with that of previous offline studies, we also reused the collected training data for a standard offline grasp recognition experiment. In the remainder of this section, we detail the experimental setup and protocol, the evaluation measures of the online experiment, and the design of the offline analysis.

2.1. Participants

Fourteen able-bodied subjects (age 27.9 ± 5.8 years, 10 men and 4 women) were recruited to participate in the experiment. All of them were in good health and none of them had a previous history of disorders that might have influenced the experiment. Four of the participants had prior experience in myocontrol, gained during previous studies, while the others were completely naive to myocontrol. Before the experiment, the subjects received an oral and written description of the experiment and signed an informed consent form. The study was conducted at the German Aerospace Center (DLR) according to the WMA Declaration of Helsinki and approved by DLR's internal committee for personal data protection.

2.2. Experimental Setup

Each subject wore a *Myo* armband[1] by Thalmic Labs on both forearms about 5 cm below the elbow. This bracelet contains 8 uniformly spaced sensors, each of which records an sEMG signal at a sampling rate of up to 200 Hz. An orthotic hand/wrist splint was used to hold an *i-LIMB™ Revolution* prosthetic hand[2] by Touch Bionics at the extremity of either forearm. **Figure 1A** depicts the described hardware. The i-LIMB Revolution comprises six motors under direct independent current control, permitting flexion/extension of each of the five fingers plus abduction/adduction of the thumb. All devices communicated via a serial-port-over-Bluetooth with a laptop that ran the intent detection system. Software on this laptop also guided subjects during data collection, processed the data, trained and ran the controller of each prosthesis. In this manner, an unobtrusive, realistic bimanual prosthetic manipulation setup was implemented, which could be used by unimpaired subjects.

The experiment was conducted in a domestic-like environment, which included some common household objects, two tables, a clothesline, and a system of three shelves. The shelves were placed at a height of 40 cm, 100 cm, and 150 cm. The dining table and the clothesline were placed on the two sides of the shelves. The second table was 2 m away from the clothesline. Certain objects needed some minor modifications to be grasped by the prosthetic hands. The handles of some cutlery, a clothes hanger, and the extremities of small clothespins were padded to grasp them more easily. The study was videotaped for offline performance assessment. An overview of the setup and the environment is shown in **Figure 1B**.

2.3. Data Processing and Training

A custom software suite written in the C# and Python languages was used to acquire, process, and label the input data. The signal from each sEMG channel was rectified, computing its absolute value, and low-pass filtered with a second-order Butterworth filter with a cut-off frequency of 1 Hz. These signals and labels were passed to two instances of non-linear Ridge Regression, one per arm, which were trained with the data of the respective limb. The resulting models mapped sEMG signals onto torque commands for the motors of the prosthetic hands. In its canonical form, Ridge Regression (RR) predicts outputs via a linear model

$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x}, \tag{1}$$

where $\mathbf{w}$ is a vector of scalar weights obtained by minimizing

$$\min_{\mathbf{w}} \sum_{i=1}^{N} \left(y_i - f(\mathbf{x}_i)\right)^2 + \lambda \left\|\mathbf{w}\right\|^2 \tag{2}$$

over a training set of labeled samples $\left\{(\mathbf{x}_i, y_i)\right\}_1^N$. The term $\|\mathbf{w}\|^2$ penalizes the complexity of the model and its importance relative to minimizing the squared residuals is controlled via the non-negative hyperparameter λ. In the present work, we use a variant of RR that achieves non-linearity by mapping the feature vectors into a high-dimensional representation using so-called Random Fourier Features (RFFs) (Rahimi and Recht, 2008). A detailed treatment of RFF-RR and its use in myocontrol is given in Gijsberts et al. (2014). The prediction function of RFF-RR is written as

$$f(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}), \tag{3}$$

where ϕ is the finite D-dimensional RFF mapping, which consists of cosines weighted through randomly-sampled frequencies. Without going into details, an appealing property of this mapping is that it approximates a Gaussian kernel without incurring the typical computational overhead of actually using that kernel (Rahimi and Recht, 2008), provided that the chosen mapping dimensionality D is sufficiently high. The formulation of RFF-RR allows fast training of the model and computation of new predictions, can be made incremental, and is bounded in space (Gijsberts and Metta, 2011), which makes it suitable for realtime myocontrol. Strazzulla et al. (2017), in fact, already used an incremental version of RFF-RR for online bimanual manipulation.

The regularization parameter λ of each regressor was set to 1, while the bandwidth γ and the dimensionality D of the RFF mapping to 0.5 and 300, respectively. This regression setup allowed the simultaneous and proportional control of the degrees of freedom (DoFs) of each prosthesis.

2.4. Experimental Protocol

The participants donned the prosthetic system, i.e., the sEMG armbands and the prosthetic hands, at the beginning of the experiment, and no doffing or adjustment of the sensors was permitted afterward. This was necessary to isolate the effect of limb position variations from those of other confounding factors, such as the electrode shift.

All subjects in the study tested both the static and dynamic data acquisition protocols. After each data acquisition, the system was trained and the participants were asked to perform a sequence of bimanual activities. This sequence was repeated

[1] https://support.getmyo.com/hc/en-us/articles/203398347-Getting-started-with-your-Myo-armband
[2] https://www.ossur.com/en-us/prosthetics/arms/i-limb-ultra

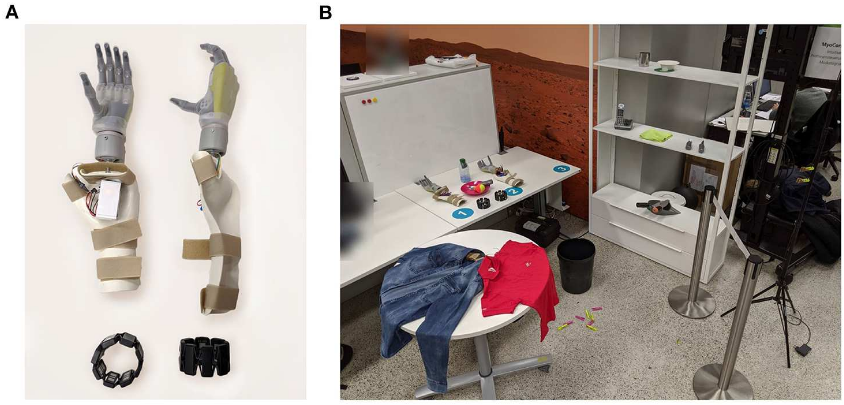


FIGURE 1 | Experimental setup. **(A)** The bimanual prosthetic system consisted of two Myo armbands for sEMG measurement and two Touch Bionics i-Limb Ultra prosthetic hands mounted on orthotic splints. **(B)** The experiment took place in a domestic-like laboratory setting. Tableware, clothes, and other common objects were laid on two tables, three shelves, or on the floor. A clothesline and a vertical support for clothespins were placed next to the shelves.

TABLE 1 | Experiment organization.

Phase#	Description
1	Collect training data using the first acquisition procedure
2	Familiarize on bimanual ADLs
	Measure performance on bimanual ADLs
3	Collect training data using the other acquisition procedure
4	Familiarize on bimanual ADLs
	Measure performance on bimanual ADLs

twice: the first time to let them familiarize themselves with the prosthetic control, the second time to measure their performance. These four segments of the experiment are reported in **Table 1**. To counterbalance any learning effects, we inverted the order of the acquisition types for half of the subjects: seven randomly selected subjects started with the static acquisition protocol, while the remaining subjects started with the dynamic acquisition protocol.

2.4.1. Data Acquisition

In each data acquisition routine, the participants performed some predefined combinations of grasps and arm postures. After receiving a detailed description of the routines, the participants tried them under the supervision of the experimenter. Then, the experimenter guided them throughout the acquisition procedure, supported by acoustic signals from the acquisition software. This helped to ensure that all subjects performed the same arm configurations and movements. We opted for such direct guidance because the participants did not manage to precisely follow a videotaped execution of the acquisition protocol in preliminary trials. The desired grasp types were chosen based on their relevance in ADLs according to the literature (Wang et al., 2018) and proved to be sufficient to execute our evaluation protocol during preliminary tests. We selected a resting posture, a power grasp, and a pointing posture with the index finger. Since our myocontrol approach was based on proportional control and thus regression, the model was not trained to distinguish these three grasp classes from one another, but rather to predict the corresponding hand configurations in terms of the degree of flexion of each finger. While the participants were performing the grasps during the acquisition phase, the laptop collected the related sEMG samples and labeled them based on whether or not a given DoF was activated in those configurations. In the case of index pointing, the system would record a 0 for the index finger (i.e., no flexion) and 1 for all other DoFs (i.e., flexion). The resting posture consisted of all 0 (all fingers extended), whereas the configuration for the power grasp contained all 1 (all fingers flexed). We intentionally avoided capturing intermediate activation values to avoid the inevitable delay introduced by the subjects' reaction time and to keep the procedure as straightforward as possible for the subjects, which is particularly relevant when considering a possible application with amputees (Sierra González and Castellini, 2013). Moreover, it has been shown that training on binary activation values yields usable proportional control (Gijsberts et al., 2014; Meattini et al., 2019).

We chose a set of limb positions that evenly covered the subject's reachable space, that is, the space they could reach with their hands while standing straight. Since it is uncommon for both hands to be crossed in bimanual activities, we excluded the intersection of the reachable spaces of the left and right hands. To speed up data acquisition, every grasp had to be done with both hands simultaneously, with the arms always symmetric to the sagittal plane. Without loss of generality, we describe the data acquisition routine for one arm only.

2.4.2. Static Protocol

During static data acquisition, each grasp was repeated once for a finite set of arm configurations. Previous studies indicated that the robustness of pattern recognition based myocontrol to the

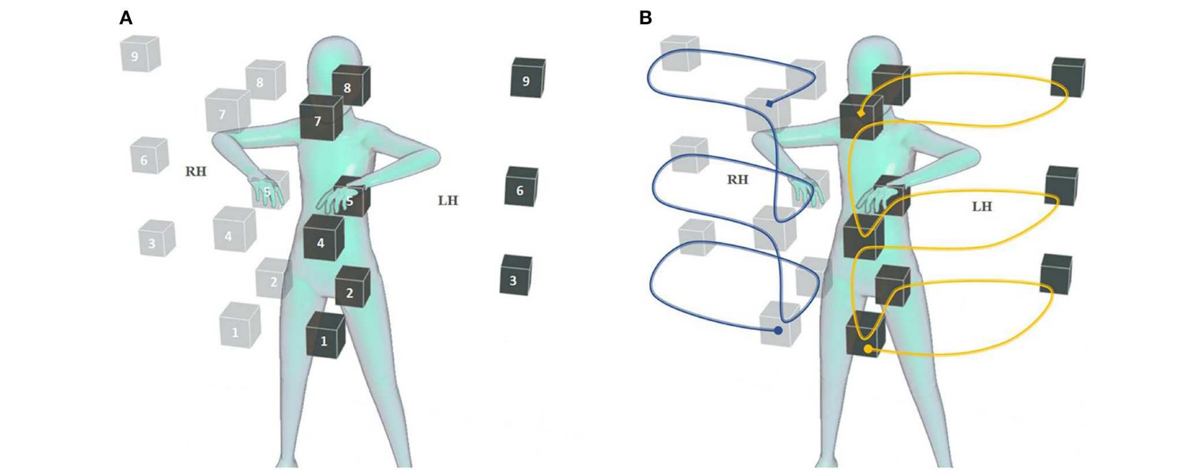


FIGURE 2 | Static and dynamic acquisition of training data. The positions occupied by the right and left hand during data acquisition are represented, respectively, by solid and transparent cubes. **(A)** Static data acquisition was performed repeating and holding the grasp in each position, first with the hand palm facing up, then facing down, for a total of 18 repetitions for each hand. **(B)** During dynamic data acquisition, the grasp was maintained while moving the hands in a trajectory that interpolated the static positions with uniform speed. The trajectory consisted of two halves, from the circle to the square and back; it was followed with the palms down in the first half, and up in the second half. Both data acquisition routines were performed while wearing the bimanual prosthetic system.

limb position effect relates to how well the training data cover the user's workspace in terms of reachable positions (Fougner et al., 2011; Radmand et al., 2014) and possible forearm rotations (Khushaba et al., 2016; Yang et al., 2017b). For this work, we selected 18 arm configurations that seemed to represent a good trade-off between a homogeneous sampling of the workspace and the duration of the resulting data acquisition. They corresponded to reaching nine positions with the hand, first with the palm facing down and then with the palm facing up (see **Figure 2A**). We defined these positions based on three height levels (waist, chest, head) and three relative distances from the trunk (close in front, far in front, far lateral). We believe that this definition favors the repeatability of the arm configuration across different subjects since it relates to one's own body rather than to external references. Each grasp was held in every position for 3 s, which was the lowest duration found in similar studies (Fougner et al., 2011; Radmand et al., 2014; Khushaba et al., 2016), and 4 s were allowed to move the arm from one configuration to the next. The acquisition of each grasp type took 126 s in total, 54 s to record data, and 72 s to reach the different arm configurations. In the case of fatigue, the participants were allowed to pause the routine and rest.

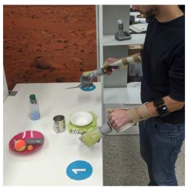
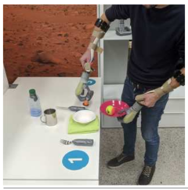
2.4.3. Dynamic Protocol

In the dynamic data acquisition, the subject performed the desired grasp type with both hands while moving the arms in a trajectory that interpolated the nine positions of static acquisition, as shown in **Figure 2B**. The movement started from the waist level with the palm down and proceeded upward, passing through all nine positions. Then the subject flipped the hand palm up and continued the movement backward until she returned to the starting position. This movement was repeated once for each grasp type, while the corresponding data was recorded. Its duration was chosen to be 27 s, exactly half the recording time of the static acquisition, and 4 s were allotted to prepare the following grasp. Even in this case, the participants could suspend the procedure to rest.

2.4.4. Activities of Daily Living

After processing the data and training the prosthesis controllers, we evaluated the system by having the subjects perform the bimanual ADLs that are described in **Table 2**. These activities were inspired by those found in assessment protocols for prosthetic users, such as ACMC (Hermansson et al., 2005) and SHAP (Kyberd et al., 2009), and for patients with motor impairments of the upper limbs, like CAHAI (Schuster et al., 2010) and the Clothespin relocation test (Hussaini and Kyberd, 2017). We preferred tasks that involved coordinated movements of the arms or walking and bending, as these were more susceptible to the limb position effect. The experimenter explained the tasks to the participants before the familiarization phase. Unless otherwise specified, participants could autonomously choose which grasp to use to carry out a certain task. For example, they could open the bottle cap by grabbing it or pushing its edge with the tip of their index finger. No constraint was imposed on task laterality, that is, which hand was to be used to perform a particular action. During pick and place tasks, the subjects could decide to move one or two objects at the same time depending on the amount of trust they had in the prostheses. The tasks proceeded without time limits and it was the subjects' responsibility to recover from errors, such as an accidental drop of an object. An exception was made for the last task where the experimenter replaced the clothespins anytime they were dropped on the floor.

TABLE 2 | Detailed description of the bimanual tasks in the performance evaluation phase.

Task	Name	Description
	Napkin	A napkin is placed on the middle shelf, unfolded. Take it, bring it to the dining table, and fold it twice.
	Table	A plate and a glass are laid out next to each other on the top shelf. Bring them to the dining table, put the plate on the folded napkin and the glass next to it. A fork and a knife are on the middle shelf. Bring them to the dining table and place them on the two sides of the plate. Move two objects at the same time if the prostheses seem reliable.
	Water	A bottle containing some fine gravel is on the dinner table. Pick it up with one hand, unscrew the cap with the other hand, pour the gravel into the glass, put the bottle back on the table with the cap next to it.
	Food	A spoon and two small balls with diameters of 3 and 6.5 cm are contained in a bowl that is placed on the dining table. Take the plate with one hand and the spoon with the other, then use the spoon to bring the balls from the bowl to the plate.
	Phone	A cordless phone is connected to its base station on the middle shelf. Take it with one hand, dial 9-1-1 with the index finger of the other hand, and then put the phone back in place.
	Sweep	A hand broom and a dustpan are positioned on the lower shelf, while some clothespins lie on the floor next to a trash bin. Take the broom with one hand and the dustpan with the other, walk to the clothespins, bend, and sweep the clothespins off the floor. Then empty the dustpan into the trash bin and bring the broom and dustpan back to their original location.
	Shirt	A dress shirt and a hanger are placed on the table. Use both hands to put the shirt on the hanger, then hang the hanger on the clothesline.

(Continued)

TABLE 2 | Continued

Task	Name	Description
	T-shirt	A t-shirt is positioned on a table and two clothespins are pinned to a vertical rod in front of the clothesline. Pick the t-shirt up with two hands, bring it to the clothesline, put it on the wire, and pin it with the clothespins.

2.5. Online Performance Evaluation

The effectiveness of the two data acquisition routines was evaluated quantitatively by measuring the completion time of the individual tasks during the performance test phase. Since we did not impose any time limits, the completion rate of the tasks was by definition 100%. At the end of the experiment, the participants were requested to fill in a questionnaire with two questions to qualitatively investigate potential differences between both acquisition types. The subjects were first asked to report how easy they found it to control the system on a visual analog scale ranging from "very difficult" to "very easy." Secondly, they had to quantify how comfortable it was to complete either data acquisition, on a similar visual analog scale from "very tiring" to "very comfortable." The effort made during data acquisition was also quantified indirectly by measuring the amount of time a subject requested to rest during data acquisition.

We expected to find differences in the task completion times and the perceived levels of fatigue associated with the two data acquisition routines. We used a two-tailed Wilcoxon signed-rank test to identify statistically significant differences between the average task completion times and the perceived fatigue of the two procedures. The choice of this test was based on the limited number of participants and the within-subject study design. The significance threshold was set to $\alpha = 0.05$.

2.6. Offline Grasp Prediction

To compare our methodology with related literature, we also conducted an offline analysis that reflects the study by Scheme et al. (2011). For every combination of subject, arm, and acquisition method, we partitioned the data of the acquisition phase in training and test sets. In the static case, we assigned the data of the odd-numbered of the 18 arm positions to the training set and the even-numbered ones to the test set. For the static case, which consisted of a continuous motion rather than a set of discrete positions, we approximated the same split by first dividing the entire data sequence into 18 parts of equal length. This particular split was chosen to minimize leakage from the test set to the training set due to temporal dependencies, while at the same time limiting the distribution shift between both sets.

Distinct RFF-RR models were trained for all four datasets (static and dynamic, left and right arm) of thirteen subjects, where we note that one subject was excluded from the offline analysis because the data had not been stored correctly. These models were trained in the same manner and with the same hyperparameters as for the online experiment. Their

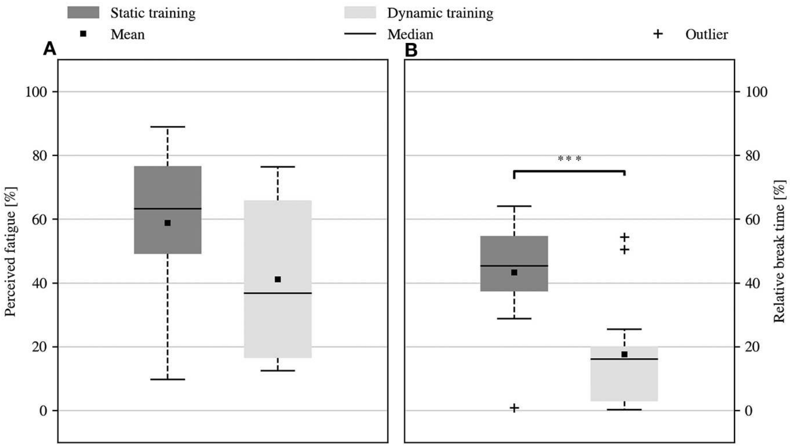


FIGURE 3 | Physical effort required by static and dynamic data acquisition. **(A)** Self-reported level of fatigue experienced during data acquisition. **(B)** Proportion of the data acquisition duration that was spent resting. The dynamic acquisition proved to be less tiring since it required significantly less break time (***$p < 0.001$). The outcome of the questionnaire seemed to confirm this result, but it was not supported by sufficient statistical evidence. The reduction of break time also allowed to collect dynamic data much faster than static data. In all the boxplots of this study, the rectangle indicates the range between the first and third quartiles, and the whiskers extend to the most extreme samples within the first and the third quartile $\mp$ 1.5 IQR. Samples outside this range are marked as outliers.

performance was then evaluated on the test set of the same type (e.g., static to static) as well as across acquisition types (e.g., static to dynamic). How well a model performed was quantified by averaging the unadjusted coefficient of determination R^2 obtained for the predicted activation levels of each DoF. The coefficient R^2 for one DoF is defined as

$$R^2(\mathbf{y}, \hat{\mathbf{y}}) = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \tag{4}$$

where $\hat{\mathbf{y}}$ is a vector of N predictions, $\mathbf{y}$ is the corresponding ground truth, and $\bar{y}$ is the average value of the ground truth.

3. EXPERIMENTAL RESULTS

We compared the two data acquisition procedures based on the physical effort of the participants, the time needed to complete the manipulation tasks using the resulting myocontrol models, and the perceived controllability of the prosthetic system. We then evaluated the effects of our methodology in offline settings to compare it with previous works in the field.

Figure 3 quantifies the physical effort needed to complete the data acquisition. The perceived level of fatigue was derived from how comfortable static and dynamic acquisition were evaluated in the questionnaire, by converting the answers into a percentage from 0% ("very comfortable") to 100% ("very tiring"). Additionally, since the subjects could suspend the data acquisition in case of weariness, a complementary metric of fatigue was obtained by measuring the proportion of acquisition time spent while resting. The subjects showed no agreement on which strategy required the least physical effort. Although the reported fatigue was lower for dynamic training, this result was not statistically significant (average level of fatigue of 58.9% vs. 41.1%, $p = 0.078$, $V = 81$). It must be noted, however, that dynamic training required significantly shorter break times (43.3% vs. 17.6% of the overall data acquisition duration on average, $p < 0.001$, $V = 105$). Taken together, these results indicate that dynamic training was indeed less tiring. Furthermore, they suggest that the discomfort during static acquisition was compensated by taking longer breaks, which would also justify the mixed opinions found in the questionnaires. Remarkably, the shorter break times made dynamic acquisition significantly faster than static acquisition, especially considering that it was already shorter by design.

The real-time performance of the prosthetic system was assessed based on the time it took subjects to complete the tasks in the performance evaluation session that followed the data acquisition. **Figure 4** reports the performance of all the subjects after static and dynamic training. The duration of the evaluation session was comparable after either acquisition procedure (mean task sequence duration of 333.8 s vs. 325.1 s, $p = 0.855$, $V = 49$). Particularly, also the completion times of the individual tasks were comparable (no statistically significant difference), regardless of their different requirements in terms of dexterity and movement coordination.

Figure 5A reports the average duration of the familiarization and the performance evaluation sessions that followed either data acquisition. The order for the static and dynamic training was randomized among subjects to counterbalance possible learning effects between the two strategies. The subjects demonstrated a strong learning effect, as they completed the evaluation session significantly faster than the familiarization session, both after static (average session duration of 438 s vs. 334 s, $p = 0.0012$, $V = 100$) and dynamic training (average session duration of 418 s vs. 325 s, $p = 0.007$, $V = 94$). The evaluation session also showed reduced variability in duration across the subjects compared to

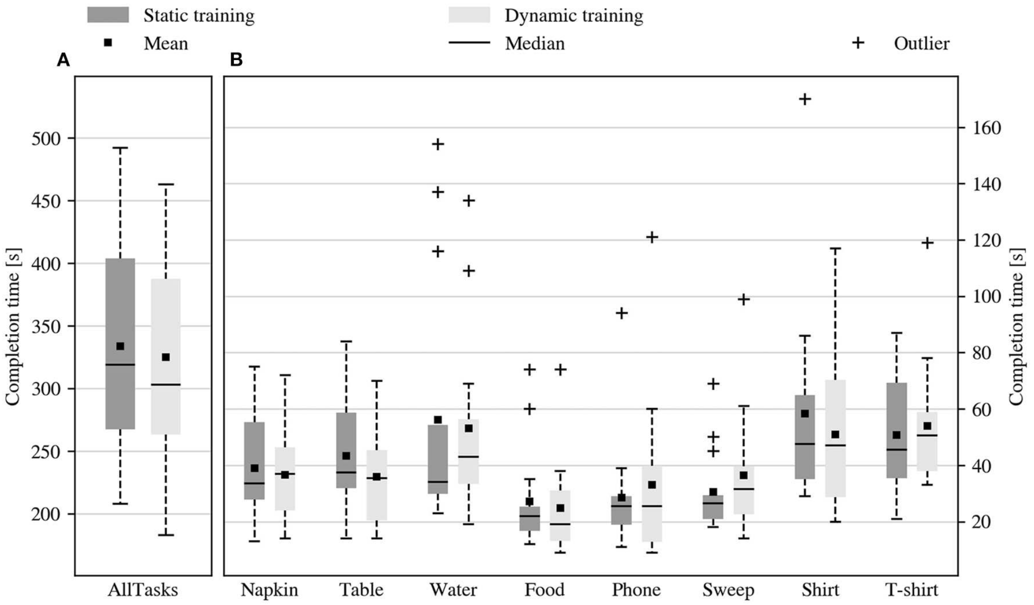


FIGURE 4 | Duration of the tasks during the performance evaluation session. Duration of **(A)** the task sequence and **(B)** of the individual tasks during the performance evaluation session, after static and dynamic training. No significant difference was found between the average duration of the performance evaluation session in the two conditions.

the familiarization session, both in the static (session duration range of 503 s vs. 284 s) and in the dynamic case (session duration range of 501 s vs. 280 s). Nonetheless, the two data collection procedures showed comparable task completion times during the respective familiarization and evaluation sessions (no statistically significant difference). In other terms, the subjects' performance improved rapidly over time due to practice, but this improvement occurred independently of the data acquisition procedure.

The analysis of the learning effect continued by separating the performance of naive and experienced subjects, and then by dividing the naive subjects based on who tested the static acquisition followed by the dynamic acquisition, defined as naive SD subjects, or vice versa, defined as naive DS subjects. Three of the four experienced subjects belonged to the SD group. Of the remaining ten naive subjects, six were SD and four DS. Naive participants, **Figure 5B**, confirmed the learning trend described before, showing comparable performance across training conditions while improving over time (average duration of the familiarization and the evaluation session after static training 505 s vs. 363 s, $p = 0.002$, $V = 45$, and after dynamic training 451 s vs. 337 s, $p = 0.0098$, $V = 52$). Experienced participants, instead, performed equivalently well regardless of the training condition and did not show a significant learning effect (average duration of the familiarization and the evaluation session after static training 269 s vs. 260 s, and after dynamic training 337 s vs. 296 s). The performance of naive subjects was characterized by a higher initial variance, but it seemed to converge rapidly to that of experienced participants over the course of the experiment. **Figures 5D,E** display the evolution over time of the performance of naive SD and naive DS participants. In both groups, the familiarization of the second tested condition was faster than that of the first condition (average familiarization time for naive SD subjects 570 s vs. 394 s, $p = 0.031$, $V = 21$; average familiarization time for naive DS subjects 537 s vs. 407 s, $p = 0.12$, $V = 10$). The lack of statistical evidence in the second case was probably due to the limited number of DS subjects. This result showed that learning did not just happen within the same training condition, but rather that the subjects transferred some of the skills acquired for the first training strategy to the second. This transfer effect could explain part of the variability of the counterbalanced results, especially during the familiarization phase.

Figure 6A describes how easy the subjects perceived the two prosthetic control variants during the online tasks. This information was reported in the questionnaire at the end of the experiment and converted in a percentage from 0% ("very difficult") to 100% ("very easy"). The subjects' opinions were mixed, which overall resulted in a comparable perceived system controllability after either acquisition strategy. Nonetheless, the perceived controllability of the system was higher after static training, but this was not supported by the statistical evidence (average controllability of 70.8% vs. 57.0%, $p = 0.059$, $V = 72.5$). Furthermore, this trend seemed to characterize only a portion of the subjects. Those who tried the static training after the dynamic one, **Figure 6B**, consistently reported improvements in the usability of the system for the last tested condition (average

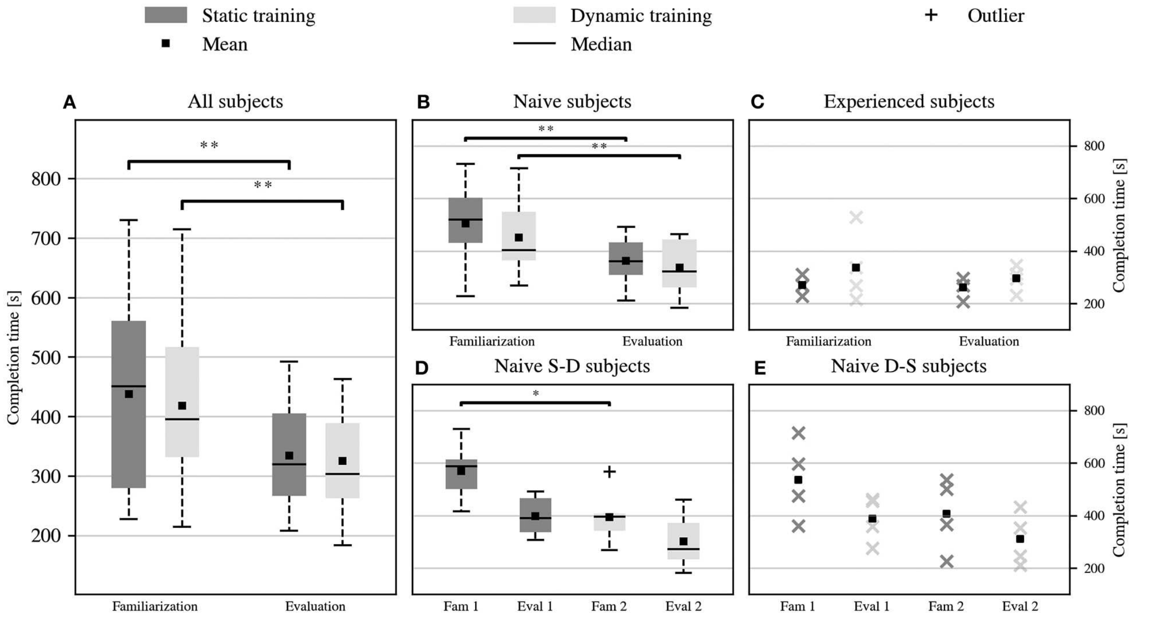


FIGURE 5 | Duration of the tasks sequence during the familiarization and the performance evaluation sessions, after static and dynamic data acquisition. **(A)** Performance of all the participants. Although the task completion time decreased significantly after the initial familiarization (**$p < 0.01$), the performance of static and dynamic data acquisition remained comparable both during the familiarization and the following evaluation session. This trend characterized the performance of **(B)** naive participants but not those of **(C)** experienced participants, for whom the average session duration did not change significantly across acquisition strategies and familiarization levels. The performance of the naive participants rapidly converged to those of the experienced ones, despite retaining a higher variance. **(D,E)** Chronological evolution of the performance of the naive subjects, divided between those who first tested the static and then the dynamic condition, and vice versa. The improvement of all the naive subjects was consistent, not only within the same training strategy but also across different strategies (*$p < 0.05$). For groups with fewer than five samples, we show the individual data points rather than a boxplot.

controllability of 75.4% vs. 51.4%, $p = 0.063$, $V = 20$). Instead, the subjects that started with static training, **Figure 6C**, found that controlling the system was equally easy under both conditions (average controllability of 66.1% vs. 62.5%, $p = 0.61$, $V = 17.5$). In any case, none of the observed effects was statistically significant, perhaps because the opinions regarding the first tested condition were always characterized by greater variance.

Figure 7 summarizes the outcomes of the offline grasp recognition task performed on the training data collected during the online experiments. The prediction of desired hand configurations in the dynamic test set was significantly better after dynamic training as compared to static training (R^2 of 0.53 vs. 0.80, $p < 0.001$, $z = -4.46$, see **Figure 7A**). In addition, the dynamic training provided better performance also when the training and the test data were acquired with different protocols, i.e., static training followed by dynamic testing, or dynamic training followed by static testing. **Figure 7B** shows that the estimation of the intended hand posture obtained by training on dynamic data and testing on static data was better than the estimation obtained by training on static and testing on dynamic data (R^2 of 0.53 vs. 0.62, $p = 0.004$, $z = -2.86$).

4. DISCUSSION AND CONCLUSIONS

4.1. General Remarks

The limb position effect requires training data to be collected in several different body postures for each desired action to be learned; this is because body postures alter the muscle configuration of the forearm, thereby changing the sEMG patterns. The traditional solution to this problem, already appearing multiple times in literature (Fougner et al., 2011; Peng et al., 2013; Betthauser et al., 2018), consists of simply asking users to hold their arm statically in multiple postures and then collecting data one posture at a time. This makes the data collection procedure longer and potentially more tiring than usual, especially since this procedure must be repeated for each grasp type. A method to make it lighter and faster is highly desirable.

The aim of this work was that of *assessing if a dynamic data-collection procedure would be better than a static one* and, if so, in which respect and why. We wanted to *test the models obtained using either data collection procedure in realistic conditions*, i.e., using prosthetic hardware to perform real-time bimanual manipulation tasks inspired by daily living. Fourteen able-bodied subjects were engaged in a set of realistic bimanual activities

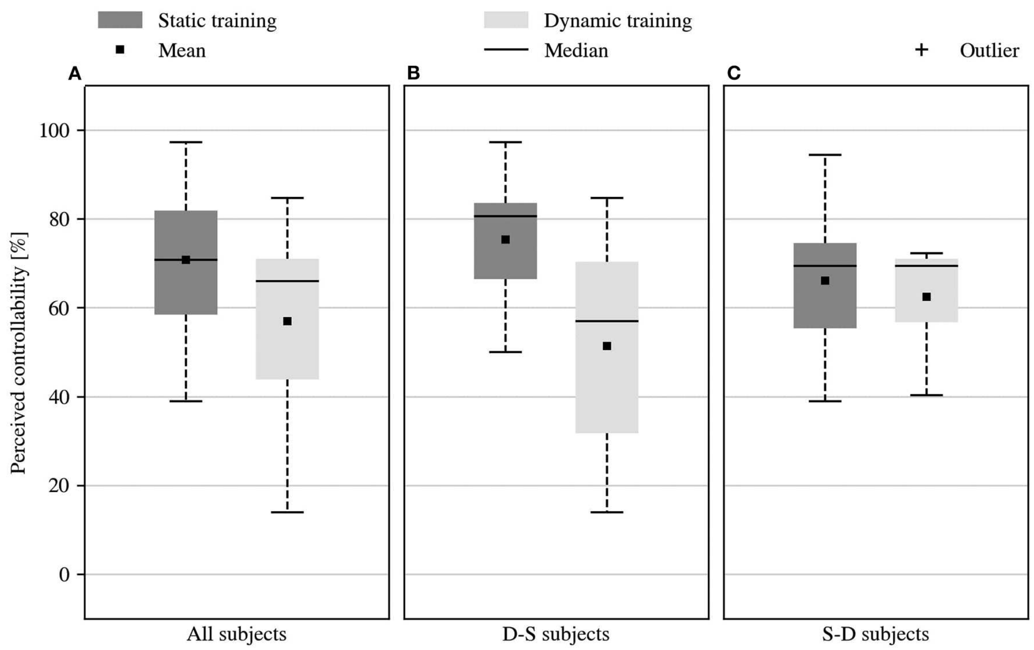


FIGURE 6 | Perceived controllability of the system. **(A)** Controllability of the system, self-assessed in the questionnaire at the end of the experiment. Subjects reported mixed opinions about the controllability of the prosthetic system. No statistical evidence supported the modest improvement of the perceived controllability provided by the static training. **(B)** The subjects who started the experiment with dynamic training and continued with static training *(D-S)* reported improved system controllability for the second condition tested. **(C)** Those who tried the static training first *(S-D)* experienced equivalent controllability in both conditions.

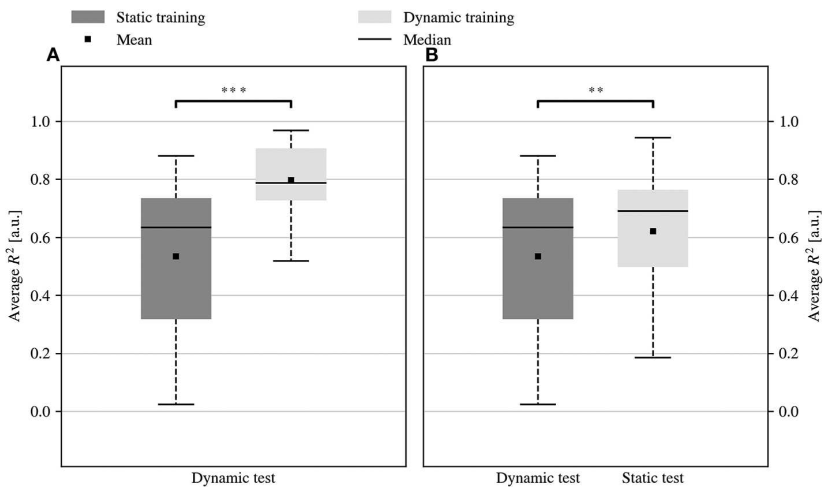


FIGURE 7 | Offline prediction of the hand configuration using RFF-RR after static or dynamic training. **(A)** Dynamic training allowed better grasp prediction from dynamically acquired data samples (***$p < 0.001$). Besides, **(B)** the performance observed by training on dynamic and testing on static data were better than those obtained by training on static and testing on dynamic data (**$p < 0.01$).

(laying a table, serving food, hanging clothes, etc.), after having performed both a static and a dynamic data collection procedure to build appropriate myocontrol models.

The first result to be noted is that all users were able to complete all tasks, in both training modalities. Given the realism of the tasks they were requested to perform, this seems to indicate that the approach of using RR with RFFs is worth pursuing. Notice that in this specific work we intentionally refrained from using the incremental characteristics of RFF-RR, making it impossible to update and correct the models online; the observed performance, therefore, only depends on the data collected at the beginning of the experiment. Secondly, it is worth remarking that the time needed to acquire the training data is relatively short in either modality. Taking into account the breaks requested by the subjects, the average acquisition time is about 9 min for the static acquisition and just 2 min for the dynamic one. Also allowing for the adaptation that users naturally put in place while doing the tasks, this indicates that both approaches rapidly yield data with a quality sufficient to cover most of the actions required in the experiment.

4.2. Dynamic and Static Data Collection Provide Comparable Real-Time Performance

The experimental results show that, quite surprisingly, there is no difference in real-time performance (time required to complete each task) between the static and the dynamic data collection procedure. No statistically significant difference in the task execution times could be found, either considering the overall times, or the duration of the individual tasks (**Figure 4**).

Notice as well (**Figure 5**) that subjects without prior experience in myocontrol manifest a quite strong learning effect as they perform the tasks over and over again. However, the uniformity between the static and dynamic conditions persists, since there is no significant difference in performance between the familiarization phases, as well as between the evaluation phases. The results for the experienced participants suggest that long-term learning of myocontrol leads subjects to reach a consistent level of performance that is irrespective of the acquisition protocol. This reduction in variability among experienced subjects is in line with the findings of previous studies on the implications of long-term user training on myocontrol (Hargrove et al., 2017).

The equivalence between the myocontrol performance provided by static and dynamic training somehow contradicts the outcome of previous studies (Fougner et al., 2011; Scheme et al., 2011), which reported improved myocontrol in offline settings by using dynamic training data. To the best of our knowledge, however, this is the first time in which the comparison between the effects of static and dynamic training is carried out online, performing realistic and complex ADLs. In line with the results by Scheme et al. (2011), we observe that in the cross-comparison in **Figure 7B** the model trained on dynamic data has higher offline accuracy on static data than vice versa. All in all, this result suggests once more that non- or quasi-realistic testing of myocontrol systems is hardly a good indicator for the efficacy or reliability of the system once put to practice in real life (Jiang et al., 2014; Ortiz-Catalan et al., 2015). This might be due to many contingent reasons, such as wrong measures of performance or wrong tasks administered to the users, but eventually it probably has to do most of all with the excellent ability of human users to compensate for control inaccuracies by adapting their muscular signals. This is even more so for proportional control since users receive immediate visual feedback of the control response of the prosthesis (Hahne et al., 2017; Shehata et al., 2017, 2018).

Considering the capability of users to smoothen control inaccuracies, one may wonder if this also means that we can shorten the data acquisition even further, for instance by reducing the number of positions. A recent study on real-time myocontrol did not find a reduction in the online grasp recognition rate in different positions even when training data was acquired in just one position (Hwang et al., 2017). This study did not involve realistic tasks and considered only one wrist orientation and three positions; regardless, in future work, it would be interesting to continue along these lines and to investigate what is the minimal amount of position variability that still yields consistent online controllability during practical tasks.

4.3. Dynamic Data Collection Is Faster and Less Tiresome

As is clear from the objective and self-assessed indices of performance, acquiring data dynamically is faster, uses fewer sEMG data, and is less tiring. Net of the possible break times requested by the participants, the dynamic procedure only takes 27 s per grasp type instead of the 126 s needed by the static one; this is advantageous in terms of the stress and frustration imposed on the subjects. Moreover, from a computational point of view, dynamic training employs roughly half the sEMG samples needed by the static one. This could be important when miniaturization of the whole system is planned, for instance on a microcontroller to be embedded in the prosthetic socket. Interestingly, while providing fewer data samples, dynamic acquisition still results in equivalent real-time controllability to the static one. We argue that this depends on the information captured during the motion that joins one limb posture to the following one, which is ignored by performing static acquisition in multiple postures.

The subjective assessment of fatigue during either procedure represents one of the main results of this study. Although not statistically significant, the results in **Figure 3A** hint that the dynamic acquisition was perceived as less tiring. This observation is supported by the amount of rest the subjects requested during either type of acquisition, shown in **Figure 3B**, which was significantly less for the dynamic procedure. This indicates that dynamic training is easier and more acceptable than the static one. Taken together, the two results indicate that dynamic training should be preferred over static training.

4.4. Further Remarks

According to the visual inspection of the recordings of the experiments, and also according to the main experimenter's experience, the myocontrol system was not free from instabilities and failures. For example, the prosthetic hands would sometimes execute unwanted actions or open unexpectedly during grasps. Mainly, these problems arose when trying to grasp while in muscle-stressing body postures, probably akin but not exactly matching those during data collection. Since we did not allow subjects the possibility to update the models online, this indicates that there still is some incompleteness of the dataset collected at the beginning of the experiments. In other words, it cannot be assumed that an initial calibration will suffice (Castellini, 2016).

The solution we propose to address this issue is, once again, the exploitation of the incremental characteristics of RFF-RR (Strazzulla et al., 2017), leading to interactive learning (Nowak et al., 2018). Notice that there is no conflict in mixing up interactive learning as described in the literature and dynamic data collection. These two strategies are orthogonal and one can imagine updating the model online already during the dynamic data acquisition. This would provide the user with immediate feedback on the control response of the prosthesis; going even one step further, the user could then guide the acquisition and interactively acquire data exactly in those postural and dynamical conditions where the behavior is unsatisfactory.

A complementary avenue to attenuate the limb position effect consists of enriching the training set with sensory modalities that directly relate to the position of the arm. Fougner et al. (2011) showed that offline myocontrol accuracy can be improved by integrating sEMG and accelerometry data collected in multiple arm positions. Radmand et al. (2014) later found that the use of inertial measurements in combination with static data acquisition only improves myoelectric control if the training data is acquired across many arm positions, whilst it is likely to undermine the grasp recognition performance if a suboptimal set of training positions is selected. When the training data is acquired dynamically, instead, inertial measurements prove beneficial for myocontrol quality even if the user's workspace is not thoroughly sampled. Finally, more recent studies confirmed that the dynamic acquisition of myographic and inertial training data improves the myocontrol performance also in online settings (Krasoulis et al., 2017).

This experiment was conducted with able-bodied subjects only, although we put them in conditions that closely mimic the everyday life of prosthetic users. How much do our results apply to subjects with an amputation? Although the answer can only be found by testing our methodology on amputated users, it seems reasonable to argue that our main result, that dynamic acquisition is quicker and more comfortable than a static one, can directly transfer to amputees—less muscular stress is always good, as long as it does not hinder performance. The range of muscle movement after an amputation is generally limited, and the distribution of the weight of the limb across the muscular structure can be dramatically different between amputees and intact users; this is a further hurdle toward the translation of our results to amputees. Nevertheless, both acquisition strategies presented in this paper could as well be tailored to each individual, also for transhumeral or even lower-limb amputees. In principle, the advantage of dynamic over static training should hold also when a tailored training protocol is designed. Lastly, sensor-shift during limb motion can be problematic for amputees and may have been mitigated in our setup. In fact, while biosignal sensors are normally integrated into the prosthetic socket and may be slightly affected by its movement, we used a tight sEMG armband that is independent of the prosthetic splint. In our experience, however, sensor-shift can be reduced effectively with a well-designed, bespoke socket that would still make the two strategies equivalent.

Last but not least, the approach shown in this work can, and probably should, be applied in realms other than upper-limb prosthetics; for instance, to control rehabilitation devices for patients of musculoskeletal degenerative conditions. Stroke survivors, for instance, might benefit from a faster data collection procedure, when engaged in rehabilitation procedures involving complex robotic devices. Rehabilitation based upon Virtual Reality is also a target to this procedure (Nissler et al., 2019). Robotic control based upon muscle activity can be also transferred to teleoperated scenarios (Porges et al., 2019) and, probably, in space. In all these scenarios it is worth investigating the usefulness and feasibility of the procedure described in this paper.

4.5. Conclusions

To summarize, to try and solve the limb position effect in myocontrol we have investigated an alternative to the classic multi-body-posture data collection. Namely, we have compared it with a dynamic data acquisition procedure, which consists in collecting data while the user was moving the arm smoothly through all the postures. To test the true controllability resulting from either procedure, we have designed a realistic evaluation protocol that required the subjects to perform a set of bimanual activities of daily living. Our results show that the two procedures yield similar performance, but that dynamic training is faster and less tiresome. This seems to indicate that the dynamic acquisition procedure should be preferred over the static one.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by DLR's internal committee for personal data protection and conducted according to the WMA Declaration of Helsinki. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

AGig had the original idea for the study, designed and carried out the user study under the supervision of CC, and performed the analysis under the supervision of AGij and CC. All authors contributed to the design of the study, discussed the results, and wrote the manuscript.

FUNDING

This work was partially supported by the Swiss National Science Foundation Sinergia project #160837 Megane Pro and the Horizon 2020 Project An.Dy (Grant Agreement No. 731540).

ACKNOWLEDGMENTS

We acknowledge Valentina Gregori for help in reviewing the relevant literature. Furthermore, we thank Dr. Bernhard Weber for useful comments on the design of the user study and the statistical analysis.

REFERENCES

Batzianoulis, I., Krausz, N. E., Simon, A. M., Hargrove, L., and Billard, A. (2018). Decoding the grasping intention from electromyography during reaching motions. *J. Neuroeng. Rehabil*. 15:57. doi: 10.1186/s12984-018-0396-5

Beckerle, P., Castellini, C., and Lenggenhager, B. (2018a). Robotic interfaces for cognitive psychology and embodiment research: a research roadmap. *Wiley Interdiscipl. Rev. Cogn. Sci*. 10:e1486. doi: 10.1002/wcs.1486

Beckerle, P., Kõiva, R., Kirchner, E. A., Bekrater-Bodmann, R., Dosen, S., Christ, O., et al. (2018b). Feel-good robotics: requirements on touch for embodiment in assistive robotics. *Front. Neurorobot*. 12:84. doi: 10.3389/fnbot.2018.00084

Betthauser, J. L., Hunt, C. L., Osborn, L. E., Masters, M. R., Lévay, G., Kaliki, R. R., et al. (2018). Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning. *IEEE Trans. Biomed. Eng*. 65, 770–778. doi: 10.1109/TBME.2017.2719400

Castellini, C. (2016). "Incremental learning of muscle synergies: from calibration to interaction," in *Human and Robot Hands: Sensorimotor Synergies to Bridge the Gap Between Neuroscience and Robotics, Touch and Haptic Systems, Chapter 11*, eds M. Bianchi and A. Moscatelli (New York City, NY: Springer International Publishing), 171–193. doi: 10.1007/978-3-319-26706-7_11

Castellini, C. (2020). "Upper Limb Active Prosthetic systems–Overview," in *Wearable Robotics: Systems and Applications, chapter 19, 1st Edn*., eds J. Rosen and P. Ferguson (Amsterdam: Elsevier), 365–376. doi: 10.1016/B978-0-12-814659-0.00019-9

Castellini, C., Artemiadis, P., Wininger, M., Ajoudani, A., Alimusaj, M., Bicchi, A., et al. (2014). Proceedings of the first workshop on peripheral machine interfaces: going beyond traditional surface electromyography. *Front. Neurorobot*. 8:22. doi: 10.3389/fnbot.2014.00022

Chadwell, A., Kenney, L., Granat, M., Thies, S., Head, J., Galpin, A., et al. (2018). Upper limb activity in myoelectric prosthesis users is biased towards the intact limb and appears unrelated to goal-directed task performance. *Sci. Rep*. 8:11084. doi: 10.1038/s41598-018-29503-6

Fougner, A., Scheme, E., Chan, A. D., Englehart, K., and Stavdahl, Ø. (2011). Resolving the limb position effect in myoelectric pattern recognition. *IEEE Trans. Neural Syst. Rehabil. Eng*. 19, 644–651. doi: 10.1109/TNSRE.2011.2163529

Geng, Y., Zhang, F., Yang, L., Zhang, Y., and Li, G. (2012). "Reduction of the effect of arm position variation on real-time performance of motion classification," in *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (San Diego, CA), 2772–2775. doi: 10.1109/EMBC.2012.6346539

Gigli, A., Gijsberts, A., and Castellini, C. (2019). "Natural myocontrol in a realistic setting: a comparison between static and dynamic data acquisition," in *2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR)* (Toronto, ON: IEEE), 1061–1066. doi: 10.1109/ICORR.2019.8779364

Gijsberts, A., Bohra, R., Sierra González, D., Werner, A., Nowak, M., Caputo, B., et al. (2014). Stable myoelectric control of a hand prosthesis using non-linear incremental learning. *Front. Neurorobot*. 8:8. doi: 10.3389/fnbot.2014.00008

Gijsberts, A., and Metta, G. (2011). "Incremental learning of robot dynamics using random features," in *IEEE International Conference on Robotics and Automation (ICRA)* (Shanghai), 951–956. doi: 10.1109/ICRA.2011.5980191

Hahne, J. M., Markovic, M., and Farina, D. (2017). User adaptation in myoelectric man-machine interfaces. *Sci. Rep*. 7:4437. doi: 10.1038/s41598-017-04 255-x

Hargrove, L. J., Miller, L. A., Turner, K., Kuiken, T. A. (2017). Myoelectric pattern recognition outperforms direct control for transhumeral amputees with targeted muscle reinnervation: a randomized clinical trial. *Sci. Rep*. 7, 1–9. doi: 10.1038/s41598-017-14386-w

Hermansson, L. M., Fisher, A. G., Bernspång, B., and Eliasson, A.-C. (2005). Assessment of capacity for myoelectric control: a new Rasch-built measure of prosthetic hand control. *J. Rehabil. Med*. 37, 166–171. doi: 10.1080/16501970410024280

Hussaini, A., and Kyberd, P. (2017). Refined clothespin relocation test and assessment of motion. *Prosthet. Orthot. Int*. 41, 294–302. doi: 10.1177/0309364616660250

Hwang, H.-J., Hahne, J. M., and Müller, K.-R. (2017). Real-time robustness evaluation of regression based myoelectric control against arm position change and donning/doffing. *PLoS ONE* 12:e186318. doi: 10.1371/journal.pone.0186318

Jiang, N., Vujaklija, I., Rehbaum, H., Graimann, B., and Farina, D. (2014). Is accurate mapping of EMG signals on kinematics needed for precise online myoelectric control? *IEEE Trans. Neural Syst. Rehabil. Eng*. 22, 549–558. doi: 10.1109/TNSRE.2013.2287383

Khushaba, R. N., Al-Timemy, A., Kodagoda, S., and Nazarpour, K. (2016). Combined influence of forearm orientation and muscular contraction on EMG pattern recognition. *Expert Syst. Appl*. 61, 154–161. doi: 10.1016/j.eswa.2016.05.031

Krasoulis, A., Kyranou, I., Erden, M. S., Nazarpour, K., and Vijayakumar, S. (2017). Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements. *J. Neuroeng. Rehabil*. 14:71. doi: 10.1186/s12984-017-0284-4

Krasoulis, A., Vijayakumar, S., and Nazarpour, K. (2019). Effect of user practice on prosthetic finger control with an intuitive myoelectric decoder. *Front. Neurosci*. 13:891. doi: 10.3389/fnins.2019.00891

Kyberd, P. J., Murgia, A., Gasson, M., Tjerks, T., Metcalf, C., Chappell, P. H., et al. (2009). Case studies to demonstrate the range of applications of the Southampton Hand Assessment Procedure. *Br. J. Occup. Ther*. 72, 212–218. doi: 10.1177/030802260907200506

Lock, B. A., Englehart, K., and Hudgins, B. (2005). "Real-time myoelectric control in a virtual environment to relate usability vs. accuracy," in *MyoElectric Controls/Powered Prosthetics Symposium (MEC)* (Fredericton, NB).

Meattini, R., Nowak, M., Melchiorri, C., and Castellini, C. (2019). Automated instability detection for interactive myocontrol of prosthetic hands. *Front. Neurorobot*. 13:68. doi: 10.3389/fnbot.2019.00068

Merletti, R., Botter, A., Cescon, C., Minetto, M., and Vieira, T. (2011). Advances in surface EMG: recent progress in clinical research applications. *Crit. Rev. Biomed. Eng*. 38, 347–379. doi: 10.1615/CritRevBiomedEng.v38.i4.20

Nissler, C., Nowak, M., Connan, M., Büttner, S., Vogel, J., Kossyk, I., et al. (2019). VITA–an everyday virtual reality setup for prosthetics and upper-limb rehabilitation. *J. Neural Eng*. 16:026039. doi: 10.1088/1741-2552/aaf35f

Nowak, M., Castellini, C., and Massironi, C. (2018). Applying radical constructivism to machine learning: a pilot study in assistive robotics. *Construct. Foundat*. 13, 250–262.

Ortiz-Catalan, M., Rouhani, F., Brånemark, R., and Håkansson, B. (2015). "Offline accuracy: a potentially misleading metric in myoelectric pattern recognition for prosthetic control," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Milan: IEEE), 1140–1143. doi: 10.1109/EMBC.2015.7318567

Peng, L., Hou, Z., Chen, Y., Wang, W., Tong, L., and Li, P. (2013). "Combined use of sEMG and accelerometer in hand motion classification considering forearm rotation," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (Osaka: IEEE), 4227–4230.

Porges, O., Connan, M., Henze, B., Gigli, A., Castellini, C., and Roa, M. A. (2019). "A wearable, ultralight interface for bimanual teleoperation of a compliant, whole-body-controlled humanoid robot," in *Proceedings of ICRA-International Conference on Robotics and Automation* (Montreal, QC).

Radmand, A., Scheme, E., and Englehart, K. (2014). On the suitability of integrating accelerometry data with electromyography signals for resolving the effect of changes in limb position during dynamic limb movement. *J. Prosthet. Orthot*. 26, 185–193. doi: 10.1097/JPO.0000000000000041

Rahimi, A., and Recht, B. (2008). "Uniform approximation of functions with random bases," in *Allerton Conference on Communication Control and Computing (Allerton08)* (Urbana-Champaign, IL), 555–561. doi: 10.1109/ALLERTON.2008.4797607

Scheme, E., Biron, K., and Englehart, K. (2011). "Improving myoelectric pattern recognition positional robustness using advanced training protocols," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (Boston, MA: IEEE), 4828–4831. doi: 10.1109/IEMBS.2011.6091196

Schuster, C., Hahn, S., and Ettlin, T. (2010). Objectively-assessed outcome measures: a translation and cross-cultural adaptation procedure applied to the Chedoke McMaster Arm and Hand Activity Inventory (CAHAI). *BMC Med. Res. Methodol*. 10:106. doi: 10.1186/1471-2288-10-106

Schweitzer, W., Thali, M. J., and Egger, D. (2018). Case-study of a user-driven prosthetic arm design: bionic hand versus customized body-powered technology in a highly demanding work environment. *J. Neuroeng. Rehabil*. 15:1. doi: 10.1186/s12984-017-0340-0

Shehata, A. W., Scheme, E. J., and Sensinger, J. W. (2017). "The effect of myoelectric prosthesis control strategies and feedback level on adaptation rate for a target acquisition task," in *2017 International Conference on Rehabilitation Robotics (ICORR)* (London: IEEE), 200–204. doi: 10.1109/ICORR.2017.8009246

Shehata, A. W., Scheme, E. J., and Sensinger, J. W. (2018). Evaluating internal model strength and performance of myoelectric prosthesis control strategies. *IEEE Trans. Neural Syst. Rehabil. Eng.* 26, 1046–1055. doi: 10.1109/TNSRE.2018.2826981

Sierra González, D., and Castellini, C. (2013). A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees. *Front. Neurorobot.* 7:17. doi: 10.3389/fnbot.2013.00017

Strazzulla, I., Nowak, M., Controzzi, M., Cipriani, C., and Castellini, C. (2017). Online bimanual manipulation using surface electromyography and incremental learning. *IEEE Trans. Neural Syst. Rehabil. Eng.* 25, 227–234. doi: 10.1109/TNSRE.2016.2554884

Vujaklija, I., Farina, D., and Aszmann, O. (2016). New developments in prosthetic arm systems. *Orthop. Res. Rev.* 8, 31–39. doi: 10.2147/ORR.S71468

Wang, S., Hsu, J., Trent, L., Ryan, T., Kearns, N., Civillico, E., et al. (2018). Evaluation of performance-based outcome measures for the upper limb: a comprehensive narrative review. *PM&R* 10, 951–962.e3. doi: 10.1016/j.pmrj.2018.02.008

Woodward, R. B., and Hargrove, L. J. (2019). Adapting myoelectric control in real-time using a virtual environment. *J. Neuroeng. Rehabil.* 16:11. doi: 10.1186/s12984-019-0480-5

Yang, D., Gu, Y., Jiang, L., Osborn, L., and Liu, H. (2017a). Dynamic training protocol improves the robustness of Pr-based myoelectric control. *Biomed. Signal Process. Control* 31, 249–256. doi: 10.1016/j.bspc.2016.08.017

Yang, D., Yang, W., Huang, Q., and Liu, H. (2017b). Classification of multiple finger motions during dynamic upper limb movements. *IEEE J. Biomed. Health Inform.* 21, 134–141. doi: 10.1109/JBHI.2015.2490718

Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

A2 Feedback-Aided Dynamic Data Acquisition

Title: Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand

Authors: Andrea Gigli, Donato Brusamento, Roberto Meattini, Claudio Melchiorri, and Claudio Castellini.

Journal: Journal of Neural Engineering.

Manuscript version: Accepted manuscript.

Citation: Andrea Gigli, Donato Brusamento, Roberto Meattini, Claudio Melchiorri and Claudio Castellini. "Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand." In: *Journal of Neural Engineering* 17.5 (2020), p. 056047.

Feedback-Aided Data Acquisition Improves Myoelectric Control of a Prosthetic Hand

Andrea Gigli[1], Donato Brusamento[1], Roberto Meattini[2], Claudio Melchiorri[2], and Claudio Castellini[1]

[1]Institute of Robotics and Mechatronics, German Aerospace Center (DLR), Wessling, Germany

[2]Department of Electrical, Electronic and Information Engineering (DEI), University of Bologna, Bologna, Italy

E-mail: `andrea.gigli@dlr.de`

September, 2020

Abstract.

Pattern-recognition-based myocontrol can be unreliable, which may limit its use in the clinical practice and everyday activities. One cause for this is the poor generalization of the underlying machine learning models to untrained conditions. Acquiring the training data and building the model more interactively can reduce this problem. For example, the user could be encouraged to target the model's instabilities during the data acquisition supported by automatic feedback guidance. Interactivity is an emerging trend in myocontrol of upper-limb electric prostheses: the user should be actively involved throughout the training and usage of the device.

In this study, 18 non-disabled participants tested two novel feedback-aided acquisition protocols against a standard one that did not provide any guidance. All the protocols acquired data dynamically in multiple arm positions to counteract the limb position effect. During feedback-aided acquisition, an acoustic signal urged the participant to hover with the arm in specific regions of her peri-personal space, de facto acquiring more data where needed. The three protocols were compared on everyday manipulation tasks performed with a prosthetic hand. Our results showed that feedback-aided data acquisition outperformed the acquisition routine without guidance, both objectively and subjectively, indicating that interaction during the data acquisition is fundamental to improve myocontrol.

Keywords: myoelectric control, training data acquisition, feedback guidance, limb position effect, online machine learning, prosthetic hand

Submitted to: *J. Neural Eng.*

1. Introduction

The loss of an upper limb can affect the ability to carry out essential activities of daily living (ADLs) [1]. A variety of prosthetic devices are clinically available to restore the missing limb's functionalities and eventually improve the person's autonomy, health, and lifestyle [2]. According to recent surveys, however, between 10 % and 40 % of the people living with a limb-loss renounce using active prostheses [3, 4]. While these statistics may be related to the etiology and the level of amputation, commonly reported causes of prosthesis rejection include lacking functionalities or unintuitive and unreliable control.

Myocontrol approaches based on pattern recognition (PR) have emerged to address typical demands of prostheses' users, such as controlling multiple hand functions, regulating the grip strength, and overcoming the complex mode-switching mechanism of sequential myocontrol [5]. PR-based approaches allow the user to produce seamless transitions between multiple grasp patterns, or even to simultaneously and proportionally (s/p) control multiple degrees of freedom (DoFs) of the prosthesis [6, 7]. A shortcoming of PR models is that their reliability is compromised when used in conditions different from the training conditions. This is often the case during myoelectric devices daily use, due to the variability of the myoelectric signal and its measurements, e.g., surface electromyography (sEMG). Sources of variability include, for example, variations of the skin connectivity, electrodes placement, limb position, as well as fatigue phenomena, and the evolution of the user's cognitive capabilities [8].

An intuitive way to improve the robustness of the control model is to capture the variability of the sEMG signal in the training data and leverage the learning algorithm's generalization capabilities. For example, data acquisition can be designed to record myoelectric data for different limb orientations or electrodes positioning. Both batch and adaptive approaches can be used to collect the training data. Adaptive learning allows updating the model with new data upon necessity, reducing the effort to forecast all the possible sources of sEMG variability at once. Numerous studies confirm the benefits of improving myocontrol by progressively refining the training dataset [8, 9, 10] and a commercially available PR-based myocontrol system, Control Coach by COAPT†, allows for incremental model updates.

We believe that the reason for the success of this approach lies in its interactivity. The user is expected to evaluate the model performance and actively address its flaws by collecting appropriate training data. This can be seen as a special case of the human-in-the-loop paradigm [11, 12], in which bidirectional user-prosthesis interaction is enforced. Involving the user in the myocontrol loop both during the training and testing of the prosthesis enables faster understanding and embodiment of the device and favors the production of more effective control signals [13, 14].

The deployment of data acquisition routines outside the laboratory could benefit from providing automatic guidance to the user during the acquisition routine. In fact, without supervision from an expert, the user may be unable to identify and address the model's weaknesses, resulting in fruitless or even harmful model updates. For example, the user can be guided by precisely structuring the data collection routine or providing instantaneous feedback on the model's performance during data collection. To this aim, Woodward and Hargrove [15] designed a virtual reality game to structure a multi-arm-position data acquisition and provide instantaneous visual feedback of the myocontrol performance. They showed that guidance via serious games increases users autonomy throughout the model adaptation process. Hahne et al. [16] highlighted that the effectiveness of adaptive myocontrol could be enhanced by overcoming the typical separation between data acquisition and model updates. They proposed a data acquisition protocol in which the model was updated and evaluated online, while users received instantaneous feedback about the evolution of the model performance. This allowed users to identify and address the model's limitations already during the data acquisition and achieve robust myocontrol performance in a Fitt's law test with few model updates.

In this work, we focus on alleviating the negative effect of limb position variations on the myocontrol of a prosthetic hand. A detailed characterization of this problem can be found in [17]. Proposed solutions include designing sEMG features [18] or control models [19] that are less sensitive to the limb position effect, or acquiring training data in multiple arm positions. Multi-position acquisition can be performed statically, by repeating the target hand gestures in different arm configurations [20], or dynamically, by executing predefined arm movements [21, 22]. Multi-position training proved to enhance myocontrol performance compared to single-position training, and dynamic protocols also reduce the time and effort needed to complete the data acquisition [23]. None of the multi-position acquisition protocols found in the literature provides feedback guidance to the best of our knowledge. Prosthesis users are typically required to perform a movement routine without being fully aware to which extent each arm position contributes

†`https://coaptengineering.com/control-coach`

to improving the myocontrol model. We argue that identifying in realtime which arm configurations are most critical for the model and signaling them to the user would improve the data acquisition efficiency.

We propose a novel protocol to collect sEMG data dynamically in multiple arm positions under automatic feedback guidance. The protocol combines data acquisition, online model building, and instantaneous feedback about the usefulness of the recorded data. We compare two variants of the novel feedback-aided acquisition protocol to a standard one that does not provide feedback guidance. All the protocols build the model online and are based on the dynamic data acquisition described in [23]. Both feedback-aided protocols adopt the same feedback mechanism, but one of them also implements automatic sample selection to discard unnecessary training samples and reduce the number of model updates.

2. Materials and Methods

This study evaluates the effects of using a feedback signal to guide the acquisition of training data for myoelectric controllers of prosthetic hands. The performances of two feedback-aided data acquisition procedures and one standard acquisition using no feedback guidance were compared based on the controllability of a prosthetic hand during a series of realistic manipulation tasks.

2.1. Participants

Eighteen non-disabled persons (aged 26.3 ± 4.6 years, 16 men and 2 women) participated in the experiment. Twelve participants had no prior experience in myoelectric control, while six had already used myoelectric prosthetic hands in previous user studies. Every participant received an oral and written description of the experiment and signed an informed consent form. The study was conducted at the German Aerospace Center (DLR) according to the WMA Declaration of Helsinki and approved by DLR's internal committee for personal data protection.

2.2. Experimental Setup

The muscular activity of the forearm of the dominant arm was measured using a Myo armband‡ by Thalmic Labs placed about 5 cm below the elbow. The bracelet comprised eight sensors, each recording an sEMG signal at a sampling rate of 200 Hz. A standard quick-release prosthetic connector fixed to a wrist/hand orthotic splint made it possible to anchor the prosthesis at the extremity of sound limbs. An i-LIMB Ultra Revolution prosthetic hand§ by Touch Bionics (now Össur) allowed independent flexion/extension of the five fingers and abduction/adduction of the thumb through six motors under direct current control. The devices communicated via a serial-port-over-Bluetooth with a laptop used to run the myocontrol software. The acoustic feedback was reproduced using the speakers of the laptop. A custom software suite written in the C# language provided the graphical interface to coordinate the data acquisition, labeled and processed sEMG data, generated the feedback signal, and implemented realtime myocontrol.

The experiment took place in a domestic-like laboratory environment. We arranged several household objects on a table, two shelves, and on the floor. We placed the table 40 cm next to the shelves, and we regulated its height to match the waist level of each participant. The shelves were 40 cm and 150 cm high. The study was videotaped in order to measure the participant's performance after the experiment. Figure 1A shows the experimental setup.

2.3. Incremental model building

The sEMG readings were preprocessed in realtime upon collection. The measurement from each of the 8 channels was rectified, computing its absolute value, and low-pass filtered using a second-order Butterworth filter with a cutoff frequency of 1 Hz.

The data acquisition software labeled incoming training samples with the activation commands for the motors of the prosthetic hand's fingers. Each command consisted of a normalized velocity ranging between 0 and 1, corresponding to extending or flexing the finger with maximum speed. Since all the hand gestures considered in this experiment could be realized by controlling one subset of the fingers with the same velocity command, the model had effectively 3 DoFs.

Training data was collected only for extreme velocity command values, that is, for hand gestures in which each finger was either fully extended or fully flexed. Intermediate velocity commands were excluded because they could lead to inaccuracies in the recorded data due to the participants' different reaction times [24]. Previous works, such as [25, 23], showed that regression models resulting from this training procedure still yield effective s/p control.

To provide appropriate feedback guidance during the data acquisition, it was necessary to incorporate each training sample into the model quickly upon collection. Therefore, we trained the s/p control model using an instance of incremental ridge regression (iRR) with random Fourier features (RFFs). iRR builds a

‡`https://support.getmyo.com/hc/en-us/articles/203398347-Getting-started-with-your-Myo-armband`

§`https://www.ossur.com/en-us/prosthetics/arms/i-limb-ultra` regression model incrementally by computing rank-one model updates when new training data is available. The iRR formulation allowed us to update the model and generate predictions with bounded time and space complexity. RFFs is a nonlinear mapping of the input space into a high-dimensional feature space obtained by using sinusoidal basis functions that have randomly sampled frequencies. By drawing those frequencies from an adequate probability distribution and choosing a sufficiently high mapping dimensionality, iRR with RFF approximates ridge regression with a Gaussian kernel [25]. Consequently, RFFs extend the capacity of iRR to perform nonlinear regression while maintaining the properties of incrementality and boundedness of the model update. This is relevant in applications that require online learning of nonlinear regression models and has proven beneficial for s/p myocontrol applications [25, 26, 27, 23]. A detailed description of iRR-RFF can be found in [25]. The prediction function of iRR-RFF is

$$\hat{\mathbf{y}} = \mathbf{W} \cdot \Phi(\mathbf{x}) \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^d$ is an input sample, $\Phi : \mathbb{R}^d \to \mathbb{R}^D$ is a nonlinear RFF mapping, $\mathbf{W}$ is an $M \times D$ matrix of scalar weights, and $\hat{\mathbf{y}} \in \mathbb{R}^M$ is the computed prediction. In this experiment, training pairs $\{\mathbf{x}, \mathbf{y}\}$ consisted of an sEMG measurement and the corresponding velocity commands for the fingers' motors. The input and output dimensionality of the model were $d = 8$ and $M = 3$. The regularization parameter λ of the ridge regression was set to 1, while the bandwidth γ and the dimensionality D of the RFF mapping were set to 0.1 and 300, respectively. The model weights were initialized to zero before the data acquisition, $\mathbf{W} = \mathbf{0}_{M,D}$.

2.4. Acoustic feedback and sample selection

The idea behind feedback-aided data acquisition is to guide the participant with an appropriate feedback signal in order to maximize the amount of informative and non-redundant data collected in a fixed amount of time. In an online learning problem, the informativeness of a correctly-labeled training sample $\{\mathbf{x}, \mathbf{y}\}$ for the model can be evaluated based on the prediction error

$$e_p(\mathbf{y}, \hat{\mathbf{y}}) = \|\mathbf{y} - \hat{\mathbf{y}}\|^2 \tag{2}$$

where $\hat{\mathbf{y}}$ is the prediction of the sample using the model. A small prediction error indicates that the model can accurately predict the label for that training sample and, therefore, the sample might be redundant for the model. A significant prediction error, instead, indicates that the model fails to predict the right label and may improve by integrating the sample. For the sake of clarity, we omit the argument of the prediction error in the remainder of the paper.

2.4.1. Feedback signal For our purposes, we designed an acoustic feedback signal with a fixed tone and variable volume. The volume of the signal ranged between 0 and a maximum value V and varied proportionally with the prediction error according to

$$f(e_p) = \max\left\{0, \min\left\{ae_p^2 + \frac{V - a\theta_u^2}{\theta_u}e_p, V\right\}\right\} \tag{3}$$

in which a was a scalar regulating the quadratic relation between error and volume, and θ_u was a threshold related to the prediction error. We set the values of the parameters to $V = 0.5$, $a = 70$, and $\theta_u = 0.05\sqrt{3}$. The value of θ_u corresponded to 5 % of the maximum theoretical value of the prediction error in our experiment, which was predicting an open hand gesture instead of a power grasp gesture.

2.4.2. Sample Selection We also used the prediction error to discard possibly redundant training samples. We defined a sample selection criterion to update the model only with those training samples for which

$$e_p \geq \theta_u \tag{4}$$

where θ_u is the update threshold defined before.

2.5. Experimental protocol

Every participant tested all the data acquisition strategies. We counterbalanced possible learning effects by administering the strategies to the participants in randomized order. We assigned each of the six permutations of the training conditions to one experienced and two naive participants picked at random. After each data acquisition, the resulting myocontrol model was tested in a sequence of realtime manipulation tasks. Participants repeated the sequence of tasks three times. The first two repetitions of the sequence allowed the participants to familiarize themselves with the prosthetic system and the myocontrol model, while the third one was used to measure the myocontrol performance. For this reason, we referred to the third repetition of the task sequence as a performance evaluation session.

2.5.1. Data acquisition All the data acquisition strategies required the participants to perform several target hand gestures while moving their arm in the reachable space. We selected three target hand gestures: namely a power grasp, a resting hand, and an index pointing. The selection was based on their relevance in ADLs, according to the literature [28]. The target hand gestures were acquired in the order reported above in every data acquisition. Since the myocontrol model was built incrementally, the

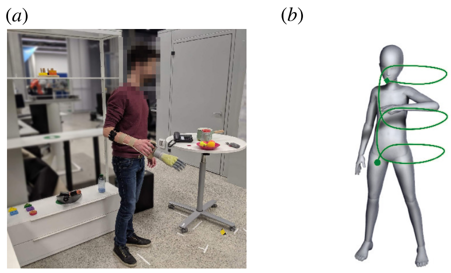


Figure 1. *Experimental setup and arm motion during data acquisition. (a)* The prosthetic system comprised a Myo armband by Thalmic Labs for sEMG reading, and an i-LIMB Ultra Revolution prosthetic hand by Össur. The experimental setup included common household objects placed onto one table and two shelves. The speakers of the control laptop provided acoustic feedback. *(b)* Participants wore the prosthetic system throughout the data acquisition. Every data acquisition routine required to perform several target hand gestures while moving the arm in a predefined trajectory. The motion proceeded from the circle to the square with the palm oriented downward and continued in the opposite direction with the palm oriented upward.

use of different orders would have possibly led to incomparable models.

Before the experiment, participants were explained the data acquisition protocols and were asked to practice them. Emphasis was put into enforcing a consistent arm movement across participants and strategies. Meanwhile, the volume of the speakers was regulated so to ensure that the feedback was distinctly audible. Nonetheless, the experimenter supervised the data acquisition and provided direct guidance when the participants performed the arm movement at the wrong pace or ignored the acoustic feedback.

Participants donned the prosthetic system on the dominant arm at the beginning of the experiment, and no adjustment of the sensors was allowed after that. Wearing the prosthesis during the data acquisition reduced the differences between the training and testing conditions caused by factors such as the electrodes' placement and the weight of the prosthetic device.

No-Feedback Data Acquisition (NF-DA) The data acquisition routine without feedback guidance adapted the dynamic acquisition presented in our previous work [23] to the setup of this study. Participants performed each target hand gesture while moving their arm in a predefined trajectory. During the procedure, they did not receive any feedback. The model was built online with each new training sample, as detailed in section 2.3. The trajectory uniformly covered the reachable space of the participant with a helical movement, Figure 1B. The movement was performed with constant speed from the level of the waist to the level of the head with the palm oriented downward; it continued in the opposite direction with the palm oriented upward. This whole sequence was repeated twice, without interruptions. The motion lasted 45 s for each hand gesture and took 135 s in total. The procedure is synthesized in Algorithm 1.

Feedback-Aided Data Acquisition (FA-DA) The data acquisition routine with feedback guidance extended NF-DA with the acoustic feedback detailed in section 2.4.1. The acquisition software used the incoming training samples to generate the acoustic feedback and to build the myocontrol model in realtime. Participants had to perform the desired grasp and follow the usual arm trajectory while modulating the arm's velocity based on the feedback. They should proceed with the same speed used during NF-DA when the feedback was not audible and hover with the arm in the areas where the feedback intensity increased. Since the feedback was proportional to the prediction error, this procedure led the participants to collect more data in critical arm configurations. The model incrementality prevented participants from slowing down indefinitely in critical areas of the reachable space. Training samples were continuously integrated into the myocontrol model, which immediately reduced the prediction error and, consequently, the volume of the feedback signal. The acquisition of each gesture lasted 45s. Differently from NF-DA, however, participants were not expected to cover the whole trajectory twice per gesture. The procedure is synthesized in Algorithm 2.

Feedback-Aided Data Acquisition with Sample Selection (FASS-DA) The data acquisition routine with feedback guidance and sample selection was obtained by integrating FA-DA with the sample selection criterion described in section 2.4.2. All the incoming training samples were used to generate the acoustic feedback, but only a limited number of non-redundant samples were selected and used to build the myocontrol model in realtime. Participants perceived no formal difference between the two feedback-aided acquisition routines. The procedure is synthesized in Algorithm 3.

2.5.2. Realistic myocontrol tasks After every data acquisition, the resulting myocontrol model was tested by engaging the participants in a series of five manipulation tasks. The tasks were inspired by realistic ADLs proposed in assessment protocols for prosthetic control, such as ACMC [29] and SHAP [30]. The tasks are described in Table 1. In the case of bimanual tasks, we assigned each action of the task either to the prosthetic hand or the sound hand.

Algorithm 1: No-Feedback Data Acquisition

```
Input: stream of sEMG samples x
init model to zero;
foreach hand gesture g do
    while participant performs g do
        acquire new sample x;
        update model with {x, label(g)};
    end
end
```

Algorithm 2: Feedback-Aided Data Acquisition

```
Input: stream of sEMG samples x
init model to zero;
foreach hand gesture g do
    while participant performs g do
        acquire new sample x;
        compute prediction error;
        generate acoustic feedback;
        update model with {x, label(g)};
    end
end
```

Algorithm 3: Feedback-Aided Data Acquisition with Sample Selection

```
Input: stream of sEMG samples x
init model to zero;
foreach hand gesture g do
    while participant performs g do
        acquire new sample x;
        compute prediction error;
        generate acoustic feedback;
        if predictionerror > threshold then
            update model with {x, label(g)};
        end
    end
end
```

The experimental protocol required the completion of all the tasks. If an object was dropped during a manipulation task, the experimenter brought it back to the place where it had been grasped, and the task continued from where it failed. The time needed to reset the position of the object was excluded from the final evaluation of performance. If repeated instabilities of the prosthesis hindered the execution of one task, the experimenter or the participant could suspend the task and request an additional model update. On-demand model updates were obtained with shorter versions of the data acquisition procedure performed at the beginning of the corresponding experimental session. Participants were instructed to hold the malfunctioning hand gesture while randomly moving the arm for 10 s in the area where the task failed, possibly enforcing movements of the shoulder, elbow, and forearm.

2.6. Performance evaluation

We evaluated the effectiveness of each data acquisition procedure based on the duration of the third repetition of the task sequence. We chose the task execution time as an objective measure of performance because it is at the base of many clinical assessment protocols for the hand function and prosthetic control [31]. A limitation of this metric is that, despite being related to the hand functionality, it does not provide information about the movements' quality. Unlike more advanced performance metrics, however, it does not require constraining the experimental setup (e.g., assessing performance in VR) and protocol (e.g., defining Fitt's law style tests), and it does not necessitate evaluation from certified examiners [28].

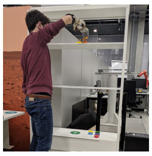
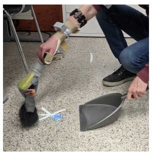
We complemented the task duration with subjective measures of the system's controllability and task difficulty collected in a questionnaire at the end of the experiment. The controllability of the prosthetic system resulting from each training condition was reported on a visual analog scale (VAS) ranging from "very easy to control" to "very difficult to control". Similarly, each task's difficulty was quantified on a VAS ranging from "very difficult" to "very easy". We verified if any of the acquisition strategies resulted in better controllability or faster task execution compared to the others, which could indicate a more robust myocontrol model and, therefore, better training data.

A Shapiro-Wilk test revealed that the task duration and the results of the questionnaire were not normally distributed across participants. For this reason, we used a Friedman test to identify differences in the average value of the statistics of the three training conditions. When the test indicated significant differences, we used repeated post-hoc Wilcoxon signed-rank tests to compare pairs of conditions. We set the significance level of all the tests to $\alpha = 0.05$, and we controlled the inflation of the significance level during repeated pairwise tests by operating a Bonferroni adjustment of the p-value [32]. In this paper, we reported unadjusted p-values (p) for the Friedman tests and Bonferroni-adjusted p-values ($\hat{p}$) for the post-hoc pairwise tests.

3. Results

The performance of the myocontrol model was measured by the duration of the tasks during the third

Table 1. Detailed description of the tasks in each performance evaluation repetition.

Task	Name	Description
	Pour water	A bottle and a jar are placed, respectively, on the lower shelf and on the table. Grasp the bottle^{p}, unscrew the cap^{s}, place the bottle and the cap on the table. Take the jar^{s}, unscrew the lid^{p}, and put it on the table. Take the bottle^{p} and pour the content into the jar. Close the jar^{p} and put it on the table. Take the bottle^{p}, close it^{s}, and bring it back to the lower shelf.
	Serve food	A pot, a plate containing three tennis balls, and a spoon are laid on the table. Use the spoon^{p} to bring the balls from the plate to the pan. Grab the pot by the handle łand tilt it by about 80 degrees, scoop the balls from the pot to the plate using the spoon^{p}.
	Phone and rolling ball	A telephone is on the table. Dial^{p} a sequence of numbers on the phone (1 to 9, 9 to 1, 0, "dial") with an index pointing gesture. A small ball is on the floor, and a target position is marked on the floor about one meter away. Use the index pointing gesture to push the ball^{p} to the target position.
	Pegboard	Three wooden shapes from one pegboard game are laid on the lower shelf, while the base is laid on the higher shelf. Pick^{p} each shape and stack it to the corresponding peg.
	Sweep the floor	A hand broom and a dustpan are placed on the lower shelf, while a bowl and some gravels are laid on the floor. Grab hand broom^{p} and dustpan^{s}, sweep the gravels onto the dustpan, empty the dustpan in the bowl, and bring the hand broom and the dustpan back to the lower shelf.

^{p} prosthetic hand; ^{s} sound hand.

repetition of the task sequence, i.e., the performance evaluation session. Figure 2A reports the duration of the evaluation session corresponding to the three data acquisition strategies. A Friedman test, followed by pairwise post-hoc Wilcoxon tests, revealed that the evaluation session in the FA-DA condition was significantly faster than in the NF-DA condition (average tasks sequence duration of 166.0 s versus 198 s, $W = 19.5$, $\hat{p} = 0.012$). The average duration of the task sequence in the FASS-DA condition, 183 s, did not differ significantly from those of the other conditions. Figure 2B and Figure 2C report the performance of the twelve naive and six experienced participants. For every training strategy, experienced participants completed the evaluation session faster than naive participants. Although not supported by statistical evidence, both groups seemed to perform better after FA-DA compared to NF-DA. The use of feedback during data acquisition reduced the average duration of the performance evaluation session by 15 % for naive participants and by 19 % for experienced participants. For both groups, the mean duration of the tasks after FASS-DA was characterized by high variability, and its average value was between those of the other two conditions. Figure 2D describes the performance of the participants during the individual tasks. Friedman tests were performed for each task and confirmed significant differences in completion time for the third task ($\chi^2(2) = 7.4$, $p = 0.024$). Post-hoc tests, however, failed to identify differences between any pair of conditions, which could be caused by the application of a conservative Bonferroni adjustment to the p-value. Nonetheless, the average duration of every task after FA-DA was slightly lower than after NF-DA.

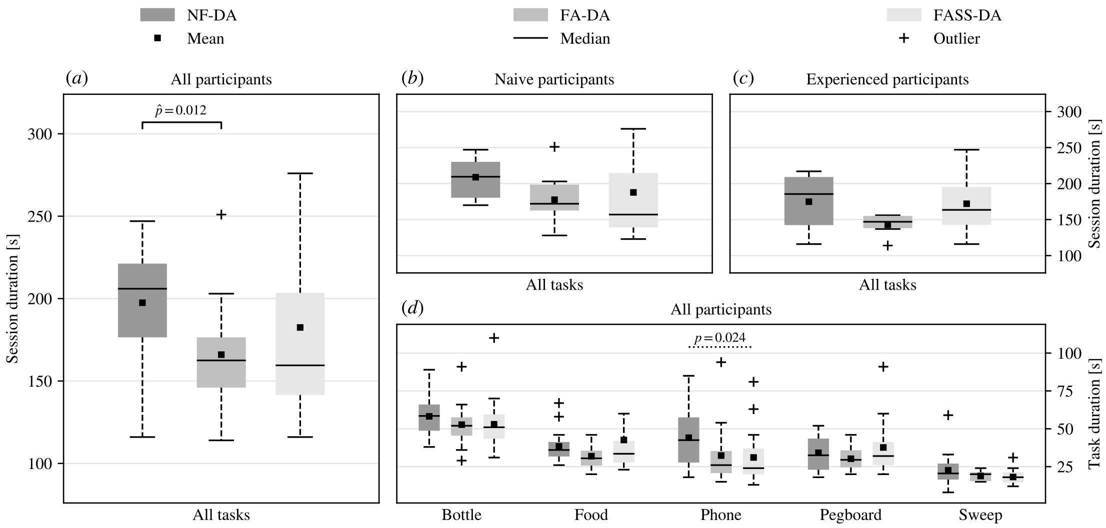


Figure 2. *Duration of the tasks in the performance evaluation session.* *(a)* Participants completed the evaluation session significantly faster in the FA-DA condition compared to the NF-DA condition ($\hat{p}$ Bonferroni-adjusted). The performance in the FASS-DA condition did not differ significantly from those of the other conditions. The same could be observed by either considering the twelve naive *(b)* or the six experienced *(c)* participants. *(d)* The average duration of each task in the FA-DA condition was slightly lower than that measured after NF-DA, although multiple Friedman tests identified significant differences (p unadjusted) only in the duration of the third task (dialing a phone number). In the paper, boxplots' whiskers extend to the most extreme samples within the first quartile −1.5 IQR and the third quartile +1.5 IQR.

The performances of FASS-DA remained equivalent to those of the other strategies.

Figure 3 shows the duration of the three repetitions of the task sequence for naive and experienced participants. We referred to these repetitions as the first and second familiarization sessions (F1 and F2), and the performance evaluation session (E). The participants tested the data collection strategies in randomized orders so to counterbalance possible transfer learning effects. Therefore, the results displayed in the figure follow a chronological order within each training condition but not across different conditions. For all the training conditions, naive participants completed the performance evaluation session around 24 % faster than the first familiarization session, Figure 3A. Friedman tests confirmed that the reduction of the task completion time during the three repetitions was significant in every training condition ($\chi^2(2) = 9.5$, $p = 0.009$ for NF-DA; $\chi^2(2) = 18.2$, $p < 0.001$ for FASS-DA; $\chi^2(2) = 18$, $p < 0.001$ for FASS-DA). At the same time, the variability of the results reduced during the familiarization process. The IQR shrunk from 208-302.5 s to 181.5-229 s for NF-DA, from 191.8-282 s to 163.8-197.5 s for FA-DA, and from 152-327.3 s to 140.3-213.5 s for FASS-DA. These results, taken together, indicate that a strong learning effect took place for naive participants during the familiarization process of each strategy. This learning trend was not as evident among the six experienced participants, Figure 3B. For them, the reduction of the task sequence duration due to familiarization was statistically significant only in the FASS-DA condition ($\chi^2(2) = 9.3$, $p = 0.009$). Nonetheless, the task execution time reduced by approximately 19 % during the familiarization process for all the training strategies.

Table 2. Median amount of training samples acquired and used to build the myocontrol model

Acquisition protocol	**# training samples**
NF-DA	27284.5 (IQR 25993-30696)[a,b]
FA-DA	28439.5 (IQR 25620-30440)[a,b]
FASS-DA	26879 (IQR 26654-32696)[a] 7228.5 (IQR 5345-8646)[b]

[a]acquired; [b]used.

Table 2 details the median number of training samples acquired by each strategy and the number of samples selected to train the myocontrol model. The number of training samples comprised the data

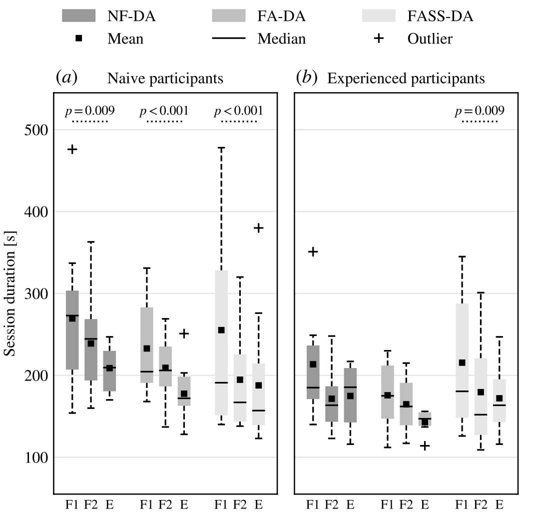


Figure 3. *Effect of learning on the duration of the task sequence.* The three repetitions of the task sequence were labeled F1, first familiarization, F2, second familiarization, and E, performance evaluation session. *(a)* The twelve naive participants showed a significant reduction in the average task completion time due to familiarization (p unadjusted). *(b)* For the six experienced participants, the familiarization with the system significantly reduced the duration of the task session only in the FASS-DA condition.

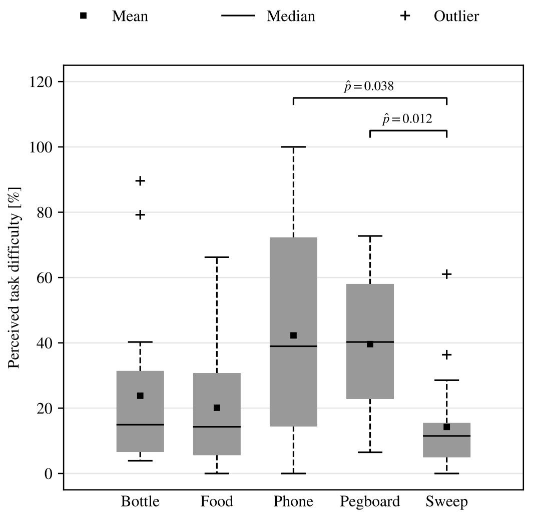


Figure 4. *Perceived tasks difficulty.* On average, participants found more difficult those tasks that required to manipulate small objects (completing the pegboard) or to precisely touch small target areas (dialing a phone number). This result was only partially supported by statistical evidence ($\hat{p}$ Bonferroni-adjusted).

acquired during the initial acquisition and during all the on-demand model updates requested by the participants. All the strategies acquired a comparable amount of training samples, about 28000, although with some variations. The median number of acquired training samples was approximately 27000 for NF-DA and FASS-DA, and 28500 for FA-DA. The median number of on-demand model updates was equal to 0.5 (IQR 0-2) for NF-DA, 1 (IQR 0-2) for FA-DA, and 0 (IQR 0-3) for FASS-DA. While NF-DA and FA-DA used all the training samples to build the myocontrol mode, FASS-DA only employed a median of $\approx$ 7000 samples, roughly corresponding to a quarter of the acquired data.

Figure 4 shows the perceived difficulty of the myocontrol tasks, assessed by the participants in the final questionnaire, and converted into a percentage from 0 % ("very easy") to 100 % ("very difficult"). The ratings seemed to split tasks into two groups. The relative difficulty of pouring water, serving food, and sweeping the floor was relatively low, around 20 % on average. Precision tasks such as dialing a phone number and completing a pegboard were given a higher average difficulty, around 40 %. In particular, a quarter of the participants found it extremely difficult to dial phone numbers, as they reported a difficulty level higher than 75 %, more than what was reported for all the other tasks. A Friedman test confirmed the existence of significant differences in the perceived complexity of the tasks ($\chi^2(4) = 23.1$, $p < 0.001$). Pairwise post-hoc tests, however, only confirmed that the sweeping task was easier than the dialing task ($W = 9$, $\hat{p} = 0.004$) and the pegboard task ($W = 11$, $\hat{p} = 0.0012$).

The controllability of the prosthetic hand during the myocontrol tasks, reported by the participants in the questionnaire, was converted into a percentage from 0 % ("very difficult to control") to 100 % ("very easy to control"). Overall, the use of feedback during the data acquisition resulted in an improvement of the controllability level of about 10% compared to acquiring data without feedback (controllability level of 60 % for NF-DA, 70 % for FA-DA, 71 % for FASS-DA), Figure 5A. A Friedman test, however, did not support this finding with statistical evidence ($\chi^2(2) = 51$, $p = 0.19$). Naive participants reported lower controllability for every training condition, by about 22% on average, compared to experienced participants. In any training condition, the average controllability reported by naive participants was about 22 % lower than that reported by experienced participants. The ratings of naive participants were mixed. Although the controllability level was slightly higher for the feedback-aided acquisition strategies (controllability

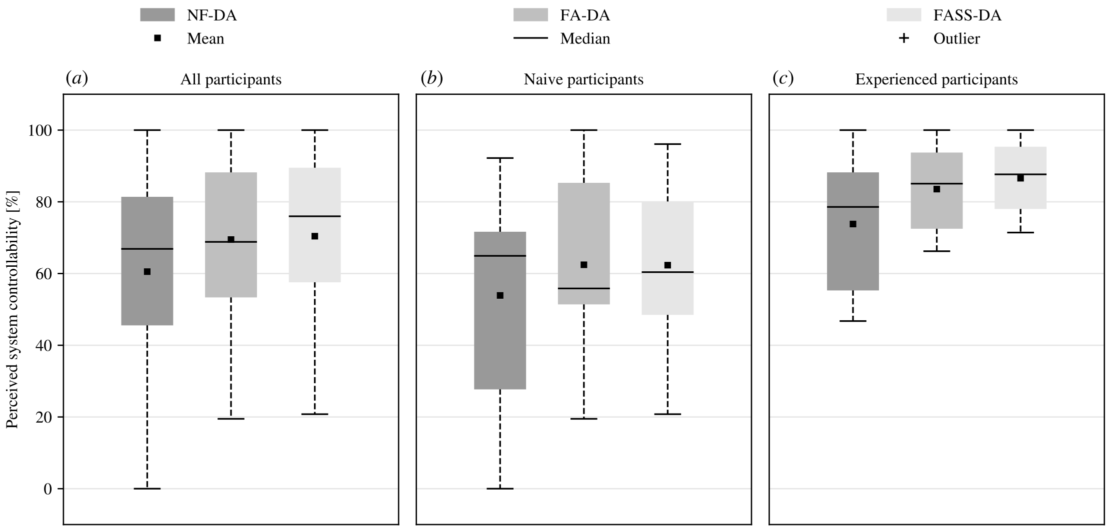


Figure 5. *Perceived controllability of the prosthetic hand. (a)* On average, participants found that the prosthetic system was easier to control after each of the HL data acquisitions compared to the OL data acquisition. *(b)* The ratings reported by the twelve naive participants were mixed and, on average, lower than those of the experienced participants. This caused the high variability observed in the overall results and possibly explained the lack of statistical significance. *(c)* The six experienced participants consistently reported that data acquisition routines with feedback resulted in better controllability of the prosthetic system.

level of 54 % for NF-DA and 62 % for FA-DA and FASS-DA), the spread of the ratings was exceptionally high, especially for the data acquisition without feedback (interquartile range, IQR, equal to 28-71 %). Experienced participants, conversely, reported sharper improvements in controllability by following feedback-aided training strategies. The average controllability increased from 74 % for NF-DA to 84 % for FA-DA, and 87 % for FASS-DA. The spread of these results was lower than that observed in naive participants (IQR equal to 56-88 % for NF-DA, 73-94 % for FA-DA, and 78-95 % for FASS-DA). However, this result was not supported by statistical evidence, possibly due to the limited amount of experienced participants.

4. Discussion and conclusions

We implemented a feedback-aided data acquisition and model building protocol in which the myocontrol model is trained online, while the participant receives instantaneous auditory feedback about the usefulness of the recorded training samples. In the experiment, we have compared two variants of the feedback-aided acquisition strategy to a traditional one, in which the user performs the acquisition routine without automatic guidance. Our results confirm that *automatically guiding the user during the data acquisition yields better myocontrol*, both *objectively*, enabling faster completion of tasks and requiring less computation space and power, and *subjectively*, increasing the perceived controllability of the prosthesis reported in quantitative questionnaires.

Participants completed the sequence of manipulation tasks significantly faster when using FA-DA compared to NF-DA, Figure 2. The average task duration after FA-DA was about 16 % shorter than after NF-DA. The performance offered by FASS-DA was characterized by higher variability and did not differ significantly from those of the other acquisition strategies. Even though half of the participants performed equivalently well with FASS-DA and FA-DA, the other half showed considerably worse performance for FASS-DA.

This may indicate that the sample selection criterion used in FASS-DA was too strict (the system discarded all the training samples that determined a prediction error below 5 % of the maximum prediction error). By relaxing that criterion, the performance of FASS-DA should tend to those of FA-DA, therefore, at least, reducing the variability. Careful tuning of the sample selection criterion should be considered for future investigation.

Nonetheless, FASS-DA considerably reduced the number of samples used to train the machine, of about three-quarters of the total on average. This is especially relevant for realtime applications where the myocontrol model needs to be updated incrementally, requiring repeated model updates for batches of incoming training samples. We then conclude that FASS-DA can be used as a second choice over FA-DA, only when less computational resources are available to the machine learning system.

Feedback-aided acquisition improved myocontrol performance both for the 6 experienced and 12 naive participants (after a short familiarization with the system), as it is apparent from Figure 2B and Figure 2C. For experienced participants, in particular, FA-DA reduced the average task duration by almost 20 % compared to NF-DA.

This suggests that even experienced myocontrol users could benefit from automatic guidance to identify the model's weaknesses during data acquisition. Figure 2D, finally, suggests that feedback-aided data acquisition improved myocontrol performance uniformly for each task.

As it was predictable, a quite evident learning effect is present in all participants' performance, from the two familiarization phases to the experimental one, Figure 3. Interestingly, this trend characterized both naive and experienced participants, albeit less so in the latter case. On the one hand, this means that the effect of feedback can be observed after a short familiarization with the system (by inexperienced participants, that is). On the other hand, automatic guidance during data acquisition retains its usefulness over time, since it allows experienced users to identify and address the flaws of the myocontrol system already during the data acquisition.

During the familiarization, participants learn to compensate distracting factors that are inherent in the myocontrol of the prosthetic device, such as the latency and the weight of the robotic hand, and the non-intuitive control of the contraction strength (nonlinear algorithms may not guarantee monotonic mappings of muscle contraction to grip strength). This contributes to reducing the variability of the results and, therefore, helps observe the effects of interest, such as the effect of different data acquisition procedures. We observed that during the familiarization process, the performance of naive participants decreased in variability and seemed to tend to those of experienced participants. However, the average duration of the task session at the end of the familiarization process remained slightly higher for naive participants. This might indicate that their performance could have further improved with a longer familiarization.

Data acquisition with feedback improved the perceived controllability of the prosthesis by about 10 % on average, Figure 5. The average controllability reported after FA-DA was similar to FASS-DA and higher than NF-DA. However, this difference was not statistically significant due to the large variability in the results. Naive participants provided disparate opinions regarding the system's controllability, and a gap of about 20 % divided the average controllability reported by naives and experienced participants. More focused questions could have been beneficial to reduce this variance. Nonetheless, the improvement reported by experienced participants exhibited a distinct trend in favor of the acquisition strategies with feedback.

The tasks perceived as most difficult were dialing a phone number and completing the pegboard game, Figure 4. They involved touching small target areas with the index finger's tip and placing small objects in positions difficult to reach. This required a significative amount of arm movements to compensate for the lack of an active wrist, which elicited the limb position effect. Interestingly, the only task in which the improvement between NF-DA and the other strategies was statistically significant was dialing the phone number, Figure 2D. This seems to indicate that the proposed feedback guidance improved the model's robustness, especially in tasks mostly affected by the limb position effect.

Interactivity during the training and during the use of the prosthesis lets the user develop more trust in the prosthesis through the usage of a friendly interface, dexterous but straightforward at the same time. In [9], a partially satisfactory result appears, mainly due, we speculate, to a suboptimally designed interaction protocol. All in all, however, the benefits of feedback guidance are not guaranteed to transfer to disabled users, and this issue must be further investigated. We have dealt with this problem already in Gigli et al. [23], to which we refer the interested reader.

Our experiment focused on evaluating the effectiveness of automatic feedback guidance in identifying and counteracting the limb position effect. To be used in everyday prosthetics, this methodology must be adapted and validated against other sources of variability in the myoelectric signal, such as electrodes shift and pressure changes within the socket due to the prosthesis weight. However, we notice that the proposed feedback targets the model's mispredictions regardless of their cause. For this reason, we argue that this feedback may be used with limited adaptation in less constrained settings.

The proposed feedback uses the prediction error to identify when the model's predictions are negatively affected by the limb position. This criterion assumes that the user is able to perform and maintain the correct gesture during the data acquisition. This can be guaranteed for non-disabled users thanks to proprioceptive and visual feedback of their hand configuration, but not for amputees. A transradial amputee, particularly a naive or distracted one (in distracting conditions), might struggle to maintain a consistent muscular activation during the data acquisition, triggering the acoustic feedback for arm configurations where more data is not required. That circumstance is potentially disruptive for the acquisition algorithm since it may lead the user to acquire more training samples while providing a wrong muscular pattern or in arm configurations that do not need to be reinforced with more data. Users with higher amputation levels could struggle even more since they might also have problems following the proper arm trajectory. This problem might be mitigated by inducing the user to perform more consistent and repeatable muscular activations. One could do so by exploiting bilateral mirrored training or using the prosthetic hand as a proxy for the missing limb during the data acquisition [33]. If this sort of training proves ineffective, then the feedback should be redesigned based on other metrics. Competences ranging from psychology to human-machine interfaces design, as well as focus groups and user studies, will be required to solve this problem.

4.1. Conclusion

This work shows that providing automatic feedback guidance during training data acquisition can improve the robustness of myocontrol models to the limb position effect. Data acquisition for myocontrol is often conducted without providing feedback guidance to the user, which may undermine the quality of the recorded data. We implemented a novel data acquisition protocol that collects myoelectric signals dynamically in multiple arm positions while building the model online and guiding the user with instantaneous acoustic feedback. We designed the feedback to induce the user to hover with the arm in the areas of the peripersonal space characterized by poor intent detection, i.e., a discrepancy between the model's prediction and the ground truth. In our experiment, data acquisition strategies that guided the participant to identify and acquire more training samples in problematic areas of the input space yielded better performance, both objective and subjective, and granted the participant a better understanding of the system.

Acknowledgments

This work was partially supported by the DFG project Deep-Hand, CA1389/1-2.

References

[1] Micera S, Carpaneto J and Raspopovic S 2010 "Control of hand prostheses using peripheral information" *IEEE reviews in biomedical engineering* **3** 48–68

[2] Cordella F, Ciancio A L, Sacchetti R, Davalli A, Cutti A G, Guglielmelli E and Zollo L 2016 "Literature review on needs of upper limb prosthesis users" *Frontiers in neuroscience* **10** 209

[3] Resnik L, Ekerholm S, Borgia M and Clark M A 2019 "A national study of veterans with major upper limb amputation: Survey methods, participants, and summary findings" *PloS one* **14** e0213578

[4] Reiber G E, McFarland L V, Hubbard S, Maynard C, Blough D K, Gambel J M and Smith D G 2010 "Servicemembers and veterans with major traumatic limb loss from vietnam war and oif/oef conflicts: Survey methods, participants, and summary findings" *Journal of rehabilitation research and development* **47** 275–298

[5] Atkins D J, Heard D C and Donovan W H 1996 "Epidemiologic overview of individuals with upper-limb loss and their reported research priorities" *Jpo: Journal of prosthetics and orthotics* **8** 2–11

[6] Hahne J M, Biessmann F, Jiang N, Rehbaum H, Farina D, Meinecke F C, Müller K R and Parra L C 2014 "Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **22** 269–279

[7] Parajuli N, Sreenivasan N, Bifulco P, Cesarelli M, Savino S, Niola V, Esposito D, Hamilton T J, Naik G R, Gunawardana U *et al.* 2019 "Real-time emg based pattern recognition control for hand prostheses: a review on existing methods, challenges and future implementation" *Sensors* **19** 4596

[8] Sensinger J W, Lock B A and Kuiken T A 2009 "Adaptive pattern recognition of myoelectric signals: exploration of conceptual framework and practical algorithms" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **17** 270–278

[9] Nowak M, Castellini C and Massironi C 2018 "Applying Radical Constructivism to machine learning: a pilot study in assistive robotics" *Constructivist Foundations* **13** 250–262 URL `http://constructivist.info/13/2/250.nowak`

[10] Meattini R, Nowak M, Melchiorri C and Castellini C 2019 "Automated instability detection for interactive myocontrol of prosthetic hands" *Frontiers in Neurorobotics* **13** URL `https://www.frontiersin.org/articles/10.3389/fnbot.2019.00068`

[11] Meattini R, Biagiotti L, Palli G and Melchiorri C 2019 "Grasp-oriented myoelectric interfaces for robotic hands: A minimal-training synergy-based framework for intent detection, control and perception" *International Workshop on Human-Friendly Robotics* (Springer) pp 110–124

[12] Hahne J M, Markovic M and Farina D 2017 "User adaptation in myoelectric man-machine interfaces" *Scientific Reports* **7** 4437

[13] Shehata A W, Scheme E J and Sensinger J W 2018 "Improving internal model strength and performance using augmented feedback" *bioRxiv* 259754

[14] Marasco P D, Kim K, Colgate J E, Peshkin M A and Kuiken T A 2011 "Robotic touch shifts perception of embodiment to a prosthesis in targeted reinnervation amputees" *Brain* **134** 747–758

[15] Woodward R B and Hargrove L J 2019 "Adapting myoelectric control in real-time using a virtual environment" *Journal of neuroengineering and rehabilitation* **16** 11

[16] Hahne J M, Dähne S, Hwang H J, Müller K R and Parra L C 2015 "Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **23** 618–627

[17] Campbell E, Phinyomark A and Scheme E 2020 "Current trends and confounding factors in myoelectric control: Limb position and contraction intensity" *Sensors* **20**

1613

[18] Khushaba R N, Takruri M, Miro J V and Kodagoda S 2014 "Towards limb position invariant myoelectric pattern recognition using time-dependent spectral features" *Neural Networks* **55** 42–58

[19] Betthauser J L, Hunt C L, Osborn L E, Masters M R, Lévay G, Kaliki R R and Thakor N V 2018 "Limb position tolerant pattern recognition for myoelectric prosthesis control with adaptive sparse representations from extreme learning" *IEEE Transactions on Biomedical Engineering* **65** 770–778

[20] Fougner A, Scheme E, Chan A D, Englehart K and Stavdahl Ø 2011 "Resolving the limb position effect in myoelectric pattern recognition" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **19** 644–651

[21] Scheme E, Biron K and Englehart K 2011 "Improving myoelectric pattern recognition positional robustness using advanced training protocols" *Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (IEEE) pp 4828–4831

[22] Radmand A, Scheme E and Englehart K 2014 "On the suitability of integrating accelerometry data with electromyography signals for resolving the effect of changes in limb position during dynamic limb movement" *JPO: Journal of Prosthetics and Orthotics* **26** 185–193

[23] Gigli A, Gijsberts A and Castellini C 2020 "The merits of dynamic data acquisition for realistic myocontrol" *Frontiers in Bioengineering and Biotechnology*

[24] Sierra González D and Castellini C 2013 "A realistic implementation of ultrasound imaging as a human-machine interface for upper-limb amputees" *Frontiers in Neurorobotics* **7** URL `https://www.frontiersin.org/articles/10.3389/fnbot.2013.00017`

[25] Gijsberts A, Bohra R, Sierra González D, Werner A, Nowak M, Caputo B, Roa M A and Castellini C 2014 "Stable myoelectric control of a hand prosthesis using non-linear incremental learning" *Frontiers in Neurorobotics* **8** URL `https://www.frontiersin.org/articles/10.3389/fnbot.2014.00008`

[26] Patel G K, Nowak M and Castellini C 2017 "Exploiting knowledge composition to improve real-life hand prosthetic control" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **25** 967–975

[27] Strazzulla I, Nowak M, Controzzi M, Cipriani C and Castellini C 2017 "Online bimanual manipulation using surface electromyography and incremental learning" *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **25** 227–234 URL `https://ieeexplore.ieee.org/document/7460959`

[28] Wang S, Hsu J, Trent L, Ryan T, Kearns N, Civillico E and Kontson K 2018 "Evaluation of performance-based outcome measures for the upper limb: a comprehensive narrative review" *PM&R*

[29] Hermansson L M, Fisher A G, Bernspång B and Eliasson A C 2005 "Assessment of capacity for myoelectric control: a new Rasch-built measure of prosthetic hand control" *Journal of rehabilitation medicine* **37** 166–71

[30] Kyberd P J, Murgia A, Gasson M, Tjerks T, Metcalf C, Chappell P H, Warwick K, Lawson S E and Barnhill T 2009 "Case studies to demonstrate the range of applications of the Southampton Hand Assessment Procedure" *British Journal of Occupational Therapy* **72** 212–218

[31] Vujaklija I, Roche A D, Hasenoehrl T, Sturma A, Amsuess S, Farina D and Aszmann O C 2017 "Translating research on myoelectric control into clinics—are the performance assessment methods adequate?" *Frontiers in neurorobotics* **11** 7

[32] Chen S Y, Feng Z and Yi X 2017 "A general introduction to adjustment for multiple comparisons" *Journal of thoracic disease* **9** 1725

[33] Igual C, Pardo L A, Hahne J M and Igual J 2019 "Myoelectric control for upper limb prostheses" *MDPI Electronics* **8** 1244

A3 Coadaptive Unsupervised Myocontrol

Title: Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping

Authors: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini.

Conference: 2022 IEEE International Conference on Rehabilitation Robotics.

Manuscript version: Accepted manuscript.

Citation: Andrea Gigli, Arjan Gijsberts, and Claudio Castellini. "Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping." In: *2022 IEEE International Conference on Rehabilitation Robotics.* Rotterdam, 2022, pp. 1–6.

Unsupervised Myocontrol of a Virtual Hand Based on a Coadaptive Abstract Motor Mapping

Andrea Gigli[1,2], Arjan Gijsberts[3] and Claudio Castellini[1,2]

***Abstract*— Applications of simultaneous and proportional control for upper-limb prostheses typically rely on supervised machine learning to map muscle activations to prosthesis movements. This scheme often poses problems for individuals with limb differences, as they may not be able to reliably reproduce the training activations required to construct a natural motor mapping. We propose an unsupervised myocontrol paradigm that eliminates the need for labeled data by mapping the most salient muscle synergies in arbitrary order to a number of predefined prosthesis actions. The paradigm is coadaptive, in the sense that while the user learns to control the system via interaction, the system continually refines the identification of the user's muscular synergies. Our evaluation consisted of eight subjects without limb-loss performing target achievement control tasks of four actions of the hand and wrist. The subjects achieved comparable performance using the proposed unsupervised myocontrol paradigm and a supervised benchmark method, despite reporting increased mental load with the former.**

I. Introduction

Simultaneous and proportional (SP) myocontrol represents a promising methodology to control dexterous prosthetic hands naturally and intuitively. In this paradigm, regression models map muscular contractions directly to continuous motor commands for the degrees of freedom (DoFs) of the prosthesis [1]. The models are typically obtained via supervised machine learning, in which muscular data acquired from the subject's forearm is associated during a training phase with the desired motor commands.

Producing accurately labeled data can be challenging, especially for subjects with limb differences who stand to gain the most from this technology. Their impairment not only poses difficulties in precisely reproducing specific muscular activations, but also makes it impossible to verify whether the activations they produce actually correspond to the desired motor commands. Standard labeling protocols, therefore, resort to collecting labels using the contralateral hand as guidance or by pairing the desired motor commands with a visual stimulus [2]. These procedures typically require supervision from trained clinicians, are time-consuming, and are often perceived as mentally demanding by the target users.

A form of myocontrol that can learn motor mappings without labeled training data would be a desirable alternative to standard supervised myocontrol (SM). Existing approaches to such unsupervised myocontrol (UM) build upon evidence that the human motor system produces movements by jointly activating groups of muscles [3]. These muscle synergies function as high-level motor commands that can be combined to produce more fine-grained motor control. Lin et al. [4] achieved quasi-unsupervised myocontrol of the DoFs of the wrist through a principled calibration protocol. First, they collected unlabeled calibration surface electromyography (sEMG) by asking the subjects to selectively move the desired DoFs of the wrist. Then, they used a nonnegative matrix factorization (NMF) algorithm with sparsity constraints to express the calibration sEMG as the activity of minimally-overlapping muscle synergies. Finally, they assigned muscle synergies to DoFs by observing which synergy was most active while activating each DoF. The work by Yeung et al. [5] extends the calibration procedure described above, accounting for the evolution of muscle synergies over time due to the subject's familiarization with the myocontrol system and the displacement of electrodes, among other factors. They accommodate for those changes by employing an adaptive version of NMF with sparsity constraints and a forgetting mechanism that progressively discounts the contribution of old input samples. The method automatically triggers unsupervised model updates when model degradation is detected during normal operation. Both approaches allowed performance comparable to a SM benchmark in target-reaching tasks involving a cursor on a screen.

The semi-unsupervised calibration procedure used by the previous works requires subjects to repeat the same muscular activations in an open-loop. This is done so that an individual synergy can be isolated and mapped to the DoF of the prosthesis that physiologically corresponds to the muscular activation. As mentioned, this can be unpractical for subjects with limb differences, who may not be able to precisely and repeatably control each DoF of their phantom limb. In these cases, it would be preferable to control hand movements via an abstract motor mapping, that is, by muscular activations that may not be physiologically related to those movements. In this manner, subjects could control their prosthesis using the muscular patterns that they can elicit best.

Numerous works on motor learning have demonstrated the human capacity to learn abstract motor mappings through closed-loop interaction with a myocontrol system [6]. Ison and Artemiadis [7] demonstrated that humans can learn non-trivial motor mappings between the combined activity of biomechanically independent muscles and the position of a cursor on a screen. Their research also showed that the

[1] Institute of Robotics and Mechatronics, German Aerospace Center (DLR), 82234 Weßling, Germany. name.surname@dlr.de
[2] Chair of Medical Robotics, Friedrich-Alexander University Erlangen-Nuremberg, 91054 Erlangen, Germany
[3] Unaffiliated

learned motor skills are retained over time and can generalize to different myocontrol tasks, such as controlling the position of a robot's end-effector on a plane. Pistohl et al. [8] showed that abstract motor mappings can be effectively used to control myoelectric hands. Their approach arbitrarily maps the activity of a specific muscle to the control of an action of the hand and relies on the subject to learn to use that mapping. However, this motor learning may be complicated if the muscles used in the motor mapping are biomechanically coupled [9], as is the case in the human forearm. To control myoelectric hands it may thus be advantageous to define abstract motor mappings based on automatically extracted muscle synergies rather than individual muscle activations.

In this work, we introduce a novel coadaptive UM paradigm that integrates incremental extraction of muscle synergies and adaptation to an abstract motor mapping that is based on those synergies. The system adaptively decomposes muscular control inputs into sparse muscle synergies using a purposedly designed incremental NMF algorithm with sparsity constraints and a forgetting mechanism to discount the contribution of old input samples. Although derived independently, our formulation is similar (but not equal) to the NMF algorithm used by Yeung et al. [5], which was published during our paper's final redaction. In contrast to their approach, this algorithm is used to implement an abstract motor mapping between the synergies' activations and a set of desired actions of the hand or wrist that may not be physiologically related to those activations. A virtual hand on a monitor visualizes the model's prediction in real-time and closes the control loop with the subject. Subjects are instructed to learn to perform the desired actions with the virtual hand, starting from eliciting arbitrary muscular contractions. This paradigm involves coadaptation between subjects and myocontrol model. Subjects aim to elicit more distinctive muscular patterns whilst the model incrementally decomposes those patterns into sparse muscle synergies. Conveniently, this paradigm does not require any initial calibration of the myocontrol system, is easily understood by the subjects, and encourages them to explore their muscular space to identify distinctive muscular patterns for myocontrol. We compare the proposed UM paradigm to a state-of-the-art SM in a series of target achievement control (TAC) tests and via a questionnaire.

The remainder of this paper is organized as follows. In section II, we describe our UM method and its experimental evaluation. The corresponding results are then described in section III. A discussion of the results follows in section IV and the paper is concluded in section V.

II. Materials and Methods

A. Coadaptive unsupervised myocontrol paradigm

We present a UM paradigm that adaptively extracts sparse muscle synergies, implements an abstract motor mapping based on those synergies, and leverages closed-loop adaptation to that mapping. Figure 1 provides an overview of this paradigm. The resulting myocontrol model uses the activation of the detected muscle synergies to control an arbitrary set of actions of the hand and wrist simultaneously and proportionally.

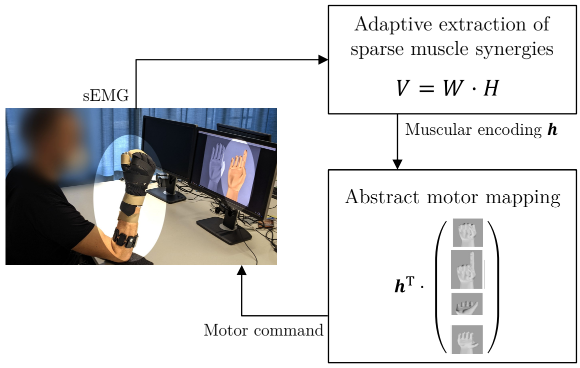


Fig. 1: *Proposed unsupervised myocontrol paradigm (UM).* While the subjects learn to control the artificial hand by interacting with the system, their muscular activity is adaptively decomposed in sparse muscle synergies. The activation levels of these synergies are used to activate a predefined set of hand actions based on an abstract motor mapping. The detected control action is fed back to the user via a skin-colored hand on a monitor. During the TAC tasks, the subject has to match the target action of the hand shown in gray on the monitor.

Incremental extraction of sparse muscle synergies: Because the subjects' adaptation to the myocontrol model causes changes in their muscular synergies, we require a factorization algorithm that can incrementally extract and update the decomposition of the input signals. To this end, we formulate incremental sparse nonnegative matrix factorization (ISNMF) with forgetting, which is an incremental version of NMF with additional sparsity constraints and a mechanism to discount the contribution of old input samples.

Standard NMF decomposes a nonnegative data matrix $\boldsymbol{V}$ of s n-dimensional samples as $\boldsymbol{V} \approx \boldsymbol{W}\boldsymbol{H}$, where factors $\boldsymbol{W}$ and $\boldsymbol{H}$ are restricted to be nonnegative. The $n \times r$ matrix $\boldsymbol{W}$ contains the basis vectors, whereas the $r \times s$ encoding matrix $\boldsymbol{H}$ contains for each sample the activations of the bases as to reconstruct $\boldsymbol{V}$ as accurately as possible.

This problem can be solved incrementally by updating the bases and encoding matrices when new data becomes available. At the m-th update, the old data matrix $\boldsymbol{V} = \begin{bmatrix}\boldsymbol{V}^1 & \cdots & \boldsymbol{V}^{m-1}\end{bmatrix}$ is extended with the new data samples $\boldsymbol{V}^m$, and the encoding matrix $\boldsymbol{H} = \begin{bmatrix}\boldsymbol{H}^1 & \cdots & \boldsymbol{H}^{m-1}\end{bmatrix}$ is extended with randomly initialized encoding coefficients $\boldsymbol{H}^m$. The basis matrix $\boldsymbol{W}^m$ and the new encoding coefficients $\boldsymbol{H}^m$ can then be found by minimizing the objective function

$$F^m = \frac{1}{2}\sum_{j=1}^{m} \mu^{m-j} \left\| \boldsymbol{V}^j - \boldsymbol{W}^m \boldsymbol{H}^j \right\|_F^2 + \gamma \sum_{j=1}^{m} \mu^{m-j} \left\| \boldsymbol{H}^j \right\|_1 + \frac{\beta}{2} \left\| \boldsymbol{W}^m \right\|_F^2 \quad , \tag{1}$$

where $\mu \in (0, 1]$ is a forgetting factor that exponentially discounts old input samples, and $\beta \geq 0$ and $\gamma \geq 0$ determine the regularization strength for the encoding and the basis matrices. With $\|\cdot\|_F$ and $\|\cdot\|_1$ we denote the Frobenius and the elementwise L_1 norms. Furthermore, we assume that the former encoding blocks $\boldsymbol{H}^1$ to $\boldsymbol{H}^{m-1}$ would not change much and therefore do not optimize these. This approximation constrains the number of parameters that need to be optimized at each update and has other computational benefits [10, 11].

The problem can be solved incrementally following the procedure in algorithm 1 based on multiplicative updates, analogous to the derivation presented in other related work [10, 11]. Model updates are performed in constant time and memory by storing the model state into constant-sized history matrices instead of retaining old data samples. Encodings of new data samples in the updated synergy space can be obtained by repeatedly applying the rule on line 17. Among the algorithm's hyperparameters, r represents the desired number of NMF components, while the tolerance $\epsilon > 0$ and the maximum number of iterations $t_{\text{max}} > 0$ are used for the stopping condition of the iterative optimization. The elements of $\boldsymbol{W}^1$ and $\boldsymbol{H}^m$ are initialized randomly to $\max(0, \mathcal{N}(\bar{\boldsymbol{V}}^m, 1))$, with $\bar{\boldsymbol{V}}^m$ being the average value of the new data samples and $\mathcal{N}$ representing the normal distribution. Subscripts ij indicate the element at the i-th row and the j-th column of the corresponding matrix.

Algorithm 1: ISNMF

Input: stream $\mathcal{S}$ of n-dim nonnegative samples
Parameters: r, β, γ, μ, ϵ, t_{max}

1 $m \leftarrow 0$
2 $\boldsymbol{A} \leftarrow [0]_{n\times r}$
3 $\boldsymbol{B} \leftarrow [0]_{r\times r}$
4 **while** *true* **do**
5 $\quad m \leftarrow m + 1$
6 $\quad \boldsymbol{V}^m \leftarrow n \times k$ matrix with k new samples from $\mathcal{S}$
7 $\quad$**if** $m = 1$ **then**
8 $\quad\quad \boldsymbol{W}^m \leftarrow n \times r$ strictly positive random matrix
9 $\quad$**else**
10 $\quad\quad \boldsymbol{W}^m \leftarrow \boldsymbol{W}^{m-1}$
11 $\quad$**end**
12 $\quad \boldsymbol{H}^m \leftarrow r \times k$ strictly positive random matrix
13 $\quad e_0 \leftarrow \|\boldsymbol{V}^m - \boldsymbol{W}^m \boldsymbol{H}^m\|_F^2$
14 $\quad t \leftarrow 0$
15 $\quad$**repeat**
16 $\quad\quad t \leftarrow t + 1$
17 $\quad\quad \boldsymbol{H}_{ij}^m \leftarrow \boldsymbol{H}_{ij}^m \frac{(\boldsymbol{W}^{m\intercal}\boldsymbol{V}^m)_{ij}}{(\boldsymbol{W}^{m\intercal}\boldsymbol{W}^m\boldsymbol{H}^m)_{ij} + \gamma\,\mathrm{sgn}\left(\boldsymbol{H}_{ij}^m\right)}$
18 $\quad\quad \boldsymbol{W}_{ij}^m \leftarrow \boldsymbol{W}_{ij}^m \frac{(\mu\boldsymbol{A} + \boldsymbol{V}^m\boldsymbol{H}^{m\intercal})_{ij}}{(\mu\boldsymbol{W}^m\boldsymbol{B} + \boldsymbol{W}^m\boldsymbol{H}^m\boldsymbol{H}^{m\intercal} + \beta\boldsymbol{W}^m)_{ij}}$
19 $\quad\quad e_t \leftarrow \|\boldsymbol{V}^m - \boldsymbol{W}^m \boldsymbol{H}^m\|_F^2$
20 $\quad$**until** $|e_t - e_{t-1}|/e_0 < \epsilon$ **or** $t > t_{max}$
21 $\quad \boldsymbol{A} \leftarrow \mu\boldsymbol{A} + \boldsymbol{V}^m\boldsymbol{H}^{m\intercal}$
22 $\quad \boldsymbol{B} \leftarrow \mu\boldsymbol{B} + \boldsymbol{H}^m\boldsymbol{H}^{m\intercal}$
23 **end**

Adaptive abstract motor mapping: The proposed UM system periodically computes the encoding of a new muscular input and regards its components as primitive motor commands. These components are normalized to the range $[0, 1]$ by dividing them by their historical 95-th percentile computed incrementally and bounded above by 1. Each of the resulting control signals is associated with one of a predefined set of hand actions, where the order depends on the random initialization of $\boldsymbol{W}^1$ and the subsequent incremental updates. We refer to this association as an abstract motor mapping, because it is not based on a physiological correspondence between muscle activity and action of the hand. Since multiple control signals may be nonzero at the same time, this allows simultaneous and proportional control of the hand.

Adaptation to the motor mapping: The control loop is closed by rendering the predicted action on a virtual hand on a screen in real-time. Subjects are induced to learn the abstract motor mapping implemented by the myocontrol model through simple instructions. First, they are told which basic actions the virtual hand can perform. Second, they are informed that those actions can be controlled by performing possibly different actions with their own (phantom) limb. Finally, they are asked to identify which actions of their hand precisely control the basic actions of the virtual hand, starting by performing random actions and observing the virtual hand's reaction. The proposed myocontrol paradigm is coadaptive because subjects and myocontrol model synergistically try to generate distinctive muscular commands and adaptively discriminate sparse muscle synergies from them.

B. Experiment: evaluation of unsupervised myocontrol

We compared the proposed unsupervised myocontrol approach to a state-of-the-art supervised one in a series of TAC tests.

Participants: Eight non-disabled subjects participated in the experiment. The study was conducted at the German Aerospace Center according to the WMA Declaration of Helsinki and approved by the Institution's internal committee for personal data protection.

Experiment setup: One Myo armband by Thalmic Labs provided 200 Hz 8-channels sEMG measurements of the forearm muscles of the subjects' right arm. Limbs movements were restricted by padding the hand with two thick gloves and securing the limb to an orthotic splint of the hand and wrist. Moreover, subjects were asked to lay their elbow on a table before them and to avoid rotating their wrist during the experiment. A monitor displayed a skin-colored virtual hand that showed the myocontrol model's prediction in real-time and a gray hand that provided reference actions during the experiment. The experimental setup can be seen in Figure 1.

Data processing and myoelectric control: The stream of sEMG measurements was band-pass filtered online using a second-order Butterworth filter with cutoff frequencies of 10 Hz and 90 Hz. Then, the envelope of each channel was computed as the root mean square of the signal over the last 200 ms and used as input signal for both tested myocontrol paradigms.

Four basic actions of the hand and wrist were selected for myocontrol in this experiment. They were a power grasp, a pointing with the index finger, a wrist flexion, and a wrist extension. The number of basic actions corresponded with the maximum number of distinct muscle synergies that could be extracted reliably from the sEMG data measured with our setup. The actions were chosen based on their relevance in activities of daily living and because they are challenging in realistic myocontrol settings.

Based on preliminary tests, the hyperparameters of the ISNMF algorithm were set to $r = 4$, $\beta = \gamma = 30$, $\mu = 0.95$, $\epsilon = 1e - 5$, and $t_{\text{max}} = 200$. The synergy model was updated at $f_u = 0.2\,\text{Hz}$ using the k samples available from the previous update. New encodings were computed at $f_p = 20\,\text{Hz}$ and used to predict the desired action.

We compared UM to an existing supervised SM approach that uses ridge regression with random Fourier features (RFFRR). This approach, based on nonlinear regression, provided state-of-the-art performance in a variety of SP myocontrol applications including prosthetic control [12]. The interested reader is referred to [12] for details about the method. We set the bandwidth and dimensionality of the RFF mapping respectively to 1 and 300, the regularization parameter of the regressor to 1, and the prediction frequency to $f_p = 20\,\text{Hz}$.

C. Experiment protocol

All subjects tested both UM and SM, in randomized order, performing two types of exercises. The first type was aimed at updating the myocontrol models, and denoted as coadaptation round for UM or calibration round for SM. The second type consisted of TAC tasks aimed at testing the models. For each condition, three coadaptation or calibration rounds were alternated with three TAC tests involving basic actions to allow subjects to reach comparable familiarization with the system; two TAC tests involving combinations of basic actions concluded the sequence of exercises. In the following, we will refer to the coadaptation (for UM) or calibration (for SM) rounds as C, to the TAC tests on basic actions as TB, and to the TAC tests on combined actions as TC. The sequence of exercises performed by the subjects for both UM and SM was, therefore: C1, TB1, C2, TB2, C3, TB3, TC1, TC2.

The unsupervised model was randomly initialized at the beginning of the experiment and progressively updated throughout the following coadaptation rounds. They consisted of 300 s long sessions allocated for the UM model to update the abstract motor mapping and for the subject to adapt to it. The supervised model was initialized to provide null predictions and updated in the subsequent calibration rounds. In each calibration round, labeled training data was obtained while asking subjects to hold each basic action and a resting hand gesture for 5 s. The model could be updated with more training data for the actions that were deemed not controllable.

In the TAC tasks, the myocontrolled virtual hand had to be matched with the target action displayed by the reference virtual hand. A task would be considered successful if the subject managed to keep the predicted DoFs within a euclidean distance of $d \leq 0.15$ from the target action for at least a continuous 1 s before the 10 s maximum task duration. During the TAC tests, the automatic updates of the unsupervised model were suspended for better comparability with the supervised strategy. The same TAC tests were performed for both conditions. The TAC tests involving basic actions included 16 tasks, corresponding to the four basic actions presented at two intensity levels, 50 % and 100 %, and repeated twice in random order. Those involving combined actions included eight tasks, corresponding to the four possible combinations of basic actions of the hand and the wrist, repeated twice in random order.

D. Performance evaluation

The performances achieved by UM and SM in the TAC tests were compared based on standard metrics. Success rate (SR) is the percentage of successful tasks in one TAC, time to complete the task (TCT) is the time to successfully complete one task, number of overshoots (NO) is the number of times the predicted actions approached the target and then moved away from it, mean error in target (MET) is the average euclidean distance between predicted and target action after reaching the target for the first time, and path efficiency (PE) is the ratio between the length of the optimal path and the predicted path from the rest action to the target action.

Moreover, subjects self-assessed performance of the myocontrol models at the end of each TAC in terms of mental effort, physical effort, and frustration. The ratings were reported on visual analog scales (VASs) ranging from ”low”, corresponding to 0 %, to ”high”, corresponding to 100 %. Subjects also assessed their satisfaction with the coadaptation rounds of UM in terms of mental effort, physical effort, and frustration level in the same questionnaire. As this is an initial study on the proposed UM paradigm with a limited number of subjects, we lack the statistical power for meaningful significance tests and instead report the individual data points when possible.

III. Experimental Results

Figure 2(a) shows the success rate achieved during each TAC test. Subjects reached comparable success rates around 50 % with UM and SM in all TAC tests involving basic actions. Controlling combined hand actions proved considerably more difficult, especially with SM. Only one subject managed to complete about 10 % of the combined actions with SM, while approximately half the subjects obtained success rates between 10 % to 50 % with UM. This discrepancy may have to do with the fact that the linear ISNMF method interpolates more predictably than RFFRR in parts of the input space that were unseen during the training phase. The comparison between UM and SM is not investigated further due to the very lacking performance of the latter.

Figure 2(b-e) focuses on the tasks on basic actions that were completed successfully and characterizes how quickly and accurately they were executed. Trends of the median

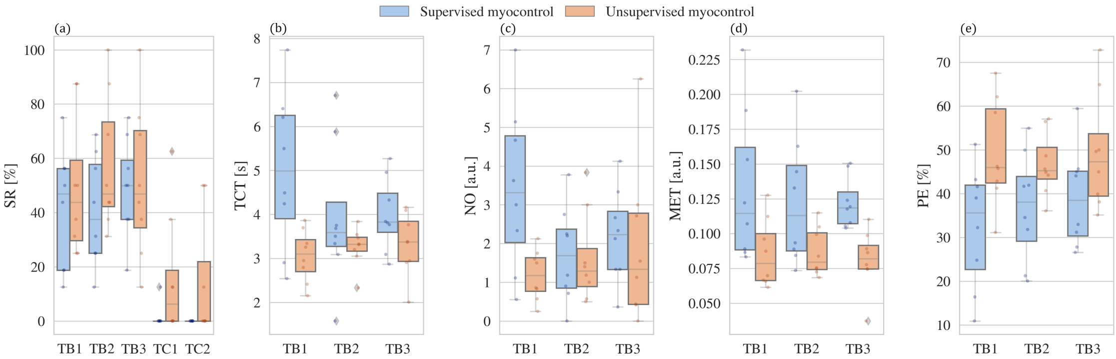


Fig. 2: *Myocontrol performance in the TAC tests.* (a) Success rate achieved during the TAC tests. (b-e) Performance achieved in tasks on basic actions that were completed successfully. Each of the points displayed within the boxplots represents the average of a statistic achieved by one subject during the tasks of the corresponding TAC.

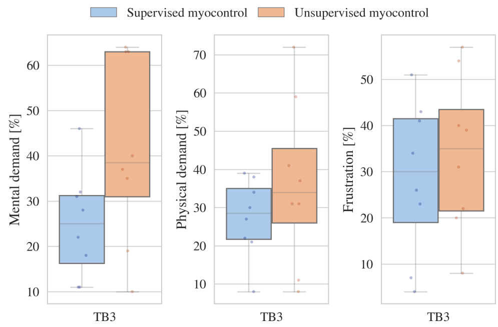


Fig. 3: *Self-assessed myocontrol performance.* Mental and physical demand, and frustration with the myocontrol model during the last TAC on basic actions, TB3.

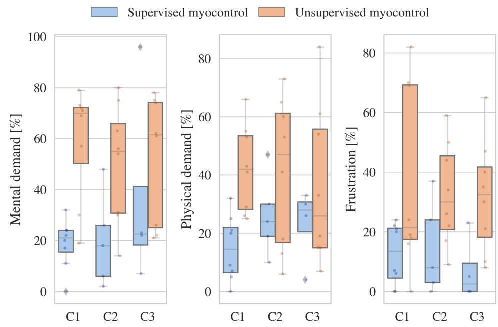


Fig. 4: *Questionnaire unsupervised coadaptation rounds.* Mental and physical demand, and frustration level related to the calibration rounds of SM and the coadaptation rounds of UM.

value and the spread of every metric suggest that subjects familiarized themselves with SM during the first TAC test and reached comparable performance to UM during the following ones. Presumably, a similar familiarization effect was not observed for UM because subjects had gained proficiency with the system already during the first coadaptation phase. During the last TAC test on basic actions, TB3, subjects completed the tasks in about 3.5 s with either myocontrol paradigm. On average, each target action was overshot two times with SM and one time with UM, indicating that the latter allowed slightly better control while approaching the target action. Nevertheless, the magnitude of the overshoots was small for both approaches. The median value of the MET, around 0.012 for SM and 0.08 for UM, was only about 5 % of the maximum possible MET. A median path efficiency around 40 % for SM and 50 % for UM, indicates that target actions were reached with comparably efficient movements. The small difference in path efficiency reflects the slightly more frequent overshoots with SM.

Despite performing equivalently well with either myocontrol paradigm, subjects deemed UM more mentally challenging, as shown in Figure 3. Most subjects reported mental loads between 10 % and 30 % for SM and between 30 % and 60 % for UM. Nonetheless, the level of physical effort and frustration with the myocontrol system were more comparable for the two approaches.

Figure 4 characterizes the coadaptation rounds of UM in terms of mental demand, physical demand, and overall frustration level, as compared to the standard calibration procedure used for SM. Most subjects found coadaptation rounds considerably more mentally challenging than calibration rounds. The physical demand and frustration levels were also slightly higher for the coadaptive procedure. These results could be explained by the subjects having to learn new abstract motor mappings, the longer duration of the calibration procedure, or the model adaptation not fully meeting the subjects' expectations.

IV. Discussion

The results of our experiment show that subjects can learn abstract motor mappings controlled by sparse muscle synergies extracted online. By the end of the first coadaptation round, most subjects had managed to control all the basic actions of the virtual hand independently. This indicates that the ISNMF algorithm adaptively identified a set of muscle synergies in the input signals that were distinctive enough to control the virtual hand's basic actions precisely. It also confirms that subjects quickly learned the abstract motor mapping implemented by the myocontrol algorithm, i.e., they identified which actions of their restricted hand controlled the desired actions of the virtual hand.

We note that our coadaptive UM paradigm induced subjects to autonomously, and perhaps subconsciously, explore their own muscular space. This could be especially beneficial for individuals with limb differences, allowing them to independently discover muscular activations that they can elicit comfortably and repeatably enough for use in myoelectric control. In future work, we hope to experimentally confirm these benefits for individuals with limb differences.

Some subjects complained about not being able to control one of the virtual actions independently of the others, despite trying numerous control inputs. This is reflected in the non-decreasing frustration about the coadaptation phase reported in the questionnaire (Figure 4). We argue that this problem relates to adopting a unique set of hyperparameters for the ISNMF algorithm for all the subjects. Although they had been optimized on preliminary tests, stronger regularization and forgetting could have been helpful for some subjects. Future investigation will include strategies to automatically tune those hyperparameters during the experiment based on codependencies between the extracted muscle synergies.

Our experiment also shows that abstract motor mappings based on adaptively extracted muscle synergies enable fully unsupervised SP myocontrol of artificial hands. The approach performed equivalently well as state of the art SM with a physiologically-inspired motor mapping (Figure 2), and the two paradigms generated comparable frustration levels in the subjects (Figure 3). Nonetheless, the mental effort required for UM was higher than for SM (Figure 3). Presumably, this is because all subjects were non-disabled; they had to learn the abstract motor mappings used in UM while they were already familiar with the physiologically-inspired mapping used in SM. We would expect to see higher levels of mental effort for subjects with limb differences when using SM.

V. Conclusions

To avoid the need for labeled training data for simultaneous and proportional myocontrol, we proposed an unsupervised and coadaptive myocontrol paradigm. Our myocontrol system incrementally refines the recognition of sparse muscle synergies from sEMG measurements and maps them arbitrarily to a set of hand actions. At the same time, the user interacts with the system in a closed-loop and learns to control this abstract motor mapping by producing more distinctive muscular patterns. In a series of TAC tests with eight non-disabled subjects, this unsupervised myocontrol paradigm performed as well as a supervised reference method in terms of task success rate, completion time, and path efficiency, despite coming at a higher self-reported mental load. This demonstrates the capacity of humans to learn to control abstract motor mappings based on adaptively extracted muscle synergies and supports the feasibility of using the proposed UM paradigm for prosthetic control.

Acknowledgements

This work was partially supported by the DFG project Deep-Hand, CA1389/1-2. The authors would like to thank the participants in the user study and Mr. Markus Nowak for his insightful feedback on the experimental protocol.

References

[1] A. Fougner, Ø. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric control—a review," *IEEE Transactions on neural systems and rehabilitation engineering*, vol. 20, no. 5, pp. 663–677, 2012.

[2] A. Hagengruber, U. Leipscher, B. M. Eskofier, and J. Vogel, "A new labeling approach for proportional electromyographic control," *Sensors*, vol. 22, no. 4, p. 1368, 2022.

[3] M. Santello, G. Baud-Bovy, and H. Jörntell, "Neural bases of hand synergies," *Frontiers in Computational Neuroscience*, vol. 7, 2013.

[4] C. Lin, B. Wang, N. Jiang, and D. Farina, "Robust extraction of basis functions for simultaneous and proportional myoelectric control via sparse non-negative matrix factorization," *Journal of neural engineering*, vol. 15, no. 2, p. 026017, 2018.

[5] D. Yeung, I. M. Guerra, I. Barner-Rasmussen, E. Siponen, D. Farina, and I. Vujaklija, "Co-adaptive control of bionic limbs via unsupervised adaptation of muscle synergies," *IEEE Transactions on Biomedical Engineering*, 2022.

[6] M. Ison and P. Artemiadis, "The role of muscle synergies in myoelectric control: trends and challenges for simultaneous multifunction control," *Journal of neural engineering*, vol. 11, no. 5, p. 051001, 2014.

[7] M. Ison and P. Artemiadis, "Proportional myoelectric control of robots: muscle synergy development drives performance enhancement, retainment, and generalization," *IEEE Transactions on Robotics*, vol. 31, no. 2, pp. 259–268, 2015.

[8] T. Pistohl, C. Cipriani, A. Jackson, and K. Nazarpour, "Abstract and proportional myoelectric control for multi-fingered hand prostheses," *Annals of biomedical engineering*, vol. 41, no. 12, pp. 2687–2698, 2013.

[9] A. De Rugy, G. E. Loeb, and T. J. Carroll, "Muscle coordination is habitual rather than optimal," *Journal of Neuroscience*, vol. 32, no. 21, pp. 7384–7391, 2012.

[10] S. S. Bucak and B. Gunsel, "Incremental subspace learning via non-negative matrix factorization," *Pattern recognition*, vol. 42, no. 5, pp. 788–797, 2009.

[11] S. Dang, Z. Cui, Z. Cao, and N. Liu, "Sar target recognition via incremental nonnegative matrix factorization," *Remote Sensing*, vol. 10, no. 3, p. 374, 2018.

[12] A. Gigli, A. Gijsberts, and C. Castellini, "The merits of dynamic data acquisition for realistic myocontrol," *Frontiers in Bioengineering and Biotechnology*, 2020.

A4 Progressive and Coadaptive Unsupervised Myocontrol

Title: Progressive Unsupervised Control of Prosthetic Upper Limbs

Authors: Andrea Gigli, Arjan Gijsberts, Markus Nowak, Ivan Vujaklija, and Claudio Castellini.

Journal: Journal of Neural Engineering.

Manuscript version: Published article.

Citation: Andrea Gigli, Arjan Gijsberts, Markus Nowak, Ivan Vujaklija and Claudio Castellini. "Progressive Unsupervised Myocontrol of Myoelectric Upper Limbs." In: *Journal of Neural Engineering* 20.6 (2023), p. 066016.

IOP Publishing J. Neural Eng. 20 (2023) 066016 https://doi.org/10.1088/1741-2552/ad0754

Journal of Neural Engineering

OPEN ACCESS

RECEIVED
23 May 2023

REVISED
18 September 2023

ACCEPTED FOR PUBLICATION
26 October 2023

PUBLISHED
24 November 2023

PAPER

Progressive unsupervised control of myoelectric upper limbs

Andrea Gigli[1,4,*], Arjan Gijsberts[2], Markus Nowak[1], Ivan Vujaklija[3] and Claudio Castellini[1,4]

[1] Institute of Robotics and Mechatronics, German Aerospace Center (DLR), Wessling, Germany
[2] Private address
[3] Department of Electrical Engineering and Automation, Aalto University, Espoo, Finland
[4] Assistive Intelligent Robotics Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg, Erlangen, Germany
[*] Author to whom any correspondence should be addressed.

E-mail: andrea.gigli@dlr.de

Keywords: coadaptive myocontrol, unsupervised myocontrol, muscle synergies, surface electromyography, motor skill learning

Supplementary material for this article is available online

Abstract

Objective. Unsupervised myocontrol methods aim to create control models for myoelectric prostheses while avoiding the complications of acquiring reliable, regular, and sufficient labeled training data. A limitation of current unsupervised methods is that they fix the number of controlled prosthetic functions a priori, thus requiring an initial assessment of the user's motor skills and neglecting the development of novel motor skills over time. *Approach.* We developed a progressive unsupervised myocontrol (PUM) paradigm in which the user and the control model coadaptively identify distinct muscle synergies, which are then used to control arbitrarily associated myocontrol functions, each corresponding to a hand or wrist movement. The interaction starts with learning a single function and the user may request additional functions after mastering the available ones, which aligns the evolution of their motor skills with an increment in system complexity. We conducted a multi-session user study to evaluate PUM and compare it against a state-of-the-art non-progressive unsupervised alternative. Two participants with congenital upper-limb differences tested PUM, while ten non-disabled control participants tested either PUM or the non-progressive baseline. All participants engaged in myoelectric control of a virtual hand and wrist. *Main results.* PUM enabled autonomous learning of three myocontrol functions for participants with limb differences, and of all four available functions for non-disabled subjects, using both existing or newly identified muscle synergies. Participants with limb differences achieved similar success rates to non-disabled ones on myocontrol tests, but faced greater difficulties in internalizing new motor skills and exhibited slightly inferior movement quality. The performance was comparable with either PUM or the non-progressive baseline for the group of non-disabled participants. *Significance.* The PUM paradigm enables users to autonomously learn to operate the myocontrol system, adapts to the users' varied preexisting motor skills, and supports the further development of those skills throughout practice.

1. Introduction

Myoelectric prosthetic hands can restore or enhance independence for individuals with limb differences, enabling them to perform various activities of daily living [1, 2]. Machine learning-based myocontrol approaches offer intuitive control of advanced prostheses [3] and are currently available in commercial systems [4, 5]. Classification techniques enable control over multiple grasp types by defining an association between muscular activity and the desired grasp [6, 7], while regression methods establish a continuous mapping between the user's muscle activations and motor commands for the degrees of freedom (DoFs) of the prosthesis [8, 9]. These techniques typically learn the myocontrol model in a supervised way, meaning that surface electromyography (sEMG) measurements of the forearm's muscles are associated with prescribed motor commands during a calibration phase.

Supervised myocontrol relies on the assumptions that the distribution of the control signal remains consistent between training and testing conditions, and that training samples are accurately labeled [10]. However, meeting these assumptions in a realistic setting poses methodological challenges. The characteristics of sEMG signals can change over time due to factors like muscle fatigue, limb position, and electrode displacement [11, 12]. Common approaches to reduce this distribution shift involve capturing more of the signal variability in the training data [13, 14] or iteratively recalibrating the system with additional data over time [15, 16]. These methods come therefore at the cost of an increased burden on users by prolonging the data acquisition process. Additionally, accurately labeling samples can be difficult for individuals with limited residual muscle control, such as those with limb differences. Extensive preprosthetic user training is often required to generate muscle signals that are sufficiently distinguishable, stable, and repeatable for myocontrol. This typically includes mental practice, emulation of specific gestures using the phantom limb, and sEMG visualization using biofeedback [17, 18]. However, such training can be demanding and requires supervision from healthcare professionals. The requirement for expert guidance typically confines preprosthetic training to clinical facilities, which increases the associated costs, limits the user's exposure to training, and potentially slows down the adoption of the myocontrol technology [18].

Unsupervised myocontrol is a desirable alternative to supervised myocontrol, as it eliminates the need for hard-to-obtain labeled training data. Existing unsupervised myocontrol approaches derive low-dimensional approximations of the muscular input, corresponding to distinct muscle coactivation patterns, and employ them as control commands for the kinematic or kinetic variables of interest [19–22]. This is based on the neuromotor control principle that the human nervous system efficiently realizes movement by recruiting and coordinating non-redundant muscle synergies [23–25]. In this context, the nervous system treats the activations of each muscle synergy as high-level motor commands that can be combined to generate the muscular activity necessary to accomplish the desired movement. This also entails that information about the synergies' structure and coactivation is encoded into multichannel sEMG measurements of the muscular activity [24].

Nonnegative matrix factorization (NMF) algorithms are commonly utilized to extract muscle synergies from sEMG signals. The advantage of this specific factorization is that it decomposes signals into linear nonnegative combinations of nonnegative components, which mirrors the central nervous system's approach of combining nonnegative antagonistic muscle activations [24–26]. In addition, using these components as control inputs for prosthetic devices enables users to naturally control multiple prosthetic functions at once and adjust their intensity proportionally. However, standard NMF solutions can be ill-posed, and they therefore need particular training procedures or formulations to enforce the identification of minimally overlapping components that could serve as reasonable proxies for muscle synergies [19, 26].

Jiang *et al* [19] proposed a minimally supervised approach for simultaneous and proportional (SP) myocontrol of a virtual cursor using muscle synergies related to wrist movements. To identify these synergies, they developed a DoF-wise calibration of the myocontrol system, which involved concatenating partial NMF models trained on sEMG data of antagonistic movement pairs, taking advantage of the distinct muscle activation patterns each pair generated. This method reduced supervision compared to traditional approaches, but still required users to perform specific movements in a predefined order, potentially posing challenges for individuals with limb differences.

Building on this work, Lin *et al* [20] developed an extension that imposed sparsity constraints on NMF to allow for a more flexible calibration procedure. During this calibration, participants were allowed to perform random wrist movements, engaging multiple DoFs of the wrist simultaneously. The sparse NMF formulation encouraged the extraction of minimally overlapping components, which were then manually associated with the control of the desired cursor directions. This manual association was performed to ensure an intuitive correspondence between muscle synergies and cursor directions but required direct supervision during the process. Moreover, their calibration procedure explicitly excluded finger movements, which could hinder the identification of potentially more effective muscle commands and could prove challenging for individuals who struggle to isolate wrist and hand movements.

Yeung *et al* [21] designed an adaptive version of the paradigm by Lin *et al* [20], in which the factorization model was automatically updated during operation to account for changes in muscle synergies caused by the nonstationarity of sEMG and the user's adaptation to the myocontrol system. The same quasi-unsupervised calibration procedure was followed to build a myocontrol model for a prosthetic wrist, which involved performing specific actions in an unstructured manner and manually defining a biomimetic motor mapping between muscle synergies and wrist actions. The myocontrol system automatically updated the factorization model when it detected model degradation, characterized by increased coactivation of antagonistic muscle synergies. Model updates were made possible by adopting an incremental NMF approach with sparsity constraints and a forgetting mechanism to gradually reduce the influence of older data. Even though this incremental NMF formulation allowed for fully unsupervised model updates, the paradigm still relied on a partially supervised and constrained calibration procedure to create a biomimetic motor mapping for myocontrol in the first place.

Other approaches have also attempted to reduce the amount of supervision necessary for defining biomimetic motor mappings. This includes methods that identify relationships between muscular activity and kinematic variables in a shared latent space [27, 28], or those leveraging musculoskeletal models to estimate forearm muscle forces directly from electromyographic recordings [29]. However, these strategies still require a loosely supervised calibration phase, involving synchronized acquisition of sEMG and ground truth data for the estimated kinematic variable.

As an alternative to biomimetic mappings, abstract motor mappings can be adopted to implement fully unsupervised myocontrol. This type of mapping, commonly used in supervised myocontrol approaches, links muscle activations to hand gestures without requiring a direct physiological relationship between them [30, 31]. Research shows that humans can learn such arbitrary mappings, including muscle synergy-based ones, through closed-loop interaction with a myocontrol system, making them a viable approach for prosthetic control [24, 32]. Abstract motor mappings based on muscle synergies provide flexibility and robustness, enabling users to control complex hand actions with comfortable, reliable, and stable muscle activations [22, 33], while also being more resistant to variations in myoelectric signals due to the muscle synergies' focus on underlying muscle coactivation structures [24].

Gigli *et al* [22] used abstract motor mappings to devise a fully unsupervised coadaptive simultaneous and proportional myocontrol paradigm for hand and wrist actions. Similarly to the method from Yeung *et al* [21], this also originated as an adaptive extension of the work of Lin *et al* [20]. However, this approach completely eliminated the need for initial model calibration and allowed users to identify viable muscle inputs autonomously. This was achieved through a combination of adaptive NMF, an abstract motor mapping, and a straightforward interaction strategy. An adaptive sparse NMF formulation was devised to extract muscle synergies from the user's sEMG in realtime. An abstract motor mapping was established by arbitrarily associating the extracted muscle synergies with predefined hand actions of the myocontrolled hand. As users interacted with the system and discovered action-triggering muscle patterns, the synergies were continuously refined for enhanced control. This approach provided an adaptive and low-dimensional visualization of the muscle space, enabling users to discover complex muscle coactivation patterns, including those difficult to discern with standard biofeedback methods. Moreover, the approach demonstrated performance comparable to state-of-the-art supervised adaptive myocontrol approaches.

A limitation of all existing unsupervised myocontrol paradigms that rely on NMF, is that the number of components for sEMG factorization must be set to match the preexisting number of independent muscle synergies that the user can generate. Specifically, allowing too many NMF components might lead the factorization model to identify components unrelated to physiological muscle synergies, potentially resulting in unintended activations of the myocontrolled hand. Determining how many independent and stable muscle synergies the user can elicit is challenging. First, the amount of sensors used by the sEMG measurement system limits the number of detectable synergies [34]. Second, the individual's preexisting motor capacities can significantly impact the number of synergies elicited [25, 35]. Lastly, the number of distinct synergies may increase over time as the individual progressively familiarizes themselves with more motor tasks [25, 36]. In practice, determining the number of independent muscle synergies often requires extensive collaboration between the user and a clinician, making more autonomous methods for identifying and refining available synergies desirable.

An alternative approach is to use a progressive learning strategy for myocontrol functions, where users begin with a single function and gradually 'unlock' additional functions as they master existing ones. This method mirrors the progressive nature of human motor development, which involves the ongoing expansion and refinement of motor functions [25, 37, 38]. Throughout an individual's life, innate reflexes are integrated with newly acquired rudimentary motor skills, which are then refined and combined to form more advanced and specialized skills. This progression is connected to the development of muscle synergies, as new motor skills are achieved by adapting preexisting muscle synergies to meet the demands of tasks and efficiency [25, 38]. Moreover, the challenge point framework theory suggests that a progressive motor learning approach would support the acquisition of new motor functions. In fact, adapting the task difficulty to an individual's current skill level has proven helpful to regulate the learning workload and ultimately accelerate motor learning [39–41].

A sequential NMF formulation could be employed to implement a progressive motor learning procedure [42, 43]. This algorithm learns the factorization model by adding one component at a time, ensuring the stability of existing components when new ones are introduced. However, existing sequential NMF methods are not suitable for incremental settings as they are based on iterative warm reinitialization of progressively larger models and retraining on historical data to preserve the continuity of the existing components. Simply discarding the historical data when attempting online sequential NMF is unlikely to be successful, as the lack of context may lead to a loss of continuity in the existing components. Therefore, there is a need for an online factorization method that maintains component continuity without requiring the storage of historical data.

In this work, we introduce progressive unsupervised myocontrol (PUM), a fully unsupervised and coadaptive paradigm inspired by the progressive nature of human motor learning. PUM enables users to autonomously learn to control the functions of a myocontrolled hand one at a time. These functions are implemented through an abstract mapping between the users' muscle synergies and the desired actions of the hand and wrist. Users refine muscle synergies for myocontrol autonomously while familiarizing themselves with the system and request to unlock new functions as they become proficient with the existing ones. The result is a coevolving and coadaptive interaction dynamics between the user and the system. To achieve this, we extend the adaptive NMF from [22] with an algorithmic procedure to increase the number of components while preserving the existing ones without explicitly storing historical data. Moreover, we adjust the loss function to reduce the overlap between the identified components and to improve their stability over time.

In a multi-session user study, we evaluate how effectively PUM enables users and the myocontrol system to synergistically learn a control model in a completely unsupervised manner. We specifically investigate the performance of individuals with limb differences (LD), who stand to benefit the most from an unsupervised myocontrol paradigm, in comparison to non-disabled (ND) participants, who represent the best-case scenario for myocontrol due to their more extensive motor skills. Moreover, we examine how PUM compares to a non-progressive unsupervised myocontrol (UM) paradigm, based on that of [22], which serves as a baseline for identifying potential advantages and limitations of our approach. Our assessments and comparisons are based on the workload associated with the progressive learning of motor skills, as well as the evolution and retention of myocontrol performance in a series of target achievement control (TAC) tests involving a virtual hand.

The paper is structured as follows. In section 2, we detail the methods employed for the PUM paradigm. Section 3 presents the study's findings, followed by a discussion of their implications in section 4. The appendix includes mathematical derivations of the factorization algorithm utilized in the myocontrol paradigms.

2. Methods

In this section, we introduce the PUM paradigm and discuss its relation to the non-progressive UM paradigm adapted from Gigli *et al* [22]. We then outline a multi-session study where we assess the effectiveness of PUM in enabling participants to progressively learn, refine, and retain control of a virtual hand's functions, and compare its performance to that of UM.

2.1. PUM

The PUM paradigm is inspired by the way humans progressively develop their motor skills when learning new tasks. The system factorizes muscular inputs into muscle synergies and arbitrarily maps them to functions of the myocontrolled virtual hand, while users learn the motor mapping by interacting with the system. Upon user request, the system adapts the number of synergies to accommodate an increasing number of functions, while aiming for minimal disruption to previously learned synergies. A schematic overview of the control paradigm is presented in figure 1.

2.1.1. Progressive incremental sEMG factorization

We introduce progressive incremental sparse nonnegative matrix factorization (P-ISNMF), an algorithm that adaptively computes an NMF model and enables online identification of additional components while preserving existing ones without model retraining. It builds upon incremental sparse nonnegative matrix factorization (ISNMF) [22], an adaptive NMF variant with sparsity constraints and a forgetting mechanism to discount outdated information. In addition to incorporating a progressive mechanism, our proposed approach features an improved objective function that results in sparser and more stable components.

NMF approximates a nonnegative matrix $\boldsymbol{V}$ of size $n \times s$ as the product of nonnegative factors $\boldsymbol{W}$ of size $n \times r$ and $\boldsymbol{H}$ of size $r \times s$, that is, $\boldsymbol{V} \approx \boldsymbol{W}\boldsymbol{H}$ [44]. When the columns of $\boldsymbol{V}$ represent a series of s n-dimensional data samples, the columns of $\boldsymbol{W}$ represent a set of r basis vectors and those of $\boldsymbol{H}$ a series of s r-dimensional encoding coefficients that indicate the relative contribution of the bases to each data sample. In the context of myoelectric control, where data samples correspond to positive envelopes of the myoelectric signal, the bases and encoding coefficients can be loosely interpreted as muscle synergies and their activations.

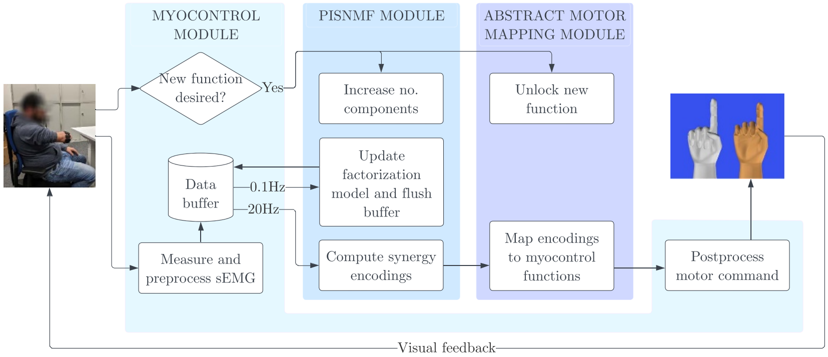


Figure 1. *Schematics for the progressive unsupervised myocontrol (PUM) paradigm.* While the user interacts with the system to learn myocontrol functions, the factorization model refines the identified muscle synergies by conducting periodic unsupervised model updates. Myoelectric control is achieved by factorizing muscle activity into muscle synergies and arbitrarily mapping the encoding coefficients to predefined myocontrol functions, obtaining motor commands for the orange myocontrolled hand. Users progressively unlock more myocontrol functions on demand. This scheme evolves to accommodate user skill evolution and allows the user and system to coadaptively refine control over new motor functions. A gray virtual hand serves as a reference during performance evaluation, presenting the users with functions to replicate in realtime with the myocontrolled hand.

Algorithm 1. ISNMF. © 2022 IEEE. Reprinted, with permission, from [22].

Input stream $\mathcal{S}$ of n-dim nonnegative samples
Parameter r, β, γ, μ, ϵ, $t_{\max}$

$m \leftarrow 0$
$\boldsymbol{A}^0 \leftarrow [0]_{n\times r}$
$\boldsymbol{B}^0 \leftarrow [0]_{r\times r}$
while true **do**
  $m \leftarrow m+1$
  $\boldsymbol{V}_m \leftarrow n\times k$ matrix with k new samples from $\mathcal{S}$
  If $m=1$ **then**
    $\boldsymbol{W}^m \leftarrow n\times r$ positive random matrix
  else
    $\boldsymbol{W}^m \leftarrow \boldsymbol{W}^{m-1}$
  end
  $\boldsymbol{H}^m_m \leftarrow r\times k$ positive random matrix
  $e_0 \leftarrow \|\boldsymbol{V}_m - \boldsymbol{W}^m\boldsymbol{H}^m_m\|_F^2$
  $t \leftarrow 0$
  repeat
    $t \leftarrow t+1$
    $\boldsymbol{W}^m \leftarrow \boldsymbol{W}^m \circ \frac{\mu \boldsymbol{A}^{m-1}+\boldsymbol{V}_m\boldsymbol{H}^{m\intercal}_m}{\mu\boldsymbol{W}^m\boldsymbol{B}^{m-1}+\boldsymbol{W}^m\boldsymbol{H}^m_m\boldsymbol{H}^{m\intercal}_m+\frac{\mu(1-\mu^m)}{1-\mu}\beta\boldsymbol{W}^m}$
    $\boldsymbol{W}^m \leftarrow \max(\boldsymbol{W}^m, \epsilon)$
    $\boldsymbol{H}^m_m \leftarrow \boldsymbol{H}^m_m \circ \frac{\boldsymbol{W}^{m\intercal}\boldsymbol{V}_m}{\boldsymbol{W}^{m\intercal}\boldsymbol{W}^m\boldsymbol{H}^m_m+\gamma\left(\boldsymbol{H}^m_m\right)^{-0.5}}$
    $\boldsymbol{H}^m_m \leftarrow \max(\boldsymbol{H}^m_m, \epsilon)$
    $e_t \leftarrow \|\boldsymbol{V}_m - \boldsymbol{W}^m\boldsymbol{H}^m_m\|_F^2$
  until $|e_t - e_{t-1}|/e_0 < \epsilon$ **or** $t > t_{max}$
  $\boldsymbol{A}^m \leftarrow \mu\boldsymbol{A}^{m-1} + \boldsymbol{V}_m\boldsymbol{H}^{m\intercal}_m$
  $\boldsymbol{B}^m \leftarrow \mu\boldsymbol{B}^{m-1} + \boldsymbol{H}^m_m\boldsymbol{H}^{m\intercal}_m$
end

ISNMF [22] is an incremental solution to the NMF problem that updates the factorization model with new data while discounting the contribution of previous data, without the need for storing it. We present a refined version of this algorithm that features an improved objective function for a sparser factorization and increased stability, and we provide a complete derivation in the appendix. In the following, we employ block notation for matrices, with subscripts identifying specific matrix blocks and superscripts representing the matrix status at particular updates. For instance, $\boldsymbol{V}_j$ denotes the data samples received during the jth update, $\boldsymbol{W}^m$ indicates the bases values at the mth update, and $\boldsymbol{H}^m_j$ corresponds to the encoding coefficients computed during the mth update for the block of data samples collected at the jth incremental update (with $m \geqslant j$ for obvious reasons). Furthermore, all product, division, or power operators applied to matrices in the update rules are understood to be elementwise. At the mth update, the algorithm refines the factorization model by minimizing the following objective function that incorporates new data and discounts past contributions

$$F^m = \sum_{j=1}^{m} \mu^{m-j}\left(\frac{1}{2}\left\|\boldsymbol{V}_j - \boldsymbol{W}^m\boldsymbol{H}^m_j\right\|_F^2 + \frac{\beta}{2}\left\|\boldsymbol{W}^m\right\|_F^2 + 2\gamma\left\|\boldsymbol{H}^m_j\right\|_{0.5}^{0.5}\right). \quad (1)$$

The forgetting factor $\mu \in (0,1]$ diminishes the influence of old data exponentially via μ^{m-j}, ensuring the model adapts without excessive reliance on historical data. $\|\cdot\|_F$ and $\|\cdot\|_{0.5}$ denote the Frobenius and the elementwise $L_{0.5}$ norms respectively. The scalars $\beta \geqslant 0$ and $\gamma \geqslant 0$ determine the regularization strength for the bases and encoding matrices.

The new objective function improves the one from the original method [22] by also scaling the regularizer of the bases with the exponential forgetting factor. The motivation for this change is to ensure that all three terms are balanced identically, regardless of the number of block updates[5]. Furthermore, the new objective function replaces L_1 regularization for

[5] Note that the scaling factor $s(m) = \sum_{j=1}^{m}\mu^{m-j}$ starts at $s(1) = 1$ and converges to $\lim_{m\to\infty} s(m) = \frac{1}{1-\mu}$.

the encoding coefficients $\boldsymbol{H}$ with a sparser $L_{0.5}$ regularizer. A preliminary empirical validation confirmed that both modifications had the desired effect on stability and sparsity.

An incremental solution to this problem based on multiplicative updates is given in algorithm 1. The derivation of the incremental algorithm, found in the appendix, relies on the assumption that the model undergoes small changes in each update, meaning that old encodings remain practically unchanged when new data arrives. As a result, they no longer have to be optimized and past data samples and encoding coefficients can be aggregated into fixed-size history matrices rather than being stored explicitly. This, in turn, leads to a significant reduction in the computational and memory complexities of an incremental update, which are now constant in the number of updates [45, 46]. The hyperparameter r specifies the number of NMF components and is chosen to be lower than the data dimension. The tolerance $\epsilon > 0$ and the maximum number of iterations $t_{\max} > 0$ establish the stopping condition for the iterative minimization of the objective function within each model update. The elements of $\boldsymbol{W}^1$ and $\boldsymbol{H}_m^m$ are initialized to strictly positive random values sampled from $\max(0, \mathcal{N}(\bar{\boldsymbol{V}}^m, 1))$, where $\mathcal{N}$ denotes the normal distribution and $\bar{\boldsymbol{V}}^m$ represents the historical average value of the data samples computed online.

Algorithm 2. Adding one component to the ISNMF model.

input $r, \boldsymbol{W}, \boldsymbol{A}, \boldsymbol{B}$

$\tilde{\boldsymbol{w}} \leftarrow n \times 1$ positive random vector

$\boldsymbol{W} \leftarrow [\boldsymbol{W} | \tilde{\boldsymbol{w}}]$

$\tilde{\boldsymbol{a}} \leftarrow [0]_{n \times 1}$

$\boldsymbol{A} \leftarrow [\boldsymbol{A} | \tilde{\boldsymbol{a}}]$

$\tilde{\boldsymbol{b}} \leftarrow [0]_{r \times 1}$

$\boldsymbol{B} \leftarrow \begin{bmatrix} \boldsymbol{B} & \tilde{\boldsymbol{b}} \\ \tilde{\boldsymbol{b}}^\intercal & 0 \end{bmatrix}$

$r \leftarrow r + 1$

The P-ISNMF method extends ISNMF to enable increasing the number of components r progressively without disrupting existing ones, while avoiding the need to store and retrain the model on past data. It achieves this by appropriately expanding the history matrices, which subsequently inform the model updates. The foundation of this method is the observation that the bases $\boldsymbol{W}$, encoding coefficients $\boldsymbol{H}$, and history matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ encode component-specific information in designated columns and rows. Specifically, $\boldsymbol{W}$ and $\boldsymbol{A}$ keep information about the *rth* component in their rth columns, $\boldsymbol{H}$ in its rth row, and $\boldsymbol{B}$ in both its rth row and column. Building on this observation, components can be introduced by extending $\boldsymbol{W}$ with strictly positive random values, sampled from the previously described distribution $\max(0, \mathcal{N}(\bar{\boldsymbol{V}}^m, 1))$. A similar extension of the old data encoding matrix $\boldsymbol{H}$ is possible but practically unnecessary as the incremental update rules only involve new data encodings, which are initialized at the appropriate size at the beginning of each update (line 12 in algorithm 1). Accordingly, history matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ are augmented through zero padding to accommodate the lack of historical information for the new component, ensuring that the data related to existing components remain unaffected. This procedure is outlined in algorithm 2.

After incorporating the additional components, the model update process resumes, utilizing the history matrices to maintain the stability of existing components, as shown in algorithm 1. Despite not providing theoretical guarantees that this method preserves the stability of existing components, extensive preliminary analyses conducted on synthetic data have confirmed this.

2.1.2. Motor mapping and learning

Muscular input signals are periodically encoded into the synergy space using the rule in line 19 of algorithm 1 and subsequently used for position control of the virtual hand. The process involves establishing an abstract motor mapping that assigns the available muscle synergies, in the order of extraction, to predefined myocontrol functions. The mapping is arbitrary because the muscle synergy extraction process depends on the subject's physiology, the movements they performed, and the random initialization of bases and encodings. The encoding coefficients are scaled to consistent magnitudes by dividing them by their historical 95th percentile computed incrementally and then clipping them within the range $[0, 1]$. These scaled coefficients are interpreted as the activation values for their corresponding functions. Specifically, since myocontrol functions are intended to be hand and wrist actions, the activation of each function is translated into the position command that realizes the corresponding action. A full activation executes the action completely, while a zero activation brings the hand to a rest position. Finally, given the graded nature of the coefficients and the possibility of activating multiple coefficients simultaneously, our system supports SP myocontrol.

Subjects learn to control the virtual hand one function at a time by practicing with the myocontrol system without expert supervision. Initially, subjects are introduced to the set of basic functions that the hand can perform and are informed that these functions may be controlled by muscular activations that are not necessarily physiologically related. During practice, subjects learn to control each function by isolating the associated muscle synergy. Once they feel confident in their command over a function, they can request unlocking another one and continue practicing, ensuring that they retain control over the previously learned functions. This procedure defines a coevolving and coadapting myocontrol paradigm. Coevolving refers to progressively increasing the number of myocontrol functions to mirror the development of the user's skills. Coadaptive refers to a synergistic adaptation process where the user produces increasingly distinctive muscle synergies while the system optimizes the sparsity of the identified synergies.

2.1.3. Comparison to UM

We compare the PUM paradigm with its non-progressive counterpart based on the ISNMF algorithm detailed in algorithm 1. The difference is that in UM all basic functions are learned simultaneously rather than sequentially.

2.2. Experiment

We designed a multi-session user study to compare the realtime performance of myocontrol models obtained with PUM and UM, to track their evolution over time, and to assess the retention of performance after a period of non-use of the myocontrol system.

2.2.1. Participants

Ten ND subjects and two subjects with a unilateral upper-limb differences participated in the study. The ND participants, aged 27 to 33, had no previous experience with unsupervised myocontrol. Half of the ND participants tested PUM, and the other half tested UM. The participants with limb differences are denoted LD1 and LD2 in this paper. LD1, 35 years old, had a trans-radial congenital difference in the right arm. They could activate only two distinct muscle groups before the experiment, corresponding to forearm extensors and flexors. They were not a prosthetic user and had limited experience with myoelectric hands, having tested them for a few months at the ages of 5 and 20. LD2, 22 years old, had a transcarpal congenital difference in the left hand. They could perform visible wrist flexion, extension, and adduction at the time of the experiment. They were not a prosthesis user and had no experience with myoelectric control. Both LD participants tested PUM, because insightful comparisons between the two paradigms with only two LD subjects would have been unattainable. The study was conducted following the WMA Declaration of Helsinki and approved by the Ethics committee of Friedrich-Alexander Universität (No. 22-275-S). All participants gave written informed consent to participate in the study.

2.2.2. Experimental Setup

A Myo armband by Thalmic Labs provided 200 Hz, 8-channel sEMG measurements of the forearm muscles on the subjects' dominant or different arm. The sEMG armband was positioned over the widest part of the forearm with the first sensor aligning with the brachioradialis muscle. This placement was done as precisely as possible to minimize electrode displacement across subjects and sessions. ND subjects and LD2 wore a resting hand orthotic splint and suitable padding to restrict hand or wrist movements and were instructed to avoid wrist rotations during the experiment. This requirement aimed at promoting isometric muscle contractions and has been found effective in making the sEMG of ND subjects more similar to that of individuals with upper-limb differences [47]. As indicated in figure 1, a monitor displayed an orange virtual hand visualizing the predictions of the myocontrol model and a gray hand serving as a reference during the experiment. Our experimental setup mirrored that of [22], who compared a state-of-the-art supervised myocontrol approach with an unsupervised myocontrol method analogous to our baseline paradigm, UM. This design was intended to facilitate an indirect comparison of the merits of our PUM paradigm with those of a standard supervised one.

2.2.3. Myoelectric control

The sEMG measurements were band-pass filtered online and in realtime using a second-order Butterworth filter with cutoff frequencies at 10 Hz and 90 Hz. The root mean square envelope of each channel was then computed over the last 300 ms and utilized as input for both myocontrol paradigms. The factorization algorithm used by both PUM and UM had hyperparameters of $r = 4$, $\beta = \gamma = 32$, $\mu = 0.8$, $\epsilon = 1 \cdot 10^{-5}$, and $t_{\max} = 200$. The factorization model was updated at 0.2 Hz, while muscular encodings were computed at 20 Hz, normalized within the $[0, 1]$ range, low-pass filtered online and in realtime with a fourth-order Butterworth filter with a 2 Hz cutoff frequency, and used as motor controls for the myocontrol functions arbitrarily associated to them.

Drawing from the work of Gigli *et al* [22], we limited the maximum number of myocontrol functions to four, as learning more functions with our setup would prove excessively demanding, even for ND subjects. For this study, we represented the four control functions with a power grasp, index finger pointing, wrist flexion, and wrist extension. This selection facilitates the evaluation of myocontrol performance on both individual and combined functions, as combinations of hand and wrist actions are usually more discernible than those of two hand actions, for example. Throughout this paper, we refer to these functions and their combinations as 'basic' and 'combined', respectively. Since our system implements position control, the myocontrolled hand automatically returns to a rest configuration when none of the functions is activated. Importantly, different control functions could be chosen without actually influencing the user's control strategy or the model performance. This is because our abstract motor mapping does not require a physiological association between muscle synergies and controlled functions.

Table 1. *Structure of the multisession experiment.* The experiment consists of five sessions held on distinct days. This table outlines the temporal organization and the specific exercises featured in each session.

	TRNF (retention)	TAC (retention)	Coadaptation	TRNF	TAC	Time since previous session
S1	—	—	x	x	x	—
S2	—	—	x	x	x	24 h–72 h
S3	x	x	x	x	x	24 h–72 h
S4	—	—	x	x	x	24 h–72 h
S5	x	x	x	x	x	7–10 d

2.2.4. Experimental protocol

The experiment, detailed in table 1, included five sessions across different days. The initial four sessions were scheduled at least 24 h apart from each other and completed within two weeks, while the fifth session occurred about one week after the fourth. Each session included a coadaptation phase in which the system and participant synergistically refined the myocontrol model, along with two tests to assess myocontrol performance. One test was conducted without visual feedback and is referred to as target reaching with no feedback (TRNF), while the other featured visual feedback and is referred to as target achievement control (TAC). The myocontrol model was randomly initialized at the beginning of the first session and updated in later sessions to account for the participant's motor skills evolution and for the sEMG armband repositioning.

During the coadaptation phase, participants learned to control the four basic myocontrol functions while the myocontrol model was refined. This phase lasted 3 to 15 min but could be terminated early upon proficiently controlling all four basic functions. In the PUM paradigm, basic functions were learned progressively, with participants requesting to unlock a new function when confident in their control of the existing ones. To maintain consistency across participants, the experimenter verified that each function could be controlled stably and independently before unlocking the next one. The functions were always unlocked in the same order: power grasp, index pointing, wrist flexion and wrist extension. The chosen order held no specific significance and could in principle be tailored to different requirements or preferences. If the participant did not unlock all functions within the coadaptation phase duration, the subsequent myocontrol tests would only focus on the functions that the subject had unlocked so far.

In certain situations, the sparsity constraint in P-ISNMF may drive a component to zero if it is not considered essential for the reconstruction of new or historical data. Newly introduced components are particularly susceptible to this effect, as there is only a small amount of data available to reliably determine their added value to the model. Once the basis of a component has shrunk to zero, it becomes locked in this deactivated state due to the multiplicative update rule, and the corresponding myocontrol function is permanently inhibited. For this reason, this problem is referred to as zero-locking [48]. To counteract this zero-locking issue, we set the bases' lower limit to a small positive threshold, as shown on line 18 and line 20 of algorithm 1. Even with this thresholding mechanism, however, new components remain prone to re-suppression because their contribution to the data reconstruction is limited due to their small magnitude. Consequently, during the experiment, bases suspected to be zero-locked were reset to their initial values. This adjustment was made when a participant reported that a new function was consistently inactive or initiated by the experimenter if such inactivity remained unreported for over one minute.

In the TRNF test, the gray virtual hand displayed a sequence of reference functions and participants had to mimic those gestures without receiving visual feedback from the orange hand. The reference functions included only the basic functions unlocked so far and were presented in a randomized sequence repeated three times. This test assessed the participant's internalization of motor skills by focusing on feedforward control and eliminating reliance on visual feedback for instantaneous error compensation.

In the TAC test, participants controlled the orange hand to match reference functions displayed by the gray hand, using visual feedback. The reference functions were presented three times in random order. These included basic functions at full and half-activation levels, and combined functions pairing one hand action with one wrist action both at half-activation levels. Therefore, our tests assessed proportional control of up to four distinct functions and simultaneous control of two functions. This test design reflects the typical functional capabilities of modern myocontrol solutions, as simultaneous control of three functions has only been achieved in a few studies with more advanced setups for measuring muscle signals [49, 50]. A task was deemed successful if the myocontrol error stayed continuously below a threshold $d \leqslant 0.18$ for at least 2 s before the maximum task duration of 10 s. This error was computed as the maximum component of the element-wise absolute difference between the predicted function and the target function. Since the system's predictions represent position commands between 0 and

1, an error threshold below 0.18 means that we tolerate a deviation of up to 18% of the full activation range between the predicted and target functions.

Retention of myocontrol performance was evaluated at the beginning of the third and fifth sessions by administering TRNF and TAC tests using the model from the previous sessions, without conducting a preliminary coadaptation phase. These tests, referred to as s3r and s5r, assessed short and long-term retention respectively. By comparing short-term retention, where sensor replacement is arguably the main cause of performance degradation, with long-term retention, we aimed to understand to which extent performance degradation over time is caused by a loss of motor skill.

2.2.5. Performance evaluation

The workload during the coadaptation exercise represented the effort made to learn and refine motor skills based on muscle synergies by interacting with the myocontrol system. Participants reported their workload using the NASA-TLX questionnaire [51], which assessed mental, physical, and temporal demands, as well as perceived performance, effort, and frustration on visual analog scales ranging from very low, 0%, to very high, 100%. The overall workload was calculated as a weighted sum of these six dimensions, with participant-specific weighting coefficients determined through a pairwise comparison process [51].

Myocontrol performance in TRNF and TAC tests was assessed in terms of overall success and by evaluating the movement quality achieved during the gross and fine parts of the movement. The distinction between gross and fine movement serves to partition the task execution before and after the target function was first approached by the myocontrolled hand [52]. The overall performance was measured based on the myocontrol error in the TRNF tests, and the success rate and the completion time for TAC tests. For both test types, the gross movement was characterized in terms of duration and path efficiency, while the fine movement was characterized by the mean and standard deviation of the myocontrol error. The success rate was determined as the proportion of successful TAC tasks to the total attempted tasks, and the task completion time recorded the duration of successful tasks. Path efficiency denoted the ratio between the minimum required distance and the actual distance traveled along each independent DoF of the controlled hand to reach the target hand configuration. Importantly, all TAC metrics were calculated solely based on successful tasks, with the exception of the success rate itself.

These metrics were averaged across tasks for each combination of subject, session, and paradigm. Statistical tests were conducted on data from ND subjects to assess significant differences in workload and performance across sessions and between paradigms. Mixed ANOVA with the session as a within-subject factor and the myocontrol paradigm as a between-subject factor was used, and multiple post-hoc t-tests were performed when necessary to identify significant differences between sessions. The Benjamini–Hochberg method was applied to control the false discovery rate due to multiple comparisons [53]. These tests were chosen because the assumptions of normality and homoscedasticity were verified for the tested data subsets. The two LD subjects were analyzed individually without statistical tests, comparing their performances to those of other subjects.

3. Results

The results of the study are organized and presented reflecting the experimental protocol. We first report the participants' workload during the coadaptation phase, we then analyze the myocontrol performance for both TRNF and TAC tests, and we finally evaluate the retention of the learned motor skills. Throughout the section, our focus is on comparing the performance of LD and ND participants using PUM, as well as comparing the performance that ND participants achieved with the two myocontrol paradigms, UM and PUM.

Figure 2 displays the participants' workload during the coadaptation phase, as reported in the NASA-TLX questionnaire. LD and ND participants reported similar overall weighted workloads of around 50% in the first session, as shown in figure 2(a). The workload of ND participants was comparable for the two myocontrol paradigms and decreased significantly to 30% by the third session. A mixed ANOVA confirmed that the reported workload was significantly affected by the session number ($F_{4,32}$, $p < 0.001$) but not by the control paradigm. Subsequent pairwise t-tests detected significant differences in workload between the initial two sessions and the subsequent ones, as depicted in figure 2(b). Conversely, LD participants maintained a consistently high workload, which may indicate that their adaptation to the myocontrol system was ongoing throughout the experiment. Figures 2(c) and (g) show that their mental demand and effort levels remained around 60% even in the final session.

The duration of each coadaptation phase appears to relate to the reported workload. This connection is expected due to the study design, as participants could request the termination of this phase when they felt in control of all the available myocontrol functions. ND subjects typically completed the coadaptation exercise in about 800 s initially, with this duration reducing to about 300 s for UM and 210 s for PUM by the last session. LD 2 always used 900 s, the maximum allowed time, while LD 1 took 900 s until the third session and then progressively less, reaching around 750 s in the final one.

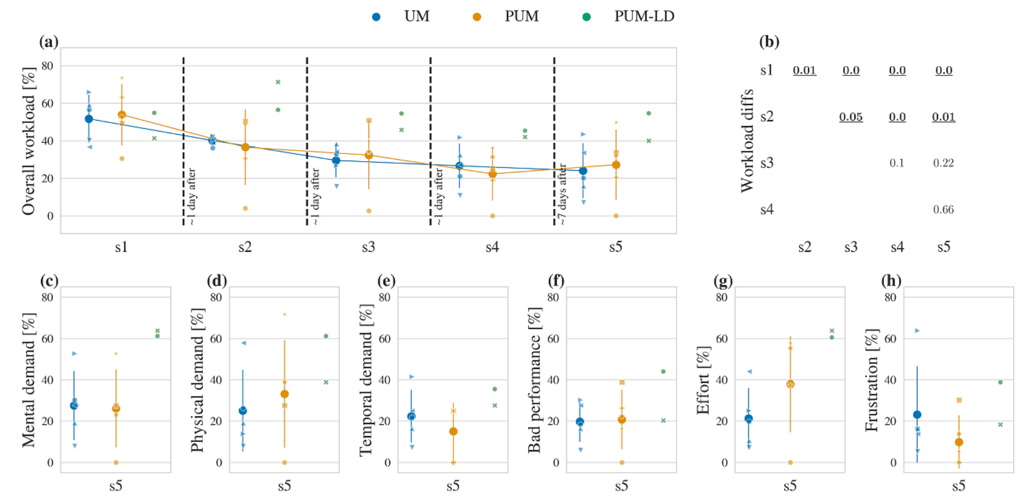


Figure 2. *Coadaptation phase workload, assessed using the NASA TLX questionnaire.* (a) Overall weighted workload per participant and session. (b) Corrected p-values for statistical tests comparing overall workload between sessions for ND participants. (c)–(h) Scores for the six TLX dimensions in the final session. Each data point represents the value of the statistic for a participant in a session, with markers identifying participants. ND participants' data points are grouped by myocontrol paradigm and the mean value within each group is denoted by a circle. LD participants are displayed in a separate column.

The number of tasks in each TRNF and TAC test varied depending on the myocontrol paradigm, with UM consistently allowing control of four functions, and PUM potentially fewer than four. All ND participants who tested PUM achieved control of all four functions in the first session, except one, marked with a square symbol, who unlocked the last function in the second session. Both LD participants were evaluated on three functions in every session. LD1, represented by a hexagon, unlocked three functions within the first session but only learned to control the third one by the end of the third session. This achievement was particularly remarkable because this participant could only control two muscle synergies before the experiment, and they autonomously isolated a previously unknown muscle synergy using PUM. To allow further familiarization with the newly learned skill and in light of the significant achievement already made, the experimenters decided not to enable the fourth function. LD2, marked with a cross, initially achieved limited control of three functions and reached proficiency in the third session. Despite managing to unlock the fourth function, the participant was unable to activate it because the factorization algorithm did not identify additional activation patterns in the muscular signal and repeatedly set the magnitude of the fourth model component to zero. Consequently, myocontrol performance was not evaluated for the fourth function.

The performance in TRNF tests, as seen in figure 3(a), indicates that LD participants performed poorly when deprived of visual feedback, obtaining mean errors above 0.4 and fine mean errors above 0.3 throughout the entire experiment. Conversely, ND participants performed well in the absence of visual feedback using both control paradigms across all sessions, achieving a final mean error of about 0.2. For them, a mixed ANOVA test revealed significant changes in mean error across sessions ($F_{6,48} = 6.08$, $p = 0.002$) but not between control paradigms, and pairwise t-tests detected significantly lower mean errors in sessions three to five compared to the first one, as reported in figure 3(b). Finally, the PUM paradigm enabled ND participants to approach the target more quickly and efficiently than UM, as indicated by the significantly lower gross motion time (by 0.6 s, $p = 0.003$) and higher gross path efficiency (by 0.1, $p = 0.004$) in figures 3(b) and (c).

Figure 4(a) presents the success rate achieved in the TAC test. In the first session, ND participants succeeded in approximately half the tasks, whereas LD participants achieved less than 25% success rate due to only being able to control two out of three functions. The performance of both groups reached equivalent success rates of 60% in the final session. Further analysis revealed that all participants controlled basic functions considerably better than combined functions, with success rates of 80% and 25% in the final session. The supplementary materials offer a visual breakdown of these success rates for basic and combined functions. The success rates of ND participants were comparable for both myocontrol paradigms and increased significantly across sessions. A mixed ANOVA test confirmed that the success rate changed significantly across sessions ($F_{6,48} = 6.88$, $p < 0.001$), but was not influenced by the myocontrol paradigm. Pairwise t-tests, summarized in figure 4(b), indicated that the success rate increased significantly between the first and third sessions and

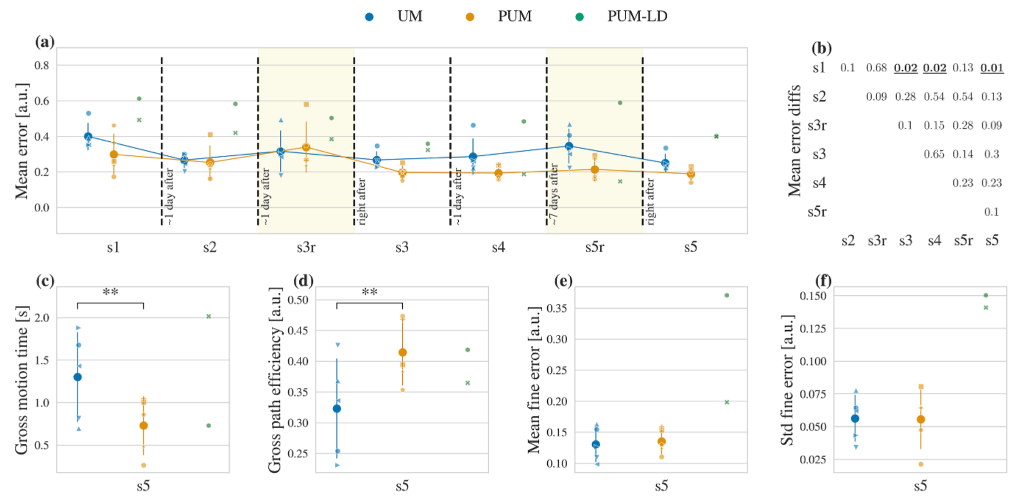


Figure 3. *Performance in the myocontrol test without visual feedback (TRNF).* (a) Mean myocontrol error per participant and session. (b) Corrected p-values for statistical tests comparing mean errors between sessions for ND participants. (c)–(f) Movement quality metrics during the gross and fine portions of the task in the final session. Markers represent the mean value of a statistic for a participant across all trials in a session. ND participants were evaluated on four myocontrol functions while LD participants on three. The ND participant marked with a square symbol had three actions assessed in the first session and four in subsequent sessions. Short and long-term retention exercises are highlighted with a yellow background. Asterisks indicate statistically significant differences between group means (*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$).

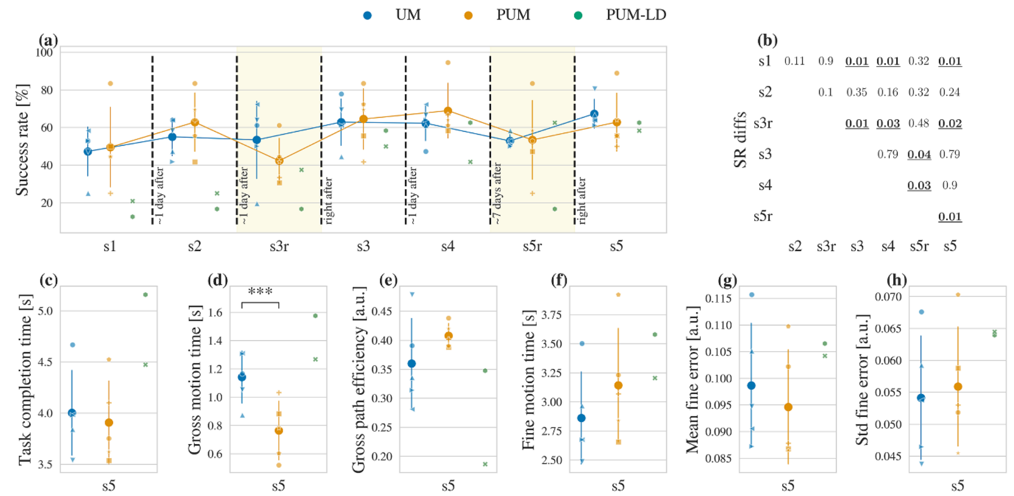


Figure 4. *Performance in the myocontrol test with visual feedback (TAC).* (a) Success rate per participant and session. (b) Corrected p-values for statistical tests comparing mean success rates between sessions for ND participants. (c)–(h) Movement quality metrics during the gross and fine portions of successful tasks in the final session. The same considerations regarding the graphical conventions and the number of myocontrol functions assessed mentioned in the previous figures apply here as well.

remained stable afterward. The success rate of LD participants also improved over time, although less uniformly. It remained below 25% during the first two sessions, markedly improved to above 50% in the third session when the participants learned to control the third function, and reached the level of ND participants in the final session.

Figures 4(c)–(g) focus on the successful TAC tasks in the final session. LD participants achieved a comparatively lower movement quality than ND participants, requiring between 0.5 s and 1 s longer to complete the TAC tasks. This seemed to stem primarily from uncertainty in reaching the target hand configuration, rather than from inadequate control stability in the target's vicinity. Indeed, they demonstrated similar fine motion time and error as ND participants, but longer gross motion time or much lower gross path efficiency. ND participants attained similar movement quality with both myocontrol paradigms. They completed the successful tasks with either paradigm in approximately 4 s. They executed the gross part of the movement significantly faster with PUM (gross motion time was about 0.4 s lower, $p < 0.001$) while demonstrating similar motion time and myocontrol error in the fine part of the movement with both control paradigms.

The evolution of movement quality across sessions, visually detailed in the supplementary materials, offers further insights into participants' motor skill development. Although subjects both with and without limb differences experienced increased success rates, only the latter group demonstrated concurrent improvement in movement quality. In fact, LD participants displayed fluctuations in movement quality across sessions, indicating slower motor skill development.

Upon examining the failed TAC tasks in the last session, it became apparent that the main cause of failure was the difficulty to maintain the controlled hand near the target configuration. Even though participants reached the target configuration in at least 80% of failed tasks, they could not sustain it, resulting in average configuration errors substantially above the TAC success threshold of 0.18 (0.3 for ND participants and 0.45 for LD participants). A thorough visualization of performance during failed TAC tasks can be found in the supplementary materials.

Short and long-term motor skill retention were assessed by comparing performance differences between sessions s2 and s3r, and between s4 and s5r, respectively. Retention sessions are highlighted in yellow in figures 3(a) and 4(a). For these assessments, the mean error from the TRNF test and the success rate from the TAC test served as performance metrics. LD participants displayed comparable retention trends with and without visual feedback. Participant LD 2, marked with a cross, exhibited consistent motor skill retention in both the short and long term, while LD 1, marked with a hexagon, maintained performance in the short term but not in the long-term retention test. This participant reported having forgotten how to control the motor skill they most recently acquired but recovered it during the subsequent coadaptation session. For ND participants, mixed ANOVA results revealed that neither TRNF nor TAC performances were significantly affected by the myocontrol paradigm or its interaction with the session number. Therefore, performance retention was analyzed using pooled data from both myocontrol paradigms. In TRNF tests, no significant performance degradation was observed during retention sessions. For the TAC, while a decrease in the average pooled success rate was observable in the short-term retention, this was not statistically significant. However, a statistically significant decline was observed in the long term (by about 20%, $p = 0.03$), as reported in figure 4(b). Performance levels were restored however by the subsequent model update.

4. Discussion and conclusions

We discuss the performance of PUM for individuals with limb differences and compare it to the non-progressive UM paradigm on a group of non-disabled participants. Our evaluation takes into account the workload experienced by participants while learning myocontrol skills, as well as the subsequent evolution and retention of myocontrol performance.

4.1. Evaluating PUM for users with LD

The study primarily evaluates the experiences of participants with limb differences with PUM and compares them to those of ND subjects. Understanding the experience of LD participants with PUM enables us to better identify their unique needs and challenges in adopting the technology. Meanwhile, ND participants serve as a best-case scenario for myocontrol in light of their wider range of motor skills.

Using the PUM paradigm, participants demonstrated proficient proportional control of multiple myocontrol functions, with LD participants controlling three functions and ND participants managing four. By the final session, LD participants achieved success rates similar to those of ND subjects in TACt tests, albeit with a comparatively lower movement quality. The average success rates were around 80% for tasks involving basic functions and 25% for those requiring combinations of two basic functions. The success rate for basic functions indicates a satisfactory level of performance and is consistent with findings from other studies on SP myocontrol [22, 49, 54]. While all participants were also able to control combinations of two functions, the corresponding success rates were considerably lower than those achieved on basic functions and below those reported in studies with similar experimental protocols [49]. This underlines a current limitation of our approach and identifies an area for future research. In any case, it should be noted that comparisons between studies on realtime myoelectric control are generally challenging due to differences in experimental setups, subjects characteristics, and tests being performed. A more detailed discussion about such comparisons will follow in section 4.2.

The internalization process of the learned myocontrol functions differed between the two subject groups. LD participants exhibited a consistently high workload during the coadaptation phase and a strong reliance on visual feedback during the tests, suggesting that they were continuously learning and adapting to the system. Conversely, ND participants adapted at a faster pace, reporting decreased workloads across sessions and showing better control without visual feedback in TRNF tests.

The long-term retention of newly acquired motor skills also varied among participants. LD 1 reportedly forgot how to control the most recently learned motor skill, although this ability was regained during subsequent coadaptation. In contrast, LD 2 exhibited no performance degradation, indicating good skill retention. Given the empirical evidence that LD individuals often require extended practice to learn new motor skills, even under expert guidance [55], it appears reasonable to speculate that LD 1 could have better internalized the new motor skill if allowed more practice sessions. Among ND subjects, the average TAC success rate during short-term retention tests exhibited a decrease that was not statistically significant. However, the performance degradation was more pronounced and reached statistical significance in the long-term retention tests. This result seems consistent with our expectation that confounding factors such as sensor displacement cause a minor degradation in both short- and long-term tests, whereas skill forgetting causes degradation that increases with time.

A noteworthy result of our study is that PUM not only enables LD users to autonomously learn myocontrol functions but also supports them in discovering previously unexpressed motor skills. For instance, LD 1, who could only control two muscle groups in their affected limb before the experiment, managed to identify a novel muscle synergy and learned to control three myocontrol functions in complete autonomy. We attribute this successful outcome largely to the unique design of the PUM paradigm. One key feature of this design is introducing one new function at a time. This helps maintaining the complexity of the motor learning process at a more manageable level, preventing the user from getting overwhelmed or frustrated. At the same time, this process continuously balances the learning difficulty with the user's evolving skill level, supporting the user to explore their muscular space and to discover new muscle synergies for control. Another distinct feature of PUM is to provide a rich yet intuitive biofeedback of the muscular activity. The paradigm associates each function of the myocontrolled hand to one distinct muscle synergy, effectively translating complex coactivation patterns into more understandable hand movements. In contrast, traditional sEMG biofeedback systems often provide separate feedback for each sEMG channel [56, 57], and this can be challenging to interpret for multi-channel systems [58].

The satisfactory realtime myocontrol performance of the two LD participants in basic functions and the fact that one of them discovered a new muscle synergy underline the practical value of the proposed PUM approach. These achievements gain further significance when considering that PUM does not demand preliminary assessment of the user's motor skills or professionally guided preprosthetic signal training used in traditional myocontrol approaches [17, 18]. Normally, a healthcare professional must assess how many distinct muscle activations the user can elicit to set up the number of myocontrol functions accordingly. In addition, the user often needs coaching to learn to generate muscle signals that are reliable and stable enough to initially calibrate the myocontrol system. Conversely, PUM only requires a brief instructional overview of the system. Then, it encapsulates motor skills assessment and signal training in an unsupervised coadaptive and coevolving learning process, thereby supporting a more autonomous engagement with myoelectric control. While learning new myocontrol functions, the user gradually generates more distinct muscle synergies and the system simultaneously improves the sparsity of the factorization model. Moreover, the system allows the user to unlock additional functions upon mastering the existing ones, which effectively tailors the number of functions to the user's current motor skills and reflects the progressive development of those skills through practice.

It seems logical to speculate that certain user's characteristics may influence the number of myocontrol functions they would be able to control. One such characteristic is the proximity of the limb difference. Transhumeral limb differences, for example, are associated with a lower amount of residual musculature compared to more distal ones, which potentially reduces the range of muscle synergies that can be generated with the residual limb [34]. Yet, it has been found that some individuals with transhumeral amputations who still experience phantom hand movements can elicit muscle signals with their residual musculature consistent with those movements [59, 60]. This unexpected ability, attributed to a preserved phantom limb neural representation and spontaneous neuronal reorganization or reinnervation, suggests that the potential for myoelectric control may not solely depend on the residual musculature. Regardless, the functional restoration of more proximal limb differences would involve control over an extended set of DoFs, possibly complicating the motor mapping. In conclusion, the influence of the limb difference proximity on the controllable myocontrol functions is not obvious and merits further research.

Another aspect that may influence the learning experience with unsupervised myocontrol paradigms such as PUM is the person's previous exposure to myoelectric control. Users with previous experience controlling a myoelectric prosthesis, or even a virtual hand, might rapidly gain control over new functions by drawing on their already refined repertoire of motor skills. In contrast, people without myocontrol experience might display more varied learning progressions. One contributing factor to this variability is that inexperienced users must not only learn new motor functions but also develop fundamental competences for myocontrol. These competences include, among others, modulating muscular contractions, actively relaxing muscles, and coordinating muscular activity with visual feedback of the controlled hand [61]. Even though none of the participants in our study voiced confusion pertaining these competences, it is reasonable to assume that some effort has gone into their development. Exactly delineating these two learning processes, however, is not possible in our experiment given that, during the coadaptation phases, participants were implicitly familiarizing themselves with myocontrol while concurrently learning new myocontrol functions.

People new to myocontrol may also face challenges determined by the nature of their limb differences. It appears plausible that amputees, drawing from their past experience with motor control on their now-absent limb, could have an advantage in identifying distinct muscle synergies. On the other hand, individuals with congenital limb differences might struggle more with this task, as they may need to concurrently form a new mental representation of the missing limb. As this aspect was not directly investigated in our study, we recommend it as an area for further exploration.

4.2. Comparing PUM to UM

We continue our evaluation by examining the performance of the PUM paradigm and its non-progressive counterpart, UM, focusing on ND participants. Participants with limb differences were not included in this comparison because none of them tested the UM paradigm. The main objectives of this comparison are to determine if PUM distributes workload more effectively than UM, leading to a lower initial workload, and to verify if the models learned with both approaches achieve equivalent performance.

Contrary to our expectations, ND participants reported similar workloads for both paradigms. This outcome might have been influenced by limiting the maximum number of myocontrol functions to four, which appeared to be the practical limit of functions learnable with our setup according to preliminary tests and a previous study [22]. This limit, however, may have unintentionally oversimplified the motor learning task for ND participants, allowing them to learn all functions more easily than expected. The benefits of PUM in reducing the learning workload could have been more pronounced by enabling an increased number of functions. This argument seems to be supported by previous studies showing that ND participants often elicit five or more different muscle synergies during grasping [35]. Moreover, conducting the workload assessment at the end of each session could have led to underestimating the difficulties experienced during the initial stages of learning with UM. In fact, participants managed to learn all functions at the beginning of the first coadaptation session using UM and first reported their workload in a questionnaire at the end of that session, potentially overlooking the challenges faced earlier.

PUM allowed ND subjects to reach equivalent myocontrol performance to its non-progressive counterpart either with or without visual feedback. Regardless of learning myocontrol functions progressively or simultaneously, participants also demonstrated a similar evolution and retention of performance. While it is difficult to compare our results with those of other studies because of the different experimental designs, we may attempt some useful comparisons. Our study design shares similarities with that of Gigli *et al* [22], where analogous TAC tests were used to compare a standard supervised myocontrol approach to an unsupervised myocontrol method that was equivalent to our baseline UM. The results of that study revealed that ND users achieved equivalent success rates with both methods. Although speculative, this equivalence appears to suggest that our progressive myocontrol approach, PUM, might perform comparably to a state-of-the-art supervised one, as both displayed equivalent performance to two similar unsupervised approaches. This line of comparison is further substantiated by the work of Nowak *et al* [49], who also used similarly designed TAC tests to evaluate another supervised myocontrol approach. A person with limb differences reportedly achieved success rates on basic actions similar to those observed in our study. While the success rates they observed for combined functions were higher, this might be attributed to using a more advanced high-density sEMG system. These comparisons provide preliminary indications that our PUM approach could perform similarly to supervised ones, even for users with limb differences. Nonetheless, these indications should be treated with caution until a direct comparison, possibly using a more advanced setup than the current one, is made through further research.

The results of this comparison indicate that both the PUM and UM paradigms resulted in equivalent learning workloads and myocontrol performance for ND participants. Speculation on how these results would translate to LD subjects could better define advantages and limitations of our PUM approach. We argue that the learning workload for each myocontrol paradigm depends on the relation between an individual's current motor skills and the number of functions they need to learn. In line with our findings for ND participants, we expect that both paradigms demand comparable learning workloads as long as the number of functions is similar to the number of distinct muscle synergies the person can elicit. Conversely, we contend that PUM might prove especially beneficial when the number of functions to be learned considerably exceeds the number of available muscle synergies. In this scenario, PUM could limit the learning workload by allowing the discovery of new muscle synergies one at a time. As opposed to that, an unsupervised myocontrol paradigm that requires simultaneous identification of multiple new synergies would be obviously more challenging for the user. In this case, moreover, the factorization algorithm could approximate a single muscle synergy generated by the user as multiple redundant components, thus activating several functions at once. This redundancy could skew the visual feedback from the myocontrolled hand, limit the understanding of the control model, and ultimately, impede learning. In terms of myocontrol performance, we expect both control paradigms to yield the same performance also for LD users, provided that the same number of myocontrol functions had been already learned. This is because the difference between UM and PUM lies in the learning process, not in their implementation of myocontrol. While informed by preliminary tests, these speculations need further validation through future studies that directly compare PUM and UM on LD subjects.

4.3. Limitations and remarks

Due to challenges in recruiting participants with limb differences, only two individuals with congenital limb differences participated in the study. This implied that, although a qualitative analysis of their experiences provided insights into the effectiveness of PUM, those insights lacked statistical significance. Moreover, both limb-different participants had to be assigned the PUM paradigm. This decision was made to ensure a more comprehensive assessment of PUM's characteristics, as assigning the participants to different paradigms would have not yielded meaningful insights, due to their varied physiological characteristics and preexisting motor capacities. However, since no LD participants tested the UM paradigm, our study cannot confirm whether PUM can effectively distribute and limit the workload compared to UM. Despite our hypothesis that PUM may prove beneficial under certain conditions, discussed in section 4.2, further research is warranted to confirm this speculation.

The performance of LD participants was evaluated on three functions instead of four, reflecting their progress during the experiment. LD 1 notably learned to control three myocontrol functions by discovering a new muscle synergy that was different from the two synergies they had controlled throughout their life. However, this new function was not learned until the end of the third session. To give LD 1 sufficient time to consolidate the newly learned ability and avoid potential confusion that could affect long-term retention, the experimenters decided not to introduce an additional fourth function at this stage. LD 2 learned three myocontrol functions early in the experiment, unlocked the remaining one at the beginning of the third session, but never managed to activate it as the corresponding basis remained consistently zero-locked. Nevertheless, we argue that LD participants might have autonomously learned additional functions if the experiment had lasted longer and included more sessions. This possibility aligns not only with the experience of LD 1, who identified a previously unknown muscle synergy when given enough time, but also with the findings of [55] where an LD subject gained progressive mastery of novel functions across multiple supervised experimental sessions extending over many months. Yet, practical system designs should offer users the flexibility to manage their learning pace. Users should not only be enabled to start practicing new functions, but also to suspend or withdraw from practice when desired.

PUM employs P-ISNMF to progressively increase the number of components in the factorization model without compromising the stability of the existing ones. This prevents users from needing to repeatedly relearn myocontrol functions when new components are introduced, thereby maintaining performance efficiency. Although we do not provide theoretical guarantees for the stability of existing components, practical evidence from our experiment suggests that incorporating new components does not adversely impact the performance of previously learned myocontrol functions. This evidence also aligns with the results of preliminary tests on synthetic sEMG data. These tests assessed the ability of NMF, ISNMF, and P-ISNMF to reconstruct physiologically plausible muscle synergies that were used to generate the synthetic data. The tests showed that P-ISNMF introduces and learns components progressively without disrupting existing ones, and that it performs comparably to other NMF variants in identifying and reconstructing muscle synergies.

5. Conclusion

We developed a PUM paradigm to address the limitations of an existing unsupervised myocontrol approach [22]. Unlike the previous approach, PUM does not require a preliminary assessment of the user's motor capacities to set up the number of myocontrol functions of the system, and also accommodates for the evolution of new motor skills over time. This is achieved through a user-driven interactive process in which additional myocontrol functions are introduced progressively and refined in an unsupervised way as the user gains proficiency with the system.

We tested the effectiveness of PUM in a multi-session experiment with both congenital LD participants and ND ones, and compared it to a non-progressive counterpart based on [22]. All participants successfully learned to control multiple myocontrol functions simultaneously and proportionally. LD participants completed the myocontrol tasks with comparable success rates to ND participants, despite showing a marginally lower movement quality and requiring a greater learning effort. Remarkably, one LD participant even learned a previously unexpressed muscle synergy and used it for myocontrol in complete autonomy. Finally, ND participants achieved similar performance with both PUM and its non-progressive baseline, which had already proved comparable to a supervised adaptive state-of-the-art myocontrol system.

Ultimately, the PUM paradigm represents a significant advancement in adaptive unsupervised myoelectric control, as it offers a user-friendly and flexible system that supports autonomous learning of myocontrol functions. By catering to users with diverse motor abilities, the coevolving system not only supports but also promotes the development and enhancement of motor skills for myocontrol, ultimately enabling effective control of dexterous prosthetic devices.

Data availability statement

The data cannot be made publicly available upon publication because the cost of preparing, depositing and hosting the data would be prohibitive within the terms of this research project. The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments

We thank Mr Fabio Egle for his assistance in recruiting participants with limb differences and his support during the experiments. Our appreciation also goes to Dr Bernhard Weber for the insightful discussions on how to plan our statistical analyses. Finally, we extend our gratitude to all the participants for their time and commitment to this study.

This research was funded by the German Aerospace Center (DLR).

Appendix. Derivation of the multiplicative update rules

This appendix details the derivation of the multiplicative update rules on line 17 and line 19 of algorithm 1, which are used to incrementally update the NMF factorization model with the data received during the mth update.

The incremental formulation of NMF is rendered here using superscripts and subscripts for matrices. Superscripts indicate the value of bases and encoding matrices at a specific update, while subscripts specify blocks in the data and encoding matrices. For example, $\boldsymbol{V}_j$ indicates the data samples received during the jth update, $\boldsymbol{W}^m$ represents the bases values at the mth update, $\boldsymbol{H}_j^m$ denotes the encoding coefficients computed during the mth update for the data samples received during the jth update. Specific subsets of blocks are indicated using a colon, as in $\boldsymbol{H}_{1:j}^m = [\boldsymbol{H}_1^m \cdots \boldsymbol{H}_j^m]$, while omitting the subscript implies the inclusion of all matrix blocks up to the current update, for example $\boldsymbol{H}^m = [\boldsymbol{H}_1^m \cdots \boldsymbol{H}_m^m]$ at the mth update. Since a data block $\boldsymbol{V}_m$ is never altered by the algorithm, that is $\boldsymbol{V}_m^m = \boldsymbol{V}_m^j \quad \forall j \geqslant m$, we omit the superscript notation for matrix $\boldsymbol{V} = [\boldsymbol{V}_1 \cdots \boldsymbol{V}_m]$. The multiplicative update rules use the elementwise product, division, and power operations, which are denoted by the circle operator, the fraction symbol, and the power operator respectively. When superscripts are applied to scalars, they indicate a standard power operation.

The rules correspond to performing alternating gradient descent minimization of the loss function in equation (1) with respect to the bases $\boldsymbol{W}$ and encoding coefficients $\boldsymbol{H}$ with step sizes set so to guarantee nonnegative updates. Both rules are calculated based on the assumption that the factorization model undergoes only minimal changes in each update. Specifically, it follows that the updated encodings for previous data blocks

$$\boldsymbol{H}_{1:m-1}^m \approx \boldsymbol{H}^{m-1} \tag{2}$$

and the solution can therefore be approximated by only calculating the encodings $\boldsymbol{H}_m^m$ corresponding to the new data block $\boldsymbol{V}_m$ at update m. Since the previous encodings $\boldsymbol{H}_{1:m-1}^m$ remain unchanged, they no longer influence the gradient of the loss function in each update, meaning that in our approximation $\frac{\partial F^m}{\partial \boldsymbol{H}^m} = \frac{\partial F^m}{\partial \boldsymbol{H}_m^m}$.

The multiplicative update rule for the encoding coefficients $\boldsymbol{H}$ in line 19 is derived from gradient descent minimization

$$\begin{aligned}\boldsymbol{H}_m^m &\leftarrow \boldsymbol{H}_m^m - \Lambda_H \circ \frac{\partial F^m}{\partial \boldsymbol{H}_m^m}\\ &= \boldsymbol{H}_m^m - \Lambda_H \circ \left(-\boldsymbol{W}^{m\intercal}\boldsymbol{V}_m + \boldsymbol{W}^{m\intercal}\boldsymbol{W}^m\boldsymbol{H}_m^m + \gamma\left(\boldsymbol{H}_m^m\right)^{-0.5}\right)\end{aligned}$$

by simply setting the step size to

$$\Lambda_H = \frac{\boldsymbol{H}_m^m}{\boldsymbol{W}^{m\intercal}\boldsymbol{W}^m\boldsymbol{H}_m^m + \gamma\left(\boldsymbol{H}_m^m\right)^{-0.5}} \ .$$

The multiplicative update rule for the model's bases $\boldsymbol{W}$ in line 17 also derives from gradient descent minimization

$$\begin{aligned}\boldsymbol{W}^m &\leftarrow \boldsymbol{W}^m - \Lambda_W \circ \frac{\partial F^m}{\partial \boldsymbol{W}^m}\\ &= \boldsymbol{W}^m - \Lambda_W \circ \left(-\sum_{j=1}^{m}\mu^{m-j}\left(\boldsymbol{V}_j\boldsymbol{H}_j^{m\intercal} + \boldsymbol{W}^m\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \beta\boldsymbol{W}^m\right)\right)\end{aligned}$$

by setting the step size to

$$\Lambda_W = \frac{\boldsymbol{W}^m}{\sum_{j=1}^{m}\mu^{m-j}\boldsymbol{W}^m\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \beta\boldsymbol{W}^m}$$

and simplifying the formulas as follows

$$\begin{aligned}\boldsymbol{W}^m &\leftarrow \boldsymbol{W}^m \circ \frac{\sum_{j=1}^{m}\mu^{m-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m\intercal}}{\sum_{j=1}^{m}\mu^{m-j}\boldsymbol{W}^m\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \sum_{j=1}^{m}\mu^{m-j}\beta\boldsymbol{W}^m}\\ &= \boldsymbol{W}^m \circ \frac{\sum_{j=1}^{m}\mu^{m-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m\intercal}}{\boldsymbol{W}^m\sum_{j=1}^{m}\mu^{m-j}\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \frac{1-\mu^m}{1-\mu}\beta\boldsymbol{W}^m}\\ &= \boldsymbol{W}^m \circ \frac{\sum_{j=1}^{m-1}\mu^{m-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m\intercal} + \boldsymbol{V}_m\boldsymbol{H}_m^{m\intercal}}{\boldsymbol{W}^m\sum_{j=1}^{m-1}\mu^{m-j}\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \boldsymbol{W}^m\boldsymbol{H}_m^m\boldsymbol{H}_m^{m\intercal} + \frac{1-\mu^m}{1-\mu}\beta\boldsymbol{W}^m}\\ &= \boldsymbol{W}^m \circ \frac{\mu\sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m\intercal} + \boldsymbol{V}_m\boldsymbol{H}_m^{m\intercal}}{\boldsymbol{W}^m\mu\sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{H}_j^m\boldsymbol{H}_j^{m\intercal} + \boldsymbol{W}^m\boldsymbol{H}_m^m\boldsymbol{H}_m^{m\intercal} + \frac{1-\mu^m}{1-\mu}\beta\boldsymbol{W}^m}\\ &\approx \boldsymbol{W}^m \circ \frac{\mu\sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m-1\intercal} + \boldsymbol{V}_m\boldsymbol{H}_m^{m\intercal}}{\boldsymbol{W}^m\mu\sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{H}_j^{m-1}\boldsymbol{H}_j^{m-1\intercal} + \boldsymbol{W}^m\boldsymbol{H}_m^m\boldsymbol{H}_m^{m\intercal} + \frac{1-\mu^m}{1-\mu}\beta\boldsymbol{W}^m} \qquad (3)\\ &= \boldsymbol{W}^m \circ \frac{\mu\boldsymbol{A}^{m-1} + \boldsymbol{V}_m\boldsymbol{H}_m^{m\intercal}}{\boldsymbol{W}^m\mu\boldsymbol{B}^{m-1} + \boldsymbol{W}^m\boldsymbol{H}_m^m\boldsymbol{H}_m^{m\intercal} + \frac{1-\mu^m}{1-\mu}\beta\boldsymbol{W}^m}\ , \qquad (4)\end{aligned}$$

where the approximation of equation (3) is possible under the assumption equation (2). The history matrices $\boldsymbol{A}^{m-1} := \sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{V}_j\boldsymbol{H}_j^{m-1\intercal}$ and $\boldsymbol{B}^m := \sum_{j=1}^{m-1}\mu^{m-1-j}\boldsymbol{H}_j^{m-1}\boldsymbol{H}_j^{m-1\intercal}$ introduced in equation (4) are used to store information about the past data samples and the corresponding coefficients. They can be recursively computed at the end of each update as $\boldsymbol{A}^m = \mu\boldsymbol{A}^{m-1} + \boldsymbol{V}_m\boldsymbol{H}^{m\intercal}$ and $\boldsymbol{B}^m = \mu\boldsymbol{B}^{m-1} + \boldsymbol{H}_m^m\boldsymbol{H}_m^{m\intercal}$, where the recursion is completed by setting $\boldsymbol{A}^0$ and $\boldsymbol{B}^0$ to zero matrices of sizes $n \times r$ and $r \times r$ respectively. This removes the need to explicitly store past data, thereby enabling incremental model updates and maintaining the computational complexity of each update constant.

ORCID iDs

Andrea Gigli https://orcid.org/0000-0001-7049-485X
Markus Nowak https://orcid.org/0000-0002-0840-5155

Ivan Vujaklija https://orcid.org/0000-0002-7394-9474
Claudio Castellini https://orcid.org/0000-0002-7346-2180

References

[1] Widehammar C, Hiyoshi A, Lidström Holmqvist K, Lindner H and Hermansson L 2022 Effect of multi-grip myoelectric prosthetic hands on daily activities, pain-related disability and prosthesis use compared with single-grip myoelectric prostheses: a single-case study *J. Rehabil. Med.* **54** jrm00245
[2] Cordella F, Lisa Ciancio A, Sacchetti R, Davalli A, Giovanni Cutti A, Guglielmelli E and Zollo L 2016 Literature review on needs of upper limb prosthesis users *Front. Neurosci.* **10** 1–14
[3] Roche A D, Lakey B, Mendez I, Vujaklija I, Farina D and Aszmann O C 2019 Clinical perspectives in upper limb prostheses: an update *Curr. Surg. Rep.* **7** 5
[4] Coapt 2023 Coapt pattern recognition (available at: https://coaptengineering.com/pattern-recognition)
[5] Ottobock 2023 MyoPlus pattern recognition (available at: www.ottobock.com/en-au/Prosthetics/UpperLimb_MyoPlus)
[6] Scheme E J, Englehart K B and Hudgins B S 2011 Selective classification for improved robustness of myoelectric control under nonideal conditions *IEEE Trans. Biomed. Eng.* **58** 1698–705
[7] Igual C, Pardo L A, Hahne J M and Igual J 2019 Myoelectric control for upper limb prostheses *Electronics* **8** 1244
[8] Hahne J M, Biebmann F, Jiang N, Rehbaum H, Farina D, Meinecke F C, Muller K-R and Parra L C 2014 Linear and nonlinear regression techniques for simultaneous and proportional myoelectric control *IEEE Trans. Neural Syst. Rehabil. Eng.* **22** 269–79
[9] Fougner A, Stavdahl Øyvind, Kyberd P J, Losier Y G and Parker P A 2012 Control of upper limb prostheses: terminology and proportional myoelectric control - a review *IEEE Trans. Neural Syst. Rehabil. Eng.* **20** 663–77
[10] Hagengruber A, Leipscher U, Eskofier B M and Vogel J 2022 A new labeling approach for proportional electromyographic control *Sensors* **22** 1368
[11] Kyranou I, Vijayakumar S and Suphi Erden M 2018 Causes of performance degradation in non-invasive electromyographic pattern recognition in upper limb prostheses *Front. Neurorobot.* **12** 58
[12] Campbell E, Phinyomark A and Scheme E 2020 Current trends and confounding factors in myoelectric control: limb position and contraction intensity *Sensors* **20** 1613
[13] Gigli A, Gijsberts A and Castellini C 2020 The merits of dynamic data acquisition for realistic myocontrol *Front. Bioeng. Biotechnol.* **8** 1–20
[14] Campbell E, Phinyomark A and Scheme E 2021 Deep cross-user models reduce the training burden in myoelectric control *Front. Neurosci.* **15** 657958
[15] Hahne J M, Dahne S, Hwang H-J, Muller K-R and Parra L C 2015 Concurrent adaptation of human and machine improves simultaneous and proportional myoelectric control *IEEE Trans. Neural Syst. Rehabil. Eng.* **23** 618–27
[16] Yeung D, Farina D and Vujaklija I 2019 Directional forgetting for stable co-adaptation in myoelectric control *Sensors* **19** 2203
[17] Widehammar C, Lidström Holmqvist K and Hermansson L 2021 Training for users of myoelectric multigrip hand prostheses: a scoping review *Prosthet. Orthot. Int.* **45** 393–400
[18] Kristoffersen M B, Franzke A W, Bongers R M, Wand M, Murgia A and van der Sluis C K 2021 User training for machine learning controlled upper limb prostheses: a serious game approach *J. NeuroEng. Rehabil.* **18** 32
[19] Jiang N, Englehart K B and Parker P A 2009 Extracting simultaneous and proportional neural control information for multiple-DOF prostheses from the surface electromyographic signal *IEEE Trans. Biomed. Eng.* **56** 1070–80
[20] Lin C, Wang B, Jiang N and Farina D 2018 Robust extraction of basis functions for simultaneous and proportional myoelectric control via sparse non-negative matrix factorization *J. Neural Eng.* **15** 026017
[21] Yeung D, Mendez Guerra I, Barner-Rasmussen I, Siponen E, Farina D and Vujaklija I 2022 Co-adaptive control of bionic limbs via unsupervised adaptation of muscle synergies *IEEE Trans. Biomed. Eng.* **69** 2581–92
[22] Gigli A, Gijsberts A and Castellini C 2022 Unsupervised myocontrol of a virtual hand based on a coadaptive abstract motor mapping *2022 IEEE Int. Conf. on Rehabilitation Robotics* (*1–6, Rotterdam*)
[23] Prevete R, Donnarumma F, d'Avella A and Pezzulo G 2018 Evidence for sparse synergies in grasping actions *Sci. Rep.* **8** 616
[24] Ison M and Artemiadis P 2014 The role of muscle synergies in myoelectric control: trends and challenges for simultaneous multifunction control *J. Neural Eng.* **11** 2880–5
[25] Emanuel Singh R, Iqbal K, White G and Edgar Hutchinson T 2018 A systematic review on muscle synergies: from building blocks of motor behavior to a neurorehabilitation tool. *Appl. Bionics Biomech.* **2018** 3615368
[26] Tresch M C, Cheung V C K and dAvella A 2006 Matrix factorization algorithms for the identification of muscle synergies: evaluation on simulated and experimental data sets *J. Neurophysiol.* **95** 2199–212
[27] Scano A, Mihai Mira R and d'Avella A 2022 Mixed matrix factorization: a novel algorithm for the extraction of kinematic-muscular synergies *J. Neurophysiol.* **127** 529–47
[28] Kumar Dwivedi S, Ngeo J and Shibata T 2020 Extraction of nonlinear synergies for proportional and simultaneous estimation of finger kinematics *IEEE Trans. Biomed. Eng.* **67** 2646–58
[29] Sartori M, Durandau G, Došen S and Farina D 2018 Robust simultaneous myoelectric control of multiple degrees of freedom in wrist-hand prostheses by real-time neuromusculoskeletal modeling *J. Neural Eng.* **15** 066026
[30] Dyson M, Dupan S, Jones H and Nazarpour K 2020 Learning, generalization and scalability of abstract myoelectric control *IEEE Trans. Neural Syst. Rehabil. Eng.* **28** 1539–47
[31] Segil J L, Kaliki R, Uellendahl J and ff. Weir R F 2020 A myoelectric postural control algorithm for persons with transradial amputations: a consideration of clinical readiness *IEEE Robot. Autom. Mag.* **27** 77–86
[32] Ison M, Vujaklija I, Whitsell B, Farina D and Artemiadis P 2016 High-density electromyography and motor skill learning for robust long-term control of a 7-DoF robot arm *IEEE Trans. Neural Syst. Rehabil. Eng.* **24** 424–33
[33] Ison M and Artemiadis P 2015 Proportional myoelectric control of robots: muscle synergy development drives performance enhancement, retainment and generalization *IEEE Trans. Robot.* **31** 259–68
[34] Brambilla C and Scano A 2022 The number and structure of muscle synergies depend on the number of recorded muscles: a pilot simulation study with OpenSim *Sensors* **22** 8584
[35] McClanahan A, Moench M and Fu Q 2020 Dimensionality analysis of forearm muscle activation for myoelectric control in transradial amputees *PLoS One* **15** e0242921
[36] Hesam-Shariati N, Trinh T, Thompson-Butel A G, Shiner C T and McNulty P A 2017 A longitudinal electromyography study of complex movements in poststroke therapy. 2: changes in coordinated muscle activation *Front. Neurol.* **8** 277
[37] Goodway J D, Ozmun J C and Gallahue D L 2019 *Understanding Motor Development: Infants, Children, Adolescents, Adults* (Jones & Bartlett Learning)

[38] Cheung V C K, Cheung B M F, Zhang J H, Chan Z Y S, Ha S C W, Chen C-Y and Cheung R T H 2020 Plasticity of muscle synergies through fractionation and merging during development and training of human runners *Nat. Commun.* **11** 4356

[39] Pollock C L, Boyd L A, Hunt M A and Jayne Garland S 2014 Use of the challenge point framework to guide motor learning of stepping reactions for improved balance control in people with stroke: a case series *Phys. Ther.* **94** 562–70

[40] Christiansen L, Nejst Larsen M, Just Madsen M, James Grey M, Bo Nielsen J and Lundbye-Jensen J 2020 Long-term motor skill training with individually adjusted progressive difficulty enhances learning and promotes corticospinal plasticity *Sci. Rep.* **10** 15588

[41] Guadagnoli M A and Lee T D 2004 Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning *J. Mot. Behav.* **36** 212–24

[42] Ren B, Pueyo L, Ben Zhu G, Debes J and Duchêne G 2018 Non-negative matrix factorization: robust extraction of extended structures *Astrophys. J.* **852** 104

[43] Zhu G 2016 Nonnegative matrix factorization (NMF) with heteroscedastic uncertainties and missing data (arXiv:1612.06037)

[44] Lee D and Sebastian Seung H 2000 Algorithms for non-negative matrix factorization *Advances in Neural Information Processing Systems* vol 13 (MIT Press)

[45] Bucak S S and Gunsel B 2009 Incremental subspace learning via non-negative matrix factorization *Pattern Recognit.* **42** 788–97

[46] Dang S, Cui Z, Cao Z and Liu N 2018 SAR target recognition via incremental nonnegative matrix factorization *Remote Sens.* **10** 374

[47] Kristoffersen M B, Franzke A W, van der Sluis C K, Bongers R M and Murgia A 2020 Should hands be restricted when measuring able-bodied participants to evaluate machine learning controlled prosthetic hands? *IEEE Trans. Neural Syst. Rehabil. Eng.* **28** 1977–83

[48] Lin C-J 2007 Projected gradient methods for nonnegative matrix factorization *Neural Comput.* **19** 2756–79

[49] Nowak M, Vujaklija I, Sturma A, Castellini C and Farina D 2023 Simultaneous and proportional real-time myocontrol of up to three degrees of freedom of the wrist and hand *IEEE Trans. Biomed. Eng.* **70** 459–69

[50] Barsotti M, Dupan S, Vujaklija I, Dosen S, Frisoli A and Farina D 2019 Online finger control using high-density EMG and minimal training data for robotic applications *IEEE Robot. Autom. Lett.* **4** 217–23

[51] Hart S G and Staveland L E 1988 Development of NASA-TLX (task load index): results of empirical and theoretical research *Advances in Psychology* (*Lecture Notes in Computer Science* vol 52) (North-Holland) pp 139–83

[52] Hagengruber A, Leipscher U, Eskofier B M and Vogel J 2021 Electromyography for teleoperated tasks in weightlessness *IEEE Trans. Hum.-Mach. Syst.* **51** 130–40

[53] Benjamini Y and Hochberg Y 1995 Controlling the false discovery rate: a practical and powerful approach to multiple testing *J. R. Stat. Soc.* B **57** 289–300

[54] Young A J, Smith L H, Rouse E J and Hargrove L J 2014 A comparison of the real-time controllability of pattern recognition to conventional myoelectric control for discrete and simultaneous movements *J. NeuroEng. Rehabil.* **11** 5

[55] Nowak M, Bongers R M, van der Sluis C K, Albu-Schäffer A and Castellini C 2023 Simultaneous assessment and training of an upper-limb amputee using incremental machine-learning-based myocontrol: a single-case experimental design *J. NeuroEng. Rehabil.* **20** 39

[56] Kristoffersen M B, Franzke A W, van der Sluis C K, Murgia A and Bongers R M 2020 Serious gaming to generate separated and consistent EMG patterns in pattern-recognition prosthesis control *Biomed. Signal Process. Control* **62** 102140

[57] Prahm C, Kayali F, Sturma A and Aszmann O 2018 PlayBionic: game-based interventions to encourage patient engagement and performance in prosthetic motor rehabilitation *PM&R* **10** 1252–60

[58] Simon A M, Lock B A and Stubblefield K A 2012 Patient training for functional use of pattern recognition-controlled prostheses *J. Prosthet. Orthot.* **24** 56–64

[59] Reilly K T, Mercier C, Schieber M H and Sirigu A 2006 Persistent hand motor commands in the amputees' brain *Brain* **129** 2211–23

[60] Jarrasse N, Nicol C, Touillet A, Richer F, Martinet N, Paysant J and Bernardina De Graaf J 2017 Classification of phantom finger, hand, wrist and elbow voluntary gestures in transhumeral amputees with sEMG *IEEE Trans. Neural Syst. Rehabil. Eng.* **25** 71–80

[61] Parr J V V, Wright D J, Uiga L, Marshall B, Omar Mohamed M and Wood G 2021 A scoping review of the application of motor learning principles to optimize myoelectric prosthetic hand control *Prosthet. Orthot. Int.* **46** 274–81