THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Towards intuitive simultaneous control of a bionic limb

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Cover:
Shown is a user of a self-contained neuromusculoskeletal prosthesis. Surgically created electro-neuromuscular constructs allow intuitive, simultaneous, and proportional control of a bionic hand.
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Abstract

Restoring arm function after limb loss with a prosthesis remains a major challenge. Recent advances in surgical techniques and engineering approaches are now enabling substantial restoration of functionality after amputation. This doctoral thesis investigates cutting-edge surgical and engineering strategies and their integration, aiming to achieve intuitive, simultaneous control over multiple bionic joints in myoelectric prostheses, thereby surpassing current clinical solutions.

A key focus was to understand how residual biological pathways after amputation, which naturally encode volitional movement, can be harnessed. We demonstrated that severed nerves can be redirected to innervate denervated native muscles and free muscle grafts, creating new, long-term stable myoelectric sources. These enabled simultaneous, proportional control of up to three degrees of freedom using a conventional one-to-one mapping strategy, improving functionality and reducing disability during extended home use. To further enhance motion-intent decoding and increase the number of controllable boinic joints, we explored deep learning methods and biologically inspired data-collection techniques for training neural networks. Our results show that deep learning architectures outperform shallow networks, facilitating intuitive simultaneous control. We further demonstrated that artificial training data can greatly reduce the burden of lengthy fitting sessions. These methods enabled intuitive, simultaneous, proportional control over 4.5 degrees of freedom in tasks representative of daily life.

Integrating these elements, we demonstrated for the first time that an individual with an above-elbow amputation could intuitively control all five fingers of a bionic hand as if it were their own.

Keywords: Prosthetics, Bionics, Prosthetic control, Myoelectric control, Neuro-musculoskeletal interface, Electro-neuromuscular constructs

List of Publications

This thesis is based on the following publications:

[A] **Jan Zbinden**, Paolo Sassu, Enzo Mastinu, Eric J. Earley, Maria Munoz-Novoa, Rickard Brånemark, Max Ortiz-Catalan.
Improved control of a prosthetic limb by surgically creating electro-neuromuscular constructs with implanted electrodes.
Science Translational Medicine, Jul. 2023.

[B] **Jan Zbinden**, Eric J. Earley, Max Ortiz-Catalan.
Intuitive control of additional prosthetic joints via electro-neuromuscular constructs improves functional and disability outcomes during home use – a case study.
Journal of Neural Engineering, May 2024.

[C] **Jan Zbinden**, Julia Molin, Max Ortiz-Catalan.
Deep learning for enhanced prosthetic control: Real-time motor intent decoding for simultaneous control of artificial limbs.
IEEE Transactions on Neural Systems and Rehabilitation Engineering, Feb. 2024.

[D] **Jan Zbinden**, Steven Edwards.
From sequential to simultaneous prosthetic control: Decoding simultaneous finger movements from individual ground truth EMG patterns.
International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Jul. 2024.

Other publications by the author, not included in this thesis, are:

[E] Towards Pose Invariant Bionic Limb Control: A comparative study of two unsupervised domain adaptation methods, "Alexander Hannius, Rita Laezza and **Jan Zbinden**". *IEEE Access*, Oct. 2025.

[F] Fine-tuning Myoelectric Control through Reinforcement Learning in a Game Environment, "Kilian Freitag, Yiannis Karayiannidis, Rita Laezza and **Jan Zbinden**". *IEEE Transactions on Biomedical Engineering*, Jun. 2025.

[G] Eric J. Earley, **Jan Zbinden**, *et al.*, "Cutting Edge Bionics in Highly Impaired Individuals: A Case of Challenges and Opportunities". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Mar. 2024.

[H] Fabian Just, Chiara Ghinami, **Jan Zbinden**, and Max Ortiz-Catalan, "Deployment of Machine Learning Algorithms on Resource-Constrained Hardware Platforms for Prosthetics ". *IEEE Access*, Jan. 2024.

[I] Max Ortiz-Catalan, **Jan Zbinden**, *et al.*, "A highly integrated bionic hand with neural control and feedback for use in daily life". *Science Robotics, Oct. 2023.*

[J] Eric J. Earley, Anton Berneving, **Jan Zbinden**, and Max Ortiz-Catalan, "Neurostimulation artifact removal for implantable sensors improves signal clarity and decoding of motor volition". *Frontiers in Human Neuroscience, Oct. 2022.*

[K] Eric J. Earley, **Jan Zbinden**, Maria Munoz-Novoa, Enzo Mastinu, Andrew Smiles and Max Ortiz-Catalan, "Competitive motivation increased home use and improved prosthesis self-perception after Cybathlon 2020 for neuromusculoskeletal prosthesis user ". *Journal of NeuroEngineering and Rehabilitation*, Feb. 2022.

[L] **Jan Zbinden**, Eva Lendaro, and Max Ortiz-Catalan, "A multi-dimensional framework for prosthetic embodiment: a perspective for translational research". *Journal of NeuroEngineering and Rehabilitation*, Nov. 2022.

[M] **Jan Zbinden**, Eva Lendaro, and Max Ortiz-Catalan, "Prosthetic embodiment: systematic review on definitions, measures, and experimental paradigms". *Journal of NeuroEngineering and Rehabilitation*, Mar. 2022.

[N] Victoria Ashley Lang, **Jan Zbinden**, Johan Wessberg, and Max Ortiz-Catalan, "Hand Temperature Is Not Consistent With Illusory Strength During the Rubber Hand Illusion". *IEEE Engineering in Medicine & Biology Society (EMBC)*, Nov. 2021.

[O] **Jan Zbinden** and Max Ortiz-Catalan, "The rubber hand illusion is a fallible method to study ownership of prosthetic limbs". *Nature Scientific Reports*, Feb. 2021.

Acknowledgments

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Acronyms

CNN:	Convolutional Neural Network
DOF:	Degree of Freedom
EMG:	Electromyography
LDA:	Linear Discriminant Analysis
LSTM:	Long Short-Term Memory Network
RNN:	Recurrent Neural Network
RPNI:	Regenerative Peripheral Nerve Interface
SVM:	Support Vector Machine
TCN:	Temporal Convolutional Network
TMR:	Targeted Muscle Reinnervation
VDMT:	Vascularized Denervated Muscle Target

Contents

Part I

Overview

CHAPTER 1

Introduction

Individuals experiencing limb loss encounter numerous challenges that can profoundly affect their quality of life. These challenges include post-amputation and phantom limb pain, diminished independence, and the struggle to perform basic daily activities. Additionally, societal biases toward disabilities further compound the difficulties faced by people with amputations. Prosthetic limbs, see Figure 1.1, play a crucial role in mitigating some of these adversities, aiding individuals in navigating their daily lives more effectively.

Among the various needs that arise following limb loss, prosthesis users often prioritize the functionality of their artificial limbs. They seek prostheses that are intuitive to control and capable of replacing as many functions of the lost limb as possible [1]–[3]. Myoelectric prostheses, which are controlled through electrical signals generated by muscle movements, are particularly valued for their ability to meet these needs.

This thesis is dedicated to enhancing the functionality of myoelectric prostheses. By improving these devices, the aim is to restore a significant portion of the lost functionality after amputation and thereby substantially improve quality of life for affected individuals.

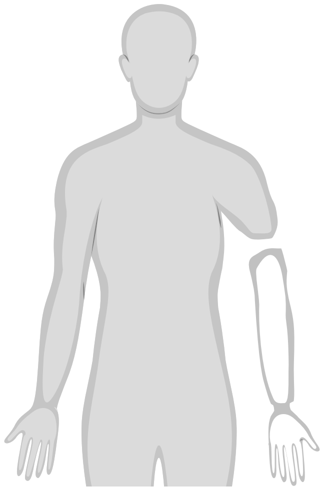

Figure 1.1: Illustration of a limb replacement. Following limb loss, individuals are confronted with the critical decision regarding a potential replacement of their lost limb. The options range from purely cosmetic prostheses that restore the appearance but not the function, to more traditional muscle-powered alternatives that offer reliability with limited functionality. Another choice is the advanced, yet complex, myoelectric prosthesis. Myoelectric prostheses aim to restore as many attributes of a biological limb as possible, with functionality being a primary goal. Improved functionality enables individuals to interact effectively with their environment and perform everyday activities, which is essential for their autonomy and quality of life. Despite ongoing advancements, identifying the optimal approach to closely replicate the full capabilities of a biological limb remains a significant challenge in ongoing research.

1.1 Scope of the thesis

Current myoelectric prostheses in clinical settings typically allow control over only a singular bionic joint, with hand articulation being the most prevalent function [4]. This restriction is predominantly due to the number and quality of the available myoelectric signals, which are largely contingent on the level of amputation. Consequently, for many people with amputation, particularly those with higher levels of limb loss, the control offered by these prosthetic devices does not align with the natural movement of a biological limb.

This misalignment creates a stark contrast between the functionality of clinically available prosthetic devices and the user's innate expectations. Prosthesis users have articulated the need for a prosthesis that allows the reliable and intuitive control of all joints that were lost due to amputation [5]. In an ideal scenario, intuitive control would be characterized by the ability to command multiple bionic joints simultaneously, with a coordination that mirrors the ease and complexity of natural human movement. Volitional motion intent should produce fluid, physiological responses from the prosthesis, allowing for a range of movements that feel both instinctive and natural.

This thesis endeavors to bridge the gap between current limitations and user demands by combining surgical and engineering strategies that facilitate this level of intuitive prosthetic control. Specifically, the research focuses on:

- Harnessing the remnant biological pathways containing natural volitional movement information by surgically creating new myoelectric sources
- Interpreting these myoelectric signals in novel ways to expand control over multiple simultaneously activated bionic joints

1.2 Structure of the thesis

This introduction is followed by Chapter 2, where the current clinical solutions for myoelectric control are summarized and their limitations are highlighted. Chapter 3 and 4 present solutions to overcome these limitations: Chapter 3 approaches the problem from a surgical perspective, and Chapter 4 approaches it from an engineering standpoint. Chapter 5 then provides an overview where the symbiosis of surgical and engineering approaches substantially surpassed the current standard of care and provided patients with advanced prosthetic systems. Chapter 6 provides a summary of the thesis contributions and presents general conclusions and future work.

CHAPTER 2

Current clinical solutions for myoelectric control

A typical myoelectric prosthesis comprises several integral components that collectively translate the motion intent of its user into corresponding movements of the prosthesis, see Figure 2.1. The first component is the attachment mechanism, which secures the prosthesis to the human body. The second component is the signal sources, which contain the information pertaining to the intended movements. Sensors constitute the third component; these devices record the information provided by the signal sources. The fourth component, more conceptual in nature, is the control strategy. The control strategy is responsible for decoding the motion intent from the acquired signals. Finally, the fifth component is the prosthesis itself, which mechanically executes the intended movements.

2.1 Components of a myoelectric prosthesis

Attachment

The predominant clinical approach to attaching prosthetic limbs to the residual limb involves the use of custom-fitted sockets. These sockets maintain a

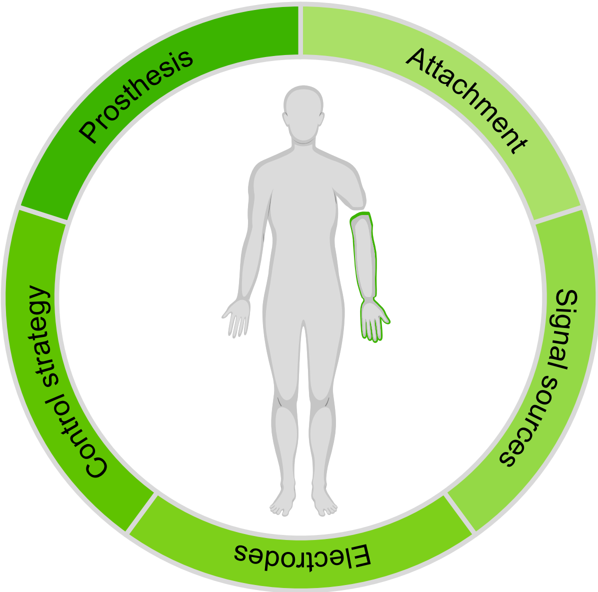

Figure 2.1: The five main components of a myoelectric prosthesis. 1) a way to attach a prosthesis to the body, 2) signal source providing information about the intended motion, 3) electrodes capable of recording said signals, 4) a control strategy that can decode the movement intent from the acquired signals, and 5) the actual prosthesis. All five are required to provide a functional myoelectric system for a person with limb loss.

mechanical connection to the residual limb by exerting compressive forces on the soft tissue of the residual limb. Although this compression method ensures a stable attachment, it is frequently associated with complications. Friction and continuous pressure exerted by the socket on the skin and soft tissues of the residual limb can cause a variety of adverse effects, from minor discomfort to significant dermatological problems [6], [7].

Furthermore, individuals with shorter residual limbs often require additional suspension mechanisms. For instance, individuals with proximal transhumeral amputations typically employ shoulder straps (see Figure 2.2a) to secure the prosthesis. This is necessary because a short residual limb does not provide sufficient surface area for the socket to maintain a stable position. However, these complementary suspension elements can induce discomfort and significantly restrict the range of motion available for prosthesis operation [8].

An innovative alternative to socket use involves direct skeletal attachment of the prosthesis (see Figure 2.2b). This method can be implemented through osseointegration, a process in which bone tissue adheres directly to the surface of a titanium implant, thus establishing a structural and functional link between the bone and the implant [9]. Osseointegration not only enhances the range of motion but also addresses the issue of skin irritation resulting from socket friction. Nevertheless, the interface between the skin and the implant has been reported as a potential site for both superficial and deep infections [10].

Signal sources

As suggested by the prefix "myo" (derived from the Greek word for muscle), a myoelectric prosthesis operates by decoding movement intent from muscle-generated electrical signals. These signals originate from the depolarizing membranes of outer muscle fibers during muscular contraction. By intentionally contracting specific muscles, users of myoelectric prostheses can generate myoelectric signals that correlate with intended movements.

However, the range of controllable actions is heavily contingent on the presence of viable muscle tissue. With more proximal amputations, the availability of native muscles, and consequently, the sources of myoelectric signals, is greatly diminished. For instance, for individuals with above-elbow amputation, only the residual segments of the biceps and triceps muscles remain accessible for signal generation.

Electrodes

Surface electrodes represent the conventional method for capturing myoelectric signals. Positioned directly on the skin, these electrodes are inherently separated from the neuromuscular activity they monitor by layers of biological tissue. This configuration results in the electrodes functioning as volume conductors, thereby providing an aggregate measure of muscle activity within

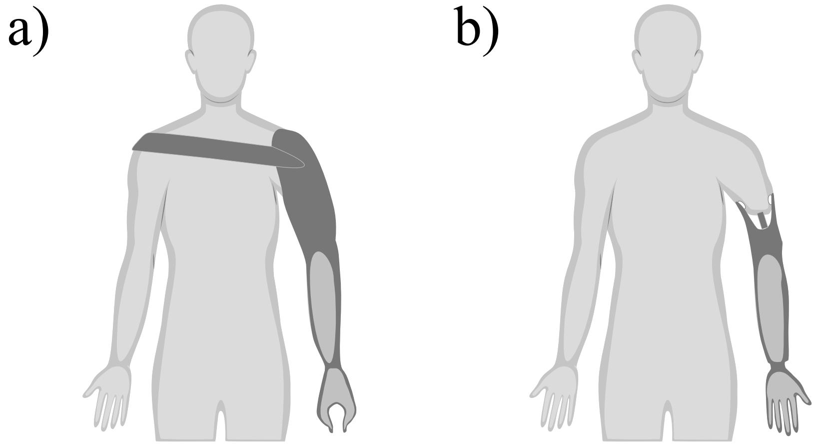

Figure 2.2: Current clinical solutions for myoelectric control. Shown are two examples of currently clinically available prosthesis solutions. **a)** The prosthesis is attached via a socket and additionally held in place by a shoulder strap. The signal sources consist of the native biceps and triceps muscle. On top of these two muscles, one surface electrode each is placed. A Direct Control strategy maps biceps and triceps activation in a one-to-one manner to the opening and closing of a simple monoarticulated gripper. **b)** The prosthesis is attached via an osseointegrated implant. The signal sources, the electrodes, and the control strategy remain the same - native biceps and triceps, surface electrodes, and Direct Control. In this example, the Direct Control strategy supports switching triggers, allowing the user to switch between different grasps on the depicted polyarticulated hand.

their vicinity. The quality and specificity of the signals obtained through this technique are influenced by several variables, including the targeted muscles' depth, the tissue's thickness, and the electrodes' size, shape, and placement [11], [12]. Furthermore, the potential for signal interference from adjacent muscles complicates data interpretation [13]. Generally, surface electrodes offer a straightforward and non-invasive means to record muscle activity. They are, however, susceptible to movement or shifting during extended use, which can cause progressively unstable and degraded signal quality, as well as reduced selectivity in isolating specific muscle activations [14], [15].

Control strategies

The prevalent method for controlling myoelectric prostheses in a clinical setting is Direct Control. This approach entails a straightforward one-to-one mapping between the electrical activity of a specific muscle and the actuation of a bionic joint. When the mean absolute value of a designated muscle's myoelectric signal exceeds a predetermined threshold, the corresponding bionic joint is activated. Given this one-to-one mapping, the number of bionic joints that can be independently controlled is inherently limited by the number of remaining muscles post-amputation. As noted above, individuals with above-elbow amputation typically only have two muscle signals available - those from the biceps and triceps. These signals are commonly assigned to control the opening and closing of a prosthetic hand. Although this mapping is not fully intuitive or biomimetic, it is highly effective for restoring function in daily activities. In cases of below-elbow amputation, residual forearm muscles that originally controlled hand movements may still be present. Mapping these muscles to prosthetic hand operations (e.g., opening and closing) can provide a more intuitive control experience.

For enhanced control robustness, clinical practices often limit the system to a single degree of freedom. However, individuals desiring to regain control over additional degrees of freedom may employ specific triggers, such as co-contraction of muscles, to switch control among different bionic joints. For example, a person with an above-elbow amputation might co-contract the biceps and triceps to toggle control from hand control to wrist or elbow movements. Subsequent activation of the selected bionic joint, however, remains individually tied to the activation of either the biceps or triceps. While switching can significantly expand the range of activities a user can perform and potentially reduce compensatory bodily movements, it may also extend the duration required to execute specific tasks and increase cognitive load.

For individuals retaining more than two residual muscles post-amputation, additional signals may be directly mapped to further degrees of freedom. However, the presence of multiple residual muscles does not guarantee the availability of multiple, linearly independent signals needed for a one-to-one mapping through the Direct Control scheme.

An alternative to the traditional Direct Control approach, which has gained commercial viability in recent years, is pattern recognition. This method utilizes machine learning algorithms to decode intended movements from muscle signals or patterns in higher-dimensional spaces that were previously not separable in the orthogonal representation used for Direct Control. The output of these pattern recognition algorithms can be mapped to individual bionic joints or, more commonly, to predefined grasps such as pinch. The efficacy of pattern recognition relies on the distinctiveness of the muscle patterns, whether intuitive or non-intuitive, to ensure reliable motion intent decoding by the algorithm.

Prosthesis

For each level of amputation, corresponding to the specific joints lost, a range of bionic replacement alternatives is available commercially. Moving from proximal to distal components, the current clinical toolkit includes bionic elbows, wrists (capable of rotation and/or flexion), and various models of bionic hands. While the distinctions among elbow and wrist units are relatively minor, the market for bionic hands is markedly diverse.

The most commonly available prosthetic hands are monoarticulated devices, featuring a single degree of freedom that allows opening and closing hand actions. This prevalence is partly attributed to the constraints of existing control strategies, which typically manage only a single degree of freedom. Nevertheless, the robustness and durability of these devices under daily usage conditions make them a favored choice among users of myoelectric prostheses.

In recent years, the advent of anthropomorphic and polyarticulated prosthetic hands has introduced a new dynamic to the market. Many models of these advanced prosthetic hands offer numerous predefined grip patterns, such as spherical, lateral, pinch, and tripod grasps, that enhance the user's ability and versatility to interact with objects in everyday environments. Many systems also permit the customization of grip patterns, allowing users to tailor interactions according to their personal needs and preferences.

2.2 Limitations of current clinical solutions

The five components of myoelectric prostheses vary significantly in their stages of development; each is at a different technology-readiness level [16]. Consequently, each component contributes differently to the overall functionality of a myoelectric prosthesis. Hence, advancements in specific components could substantially improve the user experience when using a myoelectric prosthesis in daily life.

Currently, the capabilities of the prosthetic components, particularly bionic hands, exceed the functionality users can exploit. Some designs even permit individual finger control, a feature that remains inaccessible with standard clinical solutions. Moreover, while the management of infections presents ongoing challenges, the adoption of osseointegration as an alternative to traditional socket attachments has already significantly improved patient outcomes [17]–[19].

Patients frequently highlight three aspects with the highest potential to enhance their experience: the overall functionality of the prosthesis, including its reliability [5], the intuitiveness of control [20], and the number of controllable bionic joints [2], [21]. The primary obstacles in these areas stem from the quality and availability of signal sources and the ability to decode motion intention from these signals.

The quality and number of usable signals depend heavily on the two components electrodes and signal sources. Implanting electrodes instead of attaching them on the surface of the skin has been shown to greatly increase the signal quality [22], with certain types of electrodes proving to reliably work over several years [22]–[24]. The problem of the limited number of usable signals can be approached by surgically rerouting the remnant biological pathways, i.e., nerves, to create new myoelectric signal sources. As this is one of the two foci of this thesis, a comprehensive summary of surgical methods to create additional signals for myoelectric control is presented in Chapter 3.

Decoding motion intentions from myoelectric signals is intrinsically linked to the quality and number of the available myoelectric signals. No algorithm can compensate for poor or inadequate input data. The availability of additional, surgically established myoelectric sources has broadened the potential for controlling more bionic joints than previously possible. More sophisticated control strategies now allow for simultaneous rather than sequential joint control, aiming to provide a more intuitive user experience. A detailed discussion of the second focus of this thesis, the control strategies designed to leverage increased signal input and address existing clinical constraints, is presented in Chapter 4.

CHAPTER 3

The surgical approach – creating more and better control sources

As discussed in the preceding chapter, the extent to which bionic joints can be controlled (both in terms of quantity and efficacy) depends heavily on the quality and number of usable signal sources. This poses a particular challenge in cases of proximal amputations, which necessitate the replacement of multiple biological joints with bionic counterparts. Concurrently, such amputations typically leave fewer residual muscles available, thereby reducing the number of myoelectric signals for prosthesis control.

To address this shortfall in control signals, surgical reconstruction of the residual limb can be employed as a strategic intervention, see Figure 3.1. This method involves the transfer of nerves that previously innervated the muscles lost to amputation, thereby creating additional myoelectric sources.

3.1 Established surgical techniques

The most established method for augmenting myoelectric sources is known as targeted muscle reinnervation (TMR) [25], see Figure 3.2a. During TMR

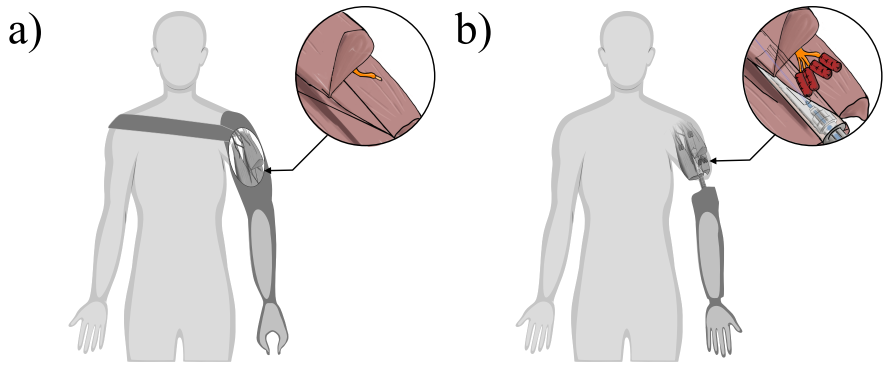

Figure 3.1: Surgically created myoelectric sites for improved control. Shown are two examples of currently clinically available prosthesis solutions, with the addition of surgically created myoelectric sites as signal sources. **a)** Shows an additional signal source created via targeted muscle reinnervation (TMR). Rerouting nerves in this manner allows for an intuitive opening and closing of the monoarticulated gripper. **b)** Shows regenerative peripheral nerve interfaces (RPNIs) as signal sources which can provide enough information to intuitively control multiple bionic joints using e.g. pattern recognition.

surgery, a selected native muscle is initially denervated, followed by the surgical transfer of an alternative nerve to reinnervate that muscle. The choice of native muscles for TMR is contingent upon the level of amputation; for instance, various chest muscles are targeted in shoulder-level amputations, whereas specific heads of the biceps or triceps are utilized for above-elbow amputations. Given the finite number of native muscles available in the chest and arm, the potential for creating new myoelectric sites using TMR is inherently limited. Since TMR replaces the original muscle functionality, creating new myoelectric sites is further limited. For example, it is beneficial for a patient with an above-elbow amputation to retain native control of at least one head of both the biceps and triceps to facilitate intuitive control of a bionic elbow. Typically, individuals who have undergone TMR surgery can manage a prosthesis with 2 to 3 degrees of freedom.

A recent alternative to TMR that does not rely on the availability of native muscles is the development of regenerative peripheral nerve interfaces (RPNIs)

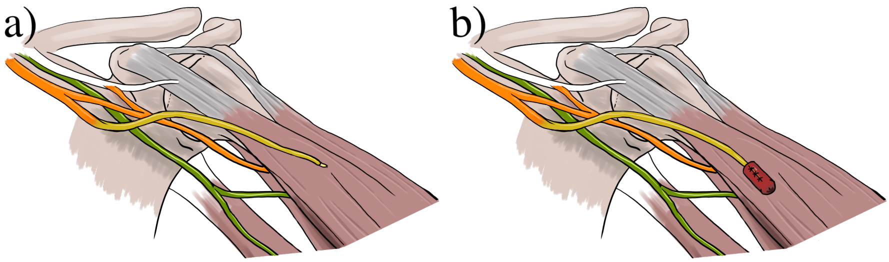

Figure 3.2: Established surgical techniques. Shown are examples of surgically created additional myoelectric sources via targeted muscle reinnervation (TMR) and regenerative peripheral nerve interfaces (RPNIs). **a)** Shows a TMR where the ulnar nerve was transferred to the native short head of the biceps. **b)** Shows a RPNI that was created by enveloping the ulnar nerve into a free muscle graft.

[26], [27], see Figure 3.2b. In this approach, a nerve is dissected into several fascicles, each of which is then enveloped in a free muscle graft. This technique enables the creation of multiple myoelectric sites per nerve.

3.2 Alternative surgical techniques

Both TMR and RPNI have been successfully employed in clinical settings to provide patients with additional, intuitive control signals for prosthetic limbs [22]–[24], [28]–[30]. Motivated by the successes of these surgical interventions, researchers have proposed additional methodologies to address the inherent limitations associated with TMR and RPNIs.

One significant challenge with RPNIs relates to the accessibility of the generated electrical signals. Unlike TMR, which utilizes larger, superficial muscles, the small size and the deeper positioning relative to the skin of the muscle grafts in traditional RPNIs result in electrical signals too weak to be detected by surface electrodes, thereby necessitating the use of implanted electrodes. One proposed solution to this issue is the development of superficial RPNIs, which would be positioned closer to the skin's surface, making the signals accessible to surface electrodes [31].

Alternatively, increasing the size of the RPNI grafts could potentially amplify the signal strength. However, because RPNIs lack vascularization, increasing the graft size could restrict passive oxygen diffusion, leading to tissue necrosis. To circumvent this, researchers have suggested the use of vascularized denervated muscle targets (VDMTs) [32], [33]. Vascularization would support larger graft sizes without compromising tissue viability. Additionally, the use of VDMTs might address the often problematic issue of donor-recipient nerve size mismatch, further enhancing the feasibility and functionality of prosthetic control systems.

CHAPTER 4

The engineering approach – fully utilize the new control sources

The core element of a control strategy for operating a myoelectric prosthesis is the algorithm that decodes the user's motion intent, see Figure 4.1. This central algorithm is supported by several additional components that are essential to its operation and that significantly affect the overall performance of the control system. Together, all these components and the motion intent decoding algorithm constitute the myoelectric control chain.

4.1 The myoelectric control chain

Acquire signals

Users of myoelectric prostheses generate signals by voluntarily contracting specific muscles. To program the prosthesis to execute the intended movements based on these contractions, myoelectric signals must first be recorded and correctly linked to those motions (see Step 1 in Figure 4.2). Conventionally, this involves recording myoelectric signals while the user performs muscle contractions associated with predefined movements, e.g., by moving

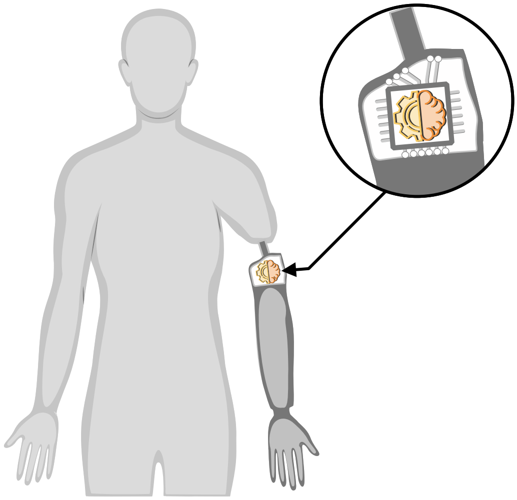

Figure 4.1: Motion intent decoding. Shown is an illustration of the embedded system within a prosthetic arm, responsible for decoding motion intent.

their phantom limb. The complexity of recording increases with the number of bionic joints to be controlled, especially if simultaneous control over multiple joints is required, leading to a combinatorial increase in the data collection phase [34]. During daily prosthesis use, the myoelectric signals are recorded without labels. In both cases, during daily prosthesis use and after a recording session to program the prosthesis, the acquired data are passed to the preprocessing stage.

Preprocessing

Prior to analysis by the motion intent decoding algorithm, the captured myoelectric data typically undergo preprocessing to enhance signal quality and relevance (see Step 2 in Figure 4.2). This generally includes filtering out irrelevant information or electrical noise - such as using low-pass filters at around 500 Hz, high-pass filters at 20 Hz, and notch filters at either 50 or 60 Hz, depending on regional power line frequencies [35], [36]. Additionally, the raw EMG signals may be transformed into a more manageable information space by extracting specific features that are relevant to the decoding process [37].

Motion intent decoding

The motion intent decoding algorithm then processes these preprocessed signals to predict the user's intended movement (see Step 3 in Figure 4.2). A variety of algorithms may be employed at this stage, each offering different advantages and limitations; a summary of these common algorithms will be discussed in the subsequent section.

Postprocessing

To enhance control performance, the outputs from the motion intent decoding algorithms can be further refined through post-processing techniques (see Step 4 in Figure 4.2). Incorporating temporal data, such as averaging past predictions, or applying prior knowledge through techniques like Bayesian inference, has been shown to improve the final movement intent decoding performance [38], [39].

Proportionality

Prosthetic limbs can ideally mimic the variable velocities and forces characteristic of biological limbs, allowing users to modulate joint actuation velocity for more nuanced interaction with their environment. This capability, known as proportional control (see Step 5 in Figure 4.2) [40], is typically achieved by linearly mapping the amplitude of the myoelectric signal to the velocity of joint actuation, based on the predicted movement [41]. This process may also be combined with the motion intent prediction, where so-called regression algorithms directly provide specific velocities or positions for bionic joints [42]. Such integration requires a recording routine that not only links myoelectric signals to intended movements but also to the desired velocities or positions.

Actuation

The final step in the control chain involves commanding the prosthetic hardware to perform the desired movement at the specified velocity (see Step 6 in Figure 4.2).

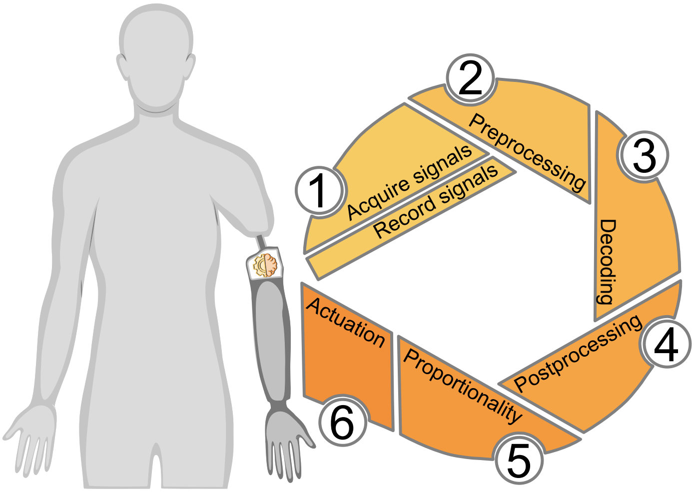

Figure 4.2: The myoelectric control chain. 1) The myoelectric signals are acquired (and labeled during a recording session). 2) The myoelectric data is filtered and preprocessed. 3) An algorithm decodes the motion intent and predicts the movement to be executed by the prosthesis. 4) The predicted movement is postprocessed to e.g. suppress erratic movement changes. 5) Based on the predicted movement, the actuation speed, i.e. proportionality, of the bionic joint is calculated. 6) The prosthesis is actuated according to the predicted movement and its proportionality.

4.2 Motion intent decoding approaches

Direct Control

Direct Control, as previously introduced in the chapter on current clinical solutions for myoelectric control, faces a principal limitation: it can only handle linearly separable signals. Because the number of linearly separable signals is limited by the few muscles' remnant after amputation, the number of controllable bionic joints is likewise limited.

Surgical techniques that create additional myoelectric sources partially overcome the limitation on controllable joints by providing extra signals that, as long as they are linearly separable, can be mapped directly to bionic joints.

Direct Control is arguably one of the more straightforward control approaches since it doesn't require extensive data recording. It only requires the adjustment of an activation threshold for each movement, unlike other algorithms which often necessitate large amounts of recorded data to tune thousands of parameters. Additionally, if a maximum voluntary contraction threshold is established, Direct Control inherently offers proportional control. It also supports simultaneous control of different bionic joints since multiple signals can surpass the activation threshold concurrently.

However, creating myoelectric sources via surgical nerve transfer does not guarantee linearly separable signals. In practice, the maximum number of linearly independent signals achievable is typically limited to four to six, permitting control over only two to three degrees of freedom [25], [43]. To manage more than three degrees of freedom, algorithms capable of handling non-linearly separable data are necessary.

Machine learning approaches

Myoelectric pattern recognition algorithms, incorporating standard machine learning techniques such as Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM), have long been used in research [25], [44]–[47] and have already been implemented in commercial and clinical settings (e.g., Complete Control, COAPT engineering or MyoPlus, Ottobock). These algorithms are capable of handling non-linearly separable data. They can either directly predict movements or can be used to eliminate the need for complex mode switching where not enough signal sources for controlling each joint individually are available [48].

As the field progresses towards decoding more complex movements, e.g., decoding individual finger movements rather than grasps, traditional machine learning algorithms are increasingly replaced by deep neural networks [49]–[51]. Compared to standard machine learning approaches, deep neural networks often provide non-linear decision boundaries that more accurately reflect the distribution of signal information. They can inherently support the prediction of multiple classes, allowing for simultaneous control of prosthetic joints [44], [52]. The benefits of applying deep learning in motion intent decoding are enhanced by the substantial and rapidly evolving resources available from other fields such as image and language processing. For instance, Convolutional Neural Networks (CNNs), originally designed for image processing [53], are adept at learning hierarchical representations of complex data, thereby eliminating the need for manual feature engineering. Integrating CNNs with architectures like Temporal Convolutional Networks (TCN), Recurrent Neural Networks (RNN), or Long Short-Term Memory Networks (LSTM) introduces not only essential temporal dynamics that would otherwise require post-processing to incorporate (see Step 4 in Figure 4.2), but can also improve motor intent decoding performance [54]–[57].

Moreover, not only the network architectures but also techniques for enhancing performance, such as fine-tuning pre-trained networks, can be translated to the field of prosthetics. Techniques such as reinforcement learning can be utilized to tailor motion intent decoding algorithms to user preferences [58], [59].

One of the greatest drawbacks of deep neural networks is their demand for significantly more labeled training data compared to standard machine learning techniques. An option to reduce the time burden for both prosthesis users and prosthetists during fitting a prosthesis with a deep neural network is to artificially create labeled data. This can, for example, be achieved by exploiting inherent anatomical relationships [34], [60]. Alternatively, large datasets of unlabeled data (such as myoelectric signals recorded during daily home use of a prosthesis) can be leveraged to enhance the robustness and accuracy of decoding algorithms using e.g. Unsupervised Domain Adaptation [61].

CHAPTER 5

Summary of the thesis contributions

Prior to this thesis, the most advanced prosthetic system for daily use was a self-contained neuromusculoskeletal arm prosthesis where patients with above-elbow amputation received an osseointegrated implant, underwent TMR surgery and had electrodes implanted [22], see Figure 5.1)a. Using a Direct Control scheme, this system allowed for intuitive control over 1.5 degrees of freedom, specifically for hand opening/closing and elbow locking/unlocking.

By the conclusion of this thesis, significant advancements had been made: a patient received a combined TMR and RPNI surgery, along with an osseointegrated implant and implanted electrodes, see Figure 5.1)b. The introduction of an enhanced motion intent decoding algorithm, which leveraged the additional myoelectric sources created surgically, markedly improved the system's capabilities. This advanced system now supports intuitive, simultaneous, and proportional control over 4.5 degrees of freedom - encompassing the thumb, index finger, a combined actuation for the middle, ring, and little fingers, wrist movements, and elbow lock/unlock. Moreover, this system allowed control over all five fingers of the hand, representing a significant leap in the functionality and intuitiveness of prosthetic systems.

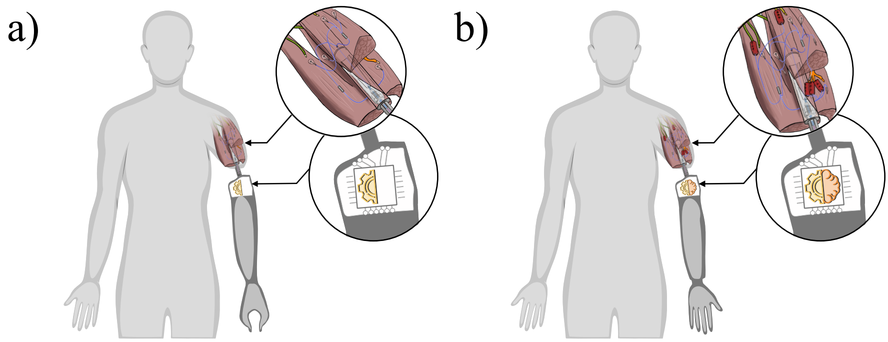

Figure 5.1: Summary of thesis contributions. Shown are two versions of the self-contained neuromusculoskeletal arm prosthesis - one prior and one after this doctoral thesis. **a)** The self-contained neuromusculoskeletal arm prosthesis prior to this thesis consisted of implanted electrodes on native and reinnervated native muscles sites (TMR). A direct control scheme allowed for control over 1.5 degrees of freedom. **b)** The improved self-contained neuromusculoskeletal arm prosthesis, featuring electro-neuromuscular constructs consisting of both reinnervated native muscles (TMR) and innervated free muscles grafts (RPNIs). Together with a deep learning based motion intent decoding algorithm, this system allows for intuitive and simultaneous control of multiple degrees of freedom, as well as sequential control over all five fingers of the hand.

This chapter provides a brief summary of the papers that constitute the basis for this thesis and led to the above-mentioned improvements. The full versions of the papers are included in Part II.

5.1 Paper A

Jan Zbinden, Paolo Sassu, Enzo Mastinu, Eric J. Earley, Maria Munoz-Novoa, Rickard Brånemark, Max Ortiz-Catalan
Improved control of a prosthetic limb by surgically creating electro-neuromuscular constructs with implanted electrodes
Published in *Science Translational Medicine*, vol. 15, no. 704, 2023.
©AAAS DOI: 10.1126/scitranslmed.abq3665 .

A prosthetic limb can restore some functionality after an amputation, and muscles remnant in the residual limb are often used to generate signals to control it. However, in high amputation levels, such as above-elbow, there are not enough muscles left to control all the many missing joints. In this study, we demonstrated that splitting the nerves severed by the amputation and rerouting them into remnant and free muscles grafts can increase the number of potential control signals. This surgical approach, in combination with our neuromusculoskeletal interface, allowed an individual with above-elbow amputation to control all five fingers of a prosthetic hand intuitively.

Student contributions: Conducted the experiments, developed software, analyzed the data, and drafted the manuscript.

5.2 Paper B

Jan Zbinden, Eric J. Earley, Max Ortiz-Catalan
Intuitive control of additional prosthetic joints via electro-neuromuscular constructs improves functional and disability outcomes during home use – a case study
Published in *Journal of Neural Engineering*, vol. 21, no. 3, 2024
©IOP DOI: 10.1088/1741-2552/ad349c .

Recent advances in surgical reconstruction allow the recreation of myoelectric control sites that were previously lost due to amputation. Ideally, each myoelectric control site would contain information about only one single intended movement and could thus be mapped one-to-one with the corresponding movement of a prosthesis. In this study, we demonstrated that surgically created myoelectric control sites allow intuitive simultaneous and proportional control of up to three degrees of freedom using a one-to-one mapping. Extended home use and the additional degrees of freedom further resulted in improved prosthesis functionality and disability outcomes.

Student contributions: Designed the study, developed the firmware and software, conducted the experiments, performed the data analysis, and drafted the manuscript.

5.3 Paper C

Jan Zbinden, Julia Molin, Max Ortiz-Catalan
Deep learning for enhanced prosthetic control: Real-time motor intent decoding for simultaneous control of artificial limbs
Published in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 32, pp. 1177–1186, 2024.
©IEEE DOI: 10.1109/TNSRE.2024.3371896 .

To intuitively control a prosthesis, a person's movement intention needs to be decoded and understood first before it can be turned into a command to actuate a bionic limb. In this study, we explored different machine learning algorithms to decode human movement intent from electromyography signals in real-time. We found that deeper neural networks were notably more effective than shallow networks in understanding and translating movement intent into precise prosthetic control. However, we observed a diminishing return effect for increasing numbers of parameters, indicating that simpler deep networks perform nearly as well as complex CNN and TCN architectures, while being small enough to fit on an embedded system that can be housed inside a prosthesis.

Student contributions: Designed the study, developed software and network architectures, conducted the experiments, performed the data analysis, and drafted the manuscript.

5.4 Paper D

Jan Zbinden, Steven Edwards
From sequential to simultaneous prosthetic control: Decoding simultaneous finger movements from individual ground truth EMG patterns
Published in *International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2024.
©IEEE DOI: 10.1109/EMBC53108.2024.10782980 .

Training deep learning algorithms to decode motor intent typically requires large sets of labeled data. This data requirement grows combinatorially with each additional degree of freedom, complicating the training process for multi-degree of freedom control. In this study, we evaluated a method to create labeled simultaneous data by linearly combining individual movement data. We found that a classifier trained on such artificial data performed equivalently in decoding 3 degree of freedom real-time finger movement to a classifier trained on ground truth data. However, its effectiveness diminishes with more complex tasks, i.e., 5 degree of freedom finger control. In both cases, linearly combining individual movements decreased the time to acquire labeled data to train the classifier by up to 85%.

Student contributions: Designed the study, developed software, performed the data analysis, and drafted the manuscript.

CHAPTER 6

Concluding Remarks and Future Work

This doctoral thesis aimed to address the current clinical limitations in the management of individuals with limb loss who utilize myoelectric upper limb prostheses to regain some of their lost functionalities. Specifically, this work sought to develop prostheses that are more intuitive to control and capable of replicating as many functions of the lost limb as possible. To achieve these goals, two synergistic strategies were explored:

- The creation of additional myoelectric sources through surgical nerve transfers to provide intuitive signals for controlling prosthetic limbs.
- The development and validation of advanced motion intent decoding algorithms that interpret these myoelectric signals, enabling simultaneous and proportional control over multiple bionic joints.

Combining these surgical and engineering approaches yielded significant advancements, which allowed us to demonstrate that:

- transferring severed nerves to native muscles and free muscle grafts resulted in long-term stable electro-neuromuscular constructs.

- the newly created myoelectric sources provided sufficient, linearly independent signals for the direct and intuitive control of three bionic joints simultaneously and proportionally.
- deep neural networks can be effectively utilized to decode simultaneous motion intent, allowing e.g., for intuitive control over all five fingers of a bionic hand.
- the linear combination of datasets from individual movements significantly reduced the time required to acquire labeled data for training deep neural networks capable of decoding simultaneous motion intent.
- collectively, these advancements improved functional and disability outcomes in daily life for users of our neuromusculoskeletal prosthesis.

While substantial progress has been made in developing more functional myoelectric prostheses, there remains a considerable gap in achieving the full natural control provided by a biological limb. Ongoing research in both surgical techniques and engineering could potentially yield further significant enhancements. Future surgical innovations could provide even more independent signals, and systems capable of recording and decoding motor unit action potentials, which represent the actual activity of motor neurons, might allow for more reliable and functional control over an increased number of bionic joints [62].

The ultimate goal is to engineer a bionic limb that fully replicates all the functions of a biological limb [63], [64]. This thesis focused on restoring the efferent pathway, which involves decoding the intent to voluntarily move an arm and hand. However, a biological limb also features an afferent pathway, which provides comprehensive sensory and proprioceptive feedback that is crucial for interacting with and understanding our environment. Addressing how to effectively relay sensory information from the environment to the brain remains an open area of research and is essential for creating a truly functional bionic limb. Successfully restoring both efferent and afferent pathways is critical for developing a technological solution that can completely replace a lost limb.

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