THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Toward Stable and Reliable Lower Limb Prosthetics Control with Signals Recorded from Muscles

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Electrical Engineering

CHALMERS UNIVERSITY OF TECHNOLOGY

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Cover:
Front: Illustration of muscle signals recorded from an individual with lower-limb amputation, used to predict her movement intentions while walking on various terrains, in this case, during stair descent.
Illustrator: Bahareh Ahkami

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Toward Stable and Reliable Lower Limb Prosthetics Control with Signals Recorded from Muscles

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Abstract

Prosthetic devices are essential in enhancing mobility and functionality for individuals with amputations, enabling them to perform daily activities with improved independence and ease. The effectiveness of these prosthetic devices depends significantly on their design, functionality, and the user's ability to intuitively control it and rely on it. In pursuit of enhancing control, our research focused on the integration of electromyography (EMG) signals into prosthetic control as a means to detect movement intention of the users. EMG signals offer a promising avenue for developing more natural and intuitive prosthetic systems. Although this technology has successfully improved the functionality of prosthetic arms, its application in prosthetic legs has been less extensively explored.

This research aimed to extend the use of EMG technology to lower limb prosthetics, drawing from the established successes in upper limb applications. While the use of EMG for lower limb prosthetics has been investigated in prior studies, it remains less extensively explored and adopted compared to upper limb applications. To this end, we developed an open-source software framework for acquiring and processing biological data, such as electromyography (EMG), and non-biological data, including inertial measurement units (IMUs). This framework aims to foster collaboration and drive innovation within the global scientific community by encouraging researchers to actively develop, compare, and enhance algorithms, thereby accelerating progress in prosthetic technology. We conducted a benchmark test using a dataset recorded as part of this thesis, comprising data from 21 able-bodied individuals, which is now openly accessible to the community, to validate the platform's effectiveness.

Building on this validation, we tested the system with individuals living with limb loss, the next critical step in achieving robust and reactive control of prosthetic legs. Furthermore, to address the challenges associated with traditional socket-based systems for EMG-controlled prosthetics—such as signal instability and user discomfort—we recorded EMG signals from individuals with osseointegration. Osseointegration eliminates the need for a socket by providing a direct connection between the prosthetic and the skeletal structure, resulting in more stable electrode placement and reducing motion artifacts caused by shifting soft tissues. This improves EMG signal quality and consistency, allowing our algorithms to interpret more accurately the users' intended movements. To further enhance the accuracy and reliability of movement predictions, we refined our intention detection algorithms by incorporating post-processing techniques specifically designed to filter out low-confidence predictions from the EMG and IMU data, reducing the risk of incorrect intention detection and preventing unintended prosthetic movements.

We also explored the integration of neural signals to enhance the responsiveness of prosthetic devices, aiming for more intuitive and seamless user interactions. In addition, the final phase of this research focused on the development of a clinical rehabilitation protocol aimed at users of active prosthetic legs and neuromusculoskeletal interfaces. These initial efforts represent the foundational steps for broader adoption of EMG-based control systems in lower-limb prosthetics, with the potential to substantially improve users' quality of life.

Keywords: Prosthetic Control, Electromyography (EMG), Osseointegration, Lower-Limb Prosthetics, Intention Detection Algorithms

List of Publications

This thesis is based on the following publications:

I Electromyography-Based Control of Lower Limb Prostheses: A Systematic Review. Bahareh Ahkami, Kirstin Ahmed, Alexander Thesleff, Levi Hargrove, Max Ortiz-Catalan. *IEEE Transactions on Medical Robotics and Bionics*, 2023

II Locomotion Decoding (LocoD): An Open-Source and Modular Platform for Researching Control of Lower Limb Assistive Devices. Bahareh Ahkami, Kirstin Ahmed, Morten Bak Kristoffersen, Max Ortiz-Catalan. *Available at SSRN: https://ssrn.com/abstract=4575926*, 2023

III Probability-Based Rejection of Decoding Output Improves the Accuracy of. Locomotion Detection During Gait. Bahareh Ahkami, Fabian Just, Max Ortiz-Catalan *2023 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*

IV Real-Time Locomotion Mode Detection in Individuals with Transfemoral Amputation and Osseointegration. Bahareh Ahkami, Morten B. Kristoffersen, Max Ortiz-Catalan. *Journal of NeuroEngineering and Rehabilitation*, vol. 22, article 142, 2025 https://doi.org/10.1186/s12984-025-01672-2

V Extra-Neural Signals from Severed Nerves Enable Intrinsic Hand Movements in Transhumeral Amputations. Bahareh Ahkami, Enzo Mastinu, Eric J. Earley, Max Ortiz-Catalan. *Scientific Reports*, 2022

VI Design of a Stepwise Safety Protocol for Lower Limb Prosthetic Risk Management in a Clinical Investigation. Alexander Thesleff, Bahareh Ahkami, Jenna Anderson, Kerstin Hagberg, Max Ortiz-Catalan. *2021 43rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*

Other Publications by the Author (not included in this thesis)

VII Walking Mode-Dependent Improvements of Locomotion Detection Through Rejection-Based Post-Processing. Fabian Just, Bahareh Ahkami, Max Ortiz-Catalan. *Proceedings of the 2024 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 1–4, July

2024
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VIII A Modular Open-Source Platform for Lower Limb Prosthetic Control and Locomotion Decoding (LocoD). Bahareh Ahkami, Kirstin Ahmed, Morten Bak Kristoffersen, Max Ortiz-Catalan. Presented at the *ISPO 19th World Congress*, 2023, Mexico

IX A Systematic Review of Electromyography-Driven Control Algorithms for Lower Limb Prostheses. Bahareh Ahkami, Max Ortiz Catalan. Presented at the *ISPO 18th World Congress (Virtual Edition)*, 2021

X Extraneural Recordings Enable the Decoding of Intrinsic Hand Movements in Transhumeral Amputations. Bahareh Ahkami, Max Ortiz Catalan. Presented at the *ISPO 18th World Congress (Virtual Edition)*, 2021

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Acronyms

DOF	Degree of Freedom
EMG	Electromyography
sEMG	Surface Electromyography
iEMG	Intramuscular Electromyography
ENG	Electroneurography
IMU	Inertial Measurement Unit
LDA	Linear Discriminant Analysis
NN	Neural Networks
OPRA	Osseointegration Prosthetic Rehabilitation Approach
SS	Steady-State
TR	Transition
Q-TFA	Questionnaire for Persons with a Transfemoral Amputation
PCA	Principal Component Analysis

Contents

1. Introductory information

This thesis investigates innovative strategies to enhance lower-limb prosthetic control, with a focus on advancing movement intention detection algorithms and addressing the challenges associated with their real-time performance. It encompasses a combination of theoretical studies, open-source platform development, and experimental testing to lay the foundation for more reliable and intuitive prosthetic systems.

This chapter begins with introductory info about this thesis, providing an overview of the challenges and advancements in lower-limb prosthetic control. It then defines the specific scope of the research and outlines the objectives of driving this work. Following the introduction, a detailed background is presented, covering key aspects of the field, including prosthetic attachment systems, the use of biological signals for control, and the current state of prosthetic technology. Following this introduction, the thesis transitions into the core research contributions, presented as individual papers, each addressing specific aspects of the study.

1.1. Prosthetic Functionality

Following limb loss, many patients opt for prosthetic limbs to facilitate their daily activities and promote independence. However, not all prosthetics offer the same level of functionality. Some serve merely as cosmetic enhancements or aids for maintaining balance, in lower limb cases, without significantly aiding in mobility or functionality. These basic prosthetics lack user input or control mechanisms. In contrast, more advanced prosthetic limbs are capable of gathering information from the body and the surrounding environment and interpreting the user's intentions, which is more common in upper limb prosthetics. In such cases, biological signals, such as electromyography signals (EMG), serve as invaluable sources of information, enabling more sophisticated control and interaction with the prosthetic limb [1].

1.2. Biological Signals for Enhanced Prosthetic Limb Control

Biological signals play a crucial role in prosthetic control as they naturally reflect the user's intentions, offering a natural and efficient means of limb control suggestive of how individuals naturally control their limbs. Among the various signals that can be captured from the body, electromyography (EMG) stands out as particularly relevant for prosthetic control. EMG records the electrical activity of muscles and can be detected either through surface electrodes placed on the skin or through electrodes implanted surgically within the muscles, resulting in two categories:

surface EMG (sEMG) and intramuscular EMG (iEMG). Each type has its own advantages and limitations. Surface EMG sensors are easy to apply and carry minimal risk, but its movement and inability to target specific muscles can affect control consistency. Conversely, while intramuscular EMG requires surgery and comes with associated risks such as infection, it offers the potential for more stable signal acquisition from specific muscles without needing frequent adjustments. Although no current prosthetic systems widely utilize intramuscular EMG, early research suggests it could provide more reliable control signals in future applications [2].

1.3. Future Directions in Prosthetic Control

Despite advancements in the current lower limb prosthetic devices, they still face significant limitations. They often lack natural control and seamless transitions, resulting in an unnatural gait that can cause discomfort and pain in other joints, such as the hips [3]. This limitation not only affects the physical well-being of users but also their societal integration, as frustration can arise from the inability to use their prosthetics effectively [4–7]. Electromyography (EMG) emerges as a promising solution for intuitive prosthetic control [8–10]. By harnessing biological signals, such as EMG, prosthetic limbs can offer more natural control, leading to increased user satisfaction and enhanced activity levels. However, integrating EMG poses its own set of challenges:

1. Socket usage and EMG Quality: The design of the socket can significantly impact the quality of EMG signals, thereby affecting the control of the prosthetic limb.
2. Unsatisfactory Control: Current EMG-based control methods require refinement. Improvements in algorithms, including better pre-processing and post-processing techniques or the development of more sophisticated algorithms capable of predicting user intent and excluding interference, are necessary for optimal prosthetic control [11,12].

2. Scope of Thesis

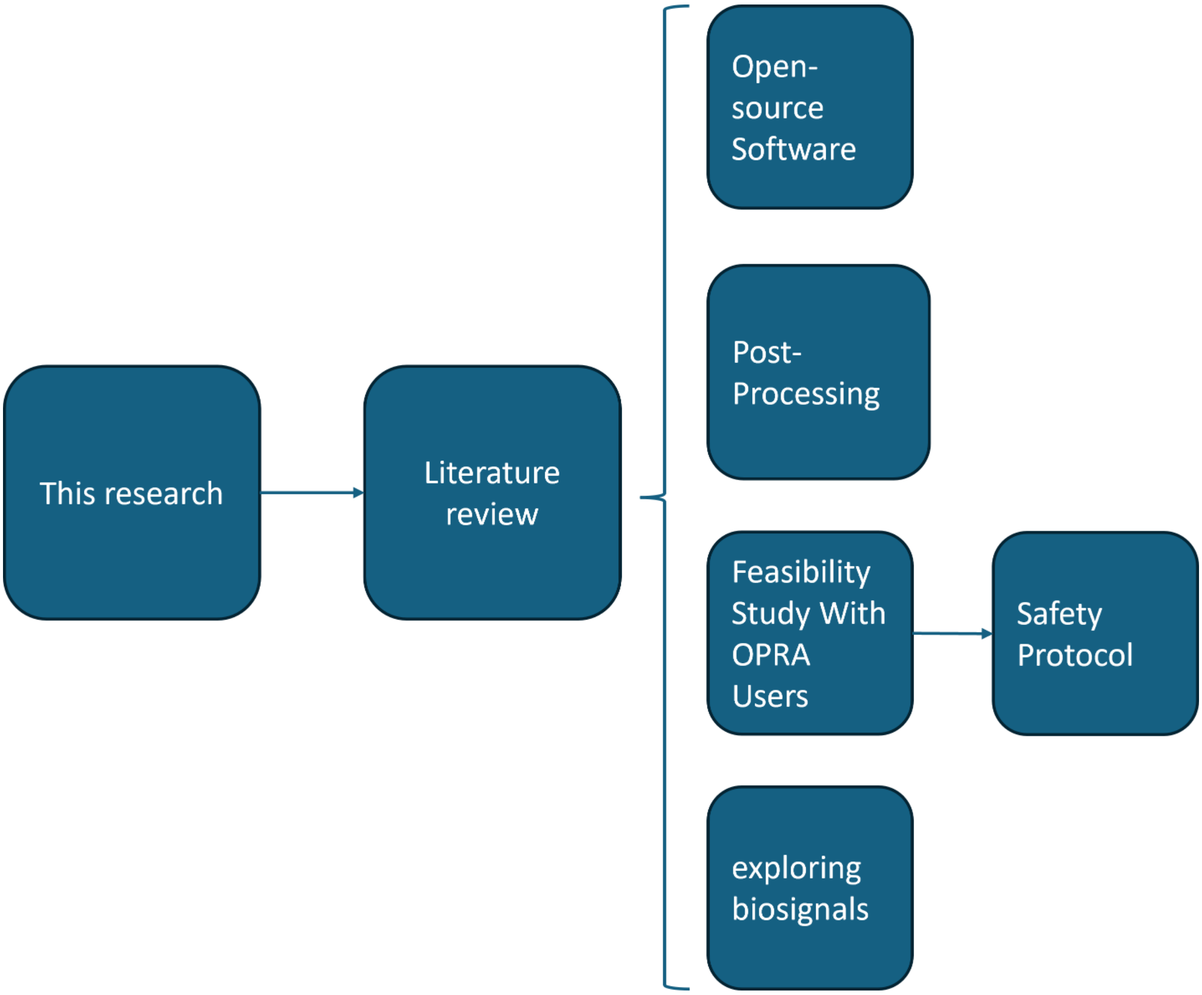

Figure 1 *Overview of the research process, highlighting key steps: conducting an in-depth literature review, developing an open-source software platform for signal recording and processing, implementing post-processing techniques to enhance accuracy of locomotion detection, performing real-time feasibility testing with individuals using osseointegrated prosthetic attachments (OPRA) and developing a step-wise safety algorithm, and exploring the integration of combined biosignals to improve prosthetic control.*

2.1. Thesis Goal

The aim of this research is to enhance the control of lower-limb prosthetics by addressing key challenges in movement intention detection algorithms. This goal is pursued through a comprehensive literature review, the development of an open-source platform for signal acquisition and analysis, and the integration of diverse biological and non-biological signals. Together, these efforts aim to advance the reliability and effectiveness of prosthetic control systems.

To achieve this objective in this project we followed these steps (Figure 1):

- Literature Review: To gain a comprehensive understanding of the latest advancements in prosthetic control and identify the gaps and limitations, we conducted an extensive literature review focusing on studies that utilized electromyography (EMG), both with and without additional non-biological signals, to control prosthetic limbs, decode movements, and detect user intent.
- **Open-Source Platform Development (LocoD):** In order to foster collaboration, facilitate algorithm development, and enable comparative analysis, we developed an open-source platform. This platform is capable of recording signals from both biological such as electromyography (EMG) and neural signals, and non-biological signals, such as data from inertial measurement units (IMUs). These signals are used to enable intention detection while walking on different terrains. This supports the development of advanced prosthetic control algorithms aimed at improving user experience and adaptability [13,14].
- **Real-Time Feasibility Study with OPRA Users and Algorithm Enhancement:** We conducted initial real-time testing of our algorithm with participants who had undergone osseointegration (OPRA) and transfemoral amputation, marking a crucial step in our research. To enhance prosthetic control, we then implemented a post-processing algorithm to filter out movement predictions with low confidence, ensuring more reliable performance. All processing and testing were carried out using LocoD, our open-source software platform.
- **Exploring Combined Biosignals:** Recognizing the inherent limitations of relying solely on EMG for control, we did a feasibility study of using neural signals alongside muscle signals. This exploration aimed to leverage the complementary nature of these signals, hypothesizing that the combined biological information could surpass the capabilities of EMG alone. Through this innovative approach, we aimed to unlock new avenues for improving prosthetic control and enhancing user experience.

2.2. Research Questions

1. What are the gaps, limitations, and latest trends in EMG-based control algorithms for prosthetic legs?

2. How can an open-source software platform for recording and processing EMG signals be utilized to enhance lower limb prosthetic control and improve user experience and functionality?
3. How do different sensor fusions affect the accuracy of control in lower limb prosthetics? Can neural signals complement EMG signals to improve control?
4. How does the movement intention detection algorithm perform during real-time testing with participants who have osseointegration implants?
5. Can post-processing of movement intention detection improve the accuracy and reliability of these algorithms?

3. Background

Projections indicate that the United States could see around 3.6 million individuals living with limb loss by the year 2050 [15]. Similarly, in Sweden, approximately 2000 amputations are anticipated each year [16]. The majority of these amputations occur in the lower limb, profoundly impacting individuals' daily lives and their integration into society. Without adequate support, many may find themselves confined to their homes, facing not only a loss of income but also a disconnection from their communities. This is not just a challenge for the individuals affected but also for society as a whole, as we risk losing valuable, active members of communities. One promising solution to mitigate the impact of amputation is to provide individuals with proper prosthetic limbs that address their specific needs. Studies have identified the five most critical needs of amputees: "Less pain," "Mobility," "Social integration," "Independence," and the ability to "Walk". These findings underscore the significance of designing and controlling prosthetic legs that can effectively meet these needs and alleviate some of the challenges faced by amputees [17].

To better understand how to support amputees effectively, it is essential to examine the standard prosthetic care available in most countries. This involves taking a closer look at the different types of prosthetic leg attachments and the various commercial prosthetic legs available on the market.

3.1. Prosthetic Attachment

Patients have access to two primary attachment options for their prosthetic devices—sockets and implants—tailored to their unique circumstances. These attachment methods are crucial for ensuring comfort, stability, and ease of use, which are key factors in encouraging consistent prosthetic use. A more comfortable attachment can significantly enhance a patient's ability to rely on their prosthetic device, helping them regain mobility and independence, and supporting their reintegration into society.

Socket Attachment: A socket is a custom-fitted interface that slips over the residual limb, connecting the limb to the prosthetic device. Designed to provide a secure fit, the socket distributes weight evenly and offers control over the prosthetic. However, socket use can lead to discomfort, skin irritation, and other skin issues, especially in warmer conditions. Despite these challenges, sockets remain a non-invasive option and are widely accessible compared to other attachment methods (Figure 2.a).

Implant Attachment: In recent years, advancements in technology have led to the development of osseointegrated implants. These implants are surgically anchored into the residual bone, providing a more direct connection between the prosthesis and the body. Osseointegration offers benefits such as increased stability, improved comfort, and enhanced proprioception for the user. It removes the drawbacks of sockets such as skin irritation and being uncomfortable but it comes with its risk of infection and surgical complications [18–25]. Therefore for now in Sweden it is only available to people who cannot use the socket due to skin issues or shortness of their stump [21] (Figure 2.b).

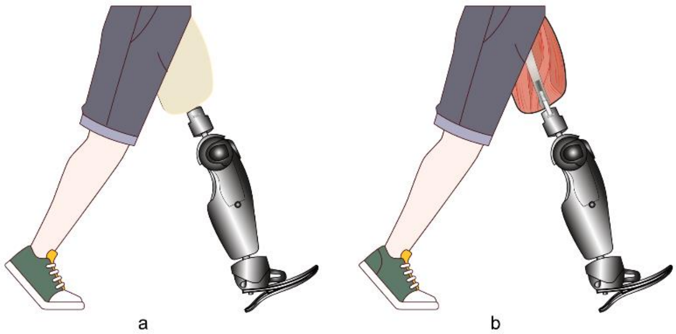

Figure 2 *(a) Socket attachment: A custom-fitted interface that slips over the residual limb to connect the prosthetic device, distributing weight and providing control. (b) Osseointegrated implants: Surgically anchored into the residual bone, offering a direct and stable connection between the prosthesis and the body.*

Alongside attachment options, there is a diverse range of prosthetic legs available on the market, each offering unique features and functionalities and they come with their pros and cons (Figure 3).

3.2. Prosthetic Legs

Passive Prosthetic Legs: Passive prostheses are designed to resemble the appearance of a natural limb and provide basic support for activities of daily living. They do not have active components like motors and are primarily used for aesthetic purposes or for individuals with low activity levels. The primary advantages of passive prosthetic legs include their lightweight and uncomplicated design, making them easy to use and manage. However, because these devices lack active components like motors and do not have control systems, they cannot provide energy support—meaning they do not contribute additional force or assistive power during movement—and cannot adapt to different activities or terrains (Figure 3).

Semi-Active Prosthetic Legs: Semi-active prostheses are innovative mechanical limbs designed to enhance both stability and mobility. These prosthetic legs feature adjustable joints and dynamic response systems. They are equipped with mechanical sensors that detect speed and gait phase during the gait cycle, allowing for adaptive movements. The lightweight and user-friendly design makes them easy to manage. However, semi-active prostheses do not provide energy compensation for movements like stair ascent or standing up, which may restrict their functionality in certain situations. Additionally, their control system relies solely on data from the interaction between the leg and the surrounding environment, and they employ simpler control logic compared to active prosthetics (Figure 3).

Active Prosthetic Legs: Active prostheses are equipped with advanced technologies, such as microprocessors, sensors, and motors, to mimic more closely the functionality of a natural limb. These prosthetic legs can adjust in real-time to changes in different terrains and movement patterns, providing users with a higher level of control and performance during dynamic activities like walking or running (Figure 3).

***Figure 3** Different types of prosthetic legs categorized into Passive Prostheses, Semi-Active Prostheses, and Active Prostheses, showcasing examples of each category: (a) Pro-Flex® LP Torsion, (b) Balance™ Knee OFM2, (c) Mauch® Knee, (d) Dynion, (e) C-Leg, (f) Rheo Knee®, (g) Genium X3, (h) Proprio Foot®, (i) Power Knee™, and (j) Empower. Images ©Ottobock and ©Össur, used with permission.*

Powered prostheses represent a significant advancement in the field of prosthetics, offering various benefits over passive and semi-active counterparts. These benefits include the capacity to provide net positive work during movement, which can help reduce compensatory behaviors often observed in prosthesis users, particularly during activities like stair climbing [26].

Additionally, powered prostheses have shown promise in increasing self-selected walking speed compared to passive prostheses, contributing to improved mobility and quality of life for users [27,28]. However, despite these advantages, several challenges impede their widespread adoption. These challenges include the increased weight, complexity, and cost associated with powered prostheses compared to passive alternatives [29]. Furthermore, the need for customized control systems tailored to individual users and specific types of movement, such as walking on different surfaces or climbing stairs, increases the complexity and expense of these devices [30–32]. To be effective, these control systems must be natural and responsive, seamlessly integrating with the user's movements. Electromyography (EMG) is emerging as a promising approach to address these challenges by providing a way to determine the user's movement intentions. By capturing the electrical signals produced by muscles during movement, EMG can be used to interpret the user's intended next movement, enabling more intuitive and responsive control of prosthetic devices. While this research does not specifically address these challenges, it explores and enhances some aspects of control system responsiveness that may contribute to more natural and user-aligned solutions in the future. This claim reflects the central perspective of this research, emphasizing the potential of aligning control with the user’s own muscle signals to enhance the performance and user experience of advanced prosthetics.

Currently, there are only two active prosthetic knees available on the market: the Power Knee [33] and Reboocon, along with one powered ankle [34]. As powered prostheses gain popularity, various research groups are utilizing research devices like the Vanderbilt Leg [35], Open Source Leg [36,37], and Utah Leg [38]. While further research and development are essential to optimize control algorithms, reduce device weight and complexity, and improve affordability and accessibility for prosthetic users, this research did not focus on addressing these hardware-specific challenges. Instead, our work concentrated on developing and validating control algorithms for prosthetic applications.

3.3. Electromyography (EMG)

Electromyography (EMG) is a widely used technique in both clinical and research settings to evaluate the electrical activity produced by muscle contractions comprehensively. It operates on the principle that contracting muscles generate electrical signals, which can be detected and recorded [39]. EMG involves the placement of electrodes either on the surface of the skin or directly into the muscle tissue, depending on the required resolution of the signal (Figure 4). In this research, surface EMG (sEMG) is utilized as the primary method for recording muscle activity. This choice is motivated by its non-invasive nature. Surface EMG (sEMG) is typically used in muscle assessment during physical therapy and sports science research. In contrast, intramuscular EMG (iEMG) offers more selective recordings by accessing muscle fibers directly, making it invaluable for diagnosing neuromuscular disorders and studying detailed muscle activation patterns.

The insights provided by EMG signals are crucial for understanding muscle function, including the timing and intensity of contractions, coordination during movement, and motor unit recruitment patterns. These details are instrumental in understanding neuromuscular control mechanisms, identifying abnormalities, designing personalized rehabilitation programs, and developing advanced prosthetic devices controlled by the user's muscle activity. Importantly, EMG offers critical information for inferring the user’s intentions since it captures signals directly from the muscles, typically the remnant muscles, which are central to movement control. EMG is therefore an indispensable tool for clinicians, researchers, and engineers, enhancing diagnostics, rehabilitation, and assistive technology.

3.3.1. EMG Revolution in Upper Limbs Prosthetics (Myoelectric control)

In recent years, the application of electromyography (EMG) in controlling upper limb prosthetics has demonstrated considerable success, showcasing the robustness and potential of this technology. EMG, which utilizes the electrical signals generated by muscle contractions, has been effectively harnessed to control prosthetic arms and fingers [40]. While achieving fully natural control remains a challenge, the integration of EMG signals has significantly improved the functionality and usability of upper limb prosthetics, paving the way for transformative advancements in assistive technology.

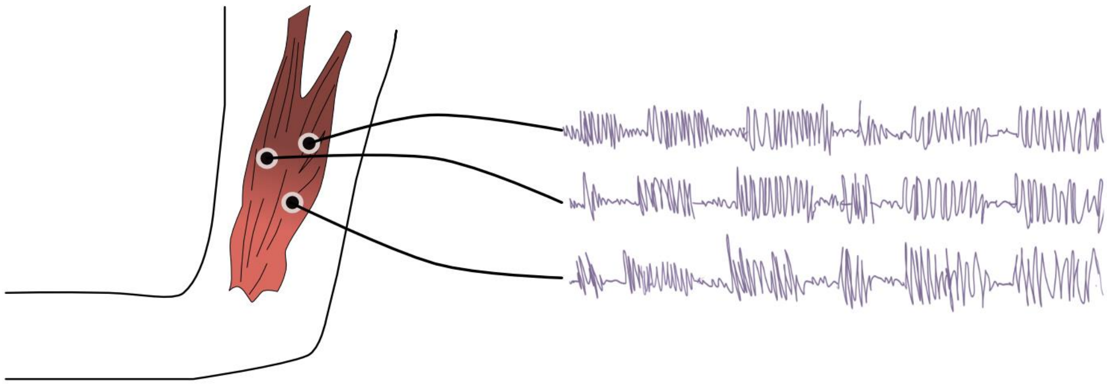

Figure 4 *Illustration of electromyography (EMG) signal acquisition, demonstrating electrode placement on a muscle and the corresponding electrical activity generated by muscle contractions. This activity forms the basis for analyzing neuromuscular function and is critical for applications such as prosthetic control.*

3.3.2. EMG in the Lower limb

While electromyography (EMG) has demonstrated significant potential in research for enhancing prosthetic control, its adoption in commercially available devices remains limited. In lower-limb prosthetics, research has also explored the combination of EMG with inertial measurement units (IMUs) to improve control, though such advancements have yet to see widespread commercial application. Most prosthetic limbs, both upper and lower, continue to rely on passive mechanical designs, favoring simplicity and durability for daily use. However, innovations like EMG-based control have the potential to move beyond these limitations, offering more intuitive and adaptable solutions for lower-limb prosthetics, as they have begun to do for upper-limb devices.

Controlling a prosthetic leg using EMG presents distinct challenges, particularly in maintaining consistent and stable signals during dynamic activities like walking [11,12,41]. Surface EMG signals, while promising in research settings, are often affected by changes in skin impedance, inconsistent electrode placement, and movement between electrodes and muscles during daily-life activities, leading to increased signal noise and user frustration due to insufficient control [10,42–44]. These challenges are especially pronounced in lower limb prosthetics, where the prosthetic socket environment further complicates signal and reliability (Figure 5).

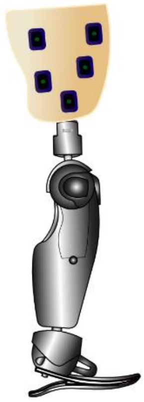

Figure 5 *Illustration of five EMG sensors integrated into a custom-made prosthetic socket. The design must accommodate precise sensor placement, which poses challenges due to the movement between residual limb (stump) and socket. These factors can lead to inconsistent signal quality, discomfort for the user, and difficulties in accurately targeting specific muscles.*

To address these issues and enhance the reliability of EMG signals, researchers are exploring potential solutions, including implantable sensors, innovative electrode designs, custom prosthetic sockets with integrated electrodes, and advanced signal decoding algorithms. While these developments have significantly improved upper limb prosthetic control, their adaptation to lower limb prosthetics remains limited. This gap underscores the need for further research to overcome these challenges and unlock the potential for more natural, reliable, and effective control of lower limb prosthetics.

By addressing these barriers, future advancements could improve the daily usability and acceptance of prosthetic legs, providing users with a level of functionality closer to that of advanced upper limb prosthetics.

3.4. Research Objectives

In this research, we aimed to improve the use of EMG signals for controlling lower limb prosthetics, striving for a system that is both natural and reliable. To establish a foundation for our approach, we first conducted a comprehensive literature review to understand the current state of the art in EMG applications for lower limb prosthetic control and to identify gaps and limitations in the field. To address one of these gaps, we developed an open-source software framework that simplifies the recording, processing, and classification of signals from diverse sources. This software lays the groundwork for enhanced collaboration and eases the integration of new algorithms.

We then conducted a benchmark test involving 21 able-bodied participants to validate our software's accuracy and reliability in recording, processing, and classifying EMG signals followed by real-time trials with individuals who have undergone transfemoral amputations. To further refine our intention detection algorithms, we incorporated post-processing techniques, which improved the accuracy and reliability of movement predictions.

Additionally, we explored other biological signals, such as electroneurography [45] to control a prosthetic device. Finally, we implemented a step-wise safety protocol to manage risks associated with research on active prosthetic legs.

4. Advancing the Understanding of EMG-Based Control for Lower Limb Prosthetics (Paper 1)

In this research, we undertook a comprehensive systematic literature review (Paper 1) to better understand the mechanisms of control used in lower limb prosthetics. Our inclusion criteria were to evaluate studies that employed electromyography (EMG) signals, either solely or in combination with other sensors, to control prosthetic limbs or facilitate lower limb movements. This review encompassed analysis of 121 distinct studies, providing crucial insights into various experimental setups and methodologies. With this paper, we address our first research question: "What are the gaps and latest trends in EMG-based control algorithms for prosthetic legs?

We examined these 121 studies from different perspectives to understand trends and identify current and emerging methods. This analysis included participant demographics, the different movements performed, the sensors used to record data, and the algorithms implemented. Notably, machine learning was the most commonly used control algorithm, and we provided detailed information about its applications. These insights are instrumental in laying the groundwork for standardized experiments. This research aims to help researchers build upon existing studies and develop their own experimental setups.

4.1. Participant demography and movements

Among the reviewed studies, fifty percent involved participants with amputations, while the remaining studies were conducted with able-bodied participants. All studies with amputee participants focused on individuals with unilateral limb loss, comprising 56 studies with transfemoral amputees and 26 with transtibial amputees. The tests included equal distribution of non-weight-bearing and weight-bearing movements. Non-weight-bearing movements consisted of isolated joint actions, such as flexion and extension of the knee and ankle, as well as tasks requiring participants to mimic predefined motion trajectories or perform movements constrained to a single degree of freedom (DOF). In contrast, weight-bearing movements included activities such as walking and transitioning across various surfaces.

4.2. Most common muscles and sensors

Muscle groups commonly used for EMG acquisition in research participants with transfemoral amputation included the semitendinosus, biceps femoris, tensor fasciae latae, rectus femoris, vastus lateralis, vastus medialis, sartorius, adductor magnus, and gracilis [46–60]. For participants with transtibial amputation, the most frequently reported muscles used for EMG acquisition were the medial and lateral gastrocnemius and the tibialis anterior[61–64]. The number of electrodes employed varied greatly, with some studies using up to 192 electrodes.

Moreover, our review explored the integration of EMG signals with other sensory technologies such as Inertial Measurement Units (IMUs), depth sensors, goniometers, laser distance sensors, or load cells. A particularly common sensor was the foot switch sensor, which is crucial for determining the gait stage based on ground contact—a critical component for timing in locomotion control (**Figure 7**) [58,65–74].

4.3. Control and Intent Detection Methods

Control methods for prosthetic limbs leverage various approaches to interpret user intent and translate it into movement. These methods vary in complexity, ranging from straightforward linear responses to advanced machine learning algorithms. The choice of method often depends on the desired level of control, the available technology, and the user's specific needs. Broadly, these methods can be categorized into direct control, model-based control, and machine learning-based approaches.

4.3.1. Direct Control

This method uses EMG signals to directly control prosthetic joints. In direct control, each muscle activation has a direct, one-to-one correspondence with a specific joint movement, meaning that the activation of a particular muscle proportionally drives the movement of the corresponding joint. While effective, this approach encounters limitations when controlling multiple degrees of freedom simultaneously, often requiring additional strategies, such as model-based or machine learning techniques, to enhance control [62,75–78].

4.3.2. Model-Based Control

In model-based control, body segments are conceptualized as rigid bodies linked by rotational joints and driven by actuators that simulate muscle functions. Most of these models derive from motion capture data gathered within specialized gait laboratories, offering a well-validated foundation for model creation. Despite its performance, the requirement for specialized equipment limits its applicability outside controlled environments. However, the generality of these models provides a significant advantage as they can be adapted for new subjects [79–81].

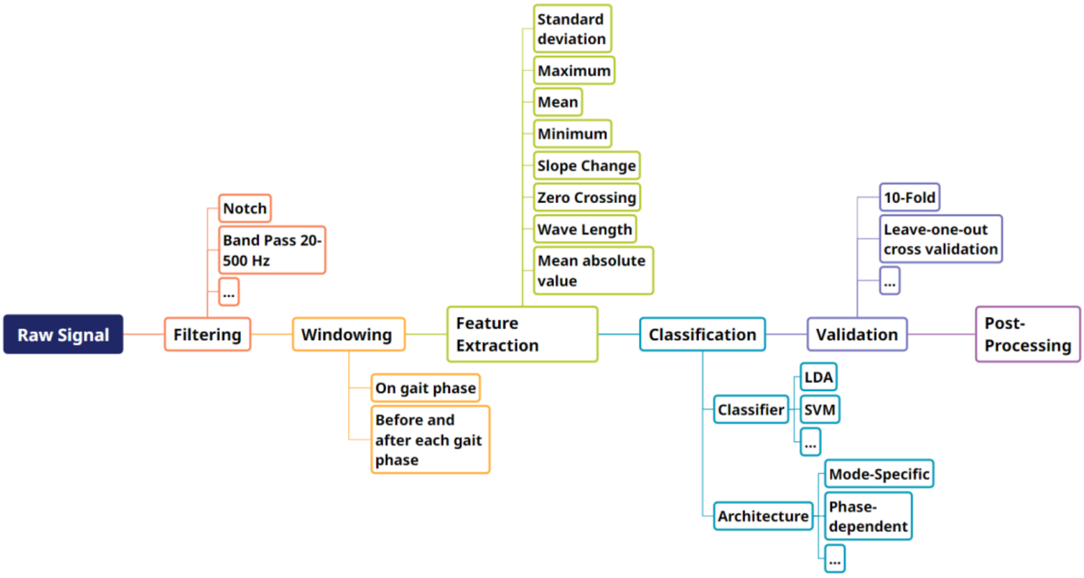

Figure 6 *The sequential steps involved in processing the raw signal for training and validating classifiers designed to detect locomotion modes. This process includes signal filtering to remove noise, segmenting the data into overlapping or non-overlapping windows, feature extraction in different domains, classification and validation.*

4.3.3. Machine Learning Control Methods:

These approaches do not rely on predefined models but utilize training data to develop effective classifiers or decoders. The process involves several steps (Figure 6):

- **Pre-processing and windowing:** Filtering and segmenting EMG signals to eliminate noise and extract relevant data. Our review showed the most common filter was between 20-500 Hz [39]. This part is not only limited to the machine learning algorithms, and it is a common step in all control methods.
- **Feature Extraction:** This involves extracting features from time windows in various domains (time, frequency, or combined), or using techniques like wavelet packet transform followed by dimensionality reduction (e.g., PCA) to focus on the most relevant data [50,58,82–85]. This step can also be a part of direct control. In direct control instead of extracting many different features, the most common feature is the EMG signal's magnitude.

- **Classification:** Sophisticated algorithms such as Support Vector Machines (SVM) classify the extracted features, tailored to find the participant's intention for different movements and transitions. Linear Discriminant Analysis (LDA) and SVM were the most common methods [58,65,72,83,86].
- **Post-processing:** Techniques like majority voting or velocity ramps are used to rectify potential misclassifications, ensuring the prosthetic's stability and reliability in real-world scenarios [60,83,87].

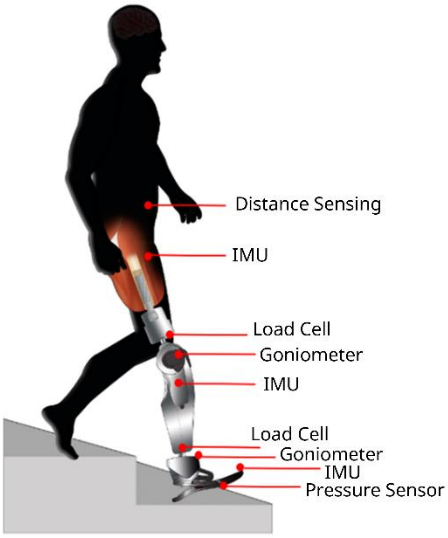

Figure 7 *Overview of various non-biological signals and their sensor placements, encompassing IMUs, load cells, goniometers, pressure sensors, and distance measurement systems. [12]. CC-BY-NC*

4.4. Performance Metrics

Performance metrics are critical to ensure that the control systems operate effectively and minimize potential errors that could compromise user safety and functionality. The most common performance metric is the accuracy/error of locomotion detection.

4.5. Challenges and Potential Solutions

Using EMG for controlling the lower limb prosthetic is not common yet and our review identified several limitations when having EMG-based control, often due to the insufficient quality of the captured data. We propose several avenues for improvement:

- **Enhanced EMG Acquisition:** Exploring advanced EMG acquisition techniques such as the use of implanted electrodes could significantly improve signal quality and reliability [50].
- **Integration of Additional Inputs:** Combining EMG with other biological or mechanical sensors could provide a richer dataset for control systems, enabling a more natural and intuitive response from the prosthetic.
- **Development of Advanced Control Algorithms:** Significant advancements have been made in control algorithms for upper limb prosthetics; however, the research into lower limb control requires more sophisticated algorithms to enhance functionality and user experience.

4.6. Conclusion from Paper 1

In this study, we systematically reviewed the most prevalent methods of EMG-based lower limb prosthetic control and identified significant gaps in the field. Our analysis revealed that, despite the existence of highly effective control algorithms, there is a noticeable absence of more advanced methods, such as neural networks, in the field. Additionally, there is a lack of an open-source software platform for implementing and comparing new algorithms. Furthermore, the scarcity of real-time studies restricts our ability to draw definitive conclusions. Moreover, weight-bearing studies involving amputees are not only limited in number but also lack the reliability needed for external testing beyond laboratory settings. This highlights the need for advancements in methodology to ensure that these techniques can be confidently applied in real-world scenarios.

5. Development of an Open-Source Platforms to Enhance Prosthetic Research (Paper 2)

To address the gaps in algorithm development for lower limb control and the absence of both commercial and open-source solutions, we have developed an open-source platform. This platform not only allows the community to create and implement their own algorithms but also facilitates the use of existing ones. Additionally, our platform simplifies the comparison of different algorithms [13,88]. Alongside the platform, we released a dataset to serve as a benchmark for algorithm comparison. This is particularly beneficial for groups that lack access to recording facilities, as they can utilize this platform to develop and refine algorithms [13,14].

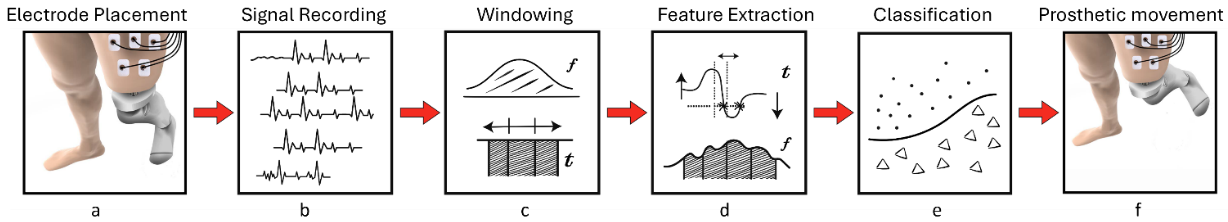

Figure 8 *Workflow of recording and processing EMG signals using LocoD, showing signal acquisition (a, b), Windowing and filtering (c), feature extraction (d), classification (e), control of the prosthetic leg (f)*

Our software supports recordings from Delsy[1]s devices, known for their stability and reliability in capturing high-quality electromyography (EMG) signals (Trigno, Delsys, USA). Additionally, LocoDs versatile communication modes ensure compatibility with other systems, facilitating broader application across various research setups. The software manages signal acquisition (Figure 8.b), preprocessing (Figure 8.c), feature extraction (Figure 8.d), classification (Figure 8.e), and post-processing—providing a comprehensive solution that streamlines data handling and analysis for prosthetic control research.

To assess the integration of EMG with mechanical sensors and benchmark our software, we analyzed the classification error across three different sensor combinations (EMG, IMU, and EMG+IMU) in 21 participants while ambulating on various surfaces. This approach combines the stability of mechanical sensors with the nuanced detection of natural movements via EMG, demonstrating that the

[1] www.delsys.com

combination of EMG signals with IMU and pressure signals can effectively predict movement intentions.

EMG data were conditioned with a 20-500 Hz bandpass filter and a notch filter. Signal blocks centered around each gait phase (heel contact and toe-off) were extracted from 200 ms before to 100 ms after, creating a 300 ms segment of data. From this segment, we extracted 200 ms windows, incrementing by 30 ms (Figure 9). For the EMG signals, we derived mean absolute value, waveform length, zero crossings, and slope sign changes [58,89]. From each window of IMU and pressure sensors, we calculated the mean, maximum, minimum, and standard deviation [90,91]. Features from selected sensor channels were combined into feature vectors for classification. For example, in the IMU+EMG scenario, we combined features from the 18 IMU channels and pressure sensors with those from 8 EMG channels, resulting in a total of 108 features per time window. These features were then analyzed using LDA classifiers with a phase-dependent, mode-specific architecture, validated through 10-fold cross-validation. We observed that integrating IMU with EMG significantly improves classification accuracy for all participants, see Table 1. This finding highlights the value of combining EMG with IMU data (IMU+EMG) for locomotion mode detection, which achieves the highest accuracy across all conditions. While IMU alone also demonstrates strong performance, EMG alone currently lacks the reliability needed for effectively predicting locomotion modes, particularly during transitions. Nonetheless, every improvement in locomotion detection accuracy is crucial for ensuring seamless and safe operation. The combination of multiple data sources, such as EMG and IMU, represents a promising avenue for future research and development, offering potential advancements in both user safety and prosthetic functionality

To progress towards our goal of developing a reliable control system for home devices, the next logical step is to test the algorithm in real-time scenarios involving individuals with amputations.

Table 1 Locomotion detection accuracy (%) for different sensor combinations (IMU+EMG, EMG alone, and IMU alone) during steady-state and transitions. Steady-state refers to continuing in the same locomotion mode, while transitions involve switching from one locomotion mode to another.

Sensors/SS or TR	**IMU+EMG**	**EMG**	**IMU**
Steady-State	96.54±1.59	90.22±4.84	94.52±2.24
Transition	92.45±2.66	67.57±14.2	87.85±3.45
All data	94.02±3.05	76.28±16	90.41±4.45

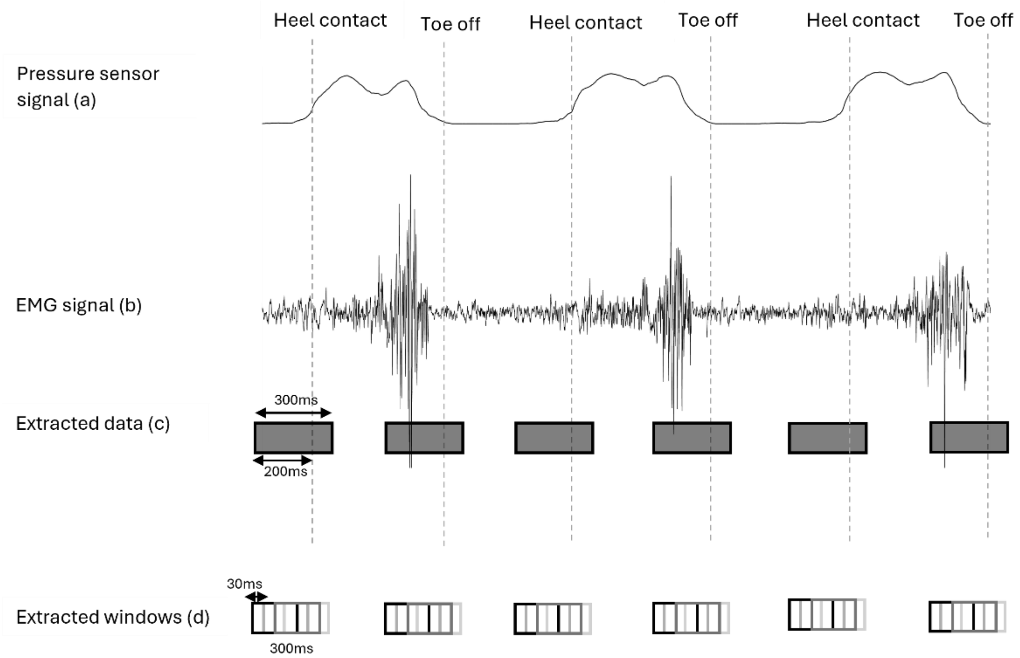

Figure 9 a) *Pressure sensor signal,* ***b)*** *EMG signal,* ***c)*** *300-millisecond segments of data centered around each gait phase, including 200 milliseconds prior and 100 milliseconds following the phase, and* ***d)*** *sequential 30-millisecond overlapping windows extracted from the segmented data [88].*

5.1. Conclusion from Paper 2

- The addition of EMG to the mechanical sensors enhances the accuracy of locomotion detection.
- sEMG alone is not reliable yet to be used in the control of prosthetics.
- Other methods of recording and more advanced and accurate processing are needed to have a reliable control

With this paper, we addressed two of our research questions:

- How can an open-source software platform for recording and processing EMG signals be utilized to enhance lower limb prosthetic control and improve user experience and functionality?
- How do different sensor combinations affect the accuracy of control in lower limb prosthetics?

6. Real-Time Evaluation of EMG-Based Locomotion Detection Algorithms in Transfemoral Amputees (Paper 3)

After successfully developing our software and testing the algorithm on able-bodied individuals, we aimed to take the next step which is testing our algorithm on people with amputation in real-time. We progressed by implementing our algorithm with five participants who had undergone transfemoral amputations and osseointegration, as documented in Paper 3. This step was crucial for understanding the implications of amputation and osseointegration implants on prosthetic control in a real-time setting.

In our prior research, we hypothesized that EMG signal quality significantly impacts the performance of our algorithms. Traditional sockets often complicate EMG measurement due to issues like improper electrode placement and pistoning—where the prosthetic limb moves within the socket. Osseointegration offers a stable limb attachment that mitigates these issues, presenting an opportunity to enhance the EMG data collection, especially when combined with implanted electrodes. However, osseointegration presents distinct features and limitations. While it provides a more stable attachment and can improve signal quality by reducing motion artifacts, it also involves surgical risks and requires ongoing care to prevent infections at the implant site. These challenges necessitate further adaptations and considerations in our approach to ensure we can gather robust data for enhancing prosthetic functionality.

In this phase of the study, we validated real-time locomotion detection using sEMG signals from the muscles of individuals with osseointegrated implants. Our methodology involved deploying a machine learning algorithm for real-time locomotion detection using LocoD, an open-source software tailored for sEMG-based locomotion detection presented in paper 2.

To better evaluate the performance of the system, we examined two outcome measures: prediction time of transitions and locomotion detection error. Prediction time refers to the elapsed time between the critical timing (an ideal moment to predict a transition safely) and the actual detection of the transition by the system. Meanwhile, locomotion detection error quantifies the percentage of misclassified windows during offline and online scenarios, highlighting the system's reliability in predicting locomotion modes accurately. Although the system operates in real time, variability in prediction time—often labeled as delays—represents the temporal gap between the critical moment of transition and its detection by the system. This does not imply a lack of real-time capability but rather reflects the system's responsiveness and anticipatory prediction ability.

Our findings revealed that while EMG signals have the potential to control prosthetic legs, there are still considerable challenges to overcome. The variability in detection accuracy and prediction delays was significantly influenced by individual participant differences. During the real-time experiments, we observed a range of error rates during transitions between locomotion modes, with some participants demonstrating near-perfect performance and others showing less reliability (Figure 10). These variations underscore the participant-dependent nature of our findings [3]. Notably, all participants in our study had medium to short residual limbs due to the osseointegration inclusion criteria, which often limits the number of muscles available for EMG signal detection. This anatomical constraint can hinder signal quality and affect the control algorithm’s performance [21]. Additionally, we noted that EMG might only effectively detect certain movements for some participants, such as transitioning from stair descent to walking. This suggests that EMG may be more suitable for a limited set of necessary transitions, where its capabilities can be maximized for reliable detection. Further analysis indicated that differences in performance could also be attributed to the type of movements, the complexities of the experimental setup, and individual variations in how movements were executed [92].

6.1. Conclusion from paper 3

In conclusion, while the potential of EMG to enhance prosthetic control is evident, the success of such systems is highly dependent on the individual characteristics of each participant. Future studies should aim to:

- Recruit a larger and more diverse participant pool.
- Incorporate active prosthetics.
- Explore advanced real-time control algorithms.

Additionally, developing a comprehensive training and feedback system for participants and investigating alternative electrode configurations such as implanted electrodes could further optimize the effectiveness of EMG-based prosthetic control.

With this paper, we addressed one of the research questions:

How does the movement intention detection algorithm perform during real-time testing with participants who have osseointegration implants?

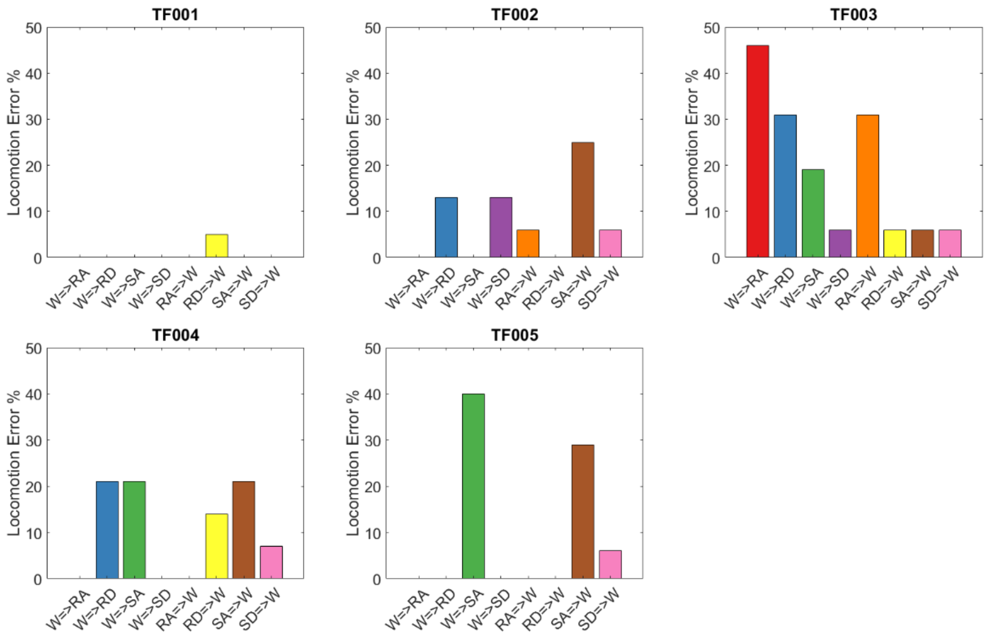

Figure 10 *Locomotion detection error of five transfemoral participants while transitioning between level ground, ramp, and stairs in real-time and in the transitional period. W is walking, RA ramp ascent, RD ramp descent, SA Stair ascent, and SD stair descent.*

7. Optimizing Accuracy in Movement Detection Through Post-Processing Techniques (Paper 4)

In Paper 4, we focused on enhancing the accuracy of locomotion detection by adapting an existing method in the post-processing step. Research on upper limb prosthetics has more extensively explored various rejection-based post-processing methods. For instance, Scheme et al. implemented a technique that combines Linear Discriminant Analysis (LDA) with Fitts' law tests to assess the confidence of each classification window. Decisions are made only if the confidence level surpasses a specified threshold; otherwise, the classification is discarded [93,94]. Inspired by these approaches, we adapted rejection-based post-processing for lower limb prosthetic control in our study.

To validate and refine each locomotion mode change decision, we implemented a post-processing technique for offline prediction, utilizing data from able-bodied individuals. This method applied a probability-based approach, where outputs with likelihoods below a specified threshold were disregarded to prevent erroneous transitions that can be unstable in real-time scenarios [95].

In the study from paper 4, we applied LDA with rejection-based post-processing to our open-access database containing EMG, IMU, and pressure sensor data from 21 able-bodied participants , as referenced in the previous study [14]. The results demonstrated that this approach significantly enhances the accuracy of locomotion detection algorithms for lower limb prosthetic control. Figure 11 provides a comprehensive comparison of locomotion detection errors across 21 participants, averaged for both steady-state and transition phases. The graph illustrates two conditions: one without rejection-based classification post-processing and the other with post-processing applied at a high rejection threshold of 0.989. The key takeaway from this figure is the notable reduction in locomotion detection error when post-processing is applied, emphasizing its effectiveness in mitigating misclassification. This improvement is particularly significant for participants with higher baseline error rates, suggesting that the method is especially beneficial for handling challenging data conditions. This improvement agrees with prior research, which suggests that rejection-based post-processing can effectively enhance classification and control.

Even though our findings are promising, the study's offline nature limited our ability to gauge the algorithm's real-time performance. Further testing on individuals with amputations, who have different muscle structures than able-bodied individuals in real-time, would provide valuable insights.

When implementing these algorithms to control a prosthetic leg, it is crucial to consider the best approach for handling windows of low confidence in classification. A detailed study is needed to determine whether it is more effective to transition the prosthetic to a standstill before resuming moving or to reassess and make a new decision at that point. The primary focus of this study was to reduce misclassification by identifying classification windows marked by low confidence, which can otherwise lead to erroneous transitions in the prosthetic's movement.

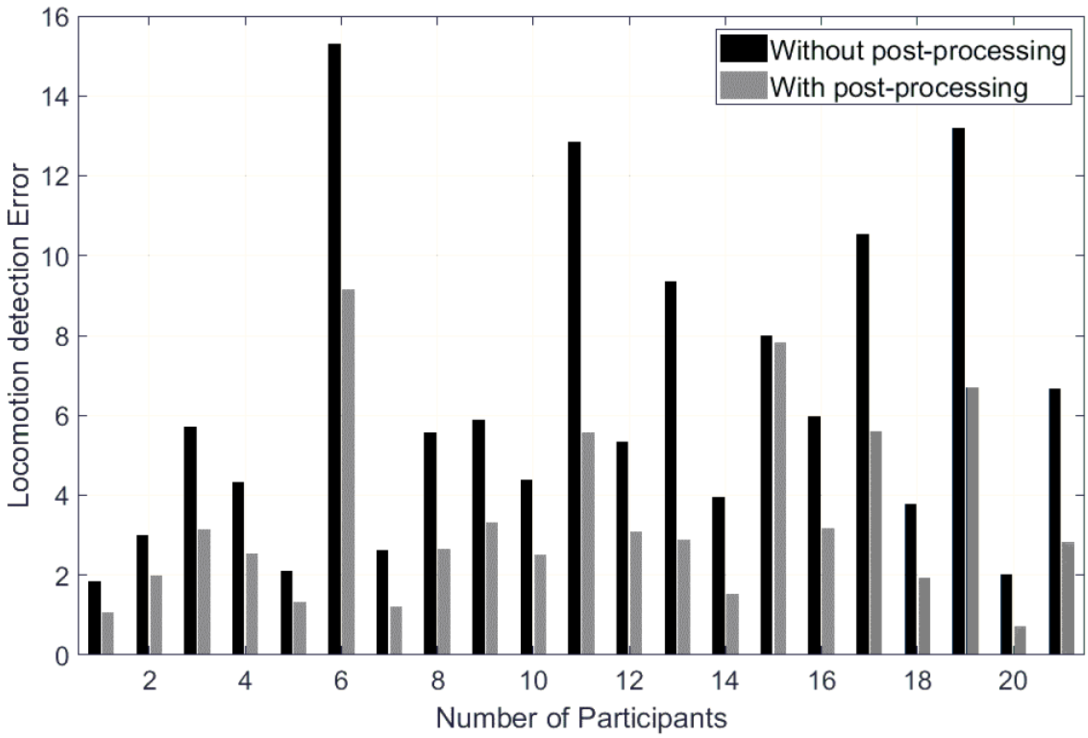

Figure 11 *The locomotion detection error for 21 participants is illustrated on this graph, with the data for both transition and steady-state phases being averaged together. The graph compares the locomotion detection error in two conditions: 1) when there was no rejection-based classification post-processing applied, and 2) when there was rejection-based classification post-processing applied with a threshold of 0.989. This comparison allows us to evaluate the impact of the post-processing technique on the accuracy of locomotion detection [95]. Copyright © 2023, IEEE*

7.1. Conclusion from paper 4

- A simple rejection-based method can enhance the quality of locomotion detection algorithms.

- This method is effective in the participants with initial low locomotion detection accuracy and in the movements with the lowest accuracy.
- This paper answered the research question “Can post-processing enhance the quality of classification algorithms?”

8. Harnessing Neural and Electromyographic Signals for Intuitive Prosthetic Control (Paper 5)

In this study, we sought to explore the hypothesis that neural signals could complement electromyographic (EMG) signals to enhance the control of prosthetic limbs. This hypothesis arises from limitations of using EMG alone, such as variability in signal quality due to inconsistent electrode placement, skin impedance, and motion artifacts during dynamic activities [11]. Neural signals, serving as an additional source of biological information, could provide rich and reliable data for detecting movement intentions. Supporting evidence from past research underscores this potential: De Luca et al. (1980s) successfully demonstrated neural signal acquisition from severed nerves, and more recent studies have highlighted the effectiveness of cuff and intra-neural electrodes in decoding motor intent with high precision [9,45,96,97].

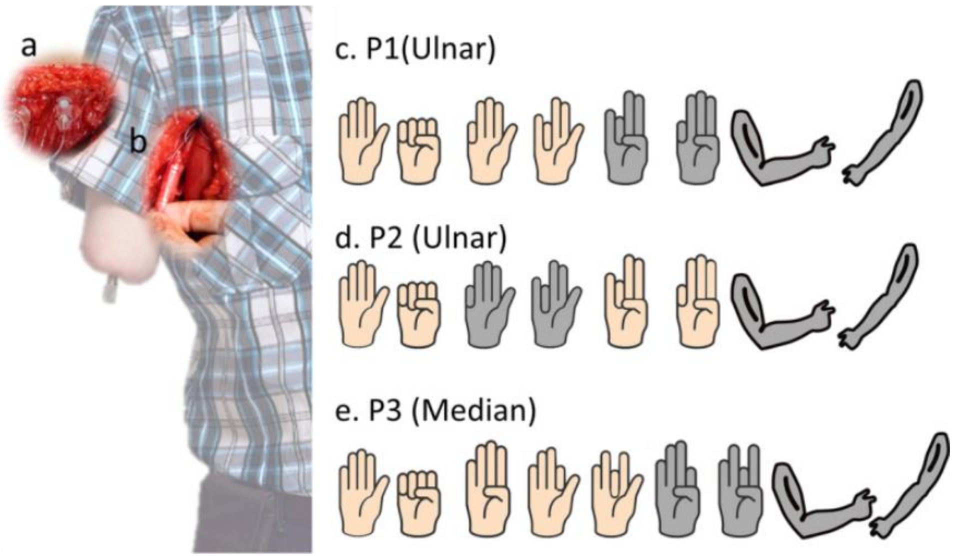

Figure 12 *(a) Implanted muscular electrodes (biceps and triceps muscles), (b) extra-neural electrodes around the nerve (P1 and P2 Ulnar, P3 median), (c–e) hand gestures attempted by the subjects in their phantom hands. Grayed gestures only used in offline experiment [99]. CC-BY-NC*

To evaluate this hypothesis, given the invasive nature of direct nerve recordings, we utilized existing implants from participants in the e-OPRA study, which focused exclusively on upper limbs, rather than performing additional implantations solely for testing our hypothesis. This approach allowed us to record neural signals using cuff electrodes around the nerves without subjecting participants to further surgical procedures [8]. The study utilized cuff electrodes around the ulnar and median nerves and epimysial electrodes on the Biceps Brachii and Triceps Brachii muscles to record neural signals associated with specific hand and finger movements [98][8]. These signals were analyzed for their ability to decode motor intent, a crucial factor for intuitive prosthetic control (Figure 12).

Our results showed that these electrodes could provide stable and detailed neural information, essential for distinguishing intended movements in individuals with amputations. However, performance varied significantly across participants, likely due to individual anatomical differences and the inherent complexity of neural signal acquisition. Personalizing control algorithms to reflect each user's unique neural patterns and optimizing electrode placement based on specific anatomy could mitigate this variability and improve overall accuracy. Additionally, the study revealed that the optimal integration of EMG and electroneurography (ENG) signals depends on the movement being performed. Aligning data sources with anatomically relevant movements or dynamically adapting signal integration to specific tasks and user needs could enhance outcomes. High-precision electrode placement and advanced recording hardware are critical to minimize interference and maximize signal fidelity.

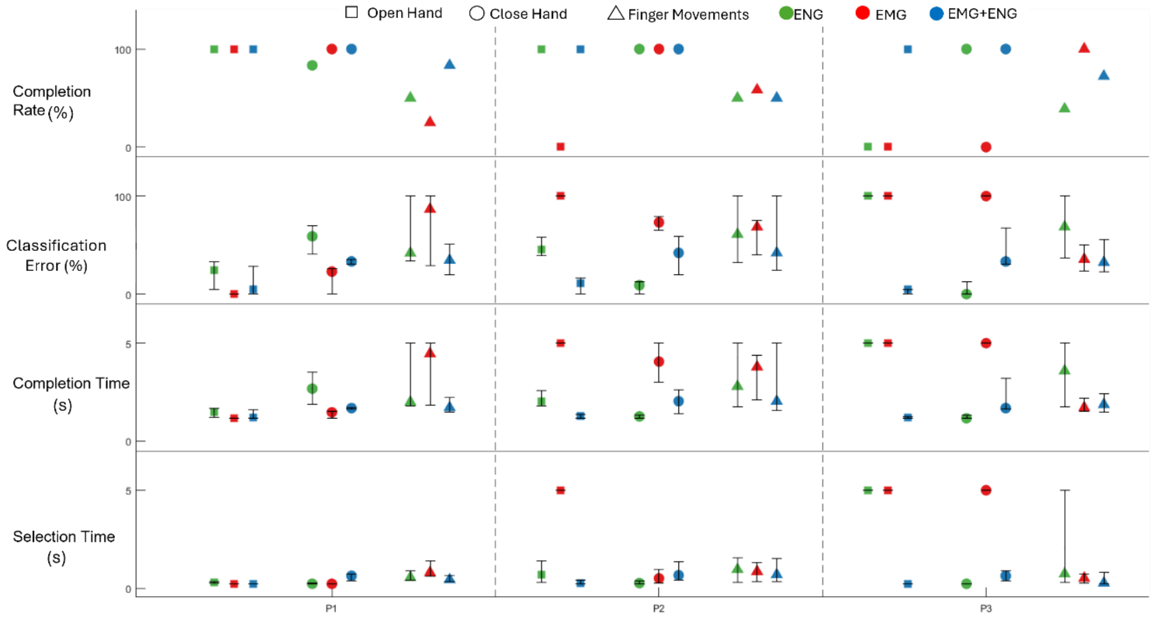

Figure 13 *Online pattern recognition results from the Motion Test performed by the three participants (P1–3) over three different scenarios: (1) ENG alone (green), (2) EMG alone (red), and (3) the combination of EMG and ENG (blue). The outcomes are completion rate, median of classification error, median of reported completion time, and median of selection time. Finger movements include ring flex, little flex, for P1, ring to thumb, little to thumb for P2 and thumb flex, index flex, and middle flex for P3. This graph is adapted from [99] under CC-BY-NC.*

One limitation of this study was the inconsistent accuracy in detecting hand opening and closing movements (Figure 13). Factors such as variations in setup, differences in amplifiers compared to previous studies, and the complexity of distinguishing hand from finger movements in cases of upper-elbow amputation contributed to this issue. Given these preliminary findings, further research involving a larger cohort and more advanced training techniques is essential to generalize results and refine motor intent decoding for extra-neural signals. Future studies should also explore the use of non-linear classifiers and deep learning algorithms to enhance decoding capabilities, laying the foundation for more nuanced and effective prosthetic solutions.

Despite these promising findings, significant challenges remain in translating this approach to lower-limb prosthetics. The unique complexities of lower-limb prosthetics—such as the need for stability during weight-bearing activities and transitions between locomotion modes—require dedicated research. Anatomical and functional differences between the upper and lower limbs necessitate careful evaluation of neural signal integration for these applications.

Given these considerations, we do not present our findings as a definitive conclusion but rather as a foundation for further investigation into whether neural signals can enhance lower-limb prosthetic control. While our results from upper-limb prosthetics illustrate the feasibility of using cuff electrodes to record neural signals and decode motor intent, additional studies are required to validate this approach for lower-limb applications. Critical questions remain, such as the reliability of neural signals during locomotion transitions and the optimal strategies for integrating these signals with other data sources. This research lays the groundwork for advancing prosthetic control and improving outcomes for users.

8.1. Conclusion from paper 5

- ENG signal has information that can be used for control of upper limb prosthetics.
- Better technology is needed to record neural signals precisely.
- The benefit is very subject-dependent
- Further studies are needed to find the long-term use of this data for the control of prosthetics.

- This paper addressed the final research question: “Can neural signals complement EMG signals to enhance control?” However, the study focuses on results related to upper-limb prosthetics. Applying these findings to lower-limb control for locomotion remains an open question for further research.

9. Establishing Comprehensive Safety Protocols for Clinical Testing of Active Prosthetics (Paper 6)

An inevitable advancement in the field of lower limb prosthetic control will be the integration of implanted electrodes, osseointegration, and prosthetic legs capable of utilizing various control algorithms. Following the surgical implantation of these technologies, it is critical to establish a comprehensive rehabilitation protocol that safeguards participant well-being and supports their reintegration into daily activities. Since the risks inherent to lower limb prosthetic research, especially those related to falls and resultant injuries, are considerably greater than those encountered with upper limb prosthetics, we have developed a safety protocol tailored for active lower limb prosthetic research, as detailed in [100].

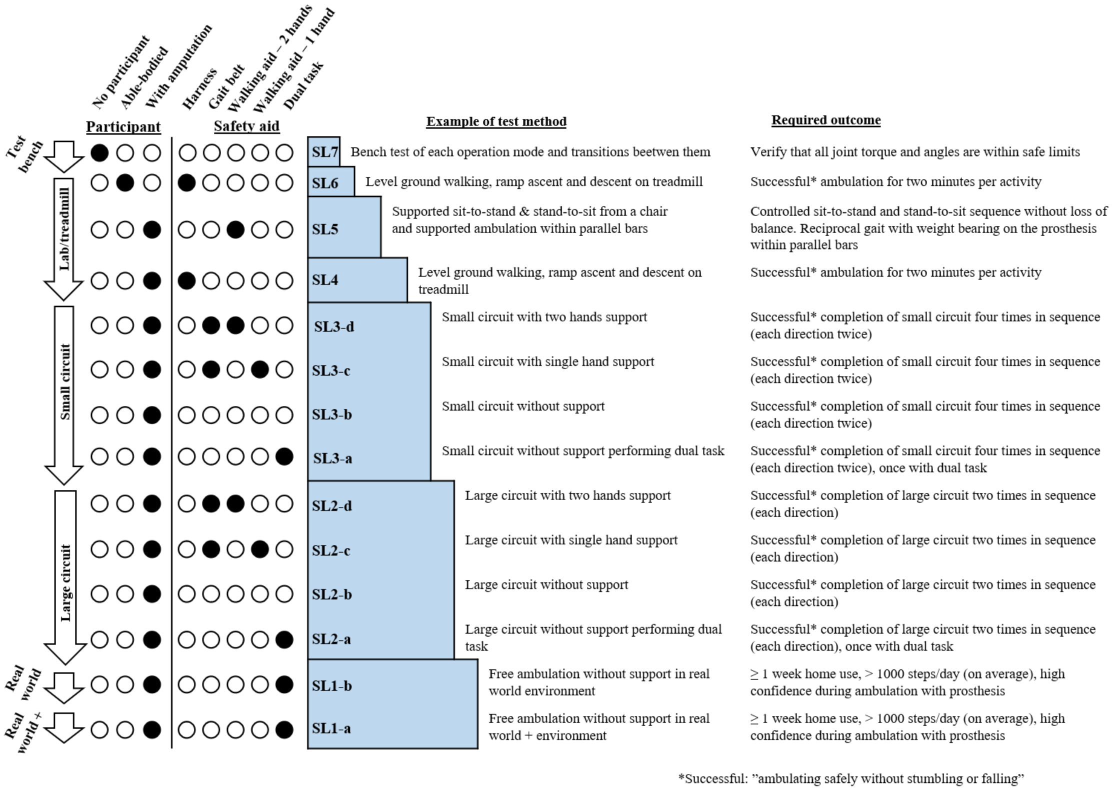

Figure 14 *Stepwise safety protocol. The protocol is implemented sequentially, progressing from the highest to lower safety levels. The columns, arranged from left to right, represent test environments, participants, safety levels, examples of test methods, and the required outcomes at each stage [100].*

We formulated a rigorous safety protocol specifically for clinical research involving lower limb prosthetics. As described in Paper 6, this protocol is versatile and suitable for testing various leg prostheses and control strategies. It ensures participant safety by establishing multiple predefined safety levels, each comprising specific test methods and necessary outcomes before progressing to subsequent phases. The protocol also outlines necessary precautions for each testing stage, including the use of walking aids and carefully chosen environments (Figure 14).

This systematic strategy was developed to address the lack of comprehensive safety protocols for clinical testing of active prosthetics. While the protocol has not undergone formal evaluation, it is proposed as a preliminary framework aimed at minimizing risks associated with the testing of prosthetic technologies. The protocol is grounded in addressing practical safety challenges observed in existing research processes, such as mitigating fall risks and ensuring participant safety during rehabilitation and testing. However, we recognize the need for future evaluation to determine its effectiveness in practice. Further work will involve validating this protocol through empirical testing and incorporating clinical evidence, expert input, and patient feedback to ensure its robustness and alignment with established standards in health-related protocol development.

10. Summary of Thesis Contributions

Within the scope of this thesis, we have developed new open-source software designed to record and process electromyography (EMG) signals and tested it both in real-time and offline with able-bodied participants and participants with amputation. Afterward, we enhanced the quality of our locomotion detection algorithm with post-processing methods. Additionally, we explored the potential of other biological signals for prosthetic control in upper limbs, particularly those obtained directly from nerves. Given the promising results and the growing consensus that implanted electrodes represent the future of prosthetic development, we have designed a comprehensive, step-wise rehabilitation protocol. This protocol supports the integration of powered knee prosthetics and various control algorithms, enhancing the adaptability and functionality of these devices for users.

- Paper 1 offered a comprehensive review of EMG-based control algorithms for lower limb prosthetic control. This review covered various recording methods, movements, and muscles involved, and detailed the specifications of different algorithms, providing a thorough exploration of the current landscape in this field.

  Research question addressed: This paper addresses the research question “What are the gaps, limitations, and latest trends in EMG-based control algorithms for prosthetic legs?”, by identifying critical gaps, including the need for advanced algorithms and tools for lower limb applications.

- Paper 2 introduced an open-source and modular platform designed for the recording and processing of EMG signals. This platform is aimed at fostering collaboration among various research groups by potentially accelerating the development of algorithms and facilitating their comparison. Instead of each group needing to develop their own algorithms from scratch, this platform allows for shared advancements and standardized evaluations. While we have not yet demonstrated external use of the platform by other researchers, it was designed with this intention in mind, providing the tools and framework necessary to enable collaborative and comparative studies. We conducted testing of the software under various sensor combinations, including IMU+EMG, EMG alone, and IMU alone. Consistent with previous literature, our findings confirm that the inclusion of EMG significantly enhances the accuracy of the system.

Research question addressed: This paper answers the research question: How can an open-source software platform for recording and processing EMG signals be utilized to enhance lower limb prosthetic control and improve user experience and functionality?

- Paper 3: This study evaluated the real-time performance of our EMG-based control algorithm in lower limb amputees who have undergone osseointegration, with the goal of facilitating daily use. Our algorithm executed by LocoD software proved successful in real-time applications. Although EMG provides valuable data, the participants in our study had shorter stumps and a limited number of muscles due to osseointegration, which restricted the full potential of EMG in detecting locomotion.

  Research question addressed: This paper addresses the research question: How does the movement intention detection algorithm perform during real-time testing with participants who have osseointegration implants?

- Paper 4: We aimed to implement a post-processing technique to enhance locomotion detection performance in prosthetic devices. This algorithm analyzes the probability of outputs from linear discriminant analysis (LDA) and selectively rejects weaker predictions. This method effectively improved classification accuracy, particularly benefiting individuals with generally lower accuracy rates and movements and transitions that are typically less accurately detected. This approach not only refines the control mechanism but also tailors the performance to better accommodate the varying needs of users.

  Research question addressed: This paper answers the research question: Can post-processing of movement intention detection improve the accuracy and reliability of these algorithms?

- Paper 5: This study explored the feasibility and potential benefits of using efferent nerve signals (ENG) alongside electromyography (EMG) for prosthetic control in upper limbs. Motivated by the possibility of leveraging other biological pathways for enhanced control, and having access to patients with implanted electrodes, we investigated whether meaningful information could be extracted from these signals to control the finger movements of the participants. Our findings indicated that for some participants, it was indeed possible to utilize ENG signals effectively for this purpose. This opened up new avenues for more intuitive and precise control mechanisms in prosthetic devices, potentially improving the overall user experience. This study is a preliminary result, as the underlying reasons for low performance in some subjects have yet to be fully understood.

Research question addressed: This paper answers the research question: Can neural signals complement EMG signals to improve control?

- Paper 6: This study proposed a stepwise safety protocol for managing risks associated with research on active prosthetic legs. We have developed a detailed protocol to address the safety concerns that arise when conducting research with powered prostheses, which utilize various control algorithms using muscle signals as inputs. This protocol serves as a comprehensive reference for safely using different prosthetic legs and control algorithms, ensuring that both researchers and participants are protected throughout the study process. This systematic approach not only promotes safety but also standardizes procedures, enhancing the reliability and efficacy of prosthetic research.

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11. General Conclusions and Future Directions

11.1. Conclusions

In summary, this thesis has explored the integration of electromyography (EMG) as a pivotal component in lower limb prosthetic control systems, driven by its potential to provide natural control and address significant challenges faced by the lower limb amputee community. We identified and addressed a critical gap with the development of an open-source software platform, which has laid the ground for widespread collaborative advancements and innovation. Our feasibility studies showed promising results yet highlighted the potential for further enhancing EMG signal quality through the use of implanted electrodes. Although not immediately pursued, this insight led to refining our methodologies and conducting targeted experiments on amputees. We also dedicated efforts to improving algorithm quality and explored the integration of other biological signals, thereby broadening the research scope and applicational possibilities. Reflecting on our journey, it is clear that significant work remains in advancing lower limb prosthetic technologies. The direct interface of these devices with the human body demands meticulous attention to ensure their robustness and accuracy, especially given the severe consequences of even minor errors. This underscores the need for ongoing precision and reliability in our work.

While our findings underscore the promise of EMG technology, it is crucial to acknowledge that the road ahead is long and complex. While EMG demonstrates potential, it requires further refinement and optimization to realize its full capabilities. Nevertheless, with continued dedication and collaborative efforts, we are poised to overcome these challenges and pave the way for innovative prosthetic solutions that truly enhance the lives of amputees worldwide.

11.2. Future Direction

Throughout this research, we have identified and addressed various challenges in prosthetic technology. While we have made progress, some issues remain unresolved. Looking forward, continued improvements in control algorithms are expected to significantly enhance the functionality of prosthetic devices. These advancements are essential for the development of active lower limb prosthetics, promising more refined and efficient movement capabilities for users. In terms of signal quality, our findings indicate that surface EMG does not always provide the necessary quality for effective control in participants with transfemoral amputations. To address this, our research suggests exploring the potential of implanted electrodes. These electrodes could drastically improve signal quality, leading to more seamless integration and enhanced functionality of prosthetic devices, marking a substantial advancement in the field.

Powered prostheses hold great potential to revolutionize lower limb prosthetic control. They can help users avoid compensatory movements, deliver positive net energy for activities like stair ascent, and can be programmed with complex algorithms due to their sophisticated systems. Unlike traditional prosthetic legs, powered prostheses can accept EMG signals as inputs, enhancing their responsiveness and functionality. Furthermore, the integration of powered prostheses with osseointegration implants and implanted electrodes presents a promising avenue for achieving more natural and effective control, making them a significant advancement in prosthetic technology.

However, there is a gap in the research regarding the effects of powered prostheses on various implants. Studies are beginning to illuminate crucial factors for safety margins, but more extensive research is needed to confirm that these implants can withstand daily use with powered prostheses [101,102]. There is also a pressing need to enhance prosthetic devices. Although powered prosthetics are potential candidates for utilizing EMG signals, they require significant improvements to address drawbacks such as their weight, noise, and cost, and to increase their compatibility with current technologies.

Our research efforts reflect a collective commitment in the scientific community to advance prosthetic technologies. We will concentrate on enhancing control algorithms, assessing the impacts of powered prosthetics on osseointegrated implants, and exploring innovative solutions like implanted electrodes. These initiatives will help individuals with limb loss regain mobility and improve their quality of life, reinforcing our dedication to bettering outcomes for amputees globally.

12. Author Contribution

Paper 1: Electromyography-Based Control of Lower Limb Prostheses: A Systematic Review

Bahareh Ahkami, Kirstin Ahmed, Alexander Thesleff, and Max Ortiz-Catalan collaborated on the design and scope of the review. Bahareh Ahkami conducted the literature search and primary analysis, while Bahareh Ahkami and Alexander Thesleff completed the literature review. Max Ortiz-Catalan supervised the research. Bahareh Ahkami drafted the manuscript, with all co-authors reviewing and editing it.

Paper 2: Locomotion Decoding (LocoD) – An Open-Source and Modular Platform for Researching Control of Lower Limb Assistive Devices

Max Ortiz-Catalan conceptualized the platform. Bahareh Ahkami designed and programmed the platform. All authors designed the study. Morten B. Kristoffersen supervised the implementation of the platform and assisted with platform testing. Max Ortiz-Catalan and Kirstin Ahmed supervised the project. Max Ortiz-Catalan secured funding. Bahareh Ahkami and Kirstin Ahmed drafted the manuscript. All authors edited and approved the final manuscript.

Paper 3: Probability-Based Rejection of Decoding Output Improves the Accuracy of Locomotion Detection During Gait

Bahareh Ahkami, Fabian Just collaborated on the study design and methodology. Bahareh Ahkami conducted analysis. Fabian Just provided technical support for algorithm development. Max Ortiz-Catalan supervised the research. Bahareh Ahkami drafted the manuscript, while Fabian Just and Max Ortiz-Catalan reviewed and edited it.

Paper 4: Real-Time Locomotion Mode Detection in Individuals with Transfemoral Amputation and Osseointegration

Bahareh Ahkami, and Max Ortiz-Catalan designed the study. Bahareh Ahkami conducted the study, analyzed the data, and developed the algorithms, while

Morten Bak Kristoffersen provided technical support and feedback. Max Ortiz-Catalan supervised the research and secured funding. Bahareh Ahkami drafted the manuscript, with Morten Bak Kristoffersen and Max Ortiz-Catalan contributing to its review and revision.

Paper 5: Extra-Neural Signals from Severed Nerves Enable Intrinsic Hand Movements in Transhumeral Amputations

Bahareh Ahkami, Enzo Mastinu, and Max Ortiz-Catalan designed the study and developed the electronics needed for the experiments. Eric J. Earley supported data processing and statistical analysis. Max Ortiz-Catalan supervised the research and secured funding. Bahareh Ahkami drafted the manuscript, with Enzo Mastinu, Eric J. Earley, and Max Ortiz-Catalan contributing to its review and revision.

Paper 6: Design of a Stepwise Safety Protocol for Lower Limb Prosthetic Risk Management in a Clinical Investigation

Alexander Thesleff, Bahareh Ahkami, Jenna Anderson, Kerstin Hagberg, and Max Ortiz-Catalan conceptualized the protocol. Alexander Thesleff and Bahareh Ahkami developed the stepwise safety protocol framework. Jenna Anderson and Kerstin Hagberg provided clinical insights and expertise. Max Ortiz-Catalan supervised the project and secured funding. Alexander Thesleff wrote the manuscript, with all co-authors reviewing and revising it.

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