POLITECNICO DI TORINO

Master's Degree Course
in Biomedical Instrumentation

Master's Degree Thesis

Development of an interface for real-time myoelectric control of external devices

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Italian version

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Abstract

The loss of upper limb functionality is a debilitating condition affecting many individuals. While the development of external devices has achieved remarkable capabilities in replicating upper limb functions, there remains a critical need for effective control strategies. The objective of this experimental Master's Thesis is to develop and validate a software application for the real-time translation of the electrical activity of forearm muscles into hand movements. Additionally, the solution provides a tool for visualizing kinematics output.
The software application was developed in Simulink as an extension of the MEACS system, the EMG amplifier developed by LISiN - Politecnico di Torino. The application receives EMG input through TCP/IP communication, processes the signal, translates it into hand kinematic state through a neural network, and displays the output as a 3D plot. The application also includes a Graphical User Interface for initiating the TCP/IP communication, adjusting signal processing parameters, and saving predicted angles.
The primary challenge of this work is to ensure real-time performance, providing visual feedback of the predicted hand gestures during their execution. The experimental results demonstrate the feasibility and potential of this approach for real-time implementation. However, it is crucial to acknowledge that the performance of the interface, specifically the accuracy of hand kinematics prediction, depends on the neural network employed.
Despite these challenges, the proposed interface could represent a significant step towards addressing the critical need for effective control strategies in the field of upper limb prosthetics. In the future, this interface could be integrated with upper limb prostheses, enabling individuals to control their artificial limbs based on forearm muscular activity, potentially mirroring their intentions and improving their quality of life. This MSc project stems from the collaboration between LISiN at Politecnico di Torino and the Nuffield Department of Surgical Sciences at the University of Oxford. It is intended as a contribution to the doctoral research led by Giovanni Rolandino at the University of Oxford.

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Part I

Introduction

Chapter 1

Introduction and Objectives

This MSc Thesis project was conducted at the LISiN Lab – Politecnico di Torino, in close collaboration with the Nuffield Department of Surgical Sciences at the University of Oxford. Specifically, it is a part of Giovanni Rolandino's DPhil project, which he is pursuing at the University of Oxford, focusing on evaluating the potential of machine learning algorithms for developing an advanced myoelectric control system for prosthetic upper limbs. Giovanni Rolandino guided and supervised me throughout the research. As part of this collaboration, I had the opportunity to visit the Nuffield Department of Surgical Sciences in Oxford, further enriching my research experience.

The following chapter provides an overview of the research conducted in this thesis, focusing on the development of an advanced control system for prosthetic limbs. This introduction serves as a guide to understanding the context, motivations, objectives, contributions, methodology, and organization of the thesis.

1.1 Background and Motivation

In today's world, many individuals face challenges due to upper limb loss or impairment, which can greatly impact their daily lives and limit their ability to perform essential tasks. While traditional prosthetic devices have provided assistance, they often lack natural control and functionality.
The motivation behind this research stems from the vision of a world where individuals with upper limb disabilities can regain control over their hand movements and seamlessly interact with their environment. By creating an intuitive and efficient interface between individuals and their artificial limbs, we aim to improve their quality of life and restore their independence.

1.2 Objectives

The main objective of this thesis is to design and implement a Control Interface that provides Visual Feedback in real-time and enables precise and natural control of a virtual hand. To achieve this, we focus on the utilization of surface electromyography (sEMG) signals, which capture the electrical activity of muscles, to interpret the user's intentions and generate corresponding commands for the virtual hand. This approach provides a more intuitive and natural way for individuals to control artificial limbs, presumably mirroring their own thoughts and intentions.
It is important to note that while the development of the control interface is the primary

objective of this thesis, the machine learning algorithm used to predict hand kinematics from sEMG signals is not the central focus. The algorithm, developed by Giovanni Rolandino during his DPhil research at the University of Oxford, is included to provide a better understanding of the thesis.

1.3 Contributions and Significance of the Research

The main contribution of this research lies in the development of a Control Interface that provides real-time visual feedback for virtual limb control. By incorporating visual feedback into the control system, individuals can receive immediate information about their limb's position and movements, enabling them to make adjustments and perform tasks with greater precision. This real-time visual feedback enhances the user experience, improves control accuracy, and can be crucial in simulating the effect of visual feedback on the performance of advanced control algorithms for hand prostheses.
The significance of this research extends beyond the technical advancements. By enabling individuals with limb impairments to control their prosthetic limbs more effectively and naturally, this research contributes to enhancing their independence, self-confidence, and overall quality of life. It opens up possibilities for individuals to participate more fully in social, occupational, and recreational activities.

1.4 Organization of the Thesis

This thesis is organized into several parts, each addressing specific aspects of the research. The following provides a brief overview of each chapter and its contents:

- **Part I: Introduction**
  - Chapter 1 introduces the thesis by providing background information, motivations, objectives, and the overall organization of the research.
- **Part II: State of the Art**
  - Chapter 2 focuses on electromyography (EMG) and its relevance in controlling prosthetic limbs. It explains the basics of EMG, including motor unit action potential, recruitment, rate coding, and EMG detection.
  - Chapter 3 explores different categories of upper limb prostheses and highlights myoelectric prostheses as a specific type that utilizes EMG signals for control.
  - Chapter 4 discusses various interfaces used in the field, including data acquisition interfaces, performance assessment interfaces, and visual feedback interfaces.
  - Chapter 5 expresses the objectives of this thesis
- **Part III: Materials and Methods**
  - Chapter 5 details the development of the control interface, explaining its design and implementation, with a particular emphasis on real-time processing.
  - Chapter 6 focuses on the neural network used in the research, covering the acquisition protocol and the architecture of the network.
  - Chapter 7 presents the methods used to evaluate the interface through RMS validation and real-time communication experiments, describing the acquisition protocols and data analysis techniques employed.

- Chapter 8 presents the instrumentation used in the research, such as Vicon Nexus, high-density surface EMG, and the Biodex System 4.

- **Part IV: Results**
  - Chapter 9 presents the results obtained from the experimental evaluations, including RMS validation, and real-time validation. It discusses the execution time and functional limitations of the interface.

- **Part V: Conclusions**
  - Chapter 10 summarizes the main findings and conclusions drawn from the research, highlighting the achievements and contributions of the thesis.

- **Bibliography**
  - Finally, the bibliography lists the references cited throughout the thesis, ensuring the credibility and academic rigor of the research.

Part II

State of the Art

Chapter 2

Electromyography (EMG)

Surface Electromyography (EMG) is a non-invasive technique used to record the electrical activity produced during muscle contractions, which is known as the electromyogram. This biological signal provides insight into the physiological processes involved in generating forces exerted over body joints to produce movement.

2.1 EMG Overview and Definition

EMG is a biomechanical method that records and analyzes the electrical activity generated by the firing of motor units in skeletal muscles. Through the use of surface or intramuscular electrodes, it's possible to capture the complex summation of motor unit action potentials within a muscle or muscle group, providing insights into muscular activity and neuromuscular diseases.

2.1.1 Motor Unit Action Potential

Muscular contractions are permitted by the Motor Unit (MU), the basic functional unit of the neuromuscular system that comprises a motor neuron and all the muscle fibers innervated by it (Figure 2.1). The fibers innervated by a single motor neuron can be of three types: slow contraction fibers (Type I or red fibers) and rapid contraction fibers (which are further categorized into Type IIa and IIb fibers). Type I fibers, smaller and more fatigue-resistant, generate less force and exhibit slower electrical conduction, consequently leading to slower mechanical contractions. Conversely, Type II fibers, larger and less resistant to fatigue, generate more force and exhibit faster electrical conduction, leading to quicker mechanical contractions. The muscle fibers innervated by a single axon are of the same type due to physiological factors. The number of motor units per muscle depends on the muscle's dimensions.

When a nervous stimulus from the Central Nervous System (CNS) triggers a discharge from the motoneuron, action potentials are generated at the neuromuscular junctions, invariably activating all muscle fibers innervated by the motoneuron. Depolarization waves propagate to the muscle fiber endings at a velocity of 2-6 m/s [28], termed conduction velocity (CV), which depends on the fiber diameter [22] (Figure 2.1).

The aggregation of the action potentials of all motor units is termed the Motor Unit Action Potential (MUAP) typically measured in microvolts (μV). The shape and size of the MUAP can be influenced by several factors, including the location of the electrode, the

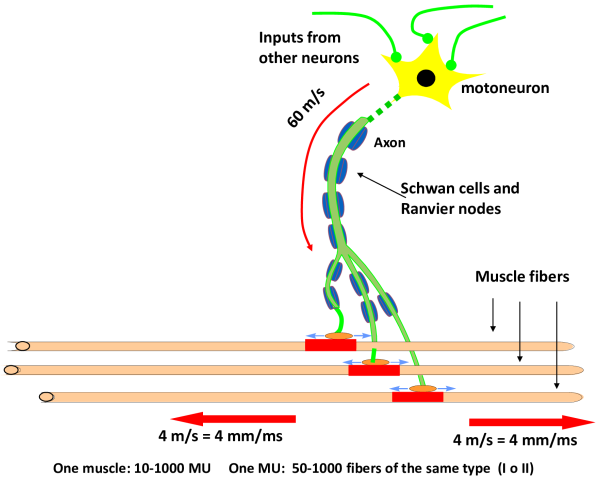

Figure 2.1. Representation of a Motor Unit: one motoneuron and its muscle fibers. The action potentials propagate to the fibers endings at 4m/s

depth of the muscle fibers, and the type and size of the muscle fibers within the motor unit, as shown in Figure 2.2.

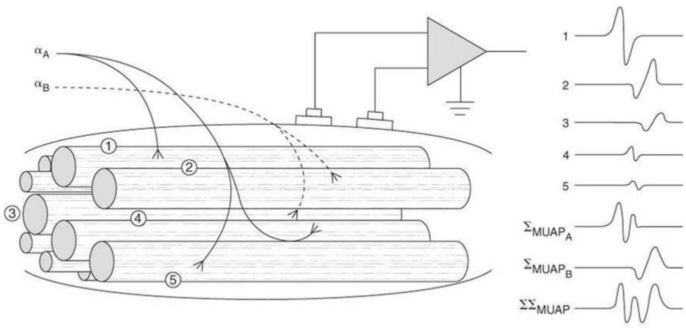

Figure 2.2. Each motoneuron, and consequently each motor unit (MU), generates a distinct MUAP. the figure demonstrates the innervation pattern of motoneuron A, which activates muscular fibers 1, 4 and 5, resulting in the formation of $MUAP_A$. [22]

EMG signal is derived from the summation of all motor unit action potentials (MUAPs) within the detection volume of the recording electrodes. Figure 2.3 illustrates the schematic representation of how the EMG interference signal is formed by the algebraic sum of individual MUAPs.

2.1.2 Recruitment and Rate Coding

The magnitude and direction of a muscle's force are determined by the number of activated motor units (recruitment) and the frequency at which they discharge action potentials (rate coding)[26][16]. These mechanisms, known as the spatial and temporal summation of MUAPs, underpin the origin of EMG signal.
During voluntary contractions, motor units are typically recruited in a fixed order as dictated by Henneman's size principle. This principle states that smaller motor neurons are recruited before progressively larger motor neurons with stronger muscle units and faster

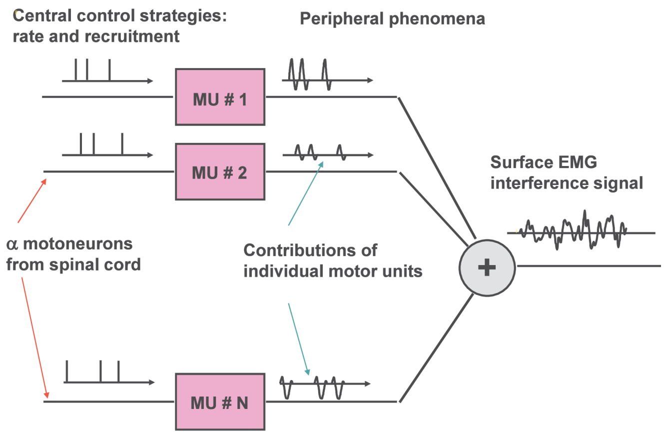

Figure 2.3. Schematic representation of the composition of the surface electromyogram signal, resulting from the algebraic sum of all motor unit action potentials (MUAPs).

contraction times[21]. This orderly recruitment begins with the smallest motor units (i.e., those with fewer muscle fibers) and progresses to the largest ones, mainly because the smallest motor neurons require the least amount of current to reach the voltage threshold. Such organized recruitment of motor units ensures better control over movements and greater accuracy in force exertion.

In addition to recruitment, the Central Nervous System regulates muscle force through rate coding, which is the frequency at which a single motor neuron discharges action potentials. As the requested force increases, the firing rate can rise from an activation frequency of 4 discharges per second to 35 discharges per second [22]. Thus, temporal summation of MUAPs suggests that the firing rate of a single MU increases as the force requested grows. Similarly, spatial summation of MUAPs suggests that the number of recruited MUs increases as the force demanded of the muscle increases.

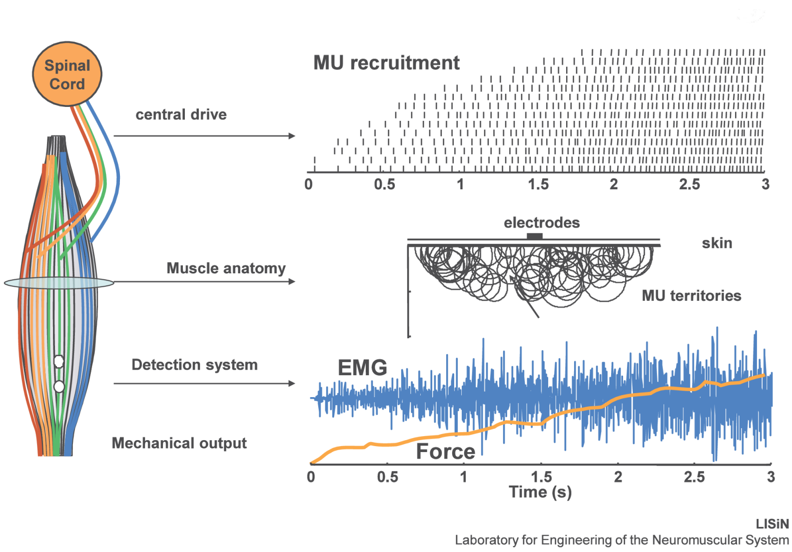

Figure 2.4. The relationship between the number of active motor units and the generated force

Tetanic contraction refers to the continuous, forceful muscular contraction without relaxation. When a muscle fiber is stimulated at a high frequency, individual twitches overlap and result in a stronger contraction known as a tetanus. This is significant in the context of motor unit recruitment and rate coding as it is the sustained firing of action potentials that allows for tetanic contractions, enabling muscles to maintain force steadily.

The combination of spatial and temporal summation of MUAPs plays a crucial role in determining the strength of muscle contraction. Activation of a larger number of MUs at a higher firing rate results in stronger contractions, while activation of fewer MUs at a lower firing rate results in weaker contractions. Figure 2.4 demonstrates the relationship between the number of active motor units and the generated force. In addition to the Henneman's size principle, other factors such as fatigue and injury can affect the recruitment and rate coding of MUs. For instance, fatigue can cause a shift in the recruitment of MUs towards larger ones, leading to a decline in muscle force, whereas injury can cause a reduction in the number of recruited MUs and a decrease in firing rate, leading to muscle weakness and atrophy [16].

2.1.3 EMG Signal Detection

The EMG signal results from the spatial and temporal summation of several MUAPs in the detection volume of electrodes. Therefore, it is essential to understand the differences between the techniques used to detect the electromyogram to record the most accurate EMG signal possible based on the purpose.
The first difference is based on the type of electrodes used to detect EMG signal. The two basic types of electrodes are intramuscular and surface ones, which give rise to two different types of EMG recording:

- **Intramuscular EMG**: This technique guarantees a highly selective signal, recording only a small number of motor units, which enables reliable estimation of MU firing patterns and recruitment thresholds (identifications of MU action potential shapes) due to its small detection volume. However, it is an invasive technique that uses indwelling electrodes inserted directly into the muscle through the skin. Its main application field is neurophysiology and neuromuscular disease diagnosis, where the study of a few MUs is necessary (Figure 2.5).

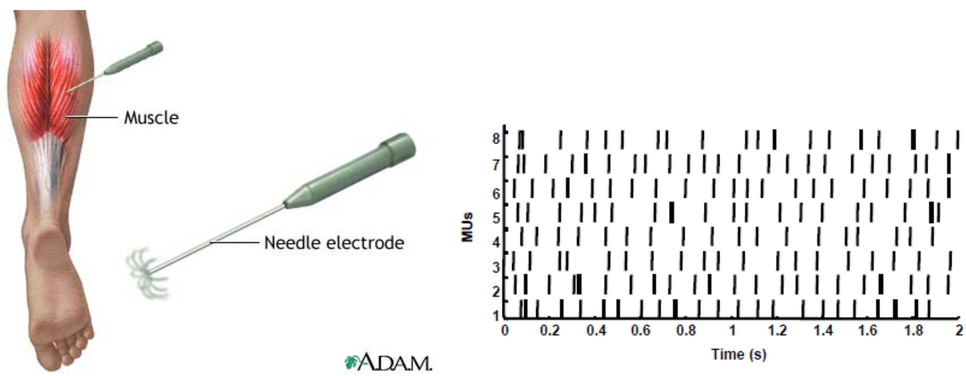

Figure 2.5. Intramuscular EMG: The left figure shows an example of indwelling electrodes inserted directly into the muscle through the skin [2]. The right figure depicts a collection of motor unit firing instances.

- **Surface EMG (sEMG)**: This technique has a larger detection volume and provides a more global view of muscle activation level and timing by analyzing and recording lots of MUAPs. It is the most commonly used technique in Biomechanics, Rehabilitation, and Sports Medicine because it provides non-invasive EMG recording using surface electrodes placed directly over the muscle on top of the skin (2.6).

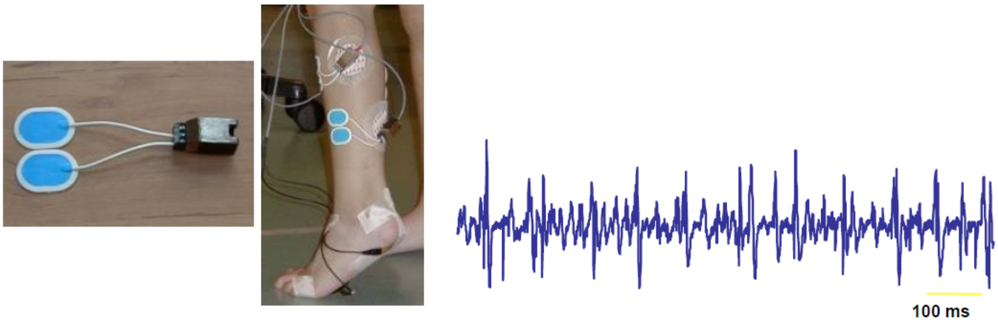

Figure 2.6. Surface EMG: The left figure shows an example of surface electrodes and how they are placed directly over the muscle on top of the skin. The right figure displays an sEMG signal.

In surface EMG recording, the electrode configuration is a major issue and source of confusion, with monopolar and differential being the most commonly used configurations. In both configurations, there are two detection electrodes (G1 and G2, for simplicity) and the ground electrode.

- **Monopolar configuration**: in the monopolar configuration, the signal is detected between an electrode placed over the muscle of interest (active recording surface G1) and an electrode placed in an electrically neutral location (reference G2) used to determine a potential difference. This configuration guarantees high-quality evoked potentials free of distortions, while it can be affected by unwanted noise [22].

- **Dfferential configuration**: in the differential configuration, also known as bipolar or single differential, both electrodes (G1 and G2) are placed over the muscle of interest. In this configuration, a differential amplifier subtracts G2 from G1, minimizing unwanted interference signals from electromagnetic fields in the surrounding environment. For this reason, the single differential configuration (SD) is the most widely used configuration. [22] [27]

Chapter 3

Upper Limb Prostheses

The detection of myoelectric signal patterns, which indicate a user's intention through muscular contractions, holds significant importance in the field of rehabilitation medicine. These patterns serve as a valuable control system for external devices like upper limb prostheses. This chapter aims to explore and elucidate the utilization of EMG signal patterns in rehabilitation, highlighting their potential applications and benefits in enhancing patient care and functional outcomes.

3.1 Categories of Upper Limb Prostheses

In rehabilitation medicine, the use of prostheses takes place after an amputation that can be more, or less proximal. As shown in Figure 3.1, amputation levels for upper extremities include:

- upper digits and partial hand
- transcarpal
- wrist disarticulation
- transradial (below elbow)
- elbow disarticulation (transection through the elbow joint)
- transhumeral (above elbow)
- shoulder disarticulation (transection through the shoulder joint)

The length of the residual limb after amputation also affects the options for prosthetic components and the potential for functional rehabilitation. A longer residual limb provides more sensory information and residual muscles that are available for moving and controlling the prosthesis. Conversely, higher amputation levels require prostheses of additional complexity (more joints), and the control options are reduced.
Regarding the differences between the different amputation levels, there are three broad categories of upper limb prostheses: passive, body-powered, and externally powered (Figure 3.2).

Passive Prostheses

The first category of prostheses, often considered the most rudimentary in terms of technological advancement, are the passive prostheses. They provide only cosmetic restoration to the patient and do not provide any active grasping capabilities lost after the amputation.

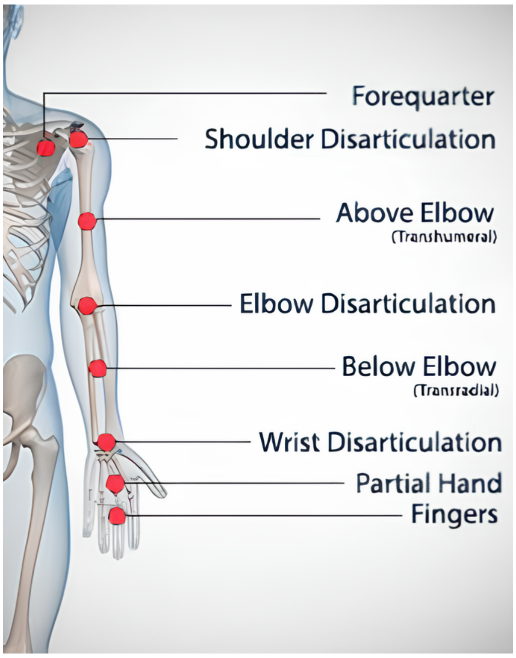

Figure 3.1. Amputation levels for upper extremities

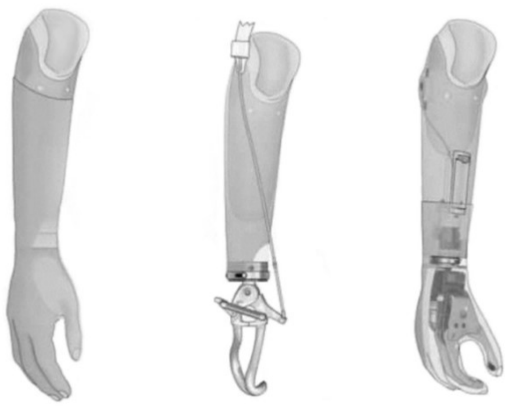

Figure 3.2. From left to right: passive (cosmetic) prosthesis, body powered (cable driven) prosthesis, and externally powered prosthesis with indicated cosmetic cover.

However, they are very useful, especially from a psychological point of view, because they guarantee a natural appearance of the lost limb (Figure 3.3). They have a lightweight design and, thanks to modern materials, can be individually optimized to the amputee's needs, including texture, skin tone, superficial veins, and other structures, making it difficult to distinguish from a natural hand.

Body-Powered Prostheses

Body-powered prostheses aim to recover some lost mechanical functions of the limb by using a harness and cable system that captures body movements, such as gross shoulder movements from a preserved anatomical area, and actuates one to three degrees of freedom (DOF) of the prosthesis (Figure 3.4). Another crucial advantage of these prostheses is the

Figure 3.3. Exemple of passive prostheses

sensitive feedback they provide to the user, as cable tension is reflected to the preserved joint. This feedback allows the user to get a sense of the position or state of the terminal device. However, there are some disadvantages to these prostheses, including limited grip force, uncomfortable harnesses, required energy expenditure for the user, an unnatural appearance, and additional loading on the shoulder joint.

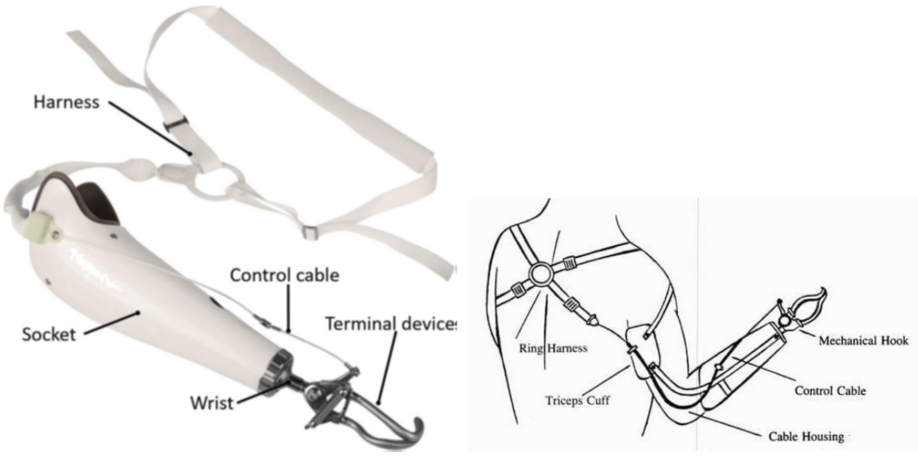

Figure 3.4. Exemple of body-powered prostheses

Externally-Powered Prostheses

Externally-powered prostheses are biomechanical prostheses that allow the recovery of lost mechanical functions through the use of actuators that are driven by electrical, hydraulic, or other external power sources. Although the power source is external, it must be wearable and integrated into the prosthetic system (Figure 3.5). Almost all externally powered prostheses available today use electric motors and rechargeable batteries. Compared to body-powered prostheses, these prostheses are heavier, more expensive, and do not provide somatosensory feedback to the user. However, they offer superior grasping force, responsiveness, speed, and, most importantly, a wide range of control options. Push buttons and harnesses with switch or linear transducer mechanisms are simple forms of control systems, but the most common means of controlling this type of prosthesis is myoelectric control [13]. Myoelectric control is derived from muscle signals generated by voluntary muscle contractions recorded from surface electrodes located in the prosthetic socket and placed over the residual muscles of the amputee's stump. The recorded surface electromyography (sEMG) is then used to control the electric motors.

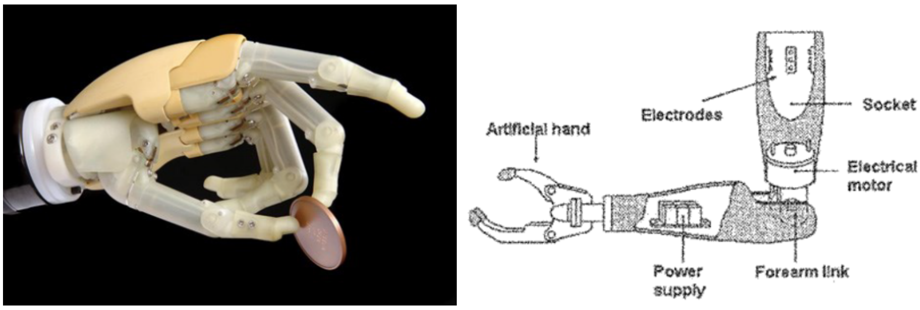

Figure 3.5. Exemple of externally-powered prostheses

3.2 Myoelectric Prostheses

Conventional myoelectric control of prosthetic devices uses surface electrodes to record voluntary surface electromyographic signals. The electrodes are integrated into a socket, necessitating careful design considerations to ensure consistent electrode placement and reliable contact with the skin. At the same time, the socket must be comfortable for the patient and the donning process should be simple. Finally, the actual placement of the socket depends on the residual muscle, the condition of the residual limb, and the control strategy [13].

Figure 3.6 illustrates the objective of such prostheses, which is to replace the normal upper limb control system, lost due to amputation, with a myoelectric prosthetic control system.

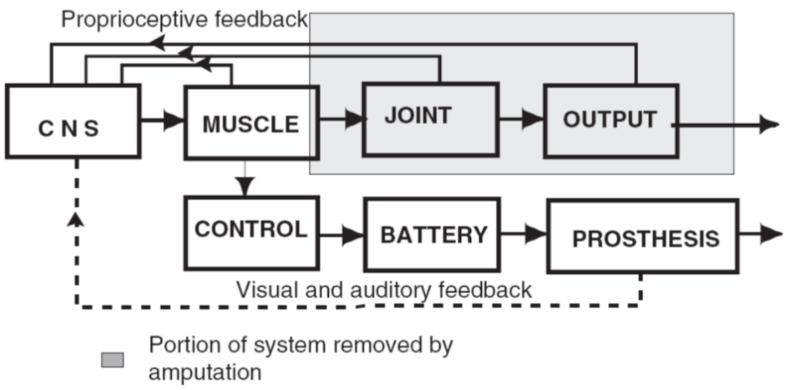

Figure 3.6. Block diagram illustrating the relationship between normal and myoelectric control system (the shaded area is removed by amputation)[30].

Typically, the electrodes are dry, since it is not possible to use conductive gel in the socket, and bipolar for single differential detection, in order to achieve an acceptable Signal-to-Noise Ratio (SNR). However, the recorded signal is affected by background noise and by the motion artifacts such as electrode shift and cable movement.

For myoelectric control of a prosthesis, the important thing is to detect muscular activations and their level of activation in order to modulate the force of the movement. Signal quality must be improved to detect the activation, thus sEMG signals are commonly filtered by a band pass filter. Properly choosing the frequency band for the band pass filter would be of importance for improving the control performance of a myoelectric prosthesis. Almost all the studies of EMG pattern recognition based prosthesis controls adopted a high pass cut off frequency ranging from 5 Hz to 20 Hz [23].

The existing control systems for myoelectric prostheses can be categorized according to the input information from the muscles, the architecture of the algorithm, and the output to the battery. Considering the EMG signal processing method in the architecture of the controller, the EMG-based control methods can be mainly classified as pattern recognition-based and non-pattern recognition-based.

Non-pattern recognition methods

Non-pattern recognition methods refer to the process of using sEMG amplitude to control the prosthetic device in either on/off or proportional mode. A common strategy is to assign a degree of freedom of the prosthetic limb to a pair of control muscles (usually an agonist/antagonist pair). This way, if the sEMG amplitude is above a cutoff threshold (S1 for the extensor and S2 for the flexor), the associated limb function (hand open for the extensor and hand close for the flexor) is selected and performed by an electric motor, as shown in Figure 3.7 [27], [29]. If a co-contraction occurs, no action will be performed

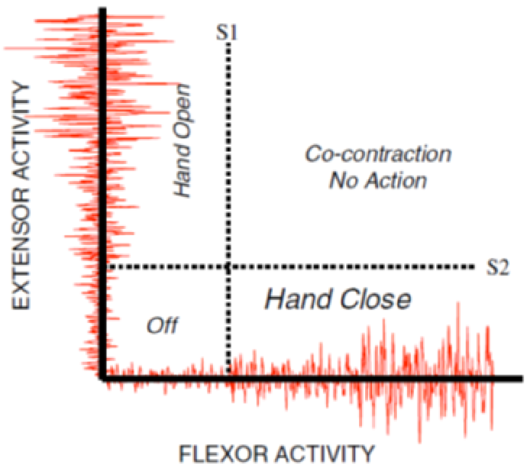

Figure 3.7. Example of a common non-pattern recognition strategy: 1) If the sEMG amplitude of the extensor muscle exceeds the cutoff threshold S1, the "Hand Open" function is activated; 2) If the sEMG amplitude of the flexor muscle surpasses the cutoff threshold S2, the "Hand Close" function is activated; 3) In the event of a co-contraction, no action is taken.

An alternative strategy is to divide the total range of myoelectric signal into many domains. In practice, the number of functions that an amputee can control with acceptable accuracy is limited to two per control muscle. In a three-state myoelectric control system, the sEMG total range is divided into three segments by two amplitude thresholds, and each segment corresponds to a specific prosthetic movement (S1 no movement, S2 hand closing, S3 hand opening), as shown in Figure 3.8

Another strategy is proportional control, in which the speed of the function is proportional to the amplitude of the control muscle sEMG. This strategy allows for more fine-grained control but requires more complex processing and more accurate sEMG signals.

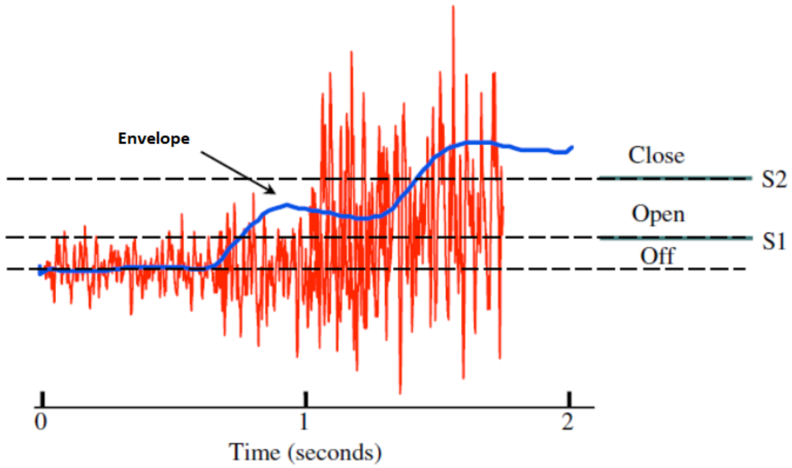

Figure 3.8. In a three-state myoelectric control system, the sEMG total range is divided into three segments by two amplitude thresholds, and each segment corresponds to a specific prosthetic movement: 1) if the sEMG amplitude is under the cutoff threshold S1 there is no movement; 2) if the sEMG amplitude is between the cutoff thresholds S1 and S2, the "Hand Open" function is activated; 3) if the sEMG amplitude is over the cutoff thresholds S2, the "Hand Close" function is activated.

The main limitation of non-pattern recognition methods is that the number of functions per control channel is limited. However, an external switch can be inserted to change the degree of freedom. In addition, using these control methods is non-intuitive and difficult for users to learn the contraction procedures of muscles. Overall, non-pattern recognition methods have the advantage of simplicity and low computational requirements, but they are limited in terms of the number of functions that can be controlled and can be challenging for users to learn. [12]

Pattern-recognition methods

Pattern-recognition methods aim to classify the patterns of muscle activation into specific movements or actions of the prosthetic device. These methods use machine learning algorithms, such as neural networks for classification or regression, to recognize different muscle activation patterns and associate them with specific movements (Figure 3.9) [25]. Pattern recognition-based control systems can provide more degrees of freedom and finer control than non-pattern recognition methods, as they allow for a wider range of movements and more natural control.

Pattern recognition-based control systems typically involve two phases: training and testing. In the training phase, the user performs a set of pre-defined movements while their sEMG signals are recorded. These signals are used to train the machine learning algorithm to recognize specific muscle activation patterns associated with each movement. In the testing phase, the user performs the same movements, and the algorithm identifies the corresponding movement and sends the control signal to the prosthetic device. [18] [27]

EMG pattern recognition-based control of multifunctional prostheses requires multichannel myoelectric recordings to accurately classify multiple classes of intentional movements based on myoelectric pattern information. However, this approach presents two primary concerns in practice: the number of myoelectric channels required and the configuration of electrode placement (Figure 3.10).[19] The number and placement of electrodes depend on

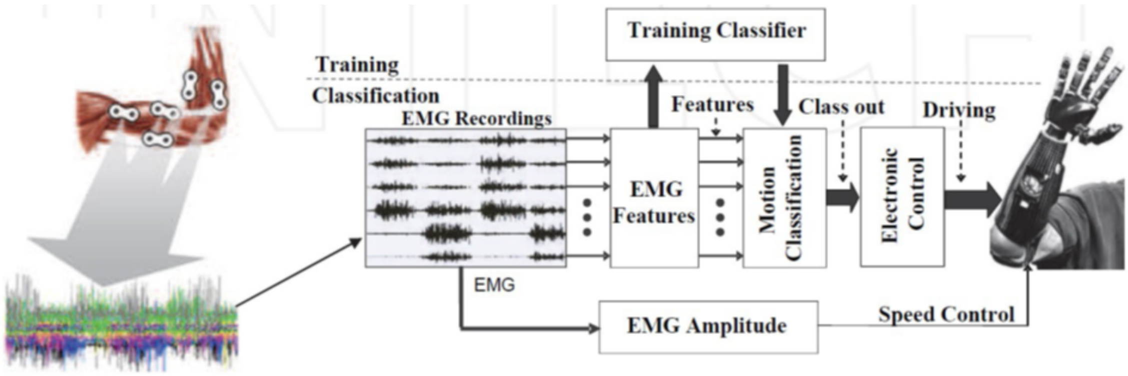

Figure 3.9. EMG pattern recognition based control strategy

the number of classes of movements required in a multifunctional prosthesis and the number of residual muscles that can be used for myoelectric control. The more classes of movements involved, the more myoelectric electrodes are needed to capture more myoelectric signals. However, increasing the number of electrodes also increases the complexity, weight, and cost of the prosthesis. The motion classes required and the remaining arm muscles available for myoelectric control can vary greatly depending on the level of upper-limb amputation of the individual.

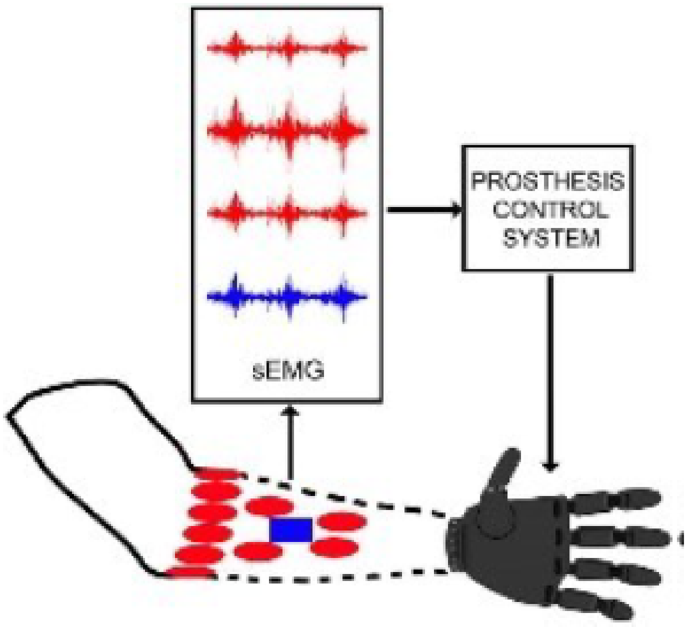

Figure 3.10. In EMG pattern recognition based control of a multifunctional prosthesis, multi channel myoelectric recordings are needed to capture enough myoelectric pattern information for the accurate classification of multiple classes of intentional movements .

To perform EMG pattern recognition, the most intuitive and used feature is the index of gross activity (e.g. variance, mean absolute value, root mean square), thus EMG data is first windowed and segmented. Typically, a window length of 100-250 ms is used, and the recordings from all channels are segmented into analysis windows with or without time overlap as shown in Figure 3.11.[17] Overlapping windows are used to maximize the utilization of the continuous data stream and produce a decision stream with high density, taking into account available computing capacity. For each analysis window, a feature set is extracted from each recording channel, resulting in an L-dimensional feature vector (corresponding to L features).

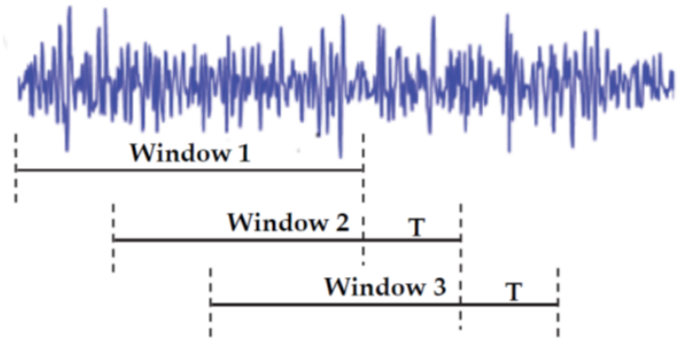

Figure 3.11. Example of EMG recordings from a single recording channel, segmented into a series of analysis windows with a time overlap T.

Pattern-recognition methods have demonstrated potential in enabling intuitive and natural control for myoelectric prostheses. However, they encounter challenges that include the requirement for calibration to account for variability in muscle activation patterns caused by factors such as fatigue, sweat, or changes in the user's residual limb.

The development of Control Interfaces, referred to as the Prosthesis Control system in Figure 3.10, is indeed the most significant challenge. These interfaces house the developed machine learning algorithm and are responsible for ensuring robust real-time myoelectric control of external devices without any noticeable delay. In addition to real-time control, these interfaces often incorporate real-time visual feedback. This is crucial because machine learning algorithm solutions typically undergo simulation testing with visual feedback before being implemented in externally powered prostheses. This approach is driven by considerations of time and cost efficiency.

Chapter 4

Interfaces

As mentioned previously, the development of supporting interfaces is a significant challenge in the field of myoelectric prostheses. Interfaces serve multiple purposes, including verifying prediction algorithms and assessing the importance of visual feedback for the user. In addition, Visual interfaces are crucial for operators as they aid in collecting EMG and kinematic data for algorithm development.

In this chapter, we will discuss three tasks performed by interfaces in myoelectric prostheses: Data Acquisition, Performance Assessment, and Visual Feedback.

4.1 Data Acquisition Interfaces

Creating a machine learning algorithm for gesture recognition requires a dataset to train the neural network. This dataset consists of sEMG signals from the limb and corresponding kinematic data of the hand collected from a variable number of healthy subjects, depending on the research purpose. To ensure high-performance of the algorithm, it's crucial to collect high-quality data. This is typically done by having the subjects perform a set of functional hand postures and grip modes that are typical of daily activities, while the operator records the data.

Visual interfaces play a critical role in this process, as they are often used to display written instructions, images, or GIFs that demonstrate the tasks the subjects should perform (Figure 4.1). This visual feedback is beneficial for both the user and the operator. It provides guidance to the user on how to perform the different movements in the set, and it allows the operator to customize the number of repetitions of each task and to randomize the order of tasks.

4.2 Performance Assessment Interfaces

Performance assessment interfaces play a crucial role in evaluating and verifying the developed prediction algorithm for myoelectric control. These interfaces allow operators to assess the accuracy and reliability of the algorithm's predictions. By providing real-time feedback and visualization of the algorithm's performance, operators can effectively evaluate the algorithm's effectiveness and make necessary adjustments or improvements.

Typically, performance assessment interfaces involve capturing real-time sEMG data from the user's muscles while they perform specific hand gestures or movements. The sEMG data is then processed in real-time using the developed prediction algorithm to generate predictions or classifications of the intended hand gesture.

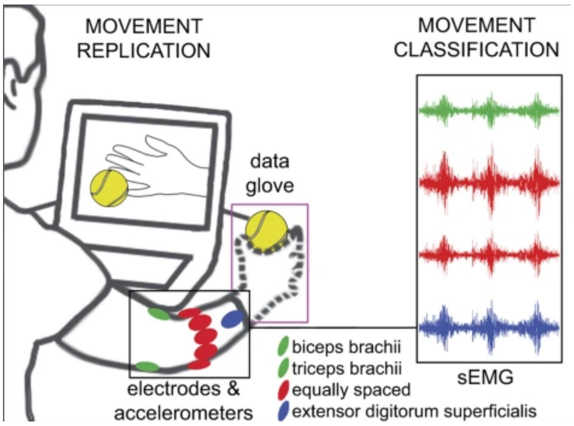

Figure 4.1. Example of a subject mimicking movements shown on a laptop screen [8]

The interface presents the predicted gesture or classification to the operator through visual means, such as visual labels, graphs, or virtual representations of the hand movements. The operator can compare the predicted gesture with the actual performed gesture and assess the accuracy of the algorithm's predictions. This real-time feedback allows the operator to verify the algorithm's performance and identify any discrepancies or errors.
Additionally, performance assessment interfaces may provide quantitative measures of the algorithm's performance, such as gesture recognition accuracy or classification rates. These metrics assist the operator in evaluating the algorithm's overall effectiveness and identifying areas for improvement.

By using performance assessment interfaces, operators can thoroughly test and validate the developed prediction algorithm before its implementation in myoelectric control systems. This verification process ensures that the algorithm provides reliable control of external devices based on the user's muscle activity.

4.3 Visual Feedback Interfaces

Human visual perception can vary slightly from person to person, but in general, it is believed that the latency for a visual application should be less than 100 milliseconds to be considered "real-time" for the human eye.
The reason behind this value is based on the fact that the human eye has a refresh rate, called the refresh frequency, which is typically around 60-75 Hz (meaning 60-75 frames per second). This means that the eye can perceive new visual information every approximately 13-16 milliseconds.
To achieve a smooth and delay-free visual experience, the application needs to be able to process and display visual information to the human eye within the maximum refresh time, which is 13-16 milliseconds. This includes both data processing and screen presentation.
Visual feedback interfaces play a critical role in assessing the significance of visual feedback for the subject in myoelectric control systems. These interfaces are designed to meet the operator's requirement of providing real-time visual feedback to the user based on the predictions made by the neural pipeline. By incorporating visual feedback, users can actively monitor and control what appears on the screen adjusting their voluntary muscle contractions to achieve the desired target predictions effectively. The process of capturing real-time sEMG data, processing it, and presenting the predicted gesture or classification is the same

as mentioned in the Performance Assessment Interfaces section 4.2.
In the context of real-time visual feedback in upper limb prostheses, a study conducted by Sebelius et al. (2005) determined that an update rate of 20 Hz (50 ms) was considered to meet the criteria for real-time performance. This update rate encompassed various processes, including the recording of sEMG signals, their transmission, translation, and display of the output [31].
Real-time visual feedback interfaces allow users to immediately verify the accuracy of the predictions and make necessary adjustments to their voluntary muscle contractions. By observing the visual feedback, users can fine-tune their muscle contractions to maintain or achieve the desired target prediction [32]. In an integrated prosthesis system, the visual interfaces are replaced by the actual bionic hand, where the neural network's predictions trigger control commands for the bionic hand's motors/actuators to execute the corresponding gesture,
Research has demonstrated the critical role of real-time feedback interfaces in pattern-recognition methods for myoelectric control of prostheses. Studies conducted by Côté-Allard et al. [14] have shown that users who receive visual feedback from the neural network output maintain a higher level of gesture recognition accuracy over time compared to those who do not receive feedback. Similarly, Hahne et al. [20] have demonstrated that real-time prediction outputs enable users to adjust their voluntary muscle contractions to achieve the desired target prediction.

Here are two examples of interfaces for real-time feedback to investigate the effect of the user in an online closed-loop myoelectric control found in literature:

- Tam et al. [32] presented an interface that captures sEMG data in real-time from the subject performing a subset of 6 functional hand postures/grip modes. The system uses the data to make predictions from the muscular activity, and the user can see the predicted gesture in real-time as a visual label for instant verification (Figure 4.2). The user then adjusts voluntary muscle contractions to reach the target gesture. The top plot displays the system's predictions, while the bottom plot shows the aligned mean Teager-Kaiser Energy (TKE) value to provide an indication of the system's responsiveness to muscle contractions.

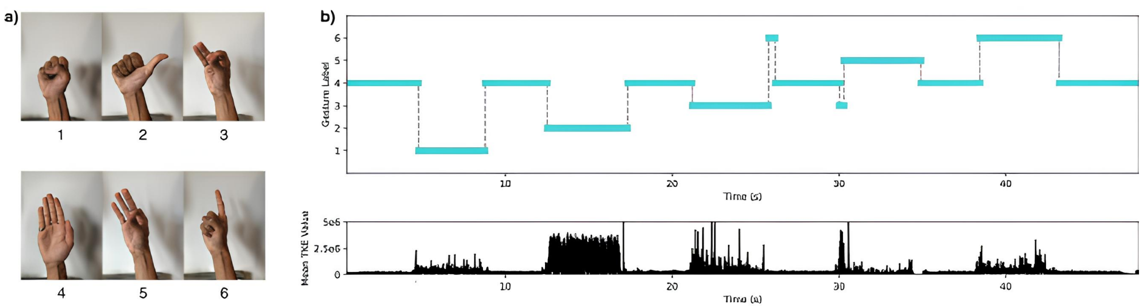

Figure 4.2. Real-time neural network output was tested on a set of six functional hand postures/grip modes. During the test, the user cycled through each gesture, holding them for a few seconds and resting in the neutral position (label 4) in between. The top plot displays the system's predictions, while the bottom plot shows the aligned mean Teager-Kaiser Energy (TKE) value to provide an indication of the system's responsiveness to muscle contractions [32]

- Hahne et al. [20] designed an interface for visualization and control in real-time. The aim of their experiment was to use a real-time feedback interface to control tasks with a cursor on a computer using voluntary muscular activity (Figure 4.3). This control interface uses a feedback window, in which a red cross appears in a two-dimensional coordinate system (cue-based trajectories). In this coordinate system, the origin corresponds to rest, the horizontal axis to the degree of freedom (DOF) flexion/extension, the vertical axis to radial/ulnar deviation, and the unity circle to a maximal voluntary contraction (MVC). The user aims to control the position of the red cross through voluntary muscular contractions.

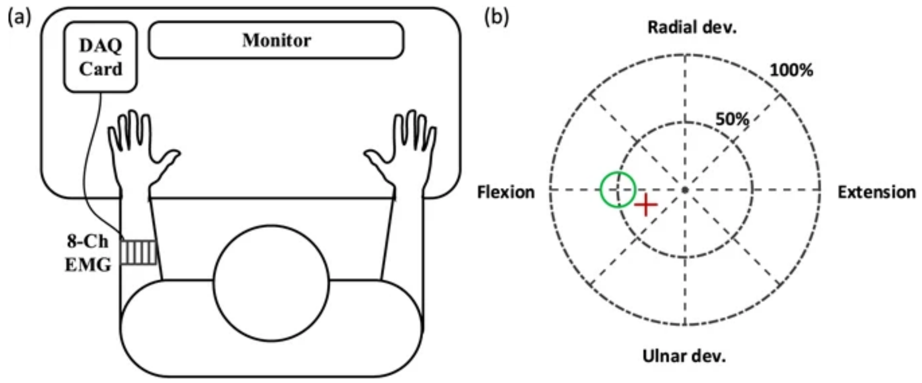

Figure 4.3. (a) Experimental setup. (b) Feedback window in real-time control tasks. The user controls the position of the red cross with his/her EMG signals. The task is to move and keep the red cross into the green circle in the conditions tested [20].

In conclusion, visual feedback interfaces in myoelectric control systems contribute significantly to the user's ability to assess and adapt their voluntary muscle contractions based on real-time predictions. By incorporating visual feedback, these interfaces enhance the performance and usability of myoelectric prosthetic devices, promoting more effective and intuitive control for the users [14].
Real-time visual feedback interfaces provide several benefits to users. They allow users to minimize errors in predictions caused by the non-stationary nature of sEMG [24]. Moreover, the immediate visual feedback enhances the user's sense of control and facilitates a more intuitive and natural interaction with the myoelectric control system.

In light of the aforementioned findings, developing effective real-time control interfaces is crucial for improving the performance and usability of myoelectric prosthetic devices. Therefore, the primary objective of this thesis is to design and implement a novel interface that enables intuitive and effective real-time feedback for users engaged in myoelectric control.

Chapter 5

Objectives

Building upon the insights gained from previous research and studies, this work aims to address the existing challenges and limitations in current control interfaces by developing a cutting-edge interface that empowers users to control simulated external devices, such as prosthetic limbs, in a more efficient and natural manner. The interface will leverage advanced machine learning techniques and pattern recognition algorithms to accurately interpret the user's muscle activation patterns and translate them into meaningful control commands.

By creating an intuitive and user-friendly visual feedback system, the developed interface aims to bridge the gap between the user's intentions and the prosthetic device's actions. The real-time feedback will provide users with immediate confirmation and verification of their intended movements, empowering them to make necessary adjustments and achieve desired control outcomes. Furthermore, this thesis aims to conduct rigorous evaluations and user studies to assess the effectiveness and usability of the developed interface.

Ultimately, the successful development and implementation of this real-time myoelectric control interface holds the potential to significantly enhance the functionality and user experience of prosthetic devices, providing a valuable tool for the development of those. By providing intuitive and effective control capabilities, the interface will contribute to improving the overall quality of life and independence for individuals with limb loss, empowering them to seamlessly interact with the external devices and regain a sense of autonomy and mobility.

Part III

Materials and Methods

Chapter 6

Development of the Interface

This chapter details the development process of the real-time Control Interface, which encompasses all stages of sEMG signal processing and control. The interface is designed to receive sEMG signals through TCP/IP communication, process the signals, make predictions using a neural network, and provide visual feedback of the predicted hand gesture. The primary objective of this work is to accomplish these tasks in real-time.

6.1 Control Interface

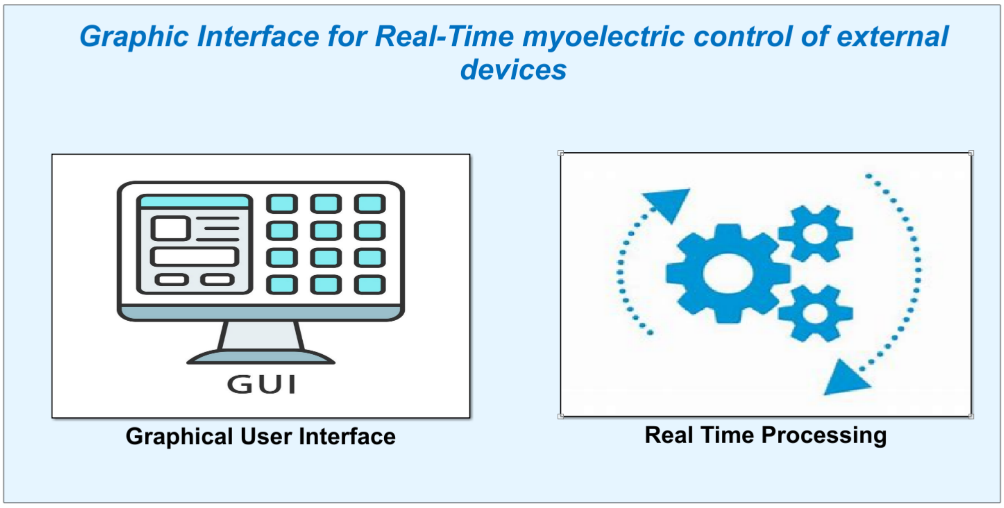

Figure 6.1. Control Interface in Simulink

The Control Interface is developed using Simulink, an environment that utilizes block diagrams for designing, analyzing, and testing dynamic systems with multidomain models [4]. To minimize latency, the Simulink Desktop Real-Time app was employed, which provides a real-time kernel for executing Simulink models on Windows or Mac OS [5]. The primary objective of the Control Interface is to acquire sEMG signals from the MEACS system, extract useful information, make hand gesture predictions using a neural network (NN), and provide real-time visual feedback. Additionally, a simple Graphical User Interface (GUI) is provided to allow users to visualize and modify parameters related to the acquisition of sEMG data.

Due to the complexity of the task, the Control Interface is divided into subsystems to facilitate understanding of the workflow. Figure 6.1 depicts the Control Interface in Simulink, showing its initial division into two subsystems.

- **Real Time Processing**: This subsystem ensures communication with the BP Software and, consequently, with the MEACS system. It handles the processing of sEMG signals, prediction of hand kinematics using a neural network, and visual feedback. It is further divided into subsystems,
- **Graphical User Interface**: The Graphical User Interface (GUI) subsystem allows users to initialize the TCP/IP communication, visualize and modify parameters related to the acquisition of sEMG data, and decide when to save predicted angles.

6.1.1 Graphical User Interface

The Graphical User Interface (GUI) plays a crucial role in the Control Interface, allowing the operator to interact with the system and perform various tasks. In the GUI, several features were implemented to enhance the operator's control and monitoring capabilities. Figure 6.2 provides an overview of the GUI organization.

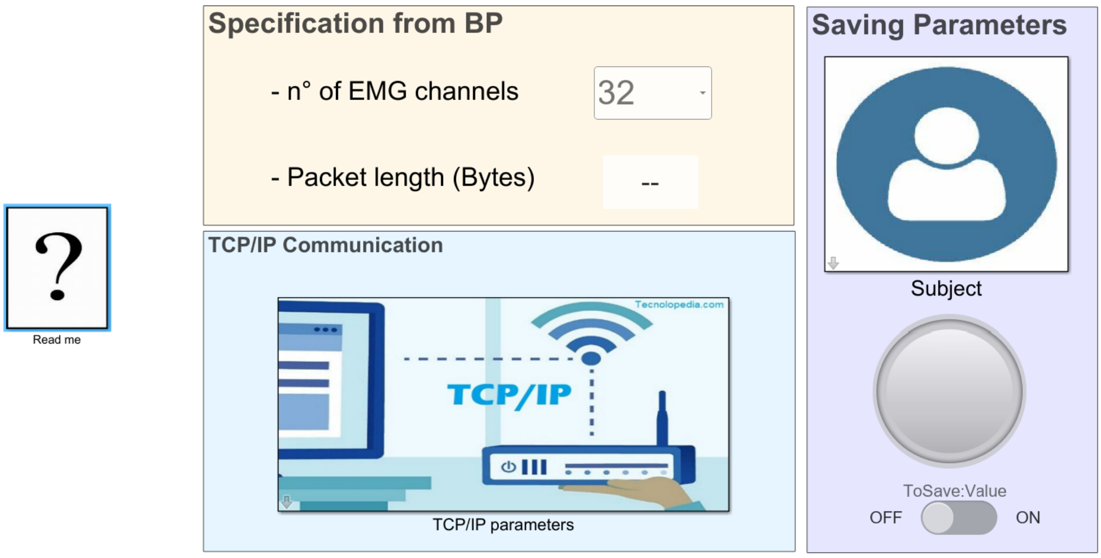

Figure 6.2. Graphical User Interface (GUI) organization

The "TCP/IP Communication" panel plays a crucial role in the Control Interface, utilizing Simulink blocks to receive data from the Internet. The user is required to input the IP Address and communication Port, where communication with the AR/VR Plugin of BP software occurs. Once a payload is received by the panel, it promptly transmits the received values, "DataIn," and the length of the received payload, "Length DataIn," to the Real-Time Processing subsystem. Timely payload reception is essential for optimal performance. Figure 6.3 illustrates the configuration of the client block responsible for receiving data.

Another crucial panel in the GUI is the "Saving" panel, which enables the operator to determine when to save the angles estimated by the Neural Network. The operator can easily initiate the saving process by toggling the slider switch to the "ON" position. Conversely, the process can be stopped by switching it to "OFF." To provide visual feedback, a green

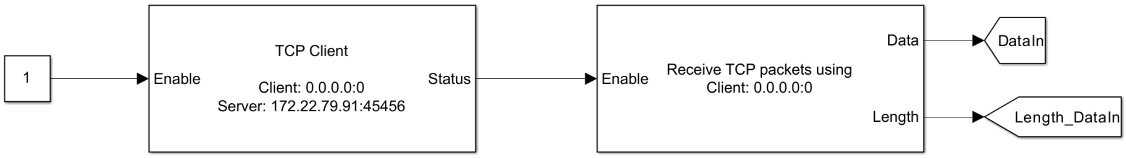

Figure 6.3. Configuration of TCP_IP Communication

lamp lights up when the saving process is active. This flexibility allows the operator to start and stop the saving process multiple times. Each saved file is uniquely identified by the subject's name and surname, entered previously in the subject block, along with the date in the format DDMMYY and the time in the format hhmmss when the saving process was stopped.

Additionally, the GUI provides a "Specifications" panel where the operator can monitor the number of channels being sampled by the Control Interface. This information helps the operator understand the payload length in terms of the number of bytes.

The user-friendly design and interactive features of the GUI significantly enhance the operator's experience, ensuring efficient control and monitoring of the system during the acquisition phase. Moreover, the "Read Me" block provides detailed explanations of all the GUI features to assist the user in utilizing the Control Interface effectively.

6.1.2 Real Time Processing

The Real Time Processing subsystem is responsible for communication with the BP Software and the MEACS system, as well as handling the processing of sEMG signals, prediction of hand kinematics using a neural network, and providing visual feedback. This subsystem comprises several components, as depicted in Figure 6.4:

- **Number of Channels:** This block allows the user to specify the number of sEMG channels received by the Control Interface. The user can modify this value through the GUI, providing flexibility in adapting to different setups.
- **Number of Bytes:** This block indicates the length, in bytes, of each payload ($n\_Bytes = 12 + 4 \times n\_ch$). The user can easily access this information through the GUI, aiding in the understanding of payload size.
- **Buffer Management:** This subsystem ensures the processing of only one payload at a time. It utilizes a MATLAB function that takes inputs such as the received data "DataIn," the length of the data received "Length DataIn," the number of channels being sent by the AR/AV Plugin, and the size in bytes of each payload. Based on this information, it creates a buffer and provides outputs including the "BufferFlag" indicating whether the buffer is empty, a payload counter tracking the number of received payloads, a variable indicating if the initialization phase is complete, and a vector containing the initialization command as well as the n_ch RMS values over time.
- **Initialization**: This subsystem ensures communication with the BP Software and the MEACS system during the initialization phase.

- **Signal Processing**: This subsystem is responsible for processing sEMG signals, predicting hand kinematics using a neural network, and providing visual feedback.
- **Save**: The "Save" variable allows users to control when to save the predictions of the neural network. When its value is equal to 1, the predictions are saved. The user can modify this value through the GUI.

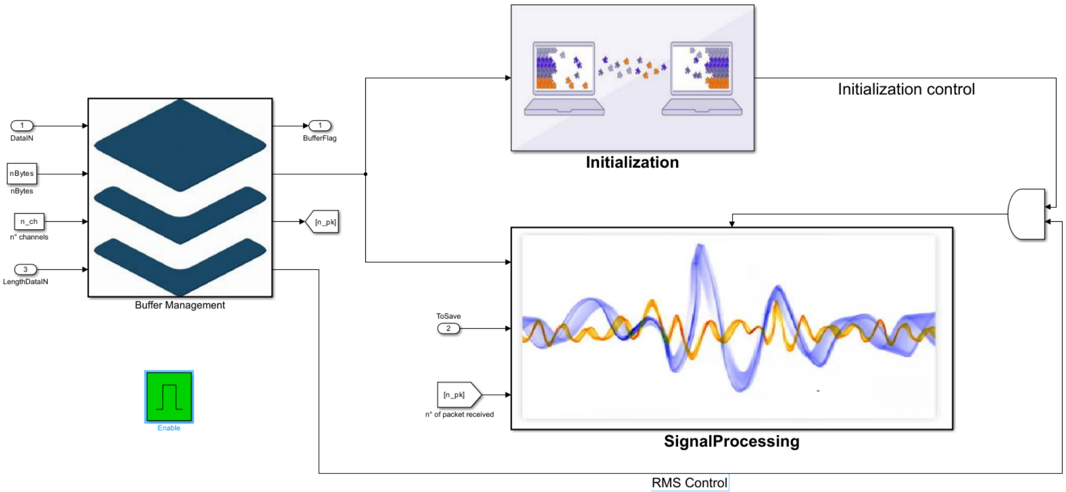

Figure 6.4. Real Time Processing Subsystem

Initialization

The first step of the Control Interface is to establish a TCP/IP communication link for receiving sEMG data from the external device called MEACS. This device, designed for acquiring high-density surface electromyographic activity (HD-sEMG), works in conjunction with the BP software, which is specifically developed for the acquisition and real-time visualization of sEMG signals [10].
To process the collected sEMG signals, the BP software utilizes the AR/VR Plugin, enabling the integration of devices interacting with third-party software developed for augmented reality (AR) or virtual reality (VR) into the BP software [11]. This plugin allows real-time calculation of the root mean square (RMS) values of the sEMG signals. To ensure reliable, ordered, and error-checked transmission of data payloads over an IP network, the Transmission Control Protocol (TCP) is employed. TCP/IP, being a connection-oriented protocol, establishes a connection between the sender (BP software) and the receiver (control interface) using a three-way handshake before transmitting any messages. Once the control interface is started, a connection is established between the sender (Bp Software) and receiver (Control Interface).

In the "Initialization" phase 6.4, the control interface handles three hexadecimal commands sent from the AR/VR Plugin, which are responsible for making the plugin appear in the BP software. The first command (0x81) requests the device name of the control interface, while the second command (0x82) asks for its version number. If the previous responses are correct, the AR/VR Plugin sends the last command (0x80), which does not expect any response as it signifies the initiation of the sampling process. Table 6.1 provides a description of these commands, their respective codes, and how the control interface responds.

Command	Description	Code	Response
CMD_DEV_NAME_REQ	Request the Device Name	0x81	"MA01AA51"
CMD_VERSION_REQ	Request the Version Number	0x82	"0.1.0a"
CMD_START_STOP	Start/Stop the Sampling Process	0x80	"-"

Table 6.1. list of commands in order to make AR/VR Plugin appear

If the initialization process is successful, the AR/VR Plugin will appear in the BP software. After configuring various parameters, such as the number of channels to send and the epoch length for RMS calculation, the user can start sending real-time EMG signals to the control interface by simply pressing the update button (as shown in Figure 6.5)

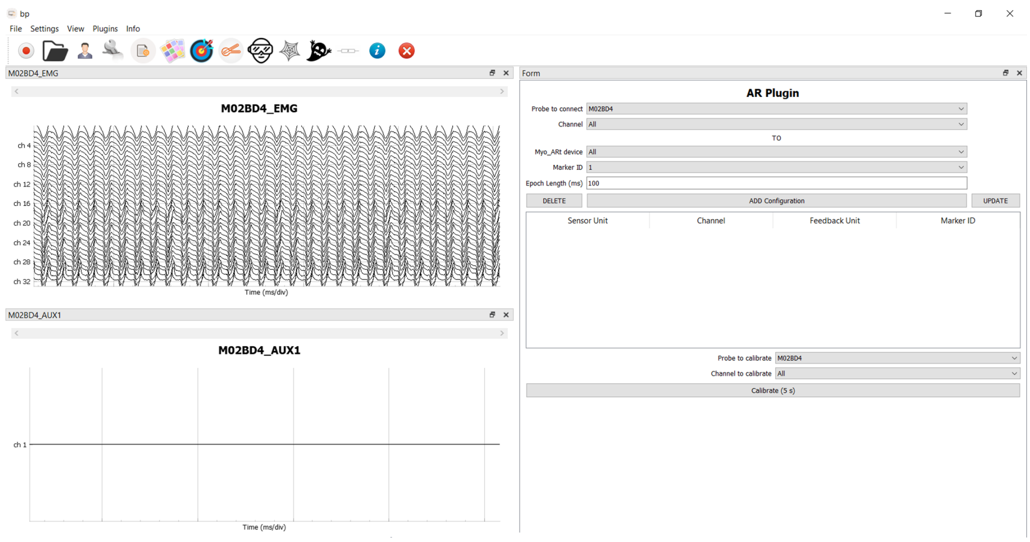

Figure 6.5. AR/VR Plugin in BP software

Signal Processing

Once the update button in the AR/VR Plugin is pressed, the sampling process, and consequently the "Signal Processing" phase, begins.
From the perspective of the AR/VR Plugin, the evaluated RMS values are organized into a payload, which serves as a data package. The specific structure composing each packet, from header to EMG samples, to control Bytes, cannot be disclosed due to intellectual property protection.

Through the TCP/IP connection, the AR/VR Plugin transmits the EMG data to the Control Interface for further processing and visualization.

By organizing and transmitting the data in this manner, the system enables efficient and reliable communication of real-time sEMG information from the Plugin to the Control Interface.

From the Control Interface's perspective, the first step is to identify each header in order to analyze one payload at a time. Once the payload is identified, the RMS value/values (depending on the number of sEMG channels sampled) need to be extracted. As per the payload composition, each RMS sample is encoded in 4 bytes. Therefore, for every timestamp at which the Control Interface receives data, n_ch (n_ch = number of sEMG channels) RMS samples are obtained. In this thesis, we consistently refer to n as 32, as we chose to utilize all the available sEMG channels that the MEACS can sample.

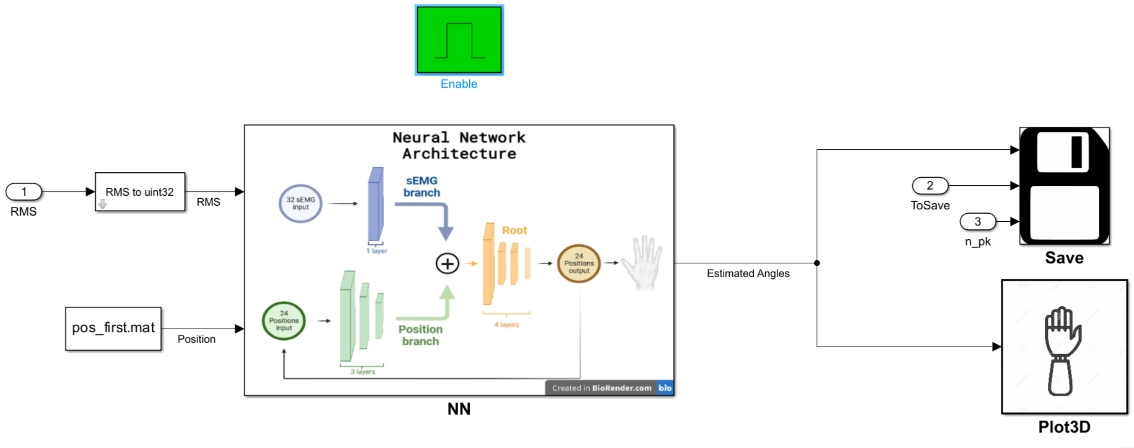

Figure 6.6. Organization of the Signal Processing phase after the extraction of RMS values

In Figure 6.6, is depicted the organization of the "Signal Processing" subsystem once the RMS samples are extracted. It's possible to notice a further division in subsystems:

- **Neural Network**: This subsystem is the Neural Network (NN), which is already trained and has the architecture presented in chapter 7. The RMS values extracted previously serve as input to the algorithm, which provides predicted angles as output after a number of matrix operations. Furthermore, the predicted angles are filtered with a second-order lowpass Butterworth filter (cutoff frequency of 1 Hz).

- **Visual Feedback**: The Visual Feedback subsystem provides real-time visualization of the predictions made by the neural network. It displays a 3D plot of the 24 Degree of Freedom hand gesture for each prediction, combining all the instances to create a video-like representation of the hand and its movements. This allows users to observe the predicted hand gestures in a more intuitive and comprehensible manner. Figure 6.7 shows an example plot of the angles predicted from sEMG during a rest phase, giving an insight into how the visual feedback represents the hand movements.

- **Save**: This subsystem, when activated through the GUI, guarantees the saving of the predicted angles for each instant. Its flexibility allows the operator to start and stop the saving process multiple times. Each saved file is uniquely identified by the subject's name and surname, entered previously in the subject block, along with the date in the format DDMMYY and the time in the format hhmmss when the saving process was stopped.

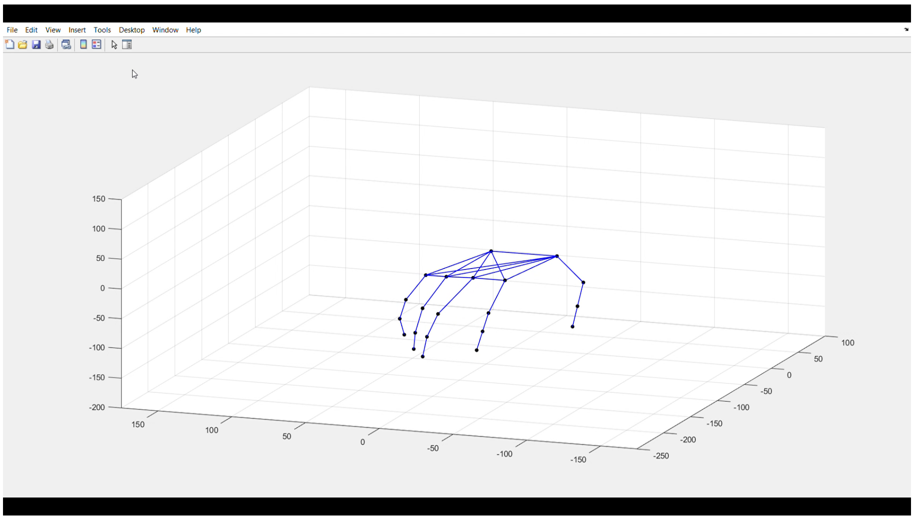

Figure 6.7. Example plot of predicted hand gesture from sEMG during a rest phase

Chapter 7

Neural Network

As previously mentioned, pattern-recognition methods utilize machine learning algorithms, such as neural networks (NN), for classifying or regressing different muscle activation patterns to specific movements. To ensure the algorithm's effectiveness, it is essential to construct a high-quality dataset of diverse sEMG data for training the neural network.

This chapter will provide a concise overview of the neural network algorithm employed in this thesis to predict hand kinematics from surface electromyography (sEMG) signals. The algorithm used in this study was developed at the University of Oxford by Giovanni Rolandino, as part of his DPhil research. While the detailed exploration of the neural network falls outside the scope of this thesis, we will present a broad understanding of its architecture and functionality. Additionally, we will outline the data acquisition protocol used to gather the training dataset for the neural network. It is important to note that the same dataset is subsequently used to evaluate the performance of the interface in terms of predictions and real-time operation.

By providing this rapid overview of the neural network and the data acquisition protocol, our objective is to offer a concise yet comprehensive understanding of the methodology employed in this thesis for predicting hand kinematics from sEMG signals.

7.1 Acquisition Protocol

During the data acquisition protocol, we focus on capturing the kinematics and muscle activations of the dominant hand and arm of each subject.

To capture the kinematics, a set of markers is placed on various body parts, including the hand, arm, chest, and back. The hand markers consist of 22 infrared reflective markers embedded in a disposable latex glove, as shown in Figure 7.1. Additionally, 10 markers with a larger diameter are positioned on the arm, chest, and back, as depicted in Figure 7.2. This configuration enables comprehensive body reconstruction and tracking using the Vicon Nexus system, utilizing a total of 32 markers.

To capture surface electromyography (sEMG), three forearm electrode arrays with 32 electrodes each are used, providing 96 sEMG channels. The electrode arrays are placed on the forearm and connected to three different Sensor Units (SU) of the MEACS system. The placement of the electrodes follows specific body landmarks, with electrode 24 positioned at 20 percent of the distance between the medial epicondyle and the pisiform. A reference

Figure 7.1. Markers embedded in a latex glove for hand kinematics capture (Created with BioRender.com).

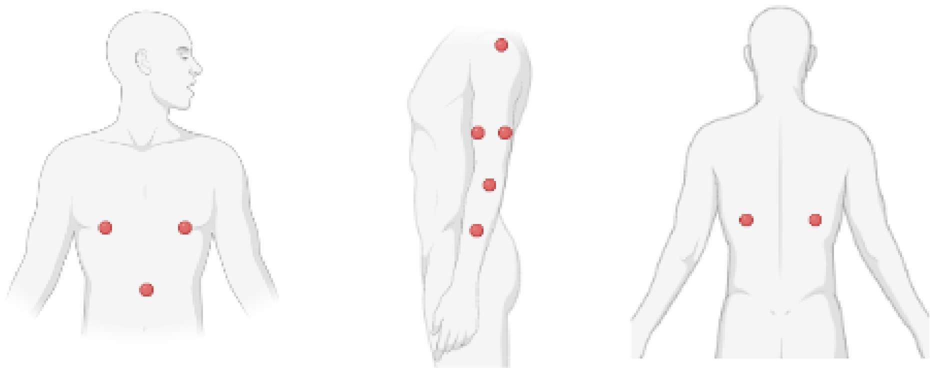

Figure 7.2. Markers placed on the chest, arm, and back for comprehensive body reconstruction and tracking (Created with BioRender.com).

electrode is placed on the medial epicondyle. To ensure optimal signal quality, the subject's skin is prepared by applying abrasive paste to reduce impedance

Once the electrodes are in place, the subject wears the latex glove with embedded Vicon markers, and the body markers are applied accordingly. The subject is then familiarized with the experiment and the required poses through pre-recorded examples, along with an explanation of the data acquisition instrumentation.

During the data acquisition, the subject stands in the center of the room with the forearm resting on a support to achieve full relaxation of the forearm muscles during the rest phase. Visual instructions for the hand movements are provided through a monitor positioned in front of the subject. Figure 7.3 illustrates the 18 possible hand movements with a single degree of freedom that the subject will perform. The order of repetitions is randomized and divided into 6 sections, each consisting of 5 repetitions of 8 seconds for each hand movement. There is a 1-minute break between each section.

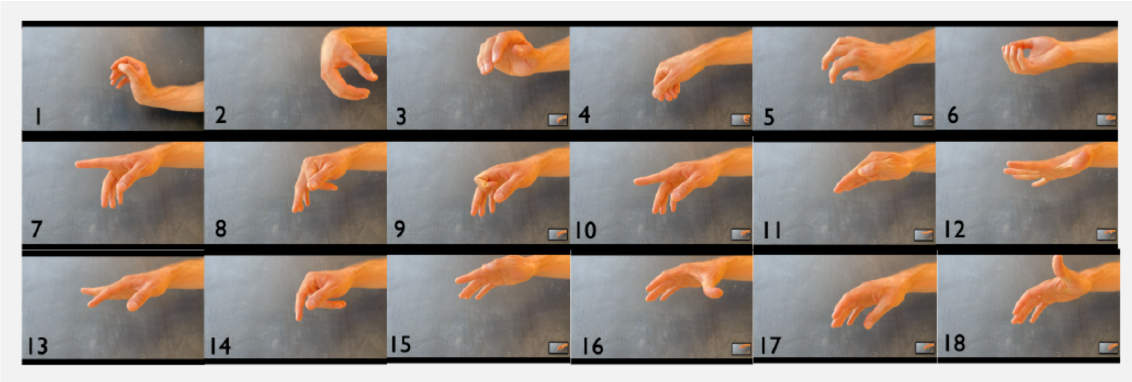

Figure 7.3. Illustration of the 18 hand movements with a single degree of freedom performed by the subject during data acquisition.

7.2 Architecture

The architecture of a Neural Network (NN) is responsible for defining the organization and connectivity of its neurons. Neurons are the fundamental processing elements of the NN, designed to emulate the behavior of neurons in the human brain. A neuron, also known as a perceptron, consists of an activation function that determines its output based on the weighted sum of inputs.

The network developed (RPC-Net) is designed as a regression prosthetic control solution that combines the benefits of regression-based approaches while maintaining computational efficiency. It is specifically developed to estimate the kinematic state of the hand, represented by 24 joint angles.

The architecture of RPC-Net consists of two branches: the EMG branch and the Position branch. The EMG branch takes the raw EMG signal as input and comprises a single layer. Its purpose is to process the EMG signal and extract relevant features.
The Position branch, on the other hand, takes the previous joint angles as input and consists of three layers. This branch focuses on capturing the temporal dependencies and patterns in the joint angles to enhance the accuracy of the predictions.
Both branches are then merged into the Root, which consists of four layers. The root layer combines the information from the EMG branch and the angular position branch to generate the final output, which represents the estimated kinematic state of the hand.

It is important to note that RPC-Net is composed of 24 individual sub-networks, with each sub-network dedicated to estimating one degree of freedom (DoF) of the hand. For each iteration, the same input is fed into all 24 sub-networks, and their outputs are merged to obtain the overall kinematic state of the hand.

This architecture allows RPC-Net to effectively process the EMG signals and incorporate temporal information from previous joint angles, enabling accurate estimation of the hand's kinematic state.

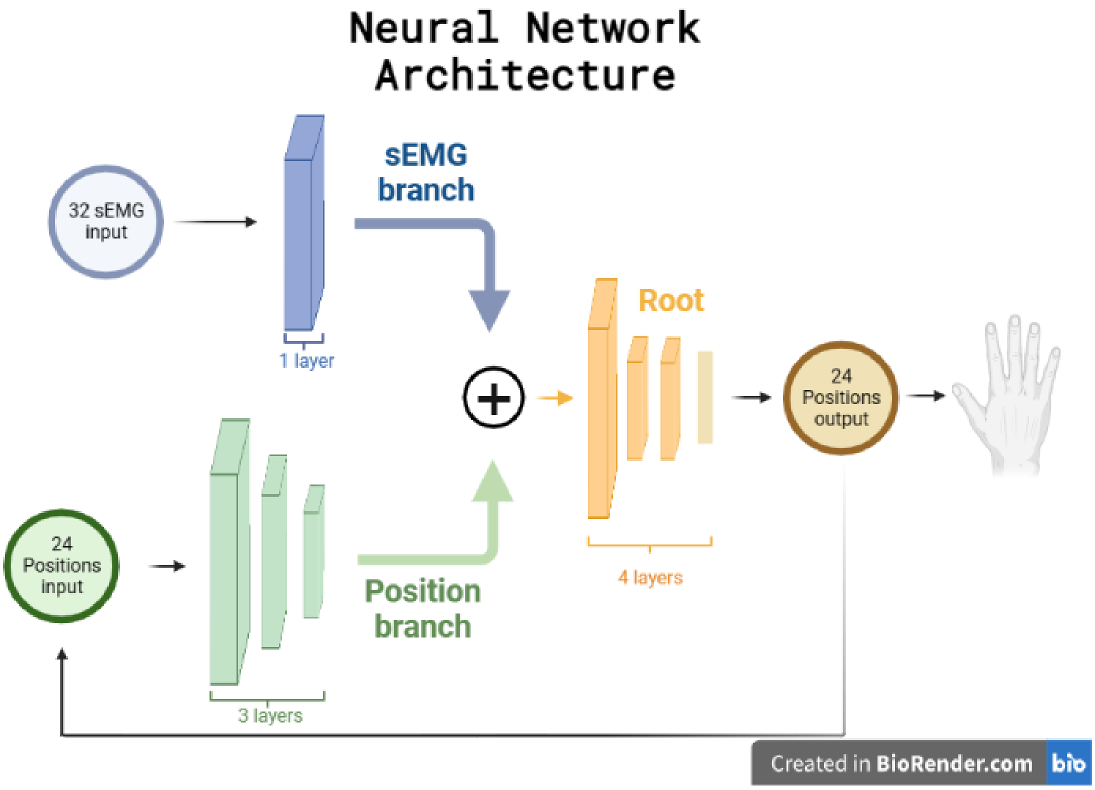

Figure 7.4. Neural Network architecture

Chapter 8

Interface Evaluation

Once the Control Interface was completed, it was important to assess its quality and efficiency. Two protocols were designed to evaluate the reliability of the reconstructed Root-Mean-Square (RMS) values and the real-time performance of the Control Interface.

8.1 RMS validation

The objective of this protocol is to investigate the accuracy of real-time RMS values calculated by the AR/VR Plugin, transmitted to the Control Interface via payloads, and reconstructed by the Control Interface. To evaluate the correctness of these values, a *biceps brachii* contraction was performed on the dominant arm while recording surface electromyography (sEMG) signals with the MEACS system (9.2). The Biceps Brachii muscle was chosen due to its long muscular fibers, which enable the collection of MUAPs at different points above the muscle fibers. Additionally, an isometric task was performed to ensure that the RMS trend resembled the strength profile.

To guarantee isometric conditions, the Biodex System 4 dynamometer (9.3) was utilized, with a focus on the elbow joint [1]. A specific sEMG channel was selected, and using the same raw sEMG signal (s(t)), the RMS values obtained from the Control Interface were compared to those calculated using Matlab, which serves as the gold standard.

The RMS validation protocol allows for the assessment of the accuracy and reliability of the Control Interface in calculating real-time RMS values and ensures the validity of the reconstructed data. The RMS amplitude of the EMG signal is considered a high-quality detector for monitoring changes in muscle activity [22].

8.1.1 Acquisition Protocol

During the acquisition protocol, it is essential to ensure precise electrode placement, adherence to the standardized contraction profile, and allow a pre-session where participants can familiarize themselves with the task. The Biodex System 4 dynamometer measures the force exerted during the isometric contractions, ensuring consistency and accuracy in the trapezoidal strength profile.

The steps below were considered for accurate acquisition of sEMG signals:

1. Define Anatomical Landmark Frames (ALF): Establish a line between the acromion and the distal insertion of the Biceps Brachii tendon to define the ALF.

2. Identify Optimal Electrode Sites: To achieve optimal results, it is recommended to place the electrodes on the muscle belly. For the Short Head of the muscle, the electrodes should be positioned laterally between 61% and 79 % of the ALF. Similarly, for the Long Head, the electrodes should be positioned medially between 62% and 80% of the ALF (Arm's Length Fraction) [9].

3. Prepare the Subject's Skin: Prior to electrode application, prepare the subject's skin by using an abrasive paste to improve conductivity.

4. Place the Electrode Array: Position a 2x16 electrode array along the direction of the muscular fibers.

5. Maximal force: The subject must perform a maximal force contraction in order to identify their maximal force using the Biodex System 4.

6. Instruct the Subject to Perform Elbow flections: Instruct the subject to perform five isometric contractions of the *biceps brachii* using their dominant arm while recording sEMG signals. During the contractions, the subject should produce an elbow flexion torque according to a trapezoidal strength profile, as shown in Figure 8.1. The profile consists of the following phases:

   - Ramp-up Phase: The subject has 2 seconds to reach 50% of their maximal force.
   - Sustained Contraction Phase: The subject must maintain 50% force for 10 seconds.
   - Return to Rest Phase: The subject should return to the rest condition in 2 seconds.

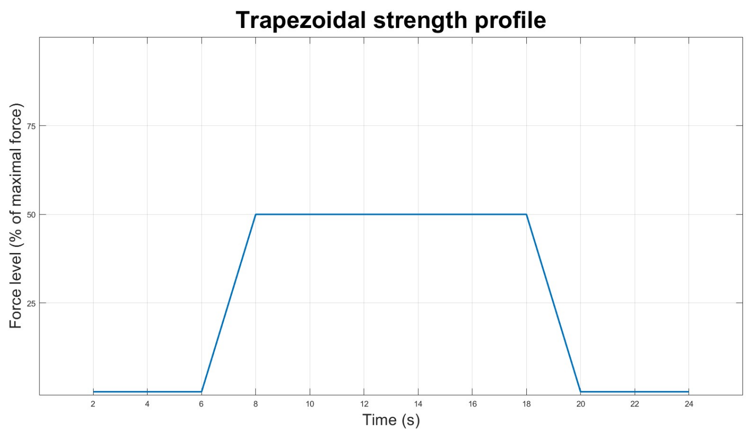

Figure 8.1. Trapezoidal strength profile that the subject should follow

7. Familiarization Contractions and sEMG Quality Verification: Before the formal recording session, have the subject perform two familiarization contractions while simultaneously verifying the quality of the sEMG signals. Identify the best channels among all 32 channels for recording.

8. Start Recording sEMG: Once the subject is familiar with the task and the signal quality is confirmed, begin recording the sEMG signals using the BP software.

9. Connect the Control Interface: When the recording of sEMG channels starts, activate the Control Interface to display the AR/AV Plugin. Then, select and transmit only the previously identified channels to the Control Interface.

10. Task Execution: Instruct the subject to follow the trapezoidal torque profile during the five recorded isometric contractions.

11. Stop Recording sEMG: After completing the task, stop the recording of the sEMG signals.

The recording channel should be saved both as raw signals using the BP Software and as RMS values using the Control Interface for subsequent comparisons.

8.1.2 Data analysis

After completing the acquisition protocol, the offline data analysis phase begins. The objective of this phase is to verify the comparability between the RMS values obtained with the Control Interface and the actual RMS values extracted from the raw sEMG signal. This procedure is performed for the selected channel during the acquisition phase, as the comparability of values for one channel can be extended to all other channels.

The comparison is carried out using the Matlab platform, and the following equation is used to evaluate the RMS values:

$$RMS = \sqrt{\frac{1}{T}\sum_{t=1}^{T} EMG^2(t_i)}. [22]$$

Here, $EMG^2(t_i)$ represents the squared value of each EMG data point within a specific data window (0, T), which selects a particular portion of the signal containing a specific number of samples [22]. Thus, from the recorded raw sEMG signal, multiple RMS values can be derived as each epoch yields an RMS value. The number of RMS values obtained from the sEMG signal is determined by the length of the EMG signals divided by the epoch length (both measured in the same unit of measurement), assuming no overlap between epochs. It is possible to choose epochs with or without overlap, allowing them to share a certain number of samples or not, depending on the desired configuration. In this study, we used an epoch length of 100 ms without overlap.

Before evaluating the sEMG values, a conversion is performed from the raw signal to sEMG values in Volts using the following equation, where V represents the value obtained in volts, n is the numeric value of the sEMG extracted with the MEACS system and saved with BP, G is the gain, Nb is the resolution in numbers of bits, and D is the dynamic range of the Analog-to-Digital Converter (ADC):

$$V = \frac{n}{G(2^{Nb} - 1)} D$$

To ensure consistency, the same parameters used by the AR/AV plugin for RMS evaluation are employed for the conversion. This includes a resolution of 16 bits, a gain of 192, and a dynamic range of 2.4 Volt. Furthermore, for the RMS evaluation, an epoch length of 100 ms without overlap was used to maintain consistency with the AR/AV plugin.

8.2 Real-Time Performace

As mentioned in section 4.3, a minimum update rate of 20 Hz (50 ms) was considered necessary to achieve real-time performance for the Control Interface, encompassing the processes of sEMG signal recording, transmission, translation, and visualization of the predicted hand gesture. Therefore, evaluating the real-time performance of the Interface is a crucial aspect of this study. However, in this protocol, we will focus solely on the performance of the developed Interface without considering the process of sEMG signal recording performed by the MEACs system. The main objective of this protocol is to investigate whether the Interface itself introduces any delays and to identify the specific subsections that may contribute to such delays.

8.2.1 Offline Protocol

To assess the presence of delays introduced by different subsections of the Interface, an offline approach was adopted. Pre-recorded EMG signals from a single subject, as described in Section 7.1, were utilized for evaluation. These EMG signals were the same ones used to train the neural network (NN) to generate Visual Feedback. The EMG signals were stored as a two-dimensional matrix, consisting of 32 RMS values per epoch, similar to the data format of the AR/AV Plugin. For the evaluation, we used two machines: one simulating the transmission of protocol of the MEACS amplifier through a Python script, and one running the visual interface. The latter has an intel(R) Core(TM) i7-7500U CPU @ 2.70GHz 2.90 GHz processor.
The Python routine functions similarly to an offline AR/AV Plugin, transmitting payloads containing 32-channel RMS values to the Interface via TCP/IP communication at a user-defined frequency. For this evaluation protocol, the Interface was tested with 1000 payloads sent at seven different frequencies (10 Hz, 20 Hz, 25 Hz, 30 Hz, 35 Hz, 40 Hz, and 50 Hz) to assess its performance under various data transmission speeds. Each frequency was tested seven times to extract the mean value and standard deviation error, ensuring statistical relevance.

From the Interface's perspective, the Simulink Profiler was employed to examine and analyze model and block execution, identifying potential factors contributing to simulation performance issues [3]. The Profiler captures performance data during model simulation and provides insights into the parts of the model that consume the most simulation time. After the simulation completes, a Profiler Report pane displays the simulation profile for the model, aiding in identifying areas that require optimization efforts.

The Profiler Report pane provides information for each row, as illustrated in Figure 8.2:

- **Path:** Represents the path of the Subsystem, indicating whether it is a Parent Subsystem with child functions or not.
- **Time Plot (Dark Band = Self Time):** Visualizes the Subsystem's time performance, with the dark blue section indicating the Self Time and the light blue section representing the Total Time.
- **Total Time (s):** Indicates the overall time spent on a Subsystem, including the time spent in any child functions called.
- **Self Time (s):** Represents the time spent exclusively within a function, excluding any time spent in child functions. For instance, if a function calls multiple other functions, the profiler only includes the time spent in the main function called from the profiler, disregarding the time spent in the other functions nested within it. The Self Time of

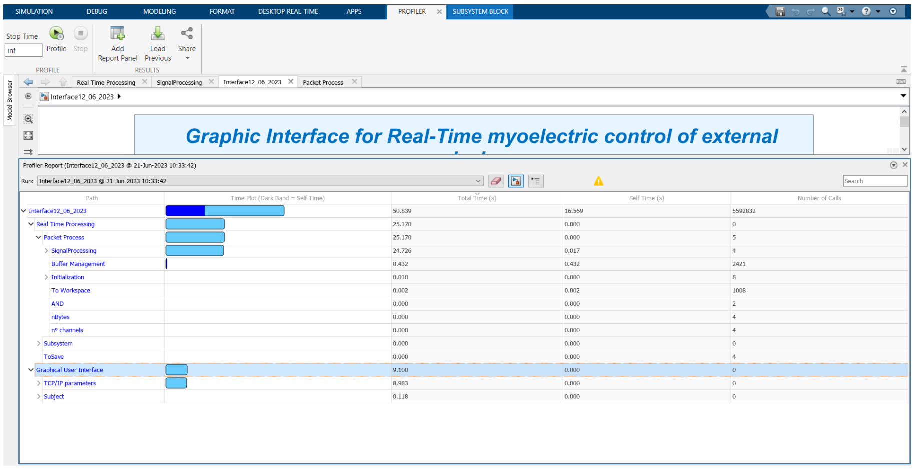

Figure 8.2. Example of a Profiler Report

the overall model excludes the time required for building the model prior to simulation, which is not considered in our evaluation.

- **Number of Calls:** Indicates the number of times the specific function is called.

8.2.2 Online Protocol

To evaluate the real-time performances of the Control System, including the MEACs system with the BP Software and the developed Interface, an online protocol was implemented. The objectives of this protocol were to assess real-time data transmission and visually evaluate the accuracy of predicted hand gestures. The protocol can be divided into three main parts.

I. Data Acquisition

During the data acquisition phase, the focus was on capturing the kinematics and muscle activations of the dominant hand and arm of a single subject. This protocol followed a similar procedure as described in Section 7.1, but with some modifications. The subject had 32 reflective markers placed on various parts of their body: 22 infrared reflective markers embedded in a disposable latex glove, and 10 markers with a larger diameter positioned on the arm, chest, and back. This setup enabled comprehensive body reconstruction and tracking using the Vicon Nexus system. Additionally, a forearm electrode array with 32 electrodes was used to capture surface electromyography (sEMG) signals. The electrode array was connected to the Sensor Unit (SU) of the MEACS system. The subject performed 18 hand movements with a single degree of freedom, as described in Section 7.1. The order of repetitions was randomized and divided into 4 sections, with each section consisting of 5 repetitions of 5 seconds for each hand movement. A 1-minute break was provided between each section.

II. Post-processing and NN training

The electromyographic and position data were post-processed using MATLAB (Release 2022b, The MathWorks, Inc., Natick, Massachusetts, USA) and VICON Nexus (VICON Nexus v2.11, Oxford Metrics plc, Oxford). The post-processing procedure for the position data involved moving average (order 20) filtering for 3D coordinates, translation from 3D position to joint angles using Inverse Kinematic Model (IKM), projection of marker positions in

3D to a 24-dimensional joint-angle space through an IKM developed by Giovanni Rolandino, subtraction of rest state (estimate of joint angles in the absence of muscle activity), normalization to ensure the signal range between 0 and 1, and linear interpolation to match the sampling rate of the post-processed electromyographic signal. The post-processing procedure for the electromyographic signal involved converting the acquired signal from level to voltage, removing signal offset, rectification (computing the absolute value), normalization (division by 5 mV) to ensure the signal range between 0 and 1, and computing the Root Mean Square (RMS) for each channel using a sliding window of 100 ms epoch length with a 25-sample window size. Once the post-processed electromyographic and position data were obtained, they were used to train the RPC-Net presented in Section 7.2.

III. Results

The trained RPC-Net, consisting of matrices of weights and biases, was imported into the developed Interface, specifically in the Neural Network (NN) subsection. Subsequently, the subject, who had been wearing the forearm electrode array with 32 electrodes throughout the entire protocol to ensure consistency in EMG signal conditions, prepared for the online evaluation. The subject was equipped only with the MEACS system, without any markers for Vicon Nexus tracking.
Finally, the Interface was launched, and the subject performed the 16 hand gestures presented in Figure 7.3. While performing the gesture, the subject observed the real-time visual feedback of the predicted hand gesture on the Interface. The objective was to contract the forearm muscles in order to match the displayed hand gesture and achieve synchronization between the visual feedback and the actual performed gesture.

Chapter 9

Instrumentation

9.1 Vicon Nexus

The Vicon Motion System [6] is a motion analysis system that utilizes a combination of infrared-sensitive optical cameras, visible-light motion-capture cameras, passive photo-reflective markers, and dedicated software (Vicon Nexus® [7]). This system enables connection, calibration, recording, and processing of motion data for various applications.
In this study, the Vicon system at the Politecnico di Torino, Turin, Italy was employed. The setup consists of 3 visible-light cameras and 12 infrared-sensitive cameras positioned to capture the subject's movements. Passive photo-reflective markers are affixed to the anatomical areas of interest, such as the arm, forearm, and hand segments. These markers facilitate the reconstruction of joint segments in three-dimensional space, enabling the extraction of kinematic parameters related to hand movement.
To ensure a comprehensive capture of hand movements, kinematic data was sampled at 100Hz. This high sampling rate allows for the precise recording of subtle details and intricate motion patterns, contributing to a comprehensive analysis of hand kinematics.
The utilization of the Vicon Nexus system in this research provides a reliable and accurate means of capturing and analyzing hand movements.

9.2 High-Density Surface EMG

The acquisition of high-density surface electromyographic activity (HD-sEMG) in this study was performed with the MEACS system, developed by LISiN - Politecnico di Torino, Turin, Italy [10]. At the core of this device is the Sensor Unit (SU), measuring approximately 30x25x15 mm, which can be connected to electrode arrays of various shapes and sizes depending on the specific requirements of the experiment.
Each SU incorporates two ports: the first port establishes a connection between the SU and an array of electrodes (EA) through 32 connection pins. The second port links the SU to a reference electrode (RE) and a pulse receiver (PR), connected in series. The pulse receiver is crucial for synchronization purposes, particularly when integrating multiple acquisition systems.
The SU performs the acquisition, processing, and transmission of 32 monopolar sEMG channels, sampled at 2048 Hz/ch with 16-bit resolution [10]. These channels are transmitted via a Wi-Fi connection to a router. Furthermore, the SU has the capability to record an additional channel dedicated to the reception of pulses. Overall, a total of 33 channels are acquired, comprising the 32 monopolar sEMG channels and the pulse channel. The acquired data, along with the received pulses, can be visualized in real-time and stored locally using

the specialized BP software developed by the LISiN Lab. BP is a versatile software tool designed for interfacing with various devices used in the acquisition of electrophysiological and biomechanical signals, as well as for neuromuscular electrical stimulation and biofeedback applications. It is compatible with multiple operating systems, including Windows, Linux, and Android [11].
The utilization of the BP software enhances the usability and flexibility of the MEACS system, enabling researchers to efficiently acquire, analyze, and interpret high-density surface electromyographic signals for a wide range of applications in the field of electromyography.

9.3 Biodex System 4

The Biodex System 4 isokinetic dynamometer is a device utilized in muscle testing and rehabilitation by medical and physiotherapy professionals. It offers a comprehensive evaluation of strength, endurance, power, and range of motion for major joints and muscles, providing precise and detailed objective data on performance. [1].
Furthermore, the Biodex System 4 is a versatile medical device used in physical medicine and rehabilitation. It serves as an evaluation tool for assessing joint functionality, not only in cases of deficits but also in sports medicine. The Biodex System 4 effectively identifies, treats, and documents physical impairments that limit functional abilities. Its applications extend to sports and orthopedic medicine, pediatric medicine, neurorehabilitation, older adult medicine, industrial medicine, and research settings where consistent, accurate, and objective data are essential [1].
Biodex Systems isokinetic dynamometers are known for providing mechanically reliable measures of torque, position, and velocity [15]. Their robust design and accurate performance make them a trusted tool for assessing and quantifying physical capabilities.
These Biodex isokinetic dynamometers play a vital role in the field of physical medicine and rehabilitation, enabling professionals to conduct comprehensive evaluations, design targeted therapies, and track progress based on objective and reliable data.

Part IV

Results

Chapter 10

Results

In this chapter, we present the results of the two evaluation protocols described in Chapter 8. Specifically, Section 10.1 presents the findings from the RMS validation protocol, while Section 10.2 presents the results of the Real-Time communication protocols.

10.1 RMS validation

In Figure 10.1, the normalized RMS values obtained from the raw EMG signals saved with BP Software ("Reference RMS normalized") are plotted in red, while the RMS values calculated by the AR/AV Plugin and saved with the Control Interface ("Control Interface RMS normalized") are shown in blue. Additionally, the green profile represents the force in Volt, measured by the Biodex System 4, providing feedback on whether the RMS values evaluated by the two different methods align with the force profile or not.

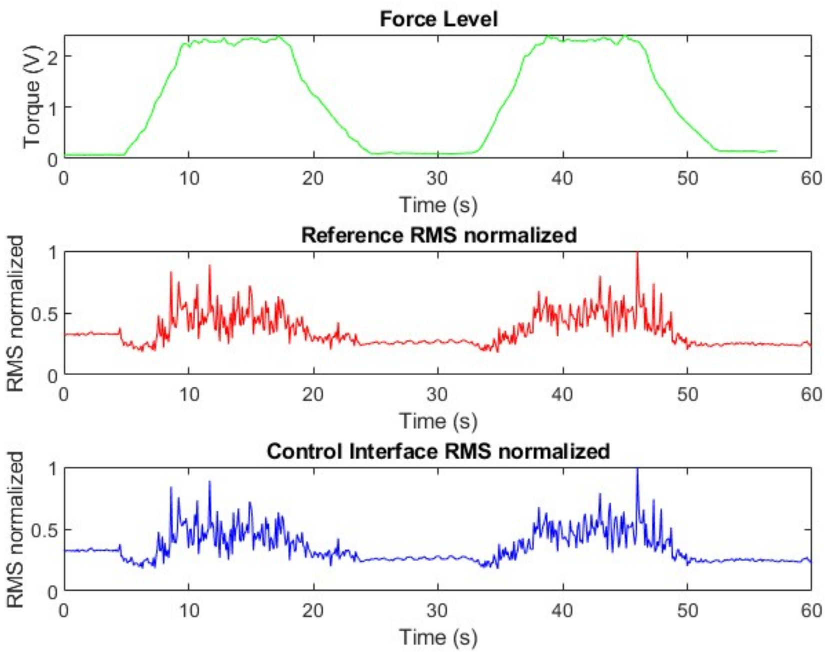

Figure 10.1. Comparison of RMS Profiles and Force Profile

From this figure, two observations can be made:

- Both RMS profiles follow the force profile. During the rest phases, the RMS profiles remain constant and close to zero, while during the Rump-up/Rump down phases and especially in the sustained contraction phases, both EMG signals exhibit interference, indicating muscular activity.

- The two RMS profiles exhibit a similar trend throughout all phases of the experiment. However, to assess their similarity more precisely, a detailed comparison is required.

To facilitate a more accurate comparison of the RMS values, a second figure was created. Figure 10.2 presents this detailed comparison, where the y-axis represents the RMS values obtained from the raw EMG signals ("Reference RMS"), and the x-axis represents the RMS values obtained from the AR/AV Plugin and reconstructed.

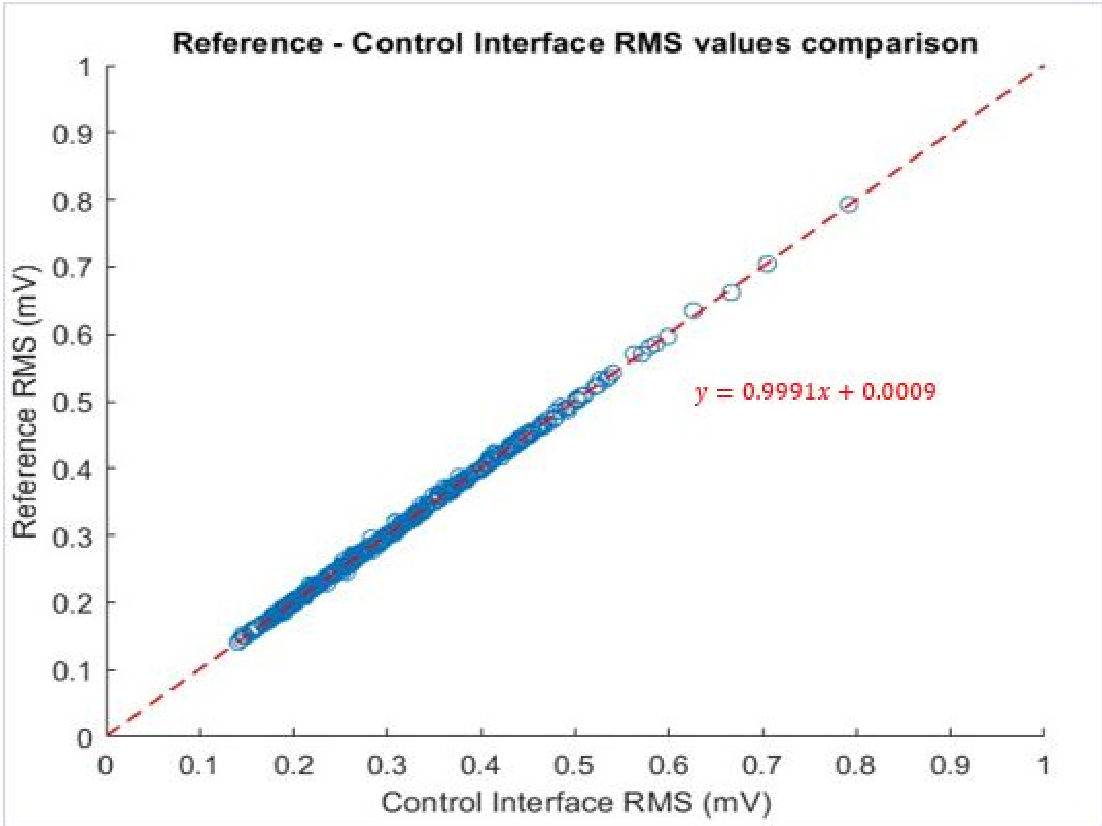

Figure 10.2. Detailed Comparison of RMS Values

Based on the findings illustrated in Figure 10.2, a strong linear correlation between the two types of RMS values is evident, with only a few minor outliers. A model II regression analysis revealed that the estimated intercept of the model was 0 ($p = 0.002$) and the estimated slope was 1 ($p < 0.001$). This indicates that there is a direct proportional relationship between the Reference RMS value and the Control Interface RMS value. These results provide strong evidence that the output of the Interface closely matches that of BP, instilling a high level of confidence in the Interface's performance.

10.2 Real-Time validation

10.2.1 Offline Protocol

To evaluate the real-time communication performance of the Interface, an offline approach was adopted, as explained in Chapter 8. Different frequencies of data transmission were tested, and the results of this protocol are illustrated in Figure 10.3. The blue bars represent the time in milliseconds (ms) required by the Interface for a single sEMG payload reception, translation, and visualization of the predicted hand gesture at seven different frequencies. The green or red boxes indicate the transmission frequencies in ms. It should be noted that in order to maintain real-time communication, the Interface must complete all these tasks before a new payload is transmitted. Therefore, for real-time communication, the blue bars should fall within the underlined boxes.

From Table 10.1, it can be observed that up to a transmission frequency of 35 Hz, the Interface does not introduce any delay. However, at 40 Hz and 50 Hz, there is a delay in the communication of approximately 2 ms and 7 ms, respectively. This delay occurs because the Interface becomes slower than the data transmission, causing the arrival of a new payload before the Interface has finished processing the previous one. It is important to note that the mentioned delays are expressed for a single payload, and during a simulation, they accumulate, potentially reaching high values. For instance, in the protocol presented at 50 Hz, the Interface introduces a delay of approximately 7 seconds (1000 payloads).

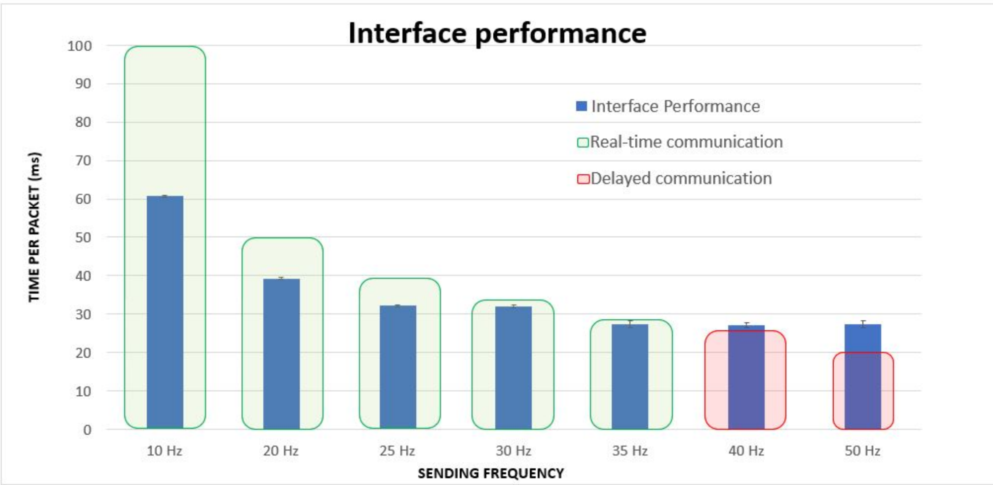

Figure 10.3. Real-time communication performance of the Interface at different frequencies of data transmission.

Once the frequencies of data transmission that guarantee real-time communication were identified, the focus shifted to the components of the model that consume the most simulation time. The following components were identified:

- **The Receiver**: Responsible for receiving data through TCP/IP communication.
- **The NN**: The Neural Network, where the Interface makes predictions.
- **The Visual Feedback**: The section responsible for providing visual feedback through 3D plots of the predicted hand gesture.

Communication frequencies	Time between 2 payload transmission	Mean of Interface time consuming	Std of Interface time consuming
10 Hz	100 ms	60,7 ms	0,25 ms
20 Hz	50 ms	39,2 ms	0,25 ms
25 Hz	40 ms	32,2 ms	0,23 ms
30 Hz	33,3 ms	32,0 ms	0,42 ms
35 Hz	28,6 ms	27,3 ms	0,83 ms
40 Hz	25 ms	27,2 ms	0,62 ms
50 Hz	20 ms	27,3 ms	0,92 ms

Table 10.1. Real-time communication performance of the Interface at different frequencies of data transmission.

Figure 10.4 presents the time consumption, in ms, of each of these components at the seven different frequencies of data transmission. As expected, the "Receiver" component is highly dependent on the data transmission frequencies, with faster receiving as the data transmission rate increases. It starts at approximately 42 ms per payload at 10 Hz and reaches approximately 3 ms per payload at 50 Hz.
On the other hand, the "NN" and "Visual Feedback" components do not exhibit a decrease in time consumption with increasing data transmission frequencies. Indeed, the "NN" component appears to become slower at higher frequencies. This indicates that the "NN" and "Visual Feedback" components are responsible for the delays in communication at high frequencies.

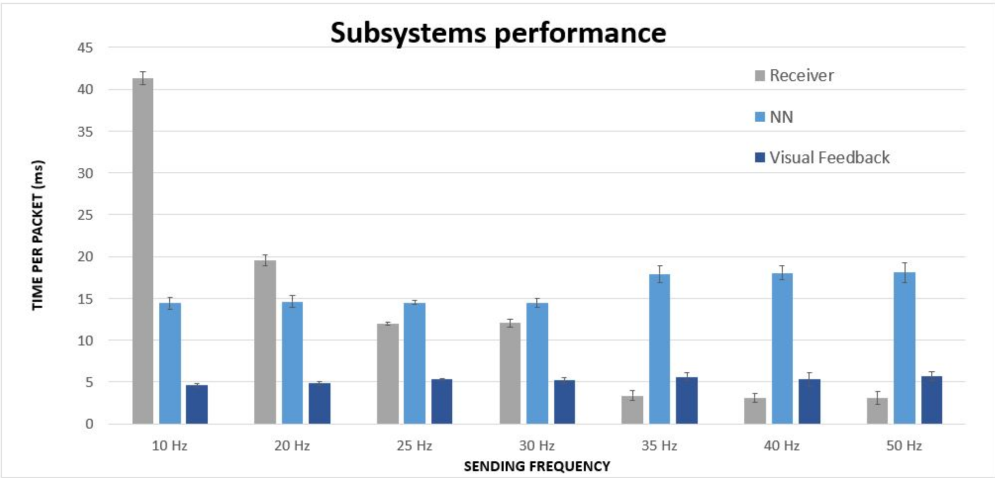

Figure 10.4. Time consumption of different components at various frequencies of data transmission.

These results provide insights into the performance of the Interface and highlight the areas that require optimization to ensure real-time communication. Addressing the delays introduced by the "NN" and "Visual Feedback.

10.2.2 Online Protocol

At the time of writing this thesis, the results of this Protocol are primarily qualitative. They indicate that real-time communication is achieved, as the Interface promptly responds to the subject's muscle contractions with corresponding modifications in the visual feedback. Additionally, the Interface accurately predicts the hand resting phases. However, it is evident that the predictions of the hand gestures are not accurate, despite the subject exerting unnatural muscle contractions in an attempt to align with the visual feedback target.

Part V

Discussion

Chapter 11

Discussion

The experimental evaluation carried out in this study provides strong evidence of the Interface's ability to accurately reconstruct RMS values of sEMG signals obtained from the MEACS system. As described in Section 10.1, there is a known offset of 10^{-6} between the RMS values, which was appropriately managed by implementing a block in the Interface to account for this offset. However, it should be noted that a few minor outliers were observed in the linear correlation between the two types of RMS values. These outliers may be attributed to the series of mathematical operations and conversions involved, such as the conversion from uint32 to uint8 and subsequent conversion to double format. Nevertheless, it is important to emphasize that these outliers do not have a significant impact as they are situated near the linear correlation line.

Furthermore, the results indicate that the Interface achieves real-time communication, encompassing the processes of sEMG signal transmission, translation, and visualization of the predicted hand gesture, up to a sending frequency of 35 Hz without introducing additional delays. However, at higher frequencies of 40 Hz and 50 Hz, the Interface starts to exhibit delays primarily attributed to the Neural Network subsystem.
The evaluation of the Interface's performance highlights the critical components that contribute to delays in communication. Specifically, the Receiver, Neural Network, and Visual Feedback subsystems are identified as key factors affecting the overall response time. The Receiver demonstrates a dependency on the data transmission frequency, while the Neural Network and Visual Feedback exhibit consistent time consumption regardless of the transmission frequency.
These findings provide valuable insights for further optimization and improvement of the Control Interface. Efforts can be directed towards optimizing the Neural Network to reduce delays experienced at higher frequencies. Additionally, exploring strategies to optimize the Visual Feedback subsystem can contribute to enhancing the overall real-time performance of the Interface.

However, it is important to consider whether further performance enhancement is necessary. Despite the challenges faced at higher frequencies, the Interface's ability to operate without introducing any delay up to 35 Hz holds significant promise for prosthetic control. As an extension of the MEACS system, the Interface's real-time performance relies on the high acquisition frequency of the MEACS system, the transmission with BP Software, and the chosen epoch length for evaluating RMS values. The proposed approach, from sEMG signal extraction to visualization of the Visual Feedback, can be completed in less than 100 milliseconds, meeting the criteria for real-time performance (latency for a visual application should be less than 100 milliseconds to be considered "real-time" for the human eye).

However, it is crucial to acknowledge that the accuracy of hand kinematics prediction, which is crucial for the Interface's performance, relies on the neural network employed. The non-stationary nature of sEMG signals, they are subject-dependent and time-dependent, pose challenges for regression-based neural network algorithms. Thus, accurate predictions of hand gestures require training the Neural Network within the Interface using the sEMG signals of the individual undergoing the interface testing on the same day. As described in Section 8.2.2, the protocol for collecting data for NN training is complex and time-consuming, and the NN predictions are not satisfying which remains a challenge.

Part VI

Conclusions

Chapter 12

Conclusions

In conclusion, this thesis presents a comprehensive investigation into the development and evaluation of a Control Interface for hand gesture recognition based on sEMG signals. The proposed Interface shows promising results and demonstrates its potential for real-time implementation.

This thesis successfully achieved its primary objective by developing a user-friendly and modular software system that extends the functionality of the MEACS system. The Control Interface allows users to easily configure TCP/IP communication parameters, choose data saving options, and modify important communication parameters related to the number of sampled sEMG channels, all without the need for coding. The experimental evaluation confirmed the effectiveness of the Interface in achieving accurate RMS reconstruction, providing satisfying results.
Furthermore, the Interface demonstrated real-time communication capabilities, successfully transmitting, translating, and visualizing the predicted hand gestures up to a sending frequency of 35 Hz without introducing any additional delays. This real-time performance holds significant promise for prosthetic control applications.

The developed Control Interface has the potential to simplify the development and testing of algorithms for prosthetic control. By providing a user-friendly interface and modular design, it allows for convenient parameter adjustments and seamless integration with existing systems.

Looking ahead, future developments can explore implementation with other programming languages, such as Python, to enhance flexibility and compatibility. A future aim is to enable parameter modification of the AR/AV Plugin directly through the developed Interface, simplifying the communication setup process and enhancing user convenience. Additionally, embedding the Interface in a microprocessor and integrating it into a socket for testing on real prosthetic devices can lead to practical applications. Furthermore, incorporating other types of feedback, such as tactile feedback, can enhance the overall control experience and user satisfaction.

In summary, the presented Control Interface, with its satisfactory results in RMS reconstruction and real-time communication, shows promise in advancing the field of prosthetic control. The potential for future developments and enhancements opens up possibilities for improving the functionality and usability of prosthetic devices, ultimately enabling individuals to control their artificial limbs based on forearm muscular activity, potentially mirroring their intentions and improving their quality of life.

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