

Master's Thesis in Biomedical Engineering

Analysis of EMG Signal Quality using Flexible
Multi-Channel Electrodes

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Abstract

Surface electromyography or sEMG is universally used as a control signal in myoelectric prosthetic hands, where muscle activation patterns are utilized to interpret the user's intended movements. However, sEMG recording quality is strongly affected by electrode-skin interface, electrode configuration and even external factors such as limb position. Traditional rigid electrode setup with limited channels may restrict spatial resolution as well as user comfort which in turn affects electrode performance. This master's thesis aims to analyze the quality of EMG signals using multi-channel flexible electrodes, with the goal of testing their suitability for prosthetic hand control. EMG recordings were gathered from 21 participants using standardized recording sessions with the flexible electrode arrays positioned according to a planned protocol. The collected signals were preprocessed to reduce noise and improve signal quality prior to analysis. Subsequently, the signal-to-noise ratio (SNR) and cross-correlation were evaluated to assess signal quality and determine the similarity between electrode channels.

Sammanfattning

Ytelektromyografi (yt-EMG) används i stor utsträckning som en styrsignal i myoelektriska proteshänder, där muskelaktiveringsmönster används för att tolka användarens avsedda rörelser. Kvaliteten på ytEMG-registreringar påverkas dock i hög grad av faktorer såsom elektrod-hud-kontakt, elektrodens konfiguration samt externa faktorer som armens position. Traditionella rigida elektrodsystem med ett begränsat antal kanaler kan begränsa både den spatiala upplösningen och användarkomforten, vilket i sin tur påverkar elektrodprestandan. Syftet med detta examensarbete är att analysera kvaliteten på EMG-signaler som registrerats med hjälp av flexibla multikanalselektroder, samt att utvärdera deras lämplighet för styrning av proteshänder. EMG-data samlades in från 21 försökspersoner genom standardiserade inspelningssessioner där de flexibla elektroder placerades enligt ett fördefinierat protokoll. De insamlade signalerna förbehandlades för att reducera brus och förbättra signalkvaliteten före analys. Därefter utvärderades signal-brusförhållandet (SNR) samt korskorrelationen för att bedöma signalkvaliteten och bestämma likheten mellan elektrodernas kanaler.

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We express our sincere gratitude to our supervisor, Nebojša Malešević for his continuous support, guidance, and help throughout the project. Finally, we want to give a special thanks to our family and friends for their encouragement throughout this project.

Authors' Contributions

The master thesis was conducted with equal collaboration between the co-authors, Nimat Shihabi, and Huda Shahin. The writing of the report, as well as the planning and execution of the testing protocol, were divided equally between the authors.

Use of Generative AI

The generative AI model ChatGPT was used for code development during the analysis phase of the sEMG data. Specifically, it assisted with the implementation of code to merge the data collected from the 21 participants. AI-generated suggestions were carefully reviewed before being incorporated into the final code. All ideas, results, discussions, and conclusions are solely those of the authors.

Abbreviations

- EMG – Electromyography
- sEMG – Surface electromyography
- CNS – Central Nervous System
- HD-sEMG – High-density surface electromyography
- SNR – Signal-to-Noise-Ratio

Contents

1	Introduction	1
1.1	Goal of the project	1
1.2	Work process	1
2	Background	3
2.1	Muscle Tissue	3
2.2	Neuromuscular Transmission	5
2.3	Excitation-Contraction Coupling	5
2.4	Neural Control of Skeletal Muscle	6
2.5	Hand Prosthetics	8
2.6	Electromyography	10
2.7	Surface EMG	10
2.8	SockEET Electrode	11
2.9	Signal Processing and Filtering	11
3	Approach and Method	13
3.1	Provided material	13
3.1.1	Electrodes	14
3.1.2	Hardware	14
3.1.3	Software	15
3.2	Framework and preparations	16
3.3	Participants	19
3.4	Acquisition setup	20
3.5	Recording protocol	21
3.6	Data Acquisition	24
3.7	Data Processing	25
3.7.1	Implementation	26
4	Result	29
4.1	Test Records	29
4.2	Comparison between different subjects	31
4.2.1	Evaluation of a subject with high signal quality . . .	31
4.2.2	Evaluation of a subject with a connected charger during recording protocol	34
5	Discussion	39
5.1	Relation to Previous Work	39
5.2	Testing issues	40

5.3	Signal to noise ratio	40
6	Conclusion	42
7	Future Improvements	43
	References	44
	Appendices	47
	Appendix A: Issues with testing	47

1 Introduction

Surface electromyography (sEMG) is widely used as a non-invasive technique to record muscle activity and serves as a control signal in myoelectric prosthetic hands. By detecting electrical potentials generated during muscle contraction, sEMG enables interpretation of the user's intended movement and facilitates multifunctional prosthetic control. Pattern-recognition-based myoelectric systems have enabled the expansion of the range of achievable movements, resulting in more dexterous and intuitive interaction [1].

Despite recent advancements, robustness and signal stability remain as major challenges in practice. The quality of sEMG recordings is heavily influenced by factors such as electrode placement, inter-electrode distance, and electrode-skin impedance. Additionally, variations in limb positions have been shown to decrease accuracy in pattern-recognition-based systems [2].

In this thesis, electromyography (EMG) signals were recorded using 24 channels arranged in double electrode grids applied to the right forearm of 21 able-bodied participants. The testing participants performed 24 different hand gestures, timed using an automated recording protocol to ensure standardized data collection across all subjects.

1.1 Goal of the project

The aim of the project is to evaluate the quality of surface electromyography signals acquired using multi-channel flexible electrode arrays, with the long-term objective of contributing to more robust and intuitive myoelectric control strategies for future hand prosthetic applications. This is achieved through quantitative analysis of signal quality using metrics such as signal-to-noise ratio (SNR) and cross-correlation.

1.2 Work process

The project was conducted in two structured phases; the experimental setup and the analytical evaluation. The first phase of the master thesis involves the preparation and optimization of the recording setup. This includes electrode choice and placement, as well as arm positioning and the determination of other external factors. The predefined protocol was finalized and then the EMG signals are collected from the participants during a standardized testing protocol. Repeatability and comparability among participants are essential

for the final evaluation.

The second phase focuses on signal processing and analysis. The recorded signals from the testing phase are filtered to remove noise and motion artifacts, followed by segmentation of the relevant data. The SNR and cross-correlation are calculated to assess the recording performance and determine the suitability of flexible electrode arrays for future prosthetic hand control applications.

2 Background

2.1 Muscle Tissue

Mammalian muscle tissue can be broadly divided into three types: skeletal, cardiac and smooth muscle [3]. The different types can be seen in Figure 1. Among these, skeletal muscle is the most relevant for voluntary movement, including the precise control of the hand, as the cardiac muscles are responsible for involuntarily pumping blood from the heart and smooth muscles are distributed within structures such as blood vessels. Muscle contraction in the human body varies according to the functional specialization of different muscle tissues. Muscle fibers are thereby divided into two main types: striated muscle fibers and smooth muscle fibers. Skeletal muscle consists of striated fibers that are under voluntary control, allowing deliberate generation of force and precise movement, such as the coordinated actions required for hand and finger motion [3],[4].

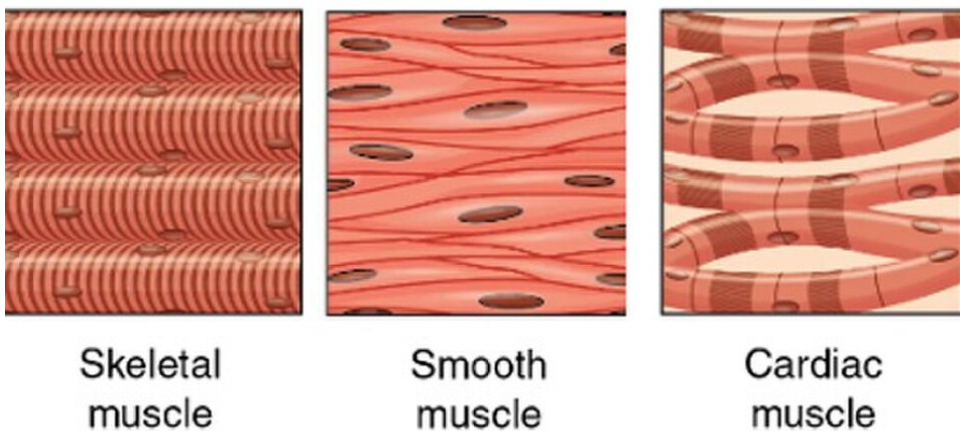


Figure 1: Comparison of the differences between skeletal, smooth, and cardiac muscle tissue. Adapted from: Nwongh, via Wikimedia Commons, licensed under CC BY-SA 4.0 [5].

To understand how striated skeletal muscle generates force, it is important to first consider its hierarchical structure. Skeletal muscle is composed of numerous elongated muscle fibers, each containing densely packed contractile elements known as myofibrils. These myofibrils consist of repeating functional units called sarcomeres, arranged along the length of the fiber. The

sarcomeres are built from intertwined thick and thin filaments [3],[4]. The structural organization of a skeletal muscle can be seen in Figure 2.

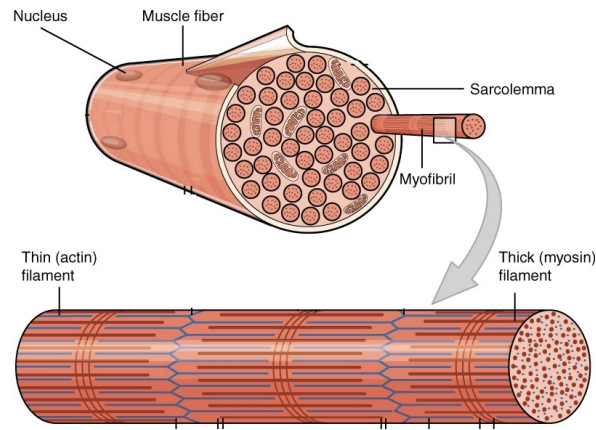


Figure 2: The Structural organization of a skeletal muscle. Modified from Anatomy and Physiology (Version 8.25), by OpenStax, 2016, via Wikimedia Commons, licensed under CC BY 4.0 [6].

The thick filaments are primarily formed by the motor protein myosin, which is responsible for force production during contraction. A myosin molecule is composed of two heavy chains that coil together to form a long structure, while each head region is associated with light chains that contribute to structural support and regulation. At the globular head of the molecule are specialized binding sites that interact with actin filaments, enabling myosin to generate movement through cyclic attachment and pulling actions [4].

The thin filaments are instead composed of actin, along with the regulatory proteins tropomyosin and troponin. Actin molecules assemble into two intertwined strands that form the structural backbone of the thin filament. Wrapped around these strands is tropomyosin, which in a resting muscle blocks the binding sites needed for interaction with myosin. Embedded within this regulatory complex is troponin, a protein assembly positioned at regular intervals along the filament. Troponin plays a key role in controlling contraction by responding to intracellular calcium signals, which initiate structural changes that allow actin and myosin to interact and produce force [4].

2.2 Neuromuscular Transmission

The initiation and execution of skeletal muscle contraction follow a sequence of coordinated physiological events. The process begins when an action potential travels along a motor neuron and reaches its terminal endings at the muscle fibers. At the neuromuscular junction, the nerve terminal releases acetylcholine (ACh), which acts locally on the membrane of the muscle fiber. This neurotransmitter binds to ACh-sensitive cation channels, causing them to open and allowing large amounts of sodium ions Na^+ to enter the muscle cell. The influx of sodium produces a local depolarization of the muscle membrane, which subsequently activates voltage-gated sodium channels and initiates an action potential within the muscle fiber [4],[7].

2.3 Excitation-Contraction Coupling

The action potential generated in the muscle fiber is initiated through a sequence of events known as excitation-contraction coupling, which links an electrical signal in the muscle fiber to mechanical force generation. The process begins when an action potential travels along the membrane of a muscle cell, causing depolarization. This electrical signal rapidly penetrates deep into the fiber through specialized membrane invaginations called transverse (T) tubules, ensuring that activation occurs throughout the entire muscle cell rather than only at its surface [4],[8].

Depolarization of T-tubules triggers voltage-sensitive receptors embedded in their membrane. This activates calcium-release channels located in the sarcoplasmic reticulum, the intracellular organelle that stores calcium ions Ca^{2+} . As these channels open, calcium is rapidly released into the cytoplasm, sharply increasing intracellular calcium concentration. This rise in calcium is the key signal that initiates contraction. Calcium binds to troponin C, one of the regulatory proteins associated with the thin filament. This binding induces a structural change in the troponin complex, which shifts tropomyosin away from its blocking position on actin. Once the myosin binding sites on actin are exposed, the thick and thin filaments can interact, allowing cross-bridge formation between myosin heads and actin [4],[8].

Contraction is then driven by the cross-bridge cycle, a repeated molecular process powered by ATP. First, ATP binds to the myosin head, causing it to detach from actin if already attached. The ATP is then hydrolyzed into ADP and inorganic phosphate, which energizes the myosin head and shifts it into a high-energy conformation. In this activated state, myosin binds to a new site

on the actin filament. The release of phosphate strengthens this attachment, and the subsequent release of ADP triggers the force generating movement in which the myosin head pivots, pulling the actin filament toward the center of the sarcomere. This sliding motion shortens the sarcomere and produces muscle contraction [4],[9].

As long as calcium remains elevated and ATP is available, this cycle continues repeatedly, generating sustained force. Relaxation occurs when calcium is actively transported back into the sarcoplasmic reticulum, lowering cytoplasmic calcium levels. Without calcium bound to troponin, tropomyosin returns to its inhibitory position, blocking the interaction between actin and myosin and bringing contraction to an end [4],[8],[9].

2.4 Neural Control of Skeletal Muscle

Neurons, commonly referred to as nerve cells, are the fundamental functional units of the nervous system that control, among other things, the voluntary movement. They are distributed throughout the human body, with a particularly high concentration in the brain and spinal cord, where they form the central nervous system (CNS) [7]. Nerves can generally be classified into two primary functional groups: sensory nerves and motor nerves. Sensory nerves transmit information from sensory receptors to the brain and spinal cord, enabling the perception of stimuli such as taste, smell and vision. In contrast, motor nerves convey signals from the CNS to muscles and glands, initiating movement and regulating physiological functions throughout the body [10].

The peripheral nervous system (PNS) carries signals from the body to the spinal cord and can be organized into two major groups of nerves: cranial nerves and spinal nerves. Cranial nerves primarily innervate structures in the head, face and neck. Spinal nerves, in contrast, arise from the spinal cord and are distributed throughout the body. These nerves provide sensory information from muscles, joints and skin to the CNS, while also transmitting motor signals that control skeletal muscle activity [11].

At the core of a nerve cell are axons, which are responsible for transmitting electrical signals over distance. Extending from nerve cells are also dendrites, branching structures that receive and transmit electrical impulses toward the cell body, as shown in Figure 4. Surrounding individual axons is a layer of connective tissue known as the endoneurium. Multiple axons that are grouped together are called fascicles, each enclosed by a protective layer

called the perineurium. Enveloping the entire nerve is the epineurium, as shown in Figure 3, [7].

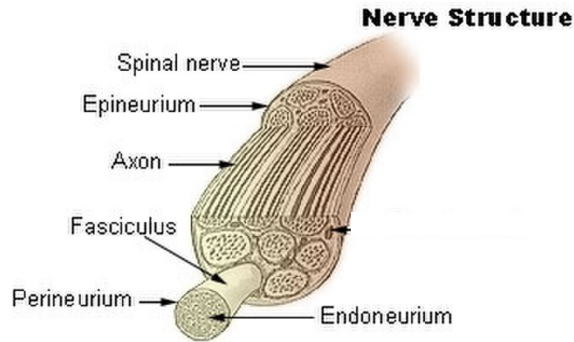


Figure 3: Illustration of peripheral nerve structure. Via Wikimedia Commons (public domain) [12].

When a nerve transmits information, an electrical impulse travels along the axon. Once the impulse reaches the terminal end of the nerve fiber, the electrical signal triggers its conversion into a chemical signal. Neurotransmitters are then released into the small gap separating adjacent cells, referred to as the synapse. These neurotransmitters diffuse across the synaptic space and bind to specific receptors located on the membrane of the next neuron or on a target cell, such as a muscle fiber. This receptor binding initiates a new electrical impulse in the receiving cell. The newly generated signal then propagates along the next neuron, and this cycle continues until the signal reaches its final target and produces the intended response [10].

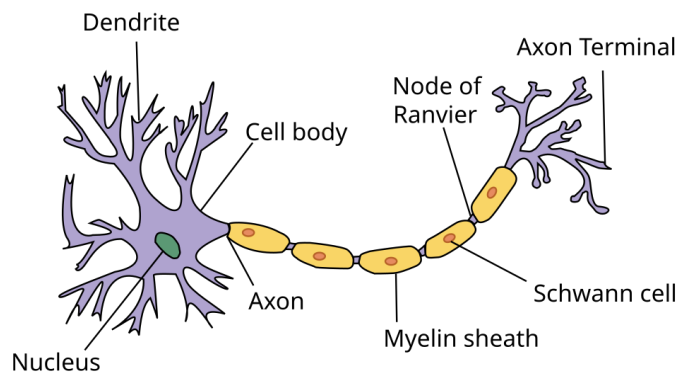


Figure 4: The Structural organization of a nerve cell. Adapted from: Nwongh, via Wikimedia Commons, licensed under CC BY-SA 4.0. [13].

Muscle fibers are innervated by motor neurons originating from the spinal cord, as illustrated in Figure 5. Each motor neuron innervates multiple muscle fibers, and together they form a structure known as a motor unit. The number of muscle fibers within a motor unit varies depending on the function of the muscle. Small muscles that require precise movements typically contain fewer muscle fibers per motor unit, whereas larger muscles responsible for generating greater force often contain many fibers per motor unit. The muscle fibers belonging to a single motor unit are not grouped together in one location. Instead, they are distributed throughout the muscle and overlap with fibers from other motor units. This arrangement enables motor units to coordinate their activity efficiently, producing smooth and controlled muscle contractions rather than isolated contractions of separate muscle segments [14].

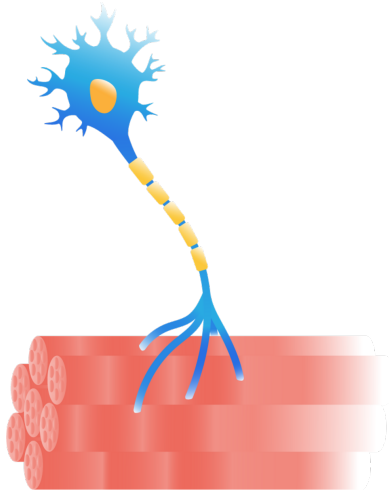


Figure 5: Illustration of a motor neuron innervating skeletal muscle fibers. Adapted from: ScholarJay, via Wikimedia Commons, licensed under CC BY-SA 4.0. [15].

2.5 Hand Prosthetics

The control of hand movement is normally performed with minimal conscious effort through a highly coordinated system of motor commands and sensory feedback exchanged between the central nervous system and the muscles [16]. More than thirty muscles contribute to hand and finger movement [17]. Many of the muscles responsible for these movements are located proximally in the forearm and connect to the hand through long tendons that

often span multiple joints and, in some cases, influence more than one finger simultaneously. As a result, even relatively simple hand actions depend on specific patterns of activation and inhibition across several muscles. The neuromuscular system becomes increasingly complex after amputation of the hand or forearm, where central motor commands and proximal neural pathways remain intact. However, the absence of the hand prevents the intended movement from being carried out [16].

Powered hand prostheses provide a means to restore grasping ability by translating user intent into mechanical movement. In myoelectric systems, this intent is inferred from sEMG signals generated by residual muscles that remain functionally connected to motor neurons after amputation. This myoelectric control strategy is widely adopted in modern prosthetic hand designs. However, despite significant technological advances, current EMG-controlled prostheses still lack the fine motor control and adaptability of a biological hand. Their functionality is often limited to relatively simple movements, such as opening and closing motions [16].

A major challenge is the difficulty of accurately interpreting sEMG signals. Although numerous computational approaches have been proposed to improve decoding performance, achieving reliable and proportional multi-degree-of-freedom control remains a significant challenge. One reason is that sEMG represents a composite signal containing overlapping electrical activity from multiple muscle units, making selective interpretation difficult. In addition, electrical signals generated by deeper muscles are attenuated as they pass through layers of biological tissue, causing muscles located closer to the skin surface to contribute more to the recorded signal than deeper muscles. sEMG recordings are also highly sensitive to motion artifacts, as relative displacement between the electrodes and the underlying muscles during movement can introduce signal distortion [16] [18].

A reliable approach for acquiring more informative EMG signals is to position electrodes in close proximity to target muscles. The development of robust multi-degree-of-freedom prosthetic controllers generally depends on access to large, well-structured datasets that reflect realistic use scenarios. Presented in this master thesis is a database of sEMG recordings collected from subjects performing basic hand movements together with a range of frequently used hand gestures [16].

2.6 Electromyography

EMG is a technique used to assess the electrical activity of the skeletal muscles and provides insight into neuromuscular function. The recorded signals originate from motor unit action potentials generated when motor neurons activate muscle fibers. Each motor unit consists of a motor neuron and the muscle fibers it innervates, and the overall EMG signal reflects the summation of multiple such units [19]. EMG can be acquired using different measurement approaches depending on the application. Intramuscular EMG (iEMG) involves inserting needle electrodes directly into muscle tissue, allowing for highly localized recordings of individual motor unit activity. In contrast, non-invasive methods capture signals at the skin surface, allowing a wider observation of muscle activation patterns without penetrating the tissue [20].

The interpretation of EMG signals is influenced by both physiological and experimental factors. Muscle fiber composition and firing rates contribute to the characteristics of the recorded signal to name a few [21][22]. In addition, external factors such as electrode placement and measurement setup can significantly affect signal quality. Due to these dependencies, EMG signals require proper acquisition and processing to ensure a meaningful analysis. Variations in signal characteristics between subjects and recording conditions must be considered when evaluating performance or comparing results between experiments. Therefore, standardized protocols and robust signal processing methods play an important role in obtaining reliable EMG measurements [21].

2.7 Surface EMG

Surface electromyography (sEMG) signals represent the electrical activity generated by muscle fibers during contraction. These signals are detected at the skin surface and reflect the summation of multiple motor unit action potentials. As a result, sEMG signals are stochastic in nature and show variability over both time and frequency [23].

The frequency content of sEMG signals is typically concentrated within the range of approximately 10–500 Hz, with most of the signal energy located between 50 and 150 Hz [18][24]. Low-frequency disturbances can arise from movement between the electrode and skin, baseline drift, or cable motion, while high-frequency components may originate from electronic noise[18]. In addition, Power-Line Interference from surrounding electrical equipment

can affect the recordings, typically around 50 Hz. The amplitude of sEMG signals depends on several factors, including muscle contraction level, electrode placement, and skin-electrode impedance [23]. To accurately capture sEMG signals, appropriate sampling rates must be used. According to the "Nyquist frequency", the sampling frequency should be at least twice the highest frequency component of the signal. In practice, sampling rates of 1000 Hz or higher are commonly used to ensure sufficient temporal resolution and to avoid aliasing [25].

In recent years, multi-channel and high-density surface EMG (HD-sEMG) systems have been developed to improve spatial resolution and capture more detailed muscle activation patterns [26]. Unlike traditional single-channel sEMG setups, these arrays use multiple closely spaced electrodes to simultaneously record signals across a larger area of the muscle, enabling a more precise mapping of motor unit activity [27].

2.8 SockEET Electrode

Current advances in wearable bioelectronic technology have led to the development of flexible and dry multi-channel EMG electrodes designed to improve signal acquisition and eventually control of hand prosthetics. One such system is the SockEET electrode developed by Tecnia, Serbia. It is a flexible 24-channel electrode array capable of recording spatially distributed sEMG activity from the forearm without the use of conductive gels. By combining multiple recording channels, the electrode aims to capture more detailed information about muscle activation patterns, while reducing motion-related artifacts and improving electrode to skin contact stability. In this master thesis, sEMG data is collected and presented from healthy subjects performing a series of predefined hand gestures and movements using the SockEET electrode system [28].

2.9 Signal Processing and Filtering

Signal processing is an essential part of EMG analysis, as raw EMG recordings often contain both useful muscle activity and unwanted noise components. Filtering is commonly used to improve signal quality by preserving the frequency range associated with muscle activation while reducing artifacts and interference. To reduce these unwanted components, EMG signals are often processed using band-pass filters, which retain the main EMG frequency range, and notch filters, which suppress narrowband interference.

Proper filtering is therefore important to ensure that the analyzed signal more accurately represents muscle activity rather than external or measurement-related disturbances [23].

In addition to filtering, EMG signals are often segmented into shorter time observation windows to isolate specific periods of muscle activity. This allows for more detailed analysis of individual movements [21].

3 Approach and Method

This section describes the methodology used to acquire and analyze EMG signals in this study. Firstly, a description of the materials and equipment provided is introduced. The chapter then outlines the preparatory steps taken to optimize the recording setup, followed by a detailed description of the testing protocol used during data collection. Finally, the methods used for data acquisition and signal processing are presented, including the techniques applied to evaluate signal quality.

3.1 Provided material

The provided materials made it possible to perform tests on the participants. The used components are shown in Figure 6.

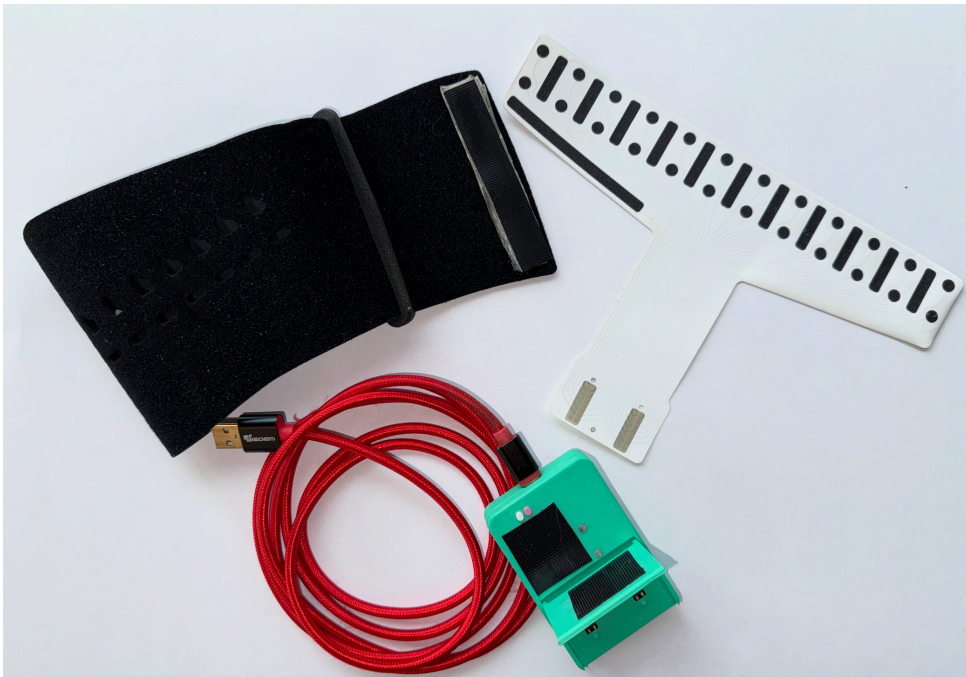


Figure 6: Provided materials with the different components used during testing protocol

3.1.1 Electrodes

The flexible SockEET electrode array consisted of 24 different electrodes fabricated using screen-printing on a stretchable thermoplastic polyurethane (TPU) with a textile-transfer substrate. The electrode structure has important characteristics such as stretchable conductive leads and insulating inks. The back side of the electrodes is covered with a thermally activated pressure adhesive layer. To help with forearm positioning for able-bodied participants, the electrodes were integrated into custom-designed bandages made of neoprene, with a Velcro layer applied on one side to ensure secure and adjustable attachment [28]. The electrode and the textile bandage can be seen together in Figure 7 below.

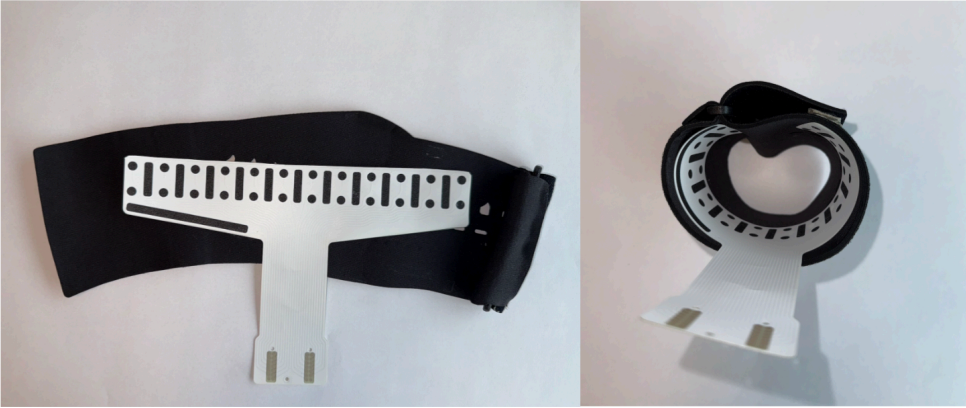


Figure 7: Stretchable SockEET electrode with printed gel integrated with textile bandage

3.1.2 Hardware

The hardware system used in this study consisted of an acquisition unit designed to interface the multi-channel electrodes with the data processing software. The recorded analog EMG signals from the 24-channel electrode array were first conditioned and converted into digital form using an analog-to-digital converter (ADC) with 24-bit resolution. The system was based on three acquisition chips (ADS1299) manufactured by Texas Instruments, USA, as shown in Figure 8. The chips are specifically designed for biopotential measurements and to allow simultaneous multi-channel recording [29]. The digital signals were then transmitted to a LabVIEW-based application developed by National Instruments, USA, where they were visualized and stored for further analysis.



(a) Data unit based on ADS1299 chips for multi-channel EMG signal recording.



(b) Electrode interface module used to connect the flexible electrode array to the acquisition system.

Figure 8: Hardware components used in the EMG amplifier.

3.1.3 Software

The custom-made software was developed in LabVIEW and served as a guide during testing protocol. The hand movements were indicated with a window showing the motion accompanied by textual commands shown in Figure 9 and 10. The movements were prompted by both visual cues in the form of a green light as well as auditory cues in the form of a short beeping sound. An increased blue force bar indicated the movement hold for the participant. Later, the bar decreased, signaling the release of movement in order to rest and prepare for the next one. Movements were indicated through changes in the displayed text and corresponding color cues. The flexion movements were identified with red, while the extension movements were identified with blue. This makes it easier for participants to differentiate movements and avoid confusion during testing protocol.

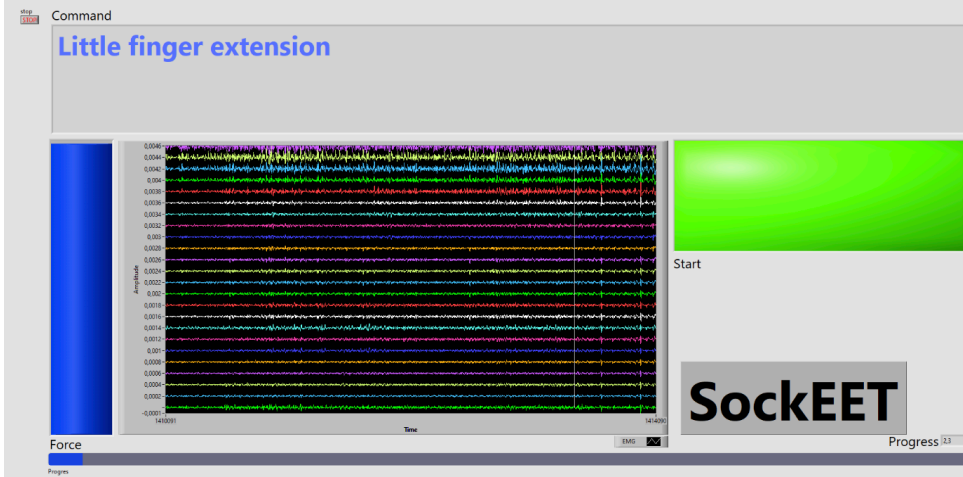


Figure 9: Real-time EMG signal visualization.

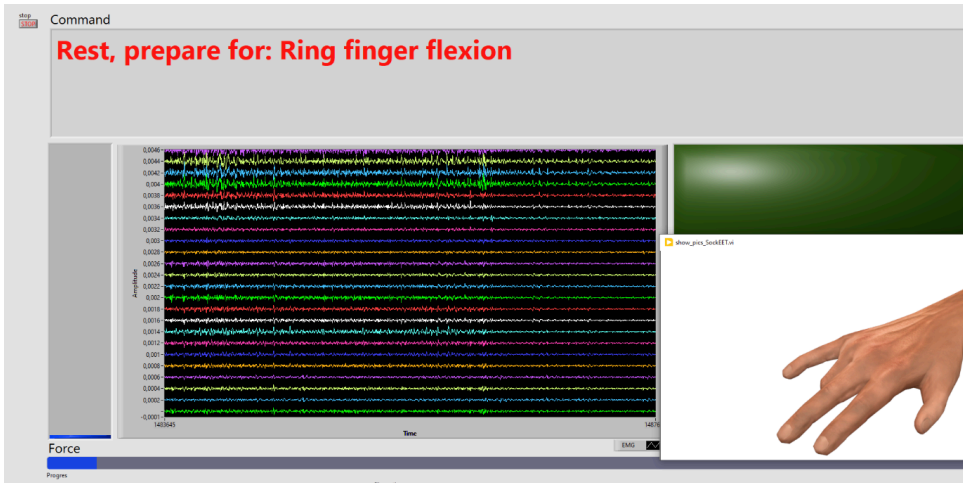


Figure 10: Real-time EMG signal visualization with a graphical cue representing the performed gesture.

3.2 Framework and preparations

Prior to the data collection phase, several preparatory steps were performed to ensure reliable and consistent EMG recordings during testing protocol. These preparations focused on optimizing electrode placement, arm positioning, and overall system performance, including cables and software.

Initial tests were conducted to determine the appropriate electrode placement

on the forearm. The electrodes were positioned over regions with high muscle activity in order to capture representative EMG signals during hand movements. Placement adjustments were made based on signal quality, ensuring that all channels provided meaningful recordings. Several full 30-minute test sessions were performed on both authors to evaluate different placement strategies before finalizing the setup for the testing protocol. During these preliminary trials, the electrode array was placed at multiple locations along the forearm, including positions closer to the wrist and closer to the elbow. In addition, lateral adjustments were made by shifting the electrodes left and right across the forearm to evaluate variations in signal quality and comfort. Placements closer to the wrist or elbow were observed to reduce signal stability and acquisition during recordings. Similarly, lateral shifts away from the central forearm region resulted in less consistent signal quality across the electrode channels. The most effective placement was found to be approximately in the middle of the forearm, where the electrode array captured strong and consistent EMG activity while maintaining a comfortable and stable position for the participant. This centrally located placement provided the best balance between signal quality, spatial coverage of active muscle groups, and finally, participant comfort, and was therefore selected for all recordings.

Secondly, to ensure consistency between participants, different arm positions and elbow angles were evaluated in order to identify a standardized setup that provided stable and repeatable EMG recordings. Several positions were tested, varying both the degree of elbow flexion and the level of support for the forearm. Based on these preliminary trials, a standardized position was selected in which the participant's elbow was flexed at approximately 90 degrees and supported on an armrest. This configuration was found to provide a comfortable posture while minimizing unnecessary movement and muscle strain during prolonged recording. The use of an armrest contributed to improved forearm stability, reduced motion artifacts, and improved consistency among participants. This was important to reduce variability between trials and improve comparability between subjects during data processing.

In addition to placement optimization, three different electrode configurations were evaluated: Stretchable electrode with printed gel (Electrode A), PET electrode combined with an external reference electrode (Electrode B) and Dry flexible electrode without gel (Electrode C). Each configuration was tested to assess the quality and stability of the signal. The stretchable electrodes with printed gel provided the most reliable recordings, as the improved electrode–skin interface resulted in lower impedance and more stable signals.

The dry electrodes showed increased variability, likely due to less consistent contact with the skin. The configuration with an external reference electrode introduced substantial noise, as the reference was not securely attached and was susceptible to movement. This made it difficult to maintain stable recordings throughout the session. Based on these observations, the stretchable electrodes with printed gel configuration (Electrode A) was selected for all measurements due to their superior signal quality and robustness.

The three types of electrode used during the preliminary testing can be seen in Figure 11 below:

- Electrode A: Stretchable electrode with printed gel, providing an improved electrode-skin interface through the use of conductive gel.
- Electrode B: PET electrode combined with an external reference electrode, where the reference electrode was attached separately from the main array.
- Electrode C: Dry flexible electrode without gel, relying solely on direct contact between the electrode surface and the skin.

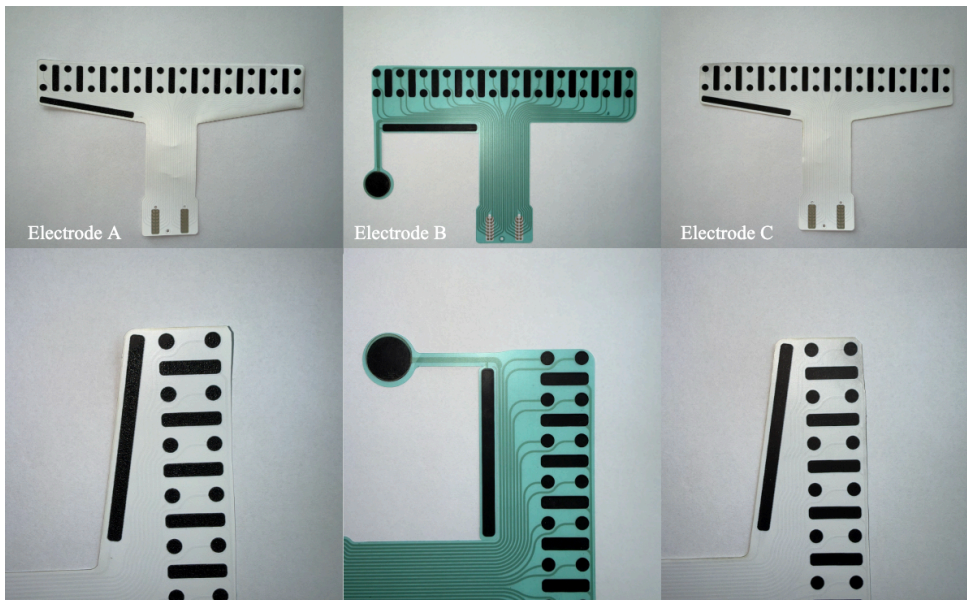


Figure 11: Comparison of electrode configurations tested during the preparatory phase, as well as close ups of the electrodes on each respective configuration.

Prior to each recording session, the EMG signals were monitored in real time to assess the quality of the electrode-skin interface. Channels exhibiting excessive noise, unstable baselines, or high-amplitude spikes were identified, and the cause was corrected. In such cases, the electrode placement was adjusted or the bandage securing the electrodes was tightened to improve contact. The preliminary test recordings were also performed to verify the functionality of the full measurement system, including updates to the software interface. These trial runs therefore allowed for correction of potential issues and the improvement of the recording signals before the actual data collection began.

3.3 Participants

The testing protocol was conducted by 21 able-bodied volunteers of which 14 identified themselves as females and 7 identified as males. The participants had ages between 19 and 49 years which resulted in a mean age of 26 years old. All subjects were right-handed and neurologically intact, the results are shown in Table 1. Before the testing sessions, participants were provided with the informed consent form. The study was approved by the Regional Ethical Review Board in Lund, Sweden (Dnr 2017-297). To improve the electrode-skin interface, participants prepared their forearms by moisturizing the skin approximately 30 minutes prior to testing and, if necessary, shaving arm hair.

Subject	Gender	Age
1	Female	21
2	Female	19
3	Female	24
4	Female	22
5	Female	22
6	Female	25
7	Female	26
8	Female	49
9	Male	25
10	Male	21
11	Male	27
12	Female	23
13	Female	26
14	Male	24
15	Male	27
16	Male	29
17	Female	27
18	Female	35
19	Female	26
20	Male	28
21	Female	24

Table 1: Subject information including gender and age.

3.4 Acquisition setup

The acquisition setup used during the recordings is shown in Figure 12. The flexible multi-channel electrode array was secured around the participant’s forearm using a textile bandage to ensure stable contact with the skin. The EMG amplifier was attached to the setup and connected via cables to the recording system. Participants were instructed to maintain a standardized arm position, with the elbow flexed at approximately 90 degrees and supported on an armrest. This configuration was selected to provide a comfortable and stable posture while minimizing movement and reducing motion artifacts during the recordings. The consistent setup across all participants contributed to improved repeatability and reliability of the collected EMG data.



Figure 12: Electrode positioning with a 90° arm placement.

3.5 Recording protocol

At the beginning of each testing session, a brief explanation of the protocol was introduced to the participant, after which they could read and later sign the informed consent before participating. Next, the participant was shown how to place their arm to ensure both comfortable body posture and correct measurement throughout the testing protocol. Before applying the electrodes on the forearm, the participant was shown the first hand movements that would be performed during the recordings, to avoid confusion. Further, an explanation of the remaining movements was introduced to the participant. When the participant was comfortable and ready to perform the hand movements, the electrodes were placed in the middle of the forearm where the greatest amount of muscle activity was detected. The participant was then asked to perform hand movements to assess the electrode-skin contact. At this stage, it was checked if there were any EMG channels containing high noise or spikes that occurred during the muscle contractions. The presence of high-amplitude signals was usually an indicator that some of the electrodes had poor contact with the skin surface. In these cases, the elastic bandage covering the electrodes was tightened. If there were still channels with high amplitude noise, the electrode was removed and reapplied at the same position. Upon confirming that the EMG channels were not contaminated with excessive noise nor movement artifacts, the automated measurement proto-

col was started. Figure 13 below shows one of the participants undergoing the recording protocol with the entire acquisition setup, including both active and rest periods.

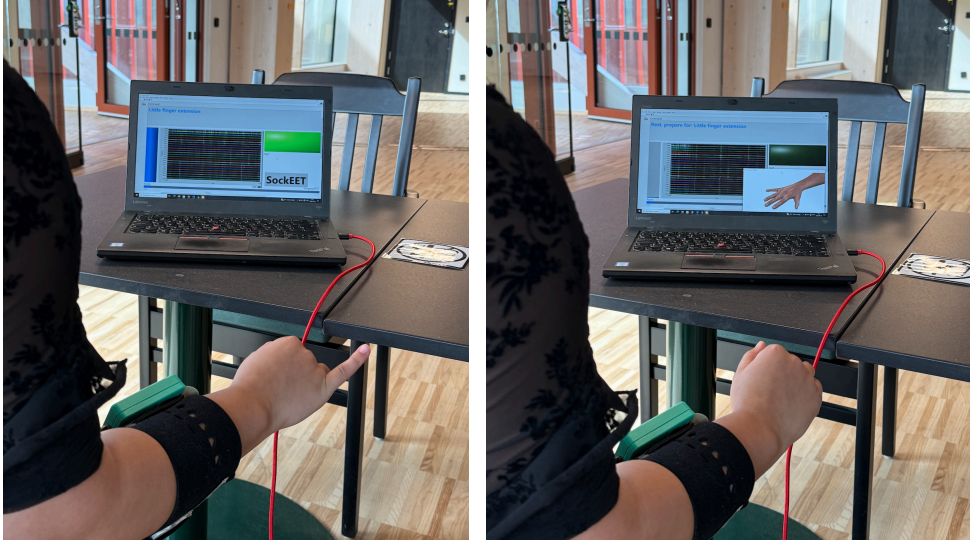


Figure 13: Acquisition setup with a 90 degree arm placement, alternating between active and rest periods.

The recording protocol consisted of 24 unique hand movements, each repeated five times, with 5-second rest periods between repetitions. The movements included flexion and extension of individual fingers, as well as compound gestures involving commonly performed movement combinations. The set of hand gestures used is shown in Figure 14, while the corresponding movement definitions are listed in Table 2.

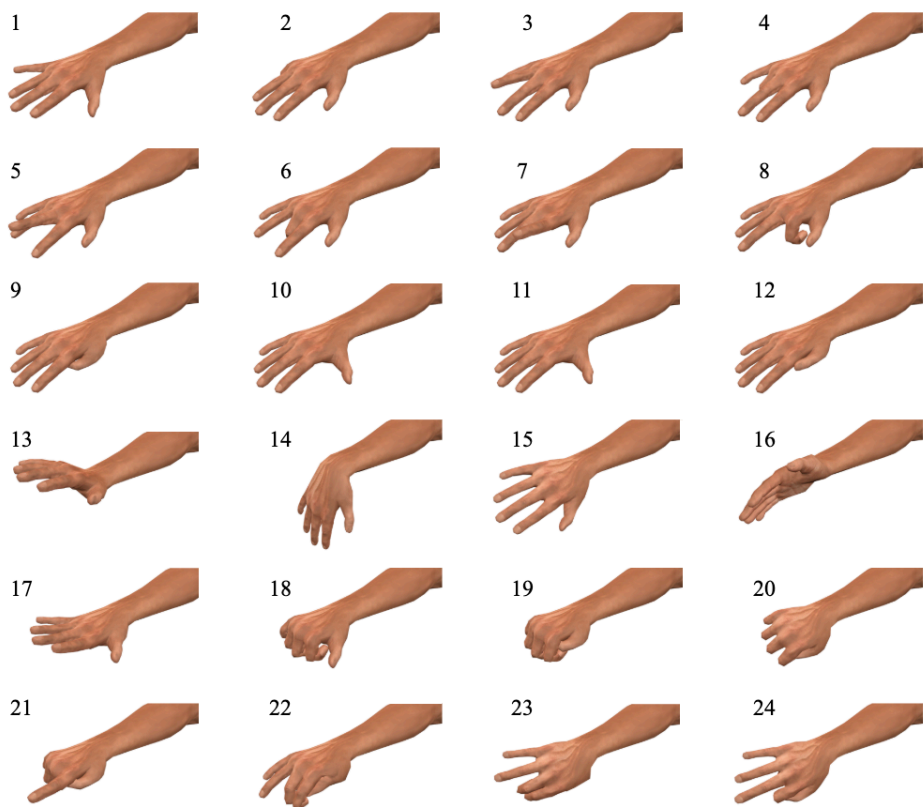


Figure 14: Set of 24 hand gestures performed by the participants during the recording protocol.

Movement Number	Movement
1	Little finger flexion
2	Little finger extension
3	Ring finger flexion
4	Ring finger extension
5	Middle finger flexion
6	Middle finger extension
7	Index finger flexion
8	Index finger extension
9	Thumb down
10	Thumb up
11	Thumb left
12	Thumb right
13	Wrist flexion
14	Wrist extension
15	Wrist rotate anti-clockwise
16	Wrist rotate clockwise
17	All fingers flexion (without thumb)
18	All fingers extension (without thumb)
19	Palmar grasp
20	Wrist rotate anti-clockwise with palmar grasp
21	Index finger extension, all fingers flexion (pointing)
22	3-digit pinch
23	3-digit pinch with wrist anti-clockwise rotation
24	Key grasp with anti-clockwise rotation

Table 2: Movement definitions.

3.6 Data Acquisition

The EMG signals were acquired using a multi-channel recording system connected to the flexible electrode array. A total of 24 channels were recorded simultaneously from the forearm during the execution of the predefined movement protocol. The recording was synchronized with the LabVIEW-based cue system, which provided visual and auditory instructions for each movement and repetition.

The signals were sampled at a fixed sampling frequency to ensure an accurate representation of the temporal dynamics of muscle activation. The ac-

quisition system provided sufficient amplitude resolution to capture the low amplitude variations characteristic of EMG signals. During recording, the signals were monitored in real time to ensure proper electrode-skin contact and to identify channels affected by excessive noise or artifacts. The acquired data consisted of raw EMG signals, which were processed and analyzed.

3.7 Data Processing

The recorded EMG signals were processed to improve signal quality and enable quantitative analysis. Due to the presence of noise and variability across the recordings, preprocessing was necessary prior to further evaluation.

Initially, raw signals were visually inspected to identify channels with excessive noise or poor electrode contact. Signals exhibiting large amplitude spikes or unstable baselines were considered to be affected by artifacts and were rerecorded with the same participant in question. If the recorded signals were visually accepted, the analysis proceeded to the next stage. To reduce unwanted signal components, filtering techniques were applied. Since the relevant EMG information is confined to a specific frequency range, filtering allows suppression of low-frequency disturbances such as motion artifacts, as well as high-frequency noise originating from electronic interference. In addition, care was taken to minimize the influence of external disturbances observed during the recordings, such as power-related interference or motion artifacts.

Following preprocessing, the continuous EMG recordings were segmented into shorter time windows corresponding to individual movement repetitions. Two segmentation approaches were considered. In the cue-based method, predefined time intervals based on the experimental protocol were used. In contrast, the best-window method selected segments with the highest signal activity, allowing a more direct representation of peak muscle activation.

To evaluate the quality of the recorded EMG signals, SNR was used as a quantitative metric. It provides a measure of how well muscle activity can be distinguished from background noise, and is defined according to equation 1.

$$SNR = 10 \log_{10} \left(\frac{P_{\text{signal}}}{P_{\text{noise}}} \right) \quad (1)$$

where P_{signal} represents the signal power and P_{noise} represents the noise power.

A higher SNR indicates better signal quality and improved detectability of muscle activation [30].

In addition to SNR, cross-correlation analysis was performed to assess the similarity between signals recorded from the electrode channels. This provided insight into the spatial characteristics of the multi-channel electrode array, where higher correlation between neighbouring channels indicates overlapping signal content, while lower correlation suggests more independent muscle activity.

Together, these processing steps enabled a structured evaluation of signal quality across channels and participants, forming the basis for the results presented in the following section.

3.7.1 Implementation

Raw EMG recordings were exported in Technical Data Management Streaming (TDMS) format and analyzed in Python within the Visual Studio Code development environment. Signal processing and analysis were performed using NumPy, SciPy, and Matplotlib libraries. The analysis pipeline consisted of data conversion, signal preprocessing, segmentation, SNR estimation, and inter-channel correlation analysis.

First, all recorded channels were extracted from the TDMS files and converted into a structured NumPy array format for efficient numerical processing. The resulting dataset consisted of 24 EMG channels and one cue channel used for experimental labeling.

Signal preprocessing was applied to reduce measurement artifacts and electrical noise interference. The sEMG signals were recorded at a sampling frequency of 1000 Hz. A second-order infinite impulse response (IIR) notch filter centered at 50 Hz with a quality factor at 30 was applied using zero-phase filtering to suppress mains interference while preserving signal characteristics. To further reduce recording artifacts, spike removal was performed using z-score thresholding. Samples exceeding ± 6 standard deviations from the channel mean were classified as outliers and replaced using linear interpolation between neighboring samples.

Following preprocessing, the cue signal was used to segment the recordings into periods of rest and steady muscle contraction. Cue values were decoded into labeled temporal segments.

For signal quality assessment, the root mean square (RMS) amplitude was

calculated using a sliding 1-second window for each EMG channel. RMS is defined according to equation 2.

$$RMS = \sqrt{\frac{1}{1000} \sum_{i=1}^{1000} x_i^2} \quad (2)$$

Where x_i is the signal amplitude at sample i and 1000 is the total number of samples in the analysis window.

Two SNR definitions were evaluated:

1. Global SNR, defined as the ratio between the maximum and minimum RMS values observed across the entire recording:

$$SNR = 20 \log_{10} \left(\frac{RMS_{\max}}{RMS_{\min}} \right) \quad (3)$$

2. Cue-based SNR, defined as the ratio between the highest RMS value during steady contraction and the lowest RMS value during rest:

$$SNR = 20 \log_{10} \left(\frac{RMS_{\text{steady},\max}}{RMS_{\text{rest},\min}} \right) \quad (4)$$

The cue-based method was used to quantify functional signal quality under experimentally controlled contraction states, whereas the global method provided an overall estimate of channel dynamic range.

Inter-channel similarity and signal overlap were evaluated by computing zero-lag cross-correlation coefficients between all EMG channels. Absolute correlation values were summarized in a 24x24 correlation matrix and visualized as a heatmap, where high correlation indicated overlapping signal content between channels.

To enable merged data record analysis, the preprocessing and feature extraction pipeline was applied independently to each of the 21 recorded sessions. All sessions were processed individually, where raw and intermediate processed data were discarded before loading the next session to reduce computational load.

For each subject, channel-wise SNR and inter-channel correlation matrices were computed per subject and then aggregated. This was done by computing the mean and standard deviation for each EMG channel. Merged SNR

estimates were obtained by averaging individual subject values, while variability was quantified using the standard deviation across subjects according to equation 5.

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (5)$$

where x_i represents the value from subject i , $\bar{x}$ is the sample mean, and N is the number of subjects.

Similarly, inter-channel correlation matrices were averaged for all channel-channel combinations across all subjects to obtain a representative correlation pattern between channels. The final results were visualized as a mean correlation heatmap.

4 Result

This section presents the results of the EMG signal analysis. Signal quality was evaluated using SNR and cross-correlation among all participants and channels. The results are first shown for the combined dataset, followed by comparisons between individual subjects to highlight variability in signal quality and electrode performance.

4.1 Test Records

The testing phase made it possible to combine the results of all 21 participants. Figure 15 below shows the average SNR for the 24 different EMG channels among the 21 participants. Overall, both of the bars, the Mean SNR best and Mean SNR cue-based, produced relatively high SNR values for all electrode channels, indicating that the recorded EMG activity could be distinguished from the background noise. The Mean SNR best generally resulted in higher SNR values than the cue-based method, especially for channels between 1 and 10. This suggests that the highest signal or lowest noise occasionally occurs outside expected periods of time, taking into consideration that the EMG is highest during cued movement and lowest during rest.

The largest difference between the two methods can be observed in the first channels, where the Mean SNR best is considerably higher but also shows larger standard deviations. This indicates that these channels sometimes captured strong muscle activity, but that the response varied substantially between the subjects. On the other hand, channels between 11 and 24 show more similar SNR values between the two methods and smaller variation, suggesting more consistent signal quality across participants.

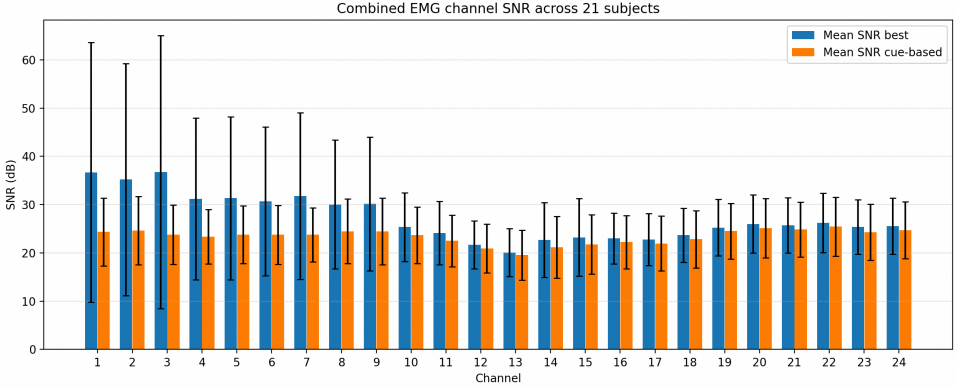


Figure 15: Combined EMG channel SNR across 21 subjects, using the best-window method and the cue-based method.

The combined median SNR was calculated to be 25.65 dB, with an interquartile range spanning 23.55 dB (Q1) to 30.84 dB (Q3). These results indicate that the majority of channels exhibited stable EMG recordings with relatively low noise levels across subjects.

Figure 16 shows the average cross-correlation between EMG channels across all participants. The diagonal values equal one, as each channel is perfectly correlated with itself. Higher correlations are mainly observed between neighbouring channels, while channels farther apart generally show lower correlations. This indicates that adjacent electrodes record overlapping muscle activity, whereas spatially separated electrodes capture more independent signal components.

Clustered regions of higher correlation are visible among neighbouring channel groups, likely reflecting the physical arrangement of the electrodes over similar muscle regions. The lower correlation between distant channels suggests that the multi-channel electrode setup captures spatial differences in muscle activation, which is beneficial for future prosthetic control applications.

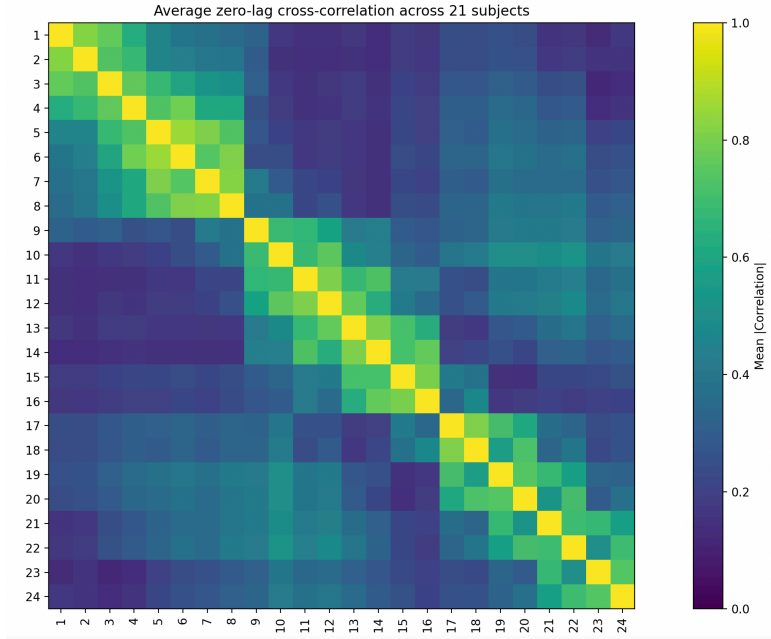


Figure 16: Average cross-correlation across 21 subjects.

4.2 Comparison between different subjects

In addition to the combined analysis across all 21 participants, the EMG signal quality was also evaluated on an individual level in order to assess variability between subjects.

4.2.1 Evaluation of a subject with high signal quality

Figures 17 - 20 illustrate multi-channel EMG recordings, SNR and cross-correlation results for a single subject with high signal quality.

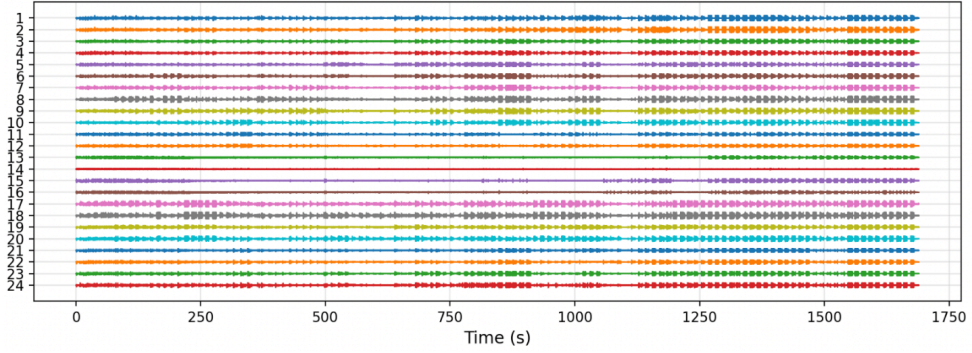


Figure 17: Multi-channel EMG recordings across 24 channels for a single subject with high signal quality.

The results show that while all 21 subjects generally exhibited high and similar SNR values across channels, the magnitude and distribution of SNR vary noticeably between individuals. Some participants demonstrate consistently higher SNR values across most channels, indicating strong and stable muscle activation combined with good electrode–skin contact, as shown in Figures 18 and 19 . In contrast, other subjects show lower or more uneven SNR distributions, suggesting reduced signal quality or less optimal recording conditions, as shown in Figures 22 and 23 . This variability can be attributed to several factors, including differences in muscle anatomy or forearm skin properties. For example, forearm hydration and the presence of arm hair may both influence the electrode–skin interface and, consequently, signal quality. Additionally, small variations in participant posture or movement execution may further contribute to these differences.

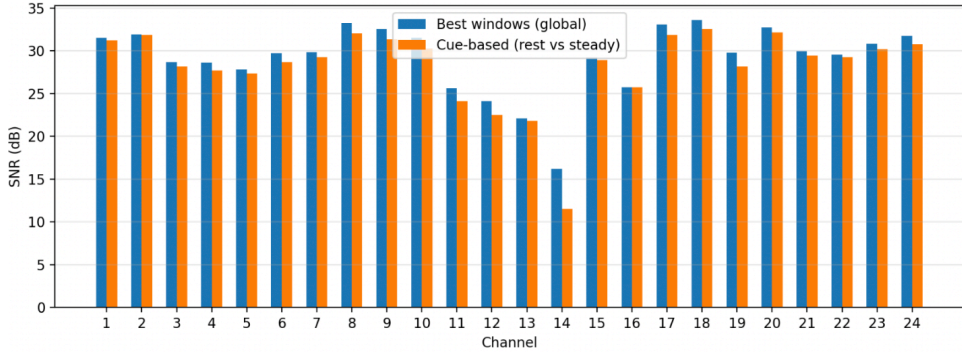


Figure 18: Comparison of SNR across all 24 channels for a single subject with high signal quality, using the best-window method and the cue-based method.

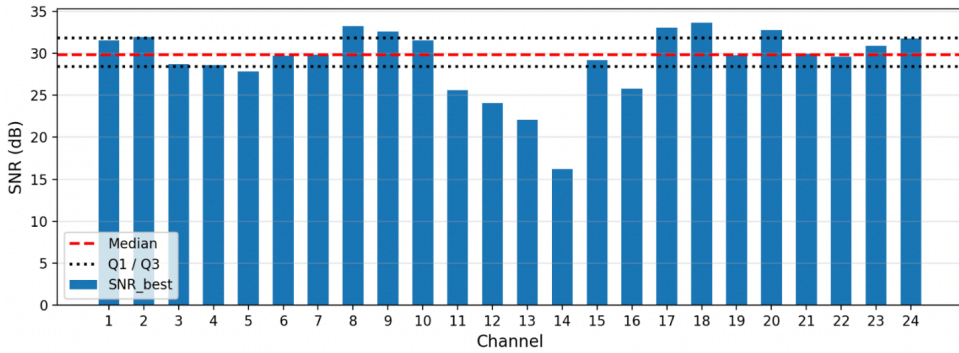


Figure 19: SNR across all 24 channels for a single subject with high signal quality, using the best-window method. The red dashed line indicates the median while the black dashed lines indicate interquartile range (Q1–Q3).

The EMG signals achieved a median SNR of 29.81 dB. The interquartile range extended from 28.41 dB (Q1) to 31.79 dB (Q3).

The cross-correlation analysis for a single subject with high signal quality is shown in Figure 20. As expected, the highest correlation values are observed along the diagonal, corresponding to each channel's correlation with itself. Elevated correlation values can be seen between neighbouring channels, indicating that adjacent electrodes capture partially overlapping muscle activity. On the other hand, channels that are further apart generally exhibit lower correlation, suggesting greater spatial separation in the recorded signals. This pattern reflects the spatial characteristics of the electrode array

and the distribution of muscle activation across the forearm. Some localized regions of higher correlation are also visible, which indicates areas where multiple channels capture activity from the same muscle group.

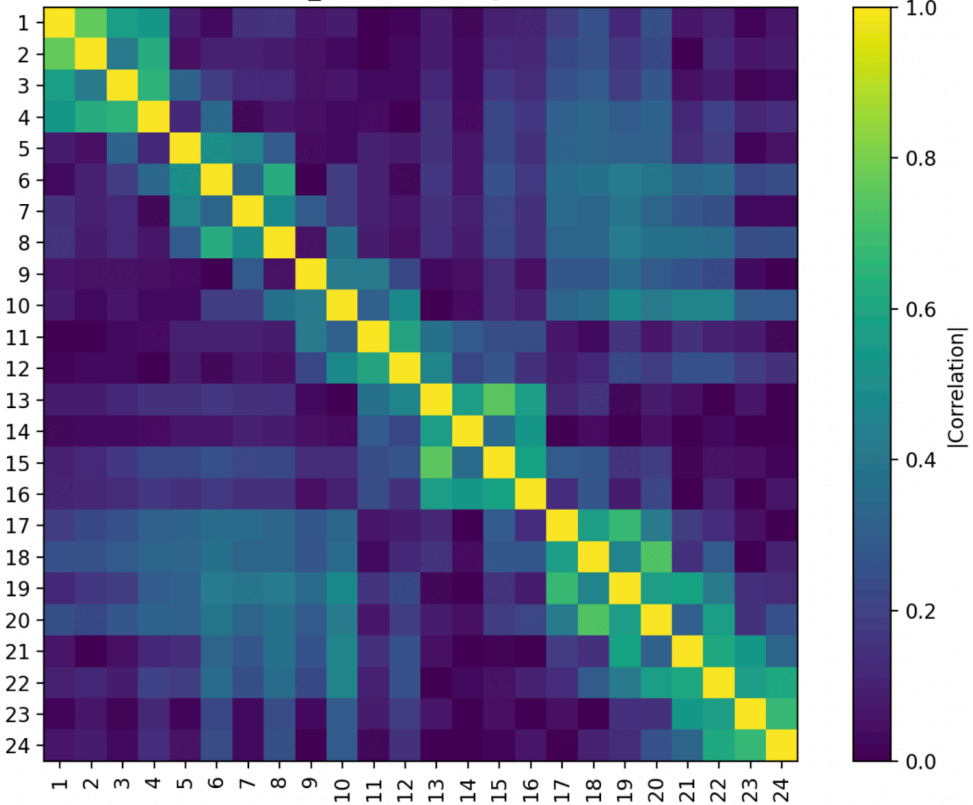


Figure 20: Cross-correlation for a single subject with high signal quality.

4.2.2 Evaluation of a subject with a connected charger during recording protocol

Figures 21 - 24 illustrate the effect of external interference on the recorded EMG signals by comparing recordings acquired with the system connected to a charger towards the end of the testing protocol. The observed difference in SNR between the two conditions appears evident in Figures 22 - 23 showing the segments during which the charger was connected during the recording protocol.

Additionally, a pronounced effect is observed in the cross-correlation patterns. When the charger is connected, the cross-correlation maps show gen-

erally higher correlation values across a larger number of channels, indicating increased similarity between signals as seen in Figure 24. In contrast, recordings obtained without the charger exhibit more distinct correlation patterns, with lower correlation between distant channels and clearer spatial separation, as observed earlier in Figure 20.

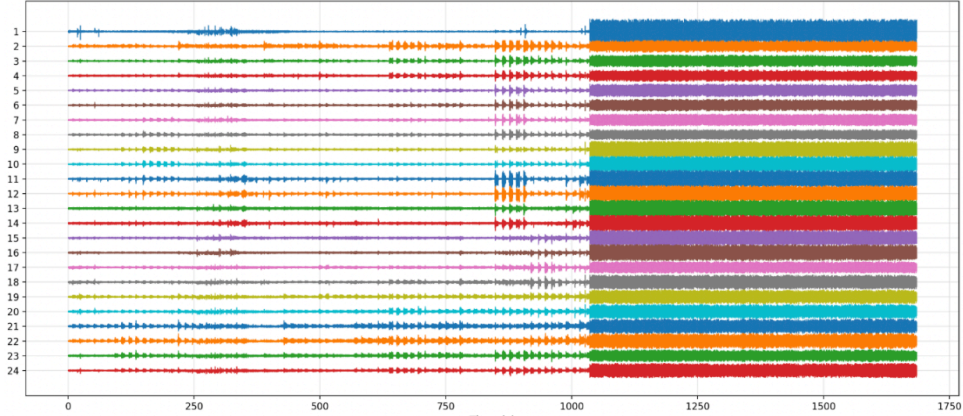


Figure 21: Multi-channel EMG recordings across 24 channels for a single subject during the recording protocol, with the charger connected from approximately 1035 seconds onward.

A comparison between the conditions shows that recordings obtained without the charger generally exhibit slightly higher SNR values and more stable distributions across channels. In contrast, recordings acquired while the charger is connected show a noticeable reduction in SNR, as shown in Figures 21 - 24.

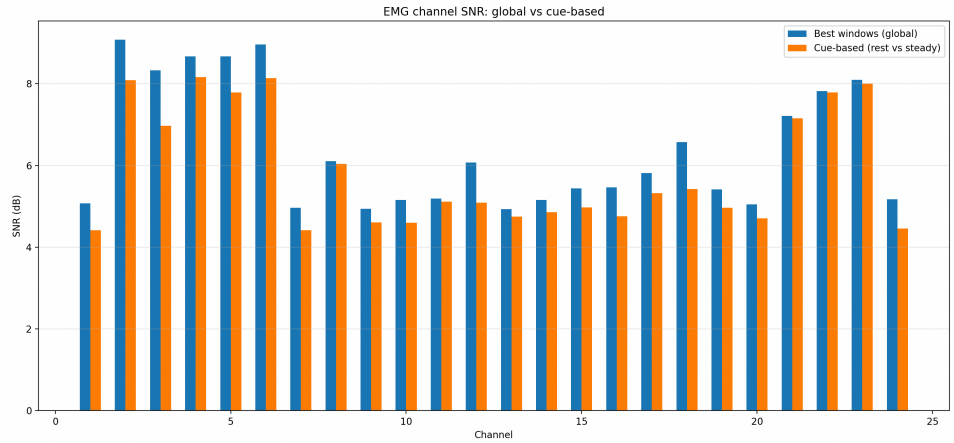


Figure 22: Comparison of SNR across all 24 channels for a single subject, using the best-window method and the cue-based method. This figure represents only the segment during which the charger was connected throughout the recording protocol, corresponding to the interval from 1035 seconds to the end of the recording.

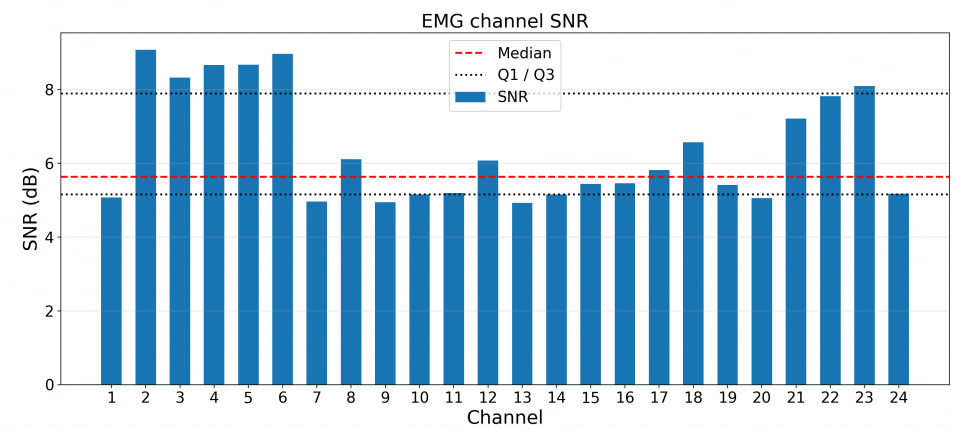


Figure 23: SNR across all 24 channels for a single subject using the best-window method. The red dashed line indicates the median while the black dashed lines indicate interquartile range (Q1–Q3). This figure represents only the segment during which the charger was connected throughout the recording protocol, corresponding to the interval from 1035 seconds to the end of the recording.

The overall SNR across the full recording exhibited a median of 28.93 dB, with an interquartile range of 27.61 dB to 30.58 dB. However, when the analysis was restricted to the segment of the recording acquired while the charger was actively connected to the computer, a significant reduction in signal quality was observed. In this interval, the median SNR decreased to 5.64 dB, with Q1 and Q3 values of 5.15 dB and 7.89 dB, respectively.

When the charger is connected, the cross-correlation maps show generally higher correlation values across a larger number of channels, indicating increased similarity between signals as seen in Figure 24. In contrast, recordings obtained without the charger exhibit more distinct correlation patterns, with lower correlation between distant channels and clearer spatial separation. This suggests that the presence of external interference affects the independence of the recorded signals, leading to increased overlap between channels and reduced spatial resolution of the EMG recordings.

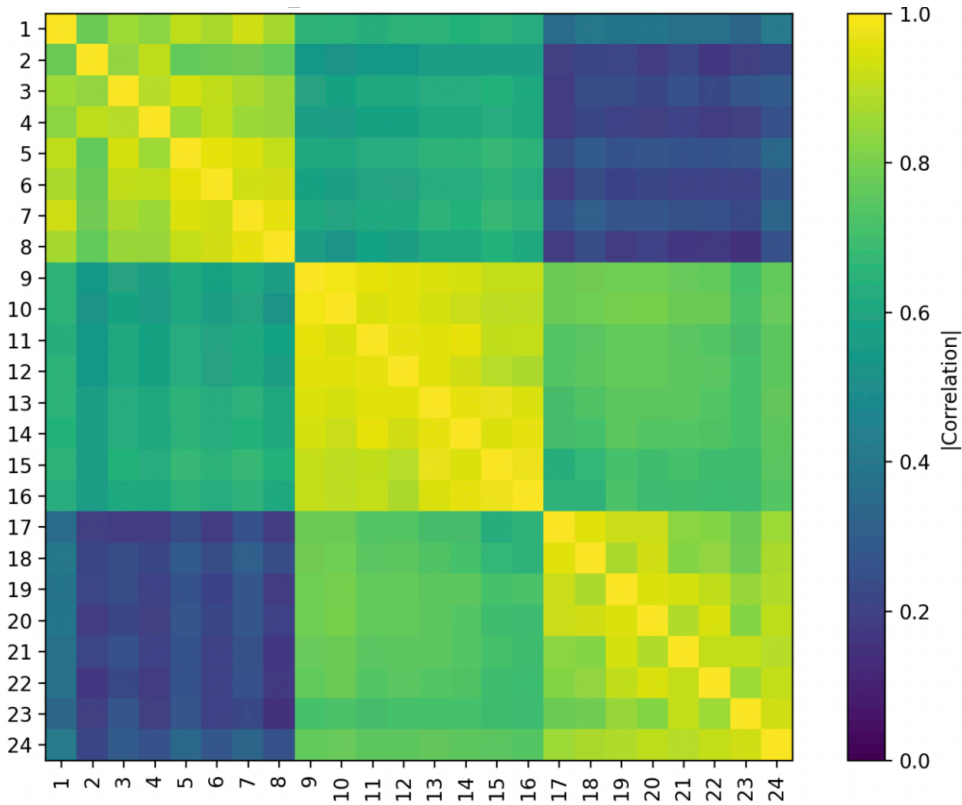


Figure 24: Cross-correlation for a single subject with a connected charger during recording protocol.

Overall, the results show that the flexible electrode array was able to record usable EMG signals across all participants. However, signal quality varied between channels, subjects, and recording conditions. The charger had a substantial effect on both SNR and cross-correlation, suggesting that external interference may reduce the spatial independence between channels.

5 Discussion

5.1 Relation to Previous Work

In order to place the findings of this study in a broader context, the results were compared with previous research on EMG signal acquisition and myoelectric control systems. Several studies have investigated the influence of electrode configuration and measurement conditions on signal quality and system performance. By comparing the observed trends in SNR and electrode stability, it is possible to assess the consistency of the present findings with established research.

The findings of this study are consistent with previous research investigating wearable EMG electrode systems for prosthetic control applications. In particular, the pilot study by Alizadeh-Meghbrazi et al. [31] emphasized that conventional gel electrodes remain the gold standard for EMG acquisition due to their low skin–electrode impedance and stable recordings. In their study, the SNR of EMG signals acquired using textile electrodes (17.4 ± 3.2 dB) was comparable to gel adhesive electrodes (17.9 ± 1.8 dB), indicating that textile interfaces can achieve reliable signal quality [31].

In comparison, the flexible multi-channel electrode arrays used in the present study produced a median SNR of 25.65 dB across all participants, with the first and third quartiles equal to 23.55 dB and 30.84 dB, respectively. This exceeds the mean values reported by Alizadeh-Meghbrazi et al. While differences in electrode design, recording setup, and participants make direct comparisons challenging, the overall trend suggests that flexible textile-integrated electrodes provide high-quality EMG recordings comparable to or exceeding previously reported textile electrode systems. These results reinforce that wearable multi-channel electrodes, when combined with stable electrode–skin contact, are capable of delivering reliable signals for myoelectric control applications.

Another relevant comparison to the present study can be found in the multi-day forearm and wrist sEMG dataset presented by Moin et al. [32]. In that study, a 16-channel forearm EMG system was used to record hand gestures for prosthetic control and gesture recognition applications. The authors reported an average SNR of approximately (14.6 ± 6.4) dB across the recorded channels. The dataset was designed to evaluate the robustness of multi-channel EMG acquisition over repeated recording sessions and realistic use conditions [32].

Several factors may contribute to the difference observed in SNR between the studies. The SockEET system utilizes a flexible multi-channel dry electrode design intended to maintain stable skin contact across the forearm surface, which may reduce motion artifacts and improve signal consistency. In addition, differences in preprocessing methods, electrode placement, recording conditions, and SNR calculation procedures may also influence the reported values.

5.2 Testing issues

Some problems were encountered during the testing protocol for some participants. The most prevalent problem was the laptop charger causing noise artifacts in the recorded signals. Another issue was the loosening of the elastic bandage during the testing, which led to reduced signal quality. It is also important to note that the cable that connects the control unit to the laptop was changed from a shorter cable to a longer one since it caused connectivity problems and increased noise artifacts.

Another issue observed during the testing sessions was related to the stability of the electrode attachment. Over time, the adhesive layer used to secure the electrodes to the skin started to delaminate, most likely due to perspiration during prolonged recordings. This reduction in adhesion negatively affected the electrode–skin interface, leading to decreased signal quality and increased variability across channels. In some cases, the conductive gel coating on the electrodes also appeared to wear off or become unevenly distributed, further degrading signal consistency. The effects on the electrode are shown in Figure A.1 in Appendix B.

To mitigate these effects, multiple copies of the gel-based electrodes were available and could be replaced when degradation in performance was observed. Without such replacement, the continued use of worn or partially detached electrodes would likely result in further deterioration of signal quality and reduced reliability of the recorded data. It is important to maintain a stable and consistent electrode-skin interface throughout the measurement process to ensure accurate comparison between the participants.

5.3 Signal to noise ratio

The higher SNR obtained with the best-window method indicates that the timing of muscle activation did not always perfectly match the cue-based recording window. This is expected, since participants may react with slight

delays or may not maintain constant contraction throughout the full movement period. Therefore, the best-window method may provide a more representative estimate of maximum signal quality, while the cue-based method gives a more realistic estimate of performance during the actual protocol timing.

The large standard deviations, especially in the early channels, suggest considerable subject-to-subject variability. This may be caused by differences in skin-electrode contact, electrode placement, or movement execution. It can also indicate that some channels may be highly informative for certain subjects but less reliable for others.

The cross-correlation results suggest that the channels are not fully redundant. Although neighbouring channels show higher similarity, the lower correlations between distant channels indicate that the flexible electrode array provides spatially diverse information. This supports the use of multi-channel electrodes for prosthetic hand control, since different channels may capture activity from different underlying muscle groups.

6 Conclusion

This study investigated the quality of sEMG signals recorded using the SockEET flexible multi-channel electrode arrays developed by Tecnia, Serbia, with the aim of assessing their suitability for prosthetic hand control applications. EMG signals were collected from 21 able-bodied participants performing a set of standardized hand movements. The signal quality was evaluated using SNR and cross-correlation analysis.

The results showed that all channels produced relatively high SNR values, indicating that the recorded EMG signals could be clearly distinguished from background noise. The best-window method consistently yielded higher SNR values compared to the cue-based method, suggesting that the timing of muscle activation does not always perfectly align with predefined recording windows. This highlights the importance of selecting appropriate analysis windows when evaluating EMG signal quality.

Furthermore, the results demonstrated variability in signal quality across both channels and subjects. Certain channels exhibited higher SNR values, indicating better electrode placement over active muscle regions, while others showed lower and more consistent values. The observed variation between subjects reflects differences in physiological factors, electrode-skin contact, and movement execution.

The cross-correlation analysis revealed that neighbouring channels tend to record more similar signals, which is expected, while channels located further apart capture more independent muscle activity. This indicates that the flexible multi-channel electrode array provides spatially diverse information, which is beneficial for applications such as prosthetic hand control where multiple degrees of freedom are required.

In conclusion, the findings of this study suggest that the SockEET flexible multi-channel electrode with printed gel is capable of capturing EMG signals with sufficient quality and spatial resolution for further use in prosthetic control systems. However, the observed variability and sensitivity to external factors highlight the need for improved electrode stability and signal processing methods to ensure robust and reliable performance in practical applications.

7 Future Improvements

Although the results of this study demonstrate that the analyzed electrode is capable of capturing EMG signals with sufficient quality, several improvements can be made to further enhance the reliability of the system.

One important improvement would be to optimize the electrode-skin interface. As observed during the testing protocol, variations in contact quality and loosening of the elastic bandage affected the signal quality. Future work could focus on improving the electrode attachment, for example by using more stable bandage or improved conductive materials to ensure consistent contact throughout the recording sessions. Another area for improvement is noise reduction. External factors, such as interference from the laptop charger, introduced artifacts in the recorded signals. Future studies should aim to minimize such interference by improving the hardware setup, for instance through better shielding, or improved grounding.

The current study was conducted on able-bodied participants under controlled conditions. To better evaluate the practical applicability of the system, future work should include testing on amputee subjects and in more realistic environments. This would provide a more accurate assessment of how the system performs in real-world prosthetic control scenarios. In addition, further analysis of the recorded dataset could be performed using advanced signal processing and machine learning techniques. While this study focused on signal quality evaluation using SNR and correlation analysis, future work could investigate classification performance and real-time control of prosthetic devices based on the recorded signals.

Finally, the electrode configuration and placement could be further optimized. Since the results showed variability across channels, future studies could explore adaptive electrode positioning or channel selection methods to identify the most informative channels for each individual user. Overall, these improvements would contribute to the development of more robust and user-friendly EMG-based control systems for prosthetic hand applications.

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Appendices

Appendix A: Issues with testing

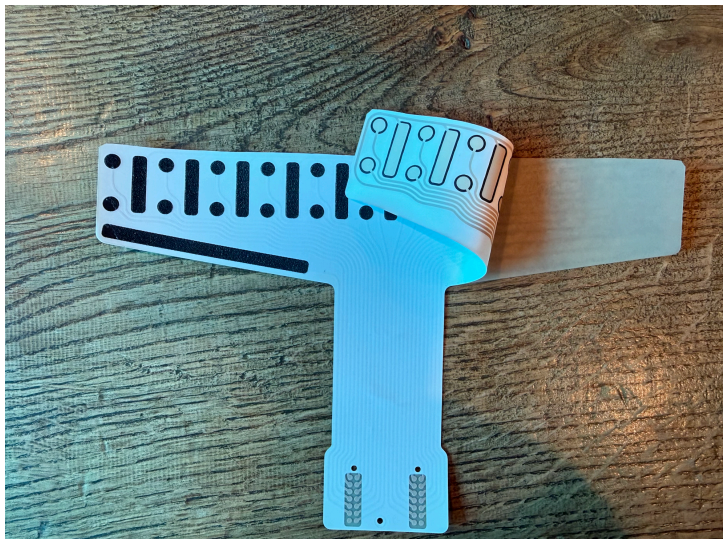


Figure A.1: Flexible multi-channel electrode array showing partial detachment of the adhesive layer after prolonged use.