Laboratory Exercise in Electromyography

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Abstract

In this report, we explore electromyography (EMG) principles, data acquisition techniques, and basic signal processing steps in the context of controlling prosthetic devices. EMG measurements were recorded under various conditions, including different wrist flexion forces, electrode orientations, and reference electrode placements. The results provide insights into how electrode configuration and muscle contraction levels affect signal characteristics. Finally, we discuss a simple processing pipeline to convert EMG signals into a usable control signal for a prosthetic arm, along with the limitations of surface EMG as a control input. These insights could develop frameworks for non-invasive, easy-to-use prostheses for hand and arm movement.

Contents

1 Introduction

Electromyography (EMG) is a technique used to evaluate and record the electrical activity of skeletal muscles. It is essentially a record of the electrical impulses generated by muscles and the motor neurons that innervate them, often visualised via a cathode ray oscilloscope (CRO) [5]. EMG can measure muscle activity using two primary electrode configurations: surface electrodes placed on the skin (metal discs) or intramuscular electrodes inserted via a hypodermic needle. In this experiment, surface electrodes were used because they are non-invasive, easy to position, and provide a sufficiently clear signal for the objectives at hand.

The basic principle of EMG is that it detects the small electrical potentials produced when muscle fibers and their corresponding motor neurons become active. When a motor neuron fires, it triggers an action potential that travels along the muscle fibers. Collectively, these action potentials form a measurable voltage fluctuation. This is what we observe and record with EMG [5]. Surface electrodes capture the aggregate electrical activity from a broader region of muscle, which is ideal for detecting overall muscle activation levels.

By examining EMG signals, we can gain insights into how muscles function under different conditions, such as varying force outputs or changes in limb position. Additionally, EMG is widely used in clinical settings to identify neuromuscular disorders, where muscle or nerve damage can alter the characteristic waveforms [4]. Beyond diagnostics, EMG has also found application in the fields of prosthetic control and rehabilitation. Processed EMG signals can serve as control inputs to drive prosthetic devices, granting individuals with limb loss or paralysis a means to manipulate robotic limbs [8]. In summary, EMG provides a window into the body's electrical signaling for muscle contraction, making it an valuable tool in both clinical diagnostics and bioengineering research.

In this laboratory exercise, we studied how changes in electrode placement and muscle contraction levels affect the amplitude and overall quality of EMG signals. We also explored a simple processing pathway to produce a usable output signal for the control of a prosthetic device.

2 Materials and Methods

2.1 Experimental Setup

- **Electrode placement:**
  - Two active electrodes (electrodes 1 and 2) placed either parallel or perpendicular to the forearm axis.

(a) Distance measurement (b) Standard setup - Forearm (c) Standard setup - Sidearm

Figure 1: Standard Experimental Setup

- One reference electrode placed on the arm, with variations including placement in the palm and between other sensors.

- **Amplifier and recording device:**
  - Reference electrode connected to the black connector.
  - Signals recorded using an EMG amplifier and appropriate data acquisition software.

- **Muscle activation protocol:**
  - Wrist flexion under different force levels, including normal flexions, prolonged flexions, and variations in flexion intensity.
  - Individual finger movements, including sequential flexion from thumb to pinky and simultaneous flexion of all fingers.
  - Comparison of different reference electrode placements to assess signal amplitude and noise effects.

2.2 Data Acquisition

- **Standard setup (parallel electrodes, reference on forearm):** Measured four wrist flexions over 7 seconds and recorded baseline noise with no movement for 7 seconds.

- **Extended flexion duration:** Recorded prolonged wrist flexion to examine sustained muscle activation.

- **Varying flexion force:** Two light flexions followed by two strong flexions to analyse amplitude differences.
- **Individual finger movement:** Sequential flexion of thumb, index, to the pinky, followed by simultaneous flexion of all five fingers.
- **Effect of reference electrode placement:**
  - Reference placed in the palm.
  - Reference placed between other electrodes but on the opposite side of the arm.
  - Reference placed between other electrodes on the same side.
- **Electrode orientation:** Perpendicular placement increased noise but reduced amplitude.
- **Electrode distance:** Shorter distance between electrodes resulted in lower amplitude compared to standard spacing.

(a) Reference electrode placed in the centre of the palm.

(b) Reference between active electrodes, on the forearm.

(c) Electrodes positioned close together for comparison.

Figure 2: Comparison of different reference electrode placements.

3 Results and Discussion

3.1 Dependence of EMG Recordings on Experimental Configuration

3.1.1 Wrist Flexion Force

Here we discuss raw data under various electrode placements and muscle contraction forces. Figure 3 plots the four flexions of consistent power, using the standard setup shown in Figure 1. As can be seen, there are four distinct spikes in the signal, indicating a clear ability to distinguish between flexion and resting action. Any signal ampltiude outside of the range 150mV and above 240 mV can be considered a motor input. We further observe a sharp peak at the $3rd$ flexion, at 2.4 seconds. This will be discussed further.

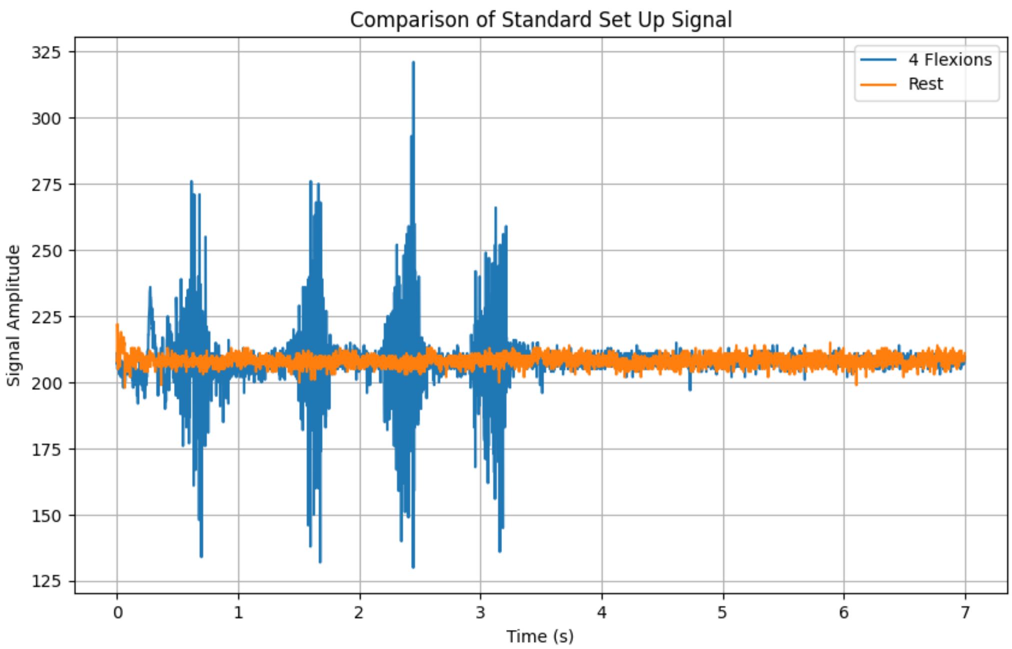

Figure 3: Four flexions

Figure 4 displays the signal of two lighter flexions followed by two stronger flexions, again plotted against the resting signal.

There are two main points to note when comparing these two figures. One point, which has already been mentioned, is that there is a distinct cut off point whereby flexions are easily detectable. The second point is that there seems to be a positive relationship between the force applied to the muscle contraction, and the size of the signal detected by the surface EMG. The later two flexions from Figure 4 show a clear increase in signal amplitude when compared to the earlier two flexions. This is supported by the literature, which states that as the force of muscle contractions increase, more motor units are recruited and firing rates rise [9].

Flexion 3 from Figure 3 and flexion 4 from Figure 4 display a sharp spike in signal amplitude. This suggests a non-linear relationship between flexion and signal amplitude. At higher force outputs, the force-signal relationship can become nonlinear [12]. Once a contraction rises above a certain threshold (outside of the range between 100 and 300 mV), the muscle recruits larger, deeper motor units, causing EMG amplitude to spike [12]. Since these spikes occurred in both 'normal' and 'stronger' contraction attempts, further investigation is needed to assess the specificity of signal detection. Additional experiments should be conducted to distinguish true signals from noise, ensuring more accurate interpretation of EMG data.

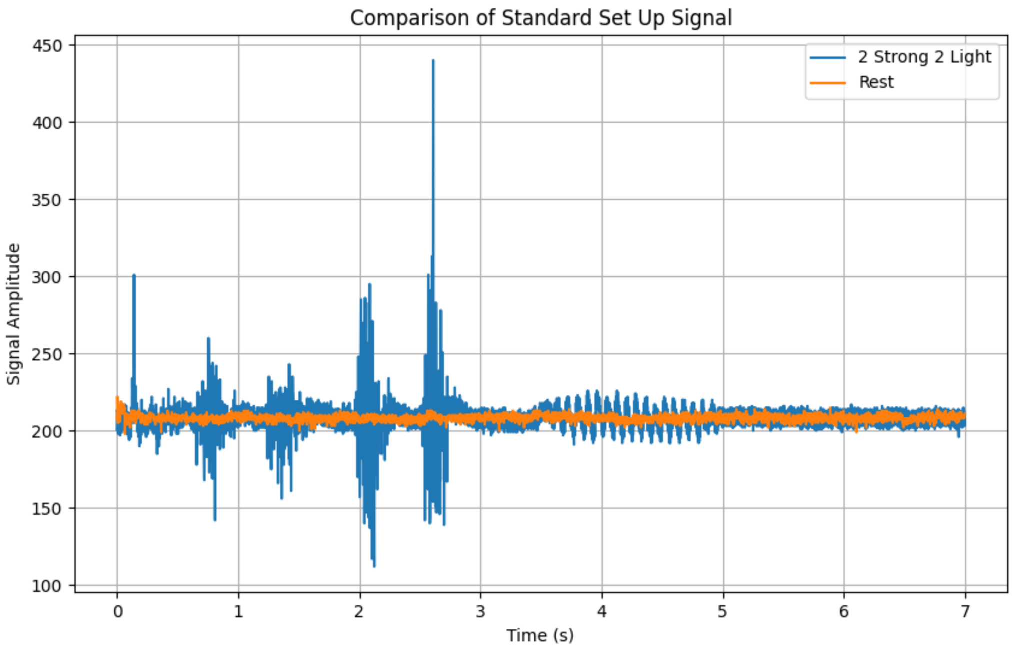

Figure 4: Two strong, two light

3.1.2 Electrode Orientation

Figure 6 and Figure 7 show the results from the perpendicular and parallel placement of the surface EMG electrodes. The parallel setup is the 'standard' considered earlier. The perpendicular setup is shown in 5.

Inspecting both figures, we can see that the resting signal of the arm is approximately 210 mV. When comparing the two figures, there are two immediate conclusions that can be drawn. One conclusion is that the amplitude of the signals produced by the flexion force are larger in the parallel electrode placement. When only considering the absolute value of the signal, discounting the nonlinear signal spikes discussed earlier, the amplitude

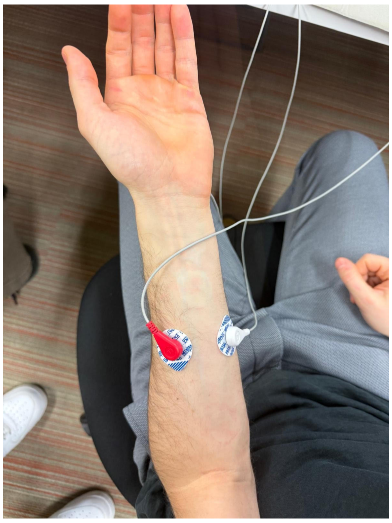

Figure 5: Perpendicular Setup

spikes at above 250 mV for the parallel electrode placement, whilst the perpendicular spikes at below roughly 240 mV. The relevant literature also supports this; electrodes placed parallel to the muscle fibres tend to capture a stronger, more coherent signal than those place perpendicular to the fibres [1]. The rationale behind this are cancellation effects. When electrodes are placed perpendicular to muscle fibres, each electrode may pick up the same muscle fibre's action potential at the same time (as they are equidistant points along the fibre). A differential amplifier, such as one use in surface EMG, will then subtract these signals, effectively cancelling out the true muscle signal [1].

The second conclusion one can draw when comparing the two signals comes from analysing the signals against the resting rate, depicted in orange. As can be seen, the perpendicular placement of electrodes results in more noise being picked up by the surface EMG. This is caused by the problem described above: as parallel placement of electrodes yields higher signal amplitudes, there is a greater signal-to-noise (SNR) ratio in perpendicular electrode placement [2]. Consequently, standard EMG guidelines recommend placing the electrodes along the longitudinal axis of the muscle.

3.1.3 Electrode Usage

In this experiment, a surface EMG was used. Surface EMG (sEMG) is a non-invasive, versatile and easy-to-use technique for monitoring muscle activity. Its ease of use and non-invasiveness were the primary reasons for its selection in this study. sEMG allows researchers to record electrical signals generated by muscle fibres during muscle contraction [2]. When muscles contract, motor neurons transmit electrical impulses that trigger action potentials in muscle fibres. These action potentials propagate along the muscle membrane and cause small voltage changes at the skin surface – it is these voltage changes that sEMG detects.

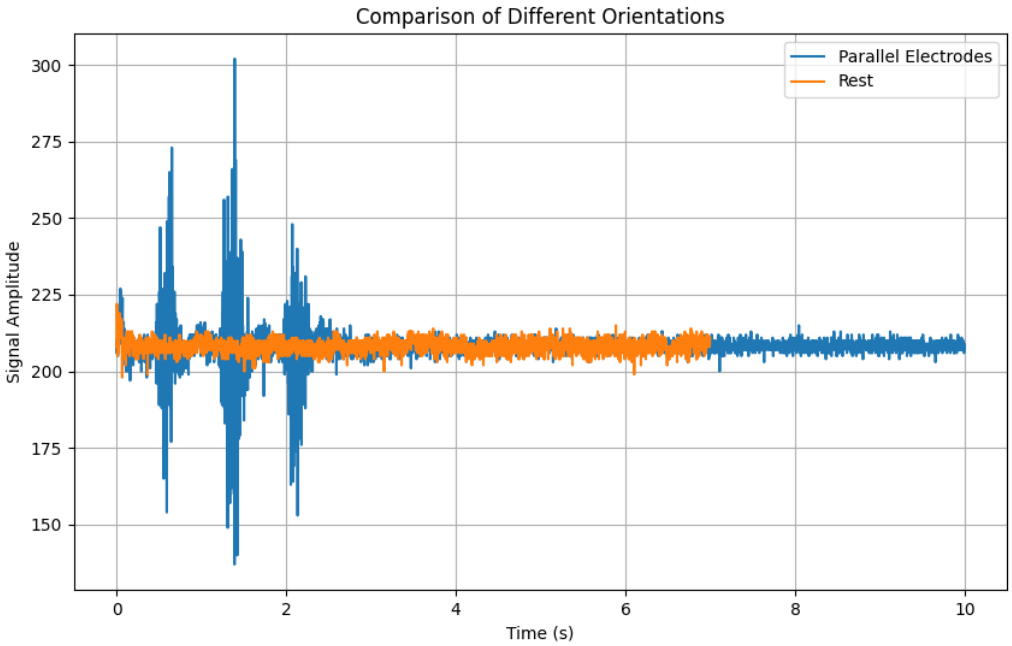

Figure 6: Parallel Orientation

Standard, disposable self-adhesive electrodes are typically Ag/AgCl bipolar surface electrodes [10]. Their design includes a conductive gel that facilitates optimal electrical contact with the skin, which is crucial for minimising impedance variability and ensuring that the recorded signals accurately reflect the underlying electrical activity [11]. In this experiment, these electrodes were chosen because they provide reliable, high-quality recordings while maintaining subject comfort. Their widespread availability and ease of application also reduce the complexity of the experimental setup, making them particularly well-suited for capturing muscle activity in real time.

3.2 Processing of EMG Recordings

3.2.1 Converting EMG to Motor Command

As can be seen throughout this report, raw EMG signals are noisy oscillatory voltages that must be processed into a smooth control output for prosthetic devices. Common real-time processing steps involve **filtering, rectification, envelope detection** and **smoothing** [6].

- **Filtering:**
  Filtering is a crucial preprocessing step in EMG signal analysis to remove noise and unwanted frequency components. According to [8], filtering techniques primarily aim to eliminate power-line interference (50/60 Hz noise), motion artifacts, and

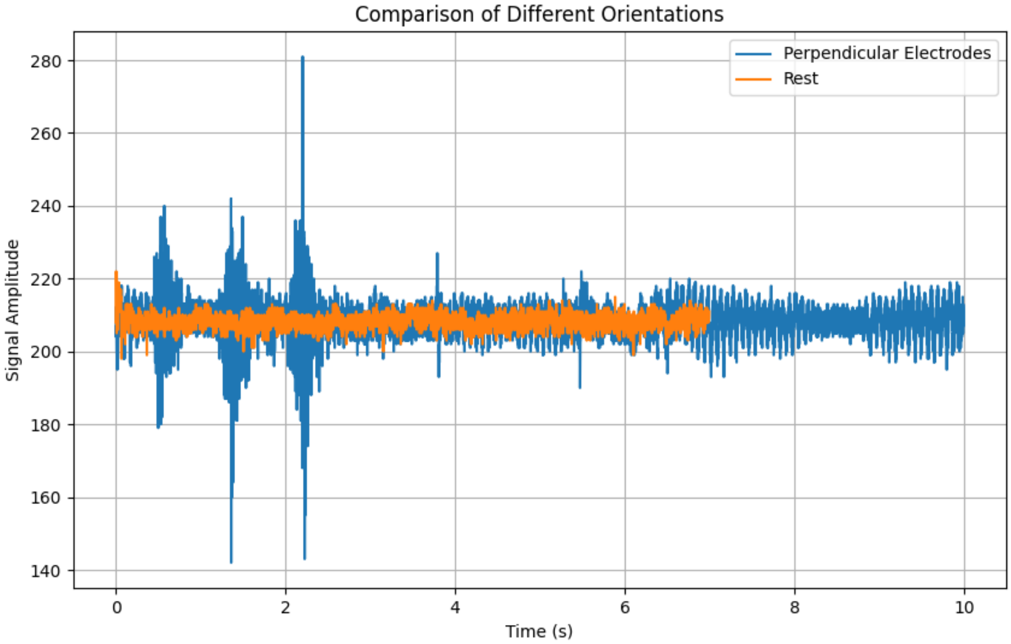

Figure 7: Perpendicular Orientation

high-frequency noise. Common filtering methods include low-pass filtering, high-pass filtering, band-pass filtering and notch filters. [8].

- **Rectification:**
  Rectification converts the EMG signal into a form suitable for further processing by ensuring that all values are positive. [8] mentions two types: Full-wave rectification, which takes the absolute value of the EMG signal, and half-wave rectification, which discards the negative values. Full-wave rectification is preferred in most applications because it preserves more information about the signal.

- **Envelope Detection:**
  The envelope of an EMG signal represents the slowly varying amplitude of the signal, which is useful for analysing muscle activation levels. [8] discusses different techniques for envelope detection. One such method is low-pass filtering the rectified signal: A common approach where a low-pass filter smooths the rectified EMG to extract the envelope.

- **Smoothing:**
  Smoothing reduces fluctuations in the EMG envelope and enhances signal clarity[8]. A simple method for smoothing is the moving average filter. This computes the average value over a sliding window.

There is an inherent trade-off in the above processing pipeline. Whilst more computational methods may extract valuable information from the signal, these result in higher latency, increasing the delay to real-time systems.

3.2.2 Processing EMG for Prosthetic Actuation

Next, we describe how to convert raw EMG data into a control signal for a prosthetic device. Figure 8 shows the EMG signal. There are six spikes in this signal. They represent each of the fingers performing a flexion (starting from the thumb and ending with the pinky) and then finally a full hand flexion.

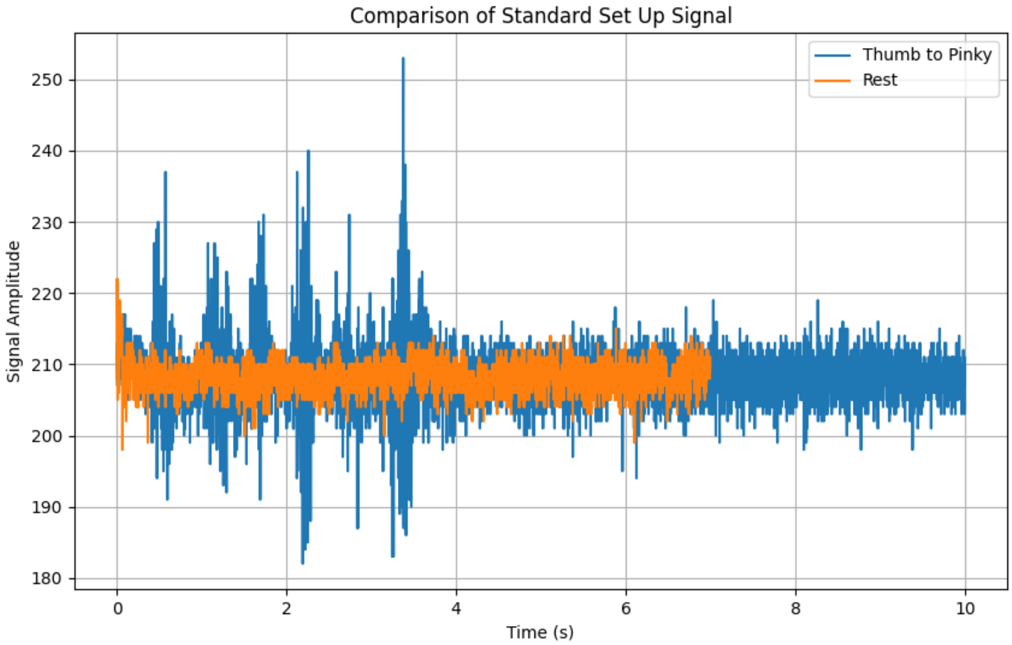

Figure 8: Individual Finger Experiments

Our method is as follows. Initially, a band-pass filter (with cut-off frequencies of 20 Hz and 450 Hz) is applied to retain only the frequency components pertinent to muscle activity, thus reducing interference from extraneous signals. Next, half-wave rectification is employed to remove negative amplitudes, ensuring maximal retention of the significant positive components. Subsequently, a low-pass filter with a 5 Hz cut-off is utilised for envelope detection, effectively smoothing the rectified signal and emphasising the amplitude modulation. Finally, a moving average filter (with a window size of 50 samples) is applied to further smooth the envelope, resulting in a stable control signal that corresponds to the observed finger flexions. Each processing step is carefully designed to diminish noise and highlight the key features of the EMG spikes, as illustrated in the noisy oscillations of Figure 8. Figure 9 demonstrates the results of this processing workflow.

There are a few points to note from our processing workflow. The activity of each individual finger is clearly differentiable, however the classification of individual finger movements is not necessarily guaranteed. Further experiments should be done to attempt

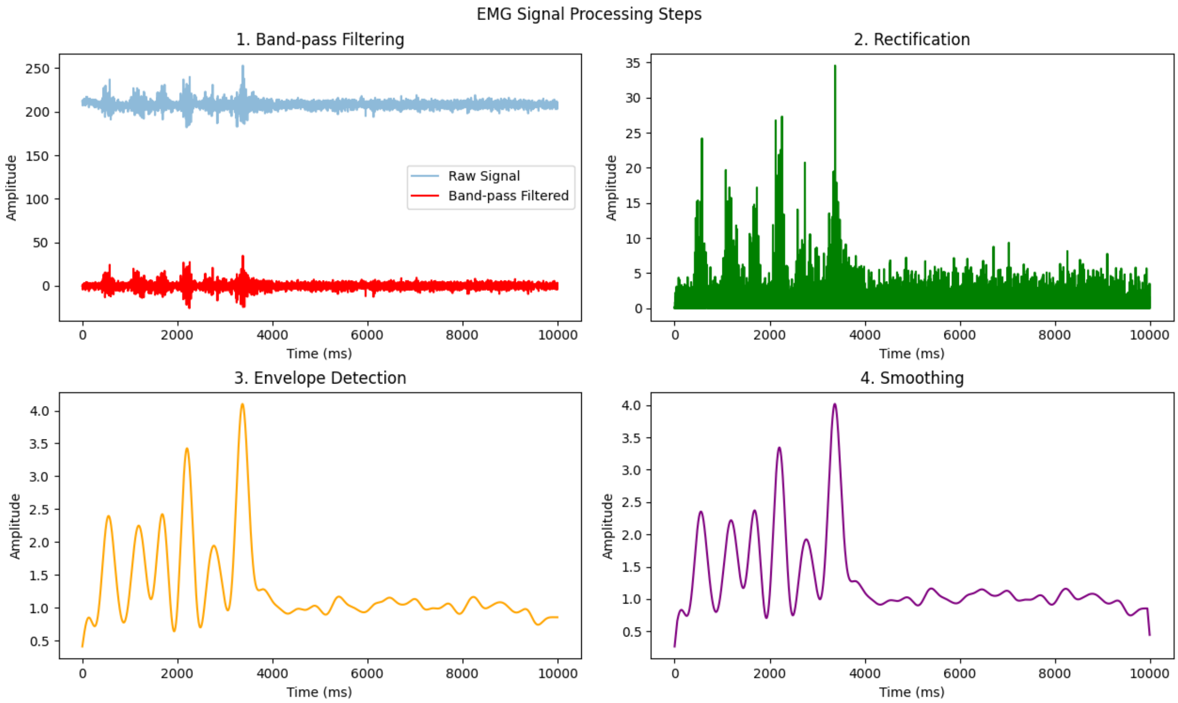

Figure 9: Processing Steps

to analyse the different signal profiles between fingers. Although this system might suffice for very basic, binary hand movements (e.g., relaxed versus clasping), it does not appear capable of capturing the full range of degrees of freedom required for the complex motions of the arm and hand.

3.3 Limitations of Surface EMG for Prostheses

There are many limitations of surface EMG for prosthetic control. Some examples are:

- **Noisiness of Readings**: Surface EMG signals have low amplitude and hence are prone to interference from external sources of noise [7]. For example, in our experiment we were told to prevent the wires connecting the electrodes from crossing and to keep relatively far away from the computer. This isn't always entirely feasible for prostheses and limits the functionality of the prospective prosthetic. The signal-to-noise ratio (SNR) can be quite low, especially for weak contractions. Hence, sEMG's inherent low SNR and high susceptibility hinder its reliable use in a controlled setting [7]. This is because spikes of noise or artifact can cause false activations and therefore unintended movements. The results described in Section 3.1.1 were only retrieved after careful experimental setup: showing the lack of robustness in some sEMG systems.

- **Nonlinear Signal Behavior:** Section 3.1.1 also illustrates how the EMG amplitude can rise sharply once a certain muscle force threshold is surpassed, reflecting the nonlinear recruitment of additional motor units. This complicates threshold-based prosthetic control strategies, as signal jumps may lead to sudden or unintended actuator responses.

- **Limited Specificity**: Standard surface electrodes detect aggregate electrical activity from a region of muscle as opposed to a singular motor unit. If adjacent muscles are active, their potentials can propagate to the recording site. This cross-talk between signals means the EMG signal is not specific to one muscle or movement [7]. This limits the number of distinct signals that can be received from the residual limb. This is a challenge when trying to control the many degrees of freedom associated with the arm and hand. As discussed in the earlier sections, EMG cannot cleanly differentiate between individual finger muscle signals due to overlapping activity. Hence, sEMG can lack the specificity needed to control a system of such high degree of freedom as the arm and hand muscles. This issue was highlighted in Section 3.1.2, whereby electrode placement greatly affected the raw signal reported. While the processing approaches in Sections 3.2.1 and 3.2.2 improve signal clarity, they do not fully resolve cross-talk nor signal specificity. As a result, it can be challenging to isolate the finer muscle activations required for precise finger or wrist movements.

- **Variation and Sensitivity to Electrode Placement**: Surface EMG readings are highly dependent on electrode positioning and contact quality. Even a slight shift in electrode placement - by as little as one centimeter - can change which motor units are predominantly recorded, significantly altering the signal amplitude and pattern [3]. Moreover, day-to-day reapplication of electrodes often leads to variability in baseline EMG levels for identical motions, as factors such as skin hydration, temperature, and changes in electrode-skin impedance come into play [3]. As can be seen in Section 3.1.2, there exists clear differences between the parallel and perpendicular placement of the electrodes. Furthermore, as can be seen in Appendix B, there is a huge amount of variation in the signal profile when considering different reference electrode positions. This lack of robustness to variation limits the functionality of using EMG as a signal for controlling hand and arm prostheses.

4 Conclusions

In this report, we examined the principles of electromyography (EMG) and its application to prosthetic control. Through a series of experiments, we demonstrated that variations in electrode placement, muscle contraction intensity, and signal processing methods significantly influence the quality and reliability of the EMG recordings. The results confirmed that standard electrode configurations yield higher signal amplitudes and lower noise compared to alternative orientations, while also highlighting a nonlinear relationship between muscle force and signal amplitude at higher contraction levels.

Our analysis indicates that while surface EMG provides a practical, non-invasive means of capturing muscle activity, it is inherently limited by factors such as low signal-to-noise ratios, cross-talk between adjacent muscles, and sensitivity to both electrode positioning and contextual conditions. The processing pipeline that was implemented consisted of band-pass filtering, rectification, envelope detection, and smoothing. This was effective in converting raw EMG signals into a stable control output for prosthetic actuation. However, the inability to distinctly differentiate individual finger movements suggests that additional refinement, possibly involving advanced signal processing or machine learning techniques, is required.

Future work should focus on mitigating the identified limitations by incorporating multi-modal inputs and developing more robust algorithms for real-time signal classification. Ultimately, these improvements will be crucial for the development of prosthetic systems capable of achieving the high degree of dexterity and natural movement required for everyday tasks.

5 Literature

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6 Compliance

Word count: (2758)
Number of figures + tables (not including Appendix): (9)

7 Appendix

7.1 Analysis Statement

For reproducibility, all data and scripts to analyse the data can be found on Github. This is available upon request.

7.2 Data Overview

CSV File	**Type of Flexion**	**Reference Position**
LongerFlexionKai_ NormalSetUp.csv	Longer Flexion	Normal Setup
NormalFlexion_ DifferentReferenceInbetweenOtherSensors.csv	Normal Flexion	Between Sensors
NormalFlexion_ DifferentReferencePalm.csv	Normal Flexion	Palm
NormalFlexion_ DifferentReferenceParallelForearm.csv	Normal Flexion	Parallel Forearm
NormalFlexion_ ParallelShortDistance.csv	Normal Flexion	Short Distance
NormalFlexion_ PerpElectrodes1.csv	Normal Flexion	Perpendicular 1
NormalFlexion_ PerpElectrodes2.csv	Normal Flexion	Perpendicular 2
NormalFlexion_ PerpElectrodes3.csv	Normal Flexion	Perpendicular 3
restKai_ normalSetUp.csv	Rest	Normal Setup
ThumbtoPinky1_ NormalSetUp.csv	Thumb to Pinky	Normal Setup
TwoLightTwoStrong_ NormalSetUp.csv	Two Light, Two Strong	Normal Setup
wristKai_ normalSetUp.csv	Wrist Motion	Normal Setup

Table 1: Summary of CSV Files, Flexion Types, and Reference Positions

7.3 Raw Signal Plots

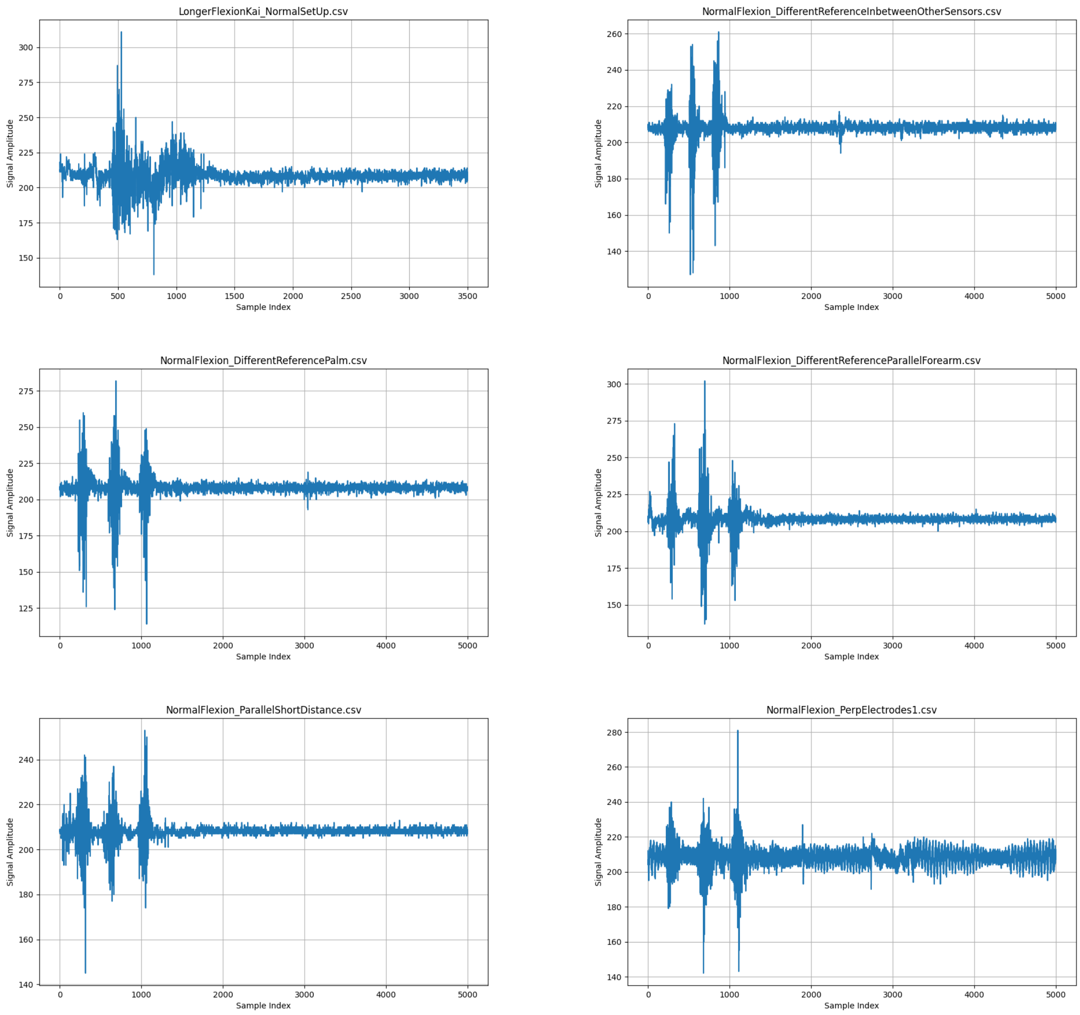

Figure 10: Comparison of Signal Plots (Page 1)

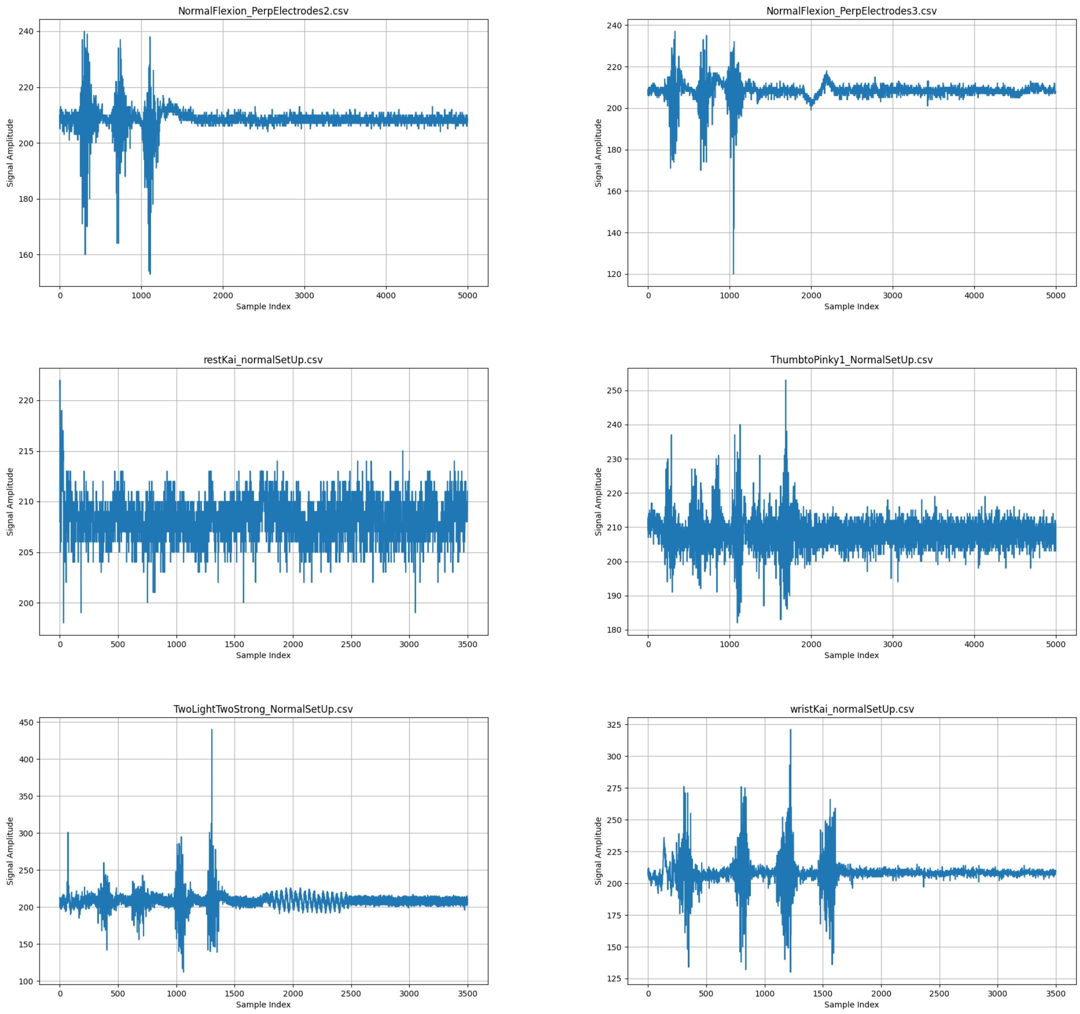

Figure 11: Comparison of Signal Plots (Page 2)