Recording and Processing of Surface Electromyogram Signal

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Abstract

This project focuses on the preprocessing and analysis of surface electromyography (sEMG) signals for the classification of purposeful hand movements. The primary objective was to develop a reliable method for processing raw sEMG data and utilizing it for movement classification tasks. Various preprocessing techniques, including bandpass and notch filtering, Z-score normalization, and feature extraction, were applied to improve signal quality and extract relevant characteristics. The features extracted from the sEMG signals were then used to train machine learning classifiers, specifically K-Nearest Neighbors (KNN) and Random Forest models. The models were evaluated based on their performance, with both achieving high accuracy and F1-scores. The results demonstrated the effectiveness of the proposed preprocessing pipeline in enhancing the performance of movement classification. The study also addressed challenges such as noise, class imbalance, and feature selection, providing solutions to improve the robustness of the analysis. This work contributes to the advancement of non-invasive methods for detecting muscle activity and holds potential applications in rehabilitation, prosthetics, and human-machine interaction.

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1 Executive and technological introduction :

1.1 sEMG : Its concept, importance and applications

Surface electromyography (sEMG) is a non-invasive technique used to record the electrical activity produced by skeletal muscles via electrodes placed on the skin. This method captures the signals generated during muscle contractions, providing valuable insights into muscle function, coordination, and fatigue. Its importance is underscored by its widespread application in diagnosing neuromuscular disorders, monitoring rehabilitation progress, and enhancing athletic performance through biofeedback. Additionally, sEMG plays a crucial role in ergonomics and human-machine interfacing, making it an indispensable tool in both clinical and research settings. [11] [4]

1.2 experimental protocol and pipeline

1. **Preparation Phase**

   The participant is first briefed on the experiment, its objectives, and the procedures. Written informed consent is obtained.

   Then, the skin areas where electrodes will be placed are cleaned using alcohol wipes to reduce impedance and ensure optimal signal quality.

   After preparing the subject, all sEMG recording devices and cables are inspected and calibrated.

2. **Electrode Placement**

   First, we identify and mark the muscles of interest (e.g., biceps brachii, quadriceps, etc.) based on standardized anatomical landmarks.

   After this, we place the electrodes on the marked sites. We need to ensure that the electrodes are securely attached and that their positioning corresponds with the guidelines for optimal signal acquisition.

3. **Baseline Recording**

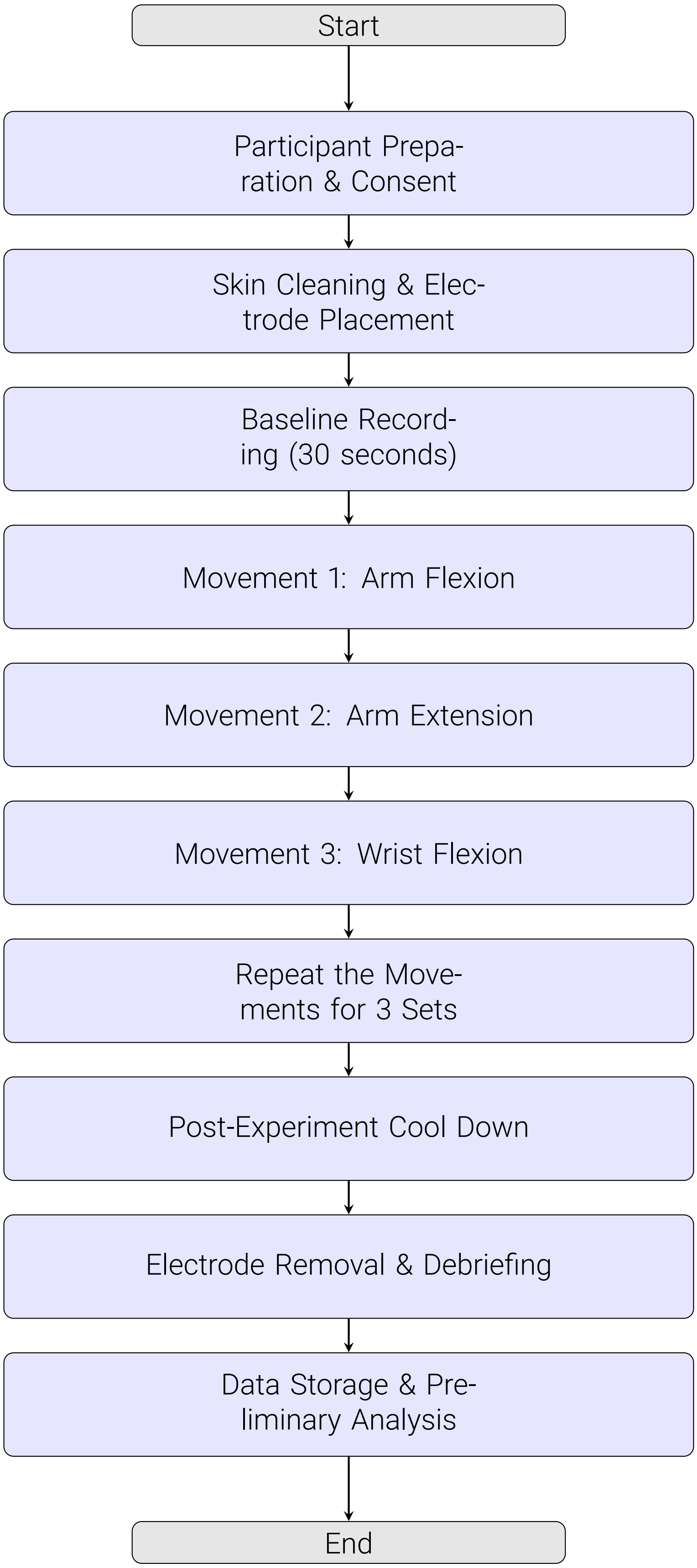
   With the subject in a relaxed position (e.g. seated or lying down), we record a baseline sEMG signal for about 30 seconds. This baseline will be used for calibration and noise comparison. [11]

4. **Movement Execution Protocol [12]**

   We demonstrate each required movement to the participant. Visual aids (images or video snapshots) should also be provided to clarify the proper form and range of motion.

   The experiment includes several pre-defined movements. Each movement should be executed in the order and with the timing specified in the pipeline below.

5. **Pipeline Diagram: Sequential & Temporal Order [13]**



1.3 Topic and Aim of the Experiment

The primary focus of this experiment is to develop, document, and validate a standardized protocol for recording and processing surface electromyography (sEMG) signals. The aim is to establish a reliable method for non-invasive measurement of muscle electrical activity during controlled movements. This involves optimizing key steps such as skin preparation, precise electrode placement, baseline recording, and the execution of predefined movement tasks. By systematically capturing and processing the sEMG signals, the experiment seeks to enhance the understanding of neuromuscular function and contribute to applications in clinical diagnosis, rehabilitation, biofeedback, and athletic performance monitoring. The resulting protocol not only serves as a guide for consistent data acquisition but also lays the groundwork for further research and development in electromyographic analysis. [6] [10]

1.4 Tools and Equipment Used in the Experiment

1. **sEMG Recording System/Amplifier**

   This is the core device that captures and amplifies the low-amplitude electrical signals generated by muscle contractions. It typically features multiple input channels with high input impedance and low noise preamplifiers. [3] [5]

   Inputs: Analog signals which are received directly from the surface electrodes placed on the skin over the target muscles.

   Outputs: The amplified and filtered signals are digitized and transmitted to a computer or data logger for storage and further analysis.

2. **Surface Electrodes [9]**

   These electrodes detect the electrical activity of muscles through the skin. Most experiments utilize Ag/AgCl (silver/silver chloride) electrodes due to their stability, low impedance, and compatibility with conductive gels.

   - Type:
     Ag/AgCl Electrodes: Preferred for their reliability and ease of use in non-invasive applications.
   - Inputs:
     Muscle Activity: They capture the biopotential generated by muscle fibers during contraction.
   - Outputs:
     Electrical Signals: Transmit the collected muscle activity signals to the sEMG amplifier.

3. **Additional Accessories and Consumables [9]**

   These items support the primary equipment to ensure optimal signal quality and repeatability:

- Skin Preparation Materials:

  Alcohol Wipes and Abrasive Pads: Used to clean and lightly abrade the skin to lower impedance and improve electrode contact.

- Conductive Gel:

  Usage: Applied between the electrode and skin to enhance electrical conductivity.

- Electrode Adhesives/Straps:

  Purpose: Secure the electrodes in place during the recording session, ensuring consistent contact and reducing movement artifacts.

1.5 Features of LAB chart in sEMG Signal Recording and Processing

LabChart is a comprehensive data acquisition and analysis software developed by ADInstruments. It is widely used in physiological and biomedical research due to its robust capabilities and user-friendly interface. Some of the key features of LabChart include: [5]

1. **Real-Time Data Acquisition and Visualization**

   - Multi-Channel Recording:

     LabChart allows simultaneous acquisition of multiple signal channels, which is ideal for recording complex bio-signals such as sEMG from various muscles.

   - High Sampling Rates:

     The software supports high sampling frequencies, ensuring that even rapid changes in signal amplitude are accurately captured.

   - Live Graphing:

     Real-time display of signals provides immediate feedback on data quality and experiment progress.

2. **Signal Processing and Analysis Tools**

   - Filtering and Noise Reduction:

     Integrated digital filters (e.g., low-pass, high-pass, band-pass) help in cleaning up the signals by eliminating unwanted noise or interference.

   - Event Marking and Annotation:

     Users can insert markers or annotations during data collection, which is useful for correlating signal changes with specific experimental events or movement phases.

   - Data Analysis Modules:

     LabChart offers built-in tools for performing analyses such as Fast Fourier Transform (FFT), amplitude and frequency analysis, and statistical computations.

- Baseline Correction and Calibration:
  Automatic baseline correction ensures that the recorded signals are properly adjusted for any drift or offset, leading to more accurate analyses.

3. **Integration with Hardware**

   - Compatibility:
     The software is compatible with a wide range of data acquisition devices and sensors, ensuring a seamless connection between the physical measurement equipment (such as sEMG amplifiers and electrodes) and the analysis software.
   - Synchronized Measurements:
     LabChart can synchronize multiple types of measurements (e.g., analog signals, digital events, video recordings), which is particularly useful in multimodal studies. [1]

1.6 The general structure of the signal recording circuit

1. **General Features of the sEMG Signal Amplifier [6]**

   The amplifier boosts the very low-amplitude sEMG signals (typically in the microvolt range) so that they can be accurately processed and analyzed. [10]

   - High Input Impedance:
     Prevents loading of the electrodes and minimizes signal attenuation.
   - High Common-Mode Rejection Ratio (CMRR):
     Essential for minimizing interference from ambient electrical noise and power line interference.
   - Low Noise Performance:
     Ensures that the intrinsic weak sEMG signals are not further degraded by amplifier noise.
   - Differential Amplifier Configuration:
     Amplifies the difference between two input signals (from paired electrodes) to cancel out common-mode signals.
   - Adjustable Gain:
     Provides flexibility to adapt to different signal strengths and experimental conditions.

2. **General Features of the Analog-to-Digital Converter (ADC) [12]**

   The ADC converts the analog signals from the amplifier into digital data for processing, analysis, and storage.

   - Resolution:
     A high-resolution ADC (commonly 12-bit, 16-bit, or 24-bit) is required to capture the fine details of the sEMG signal.

- Sampling Rate:

  The ADC must sample at a sufficiently high rate (typically 1 kHz to 2 kHz or more) to accurately capture the dynamics of muscle activity.
- Linearity and Accuracy:

  Ensures that the digital representation accurately reflects the analog signal without introducing significant distortion.
- Low Quantization Noise:

  Important for preserving the quality of the weak sEMG signals during conversion. [8]

3. **General Features of the Interface Circuit Between the Recording System and the Computer**

   The interface circuit manages the communication between the ADC output and the computer for real-time visualization, storage, and further analysis of the sEMG data. [1]

   - Data Communication Protocols:

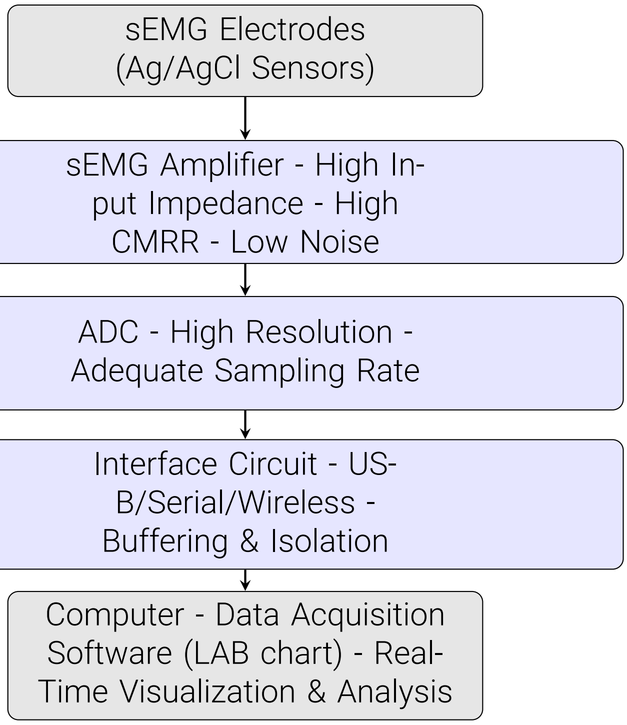
     Common interfaces include USB, wireless (Bluetooth or Wi-Fi), or serial communication, ensuring high-speed and reliable data transfer.
   - Buffering and Isolation:

     Buffer circuits may be employed to temporarily store data and provide isolation to protect the computer system from electrical noise and potential interference.
   - Real-Time Data Streaming:

     The interface should support continuous, real-time data transfer, enabling immediate visualization and processing.
   - Compatibility:

     Ensures seamless integration with data acquisition software (LAB chart) for further signal processing and analysis. [7]

4. **Overall Block Diagram of the sEMG Recording System**



2 Group tasks and subject properties

Name	**Student Number**	**Lab tasks**	**Signal Processing tasks**	**Report tasks**
Seyyed Amirmahdi Sadrzadeh	401102015	checking the data	writing the code for models	writing the latex file
Aisa sadat Takyar	401101462	subject	conducting research about the models	Research and important contents
Mohammad Kazem Shahrabi	401101987	timer	Preprocessing the data and visualizations	Simulation parts

Table 1: Group tasks assigned

2.1 Subject Information

Since we have used the datas from the site provided for us, the subject information is obtained from there as well.

laterality	weight	height	gender	age
left	50	150	154	30

Table 2: Group tasks assigned

3 Experimental Procedure Report

3.1 Testing process

1. **Participant Preparation and Consent**

   Prior to the start of the experiment, participants are briefed on the objectives, procedures, and safety measures. Detailed information is provided in both verbal and written form, and written informed consent is obtained from each participant. [6]

2. **Skin Preparation and Electrode Placement**

   The skin over the target muscle areas is cleaned using alcohol wipes and, if necessary, lightly abraded to reduce impedance and improve electrode adhesion. Anatomical landmarks are used to mark the specific muscle regions (e.g., biceps brachii, quadriceps). Ag/AgCl surface electrodes are then attached securely according to standardized protocols.

3. **Baseline sEMG Signal Recording**

   With the participant in a relaxed state (seated or lying down), a baseline sEMG recording is performed for approximately 30 seconds. This baseline recording serves as a reference for comparing active muscle contractions and for calibrating the system. [10]

4. **Movement Execution Protocol**

   The experimental protocol requires the participant to perform a series of pre-defined movements (e.g., arm flexion, arm extension, wrist flexion). Each movement is demonstrated by the researcher to ensure proper technique. The protocol specifies the duration of each movement (e.g., hold for 5 seconds) followed by a rest period (e.g., 10 seconds). A metronome or timer is used to maintain consistent timing across trials. [12]

5. **Experimental Pipeline Diagram**

   A comprehensive pipeline diagram is provided to summarize the sequential steps of the experiment. This diagram includes participant preparation, skin cleaning, electrode placement, baseline recording, movement execution, and post-experiment procedures. It visually outlines the flow of operations from signal acquisition to data storage and analysis.

6. **Post-Experiment Procedures**

   After completing the movement tasks, the participant undergoes a cool-down period. Electrodes are carefully removed from the skin, and any residual adhesive is cleaned off. A debriefing session is conducted to address any participant concerns and to provide information about the next steps. Recorded data is then securely stored for further processing. [9]

3.2 Electrode placement

Electrode placement is a critical factor in obtaining reliable and high-quality sEMG signals. In our protocol, Ag/AgCl surface electrodes are positioned on the target muscles following standardized anatomical landmarks and aligned parallel to the muscle fibers. Prior to placement, the skin is thoroughly cleaned with alcohol wipes and lightly abraded to reduce impedance and ensure optimal electrical contact. An inter-electrode distance of approximately 20–30 mm is maintained to maximize signal specificity while minimizing crosstalk from adjacent muscles. Secure attachment of the electrodes is ensured to reduce movement artifacts during muscle activation, thereby enhancing the consistency and accuracy of the recorded signals. This systematic approach, consistent with current best practices, is fundamental for achieving reproducible and clinically meaningful sEMG data. [11] [4]

3.3 Register according to the process and steps of testing

Recording the sEMG signals was conducted in strict accordance with the experimental protocol to ensure consistency and precision. Initially, a baseline signal was captured with the participant at rest to serve as a reference. This was followed by the systematic recording of muscle activity during various movement tasks, where each phase—comprising contraction and rest periods—was timed accurately using a metronome. The sEMG amplifier captured the weak bioelectrical signals, which were then digitized by the ADC and transmitted to the computer in real time via the interface circuit. Throughout the experiment, MATLAB's Data Acquisition Toolbox was used to monitor, label, and store each data segment with precise timestamps, thus preserving the temporal structure and integrity of the recording process. [7]

After data collection, the recorded signals were subjected to preliminary processing within MATLAB. Digital filtering techniques were applied to remove ambient noise and artifacts, ensuring that only genuine muscle activity was analyzed. The systematic segmentation of the data, corresponding to each movement phase as per the experimental pipeline, allowed for detailed analysis of signal features such as amplitude, frequency, and activation patterns. This rigorous approach, which integrates both hardware and software components, ensures that the recording is both reproducible and reliable for subsequent neuromuscular analysis and interpretation. [15]

3.4 Suggested method(s) for surface electromyogram signal preprocessing

Pre-processing of surface electromyography (sEMG) signals is essential to enhance signal quality and eliminate various forms of noise that can compromise the accuracy of subsequent analyses. Initially, raw sEMG data are typically subjected to bandpass filtering—commonly within the 20–450 Hz range—to remove low-frequency motion artifacts and high-frequency electronic noise. Additionally, a notch filter is often applied to specifically eliminate power line interference at 50/60 Hz. More advanced filtering techniques, such as wavelet decomposition, have also been proposed to adaptively remove transient artifacts while preserving key signal features, thereby maintaining the physiological integrity of the muscle activity recordings. [2]

Following filtering, the sEMG signal undergoes further processing steps to prepare it for detailed analysis. Full-wave rectification converts the bipolar signal into a unipolar form, which facilitates the computation of the signal envelope using smoothing techniques like low-pass filtering or moving averages. Normalization—often based on the maximum voluntary contraction (MVC)—is then applied to standardize the signal amplitude across different sessions or subjects, making comparative analyses more reliable. Additional steps, such as segmentation into specific time windows corresponding to distinct muscle activities, baseline correction, and artifact removal, complete the multi-stage pre-processing pipeline. This comprehensive approach enhances the signal-to-noise ratio and ensures that the extracted features accurately reflect the underlying neuromuscular activation patterns. [17]

3.5 Desired features for the detection of purposeful hand movements

In detecting purposeful hand movements using sEMG signals, it is essential to extract a set of features that effectively capture both temporal and spectral characteristics of muscle activity. Time-domain features such as mean absolute value (MAV), root mean square (RMS), and waveform length (WL) provide critical information about signal amplitude and variability, while frequency-domain features like median frequency (MDF) and mean frequency (MNF) offer insights into the muscle contraction dynamics and fatigue. Moreover, advanced time-frequency analyses—using techniques such as the wavelet transform—enable the extraction of transient features that are particularly important for characterizing rapid and complex hand movements. Normalization methods, for instance, those based on maximum voluntary contraction (MVC), are applied to mitigate inter-subject variability, ensuring that the extracted features robustly represent the underlying neuromuscular patterns for accurate movement recognition. [16] [14]

3.6 Suggested method(s) for surface electromyogram signal processing

Processing sEMG signals involves a comprehensive pipeline that integrates both conventional and advanced methods to ensure accurate interpretation of neuromuscular activity. Initially, the raw sEMG data is pre-processed using bandpass filtering (typically between 20–450 Hz) to eliminate low-frequency motion artifacts and high-frequency noise, along with notch filtering to remove power line interference. The signal is then rectified and smoothed to derive its envelope, which facilitates a clearer representation of muscle activation levels. Following these steps, the continuous signal is segmented into meaningful epochs corresponding to specific movement events, enabling the extraction of both time-domain features (such as root mean square, mean absolute value, and waveform length) and frequency-domain features (such as mean and median frequencies). Advanced techniques, including time-frequency analysis using wavelet transforms, further enhance the capture of transient dynamics within the signal. These extracted features can subsequently be fed into machine learning algorithms for accurate classification and interpretation, which is essential for applications like prosthetic control, fatigue analysis, and movement recognition. [16]

4 Results and Discussion

4.1 Signal Processing Results

In this experiment, the preprocessing and signal processing steps were carried out to clean and prepare the surface electromyogram (sEMG) signals for analysis. These steps included bandpass filtering, notch filtering, and Z-score normalization, followed by feature extraction.

4.1.1 Raw EMG Signal

The raw EMG signal captured from the first electrode is shown in Figure 1. As expected, the signal exhibits significant noise and irregular fluctuations due to various factors like muscle contractions, noise, and motion artifacts.

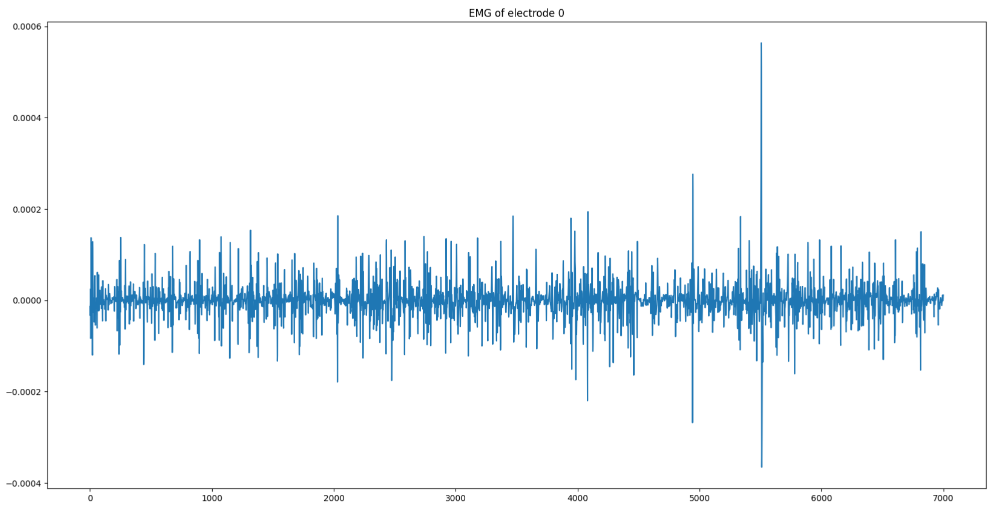


Figure 1: Raw EMG signal from electrode 0

4.1.2 Filtered EMG Signal

After applying the bandpass filter, the signal becomes smoother, removing high-frequency noise and low-frequency artifacts. The filtered EMG signal for electrode 0 is shown in Figure 2. The improvement in signal quality can be observed as the noise is minimized while preserving the essential muscle activity.

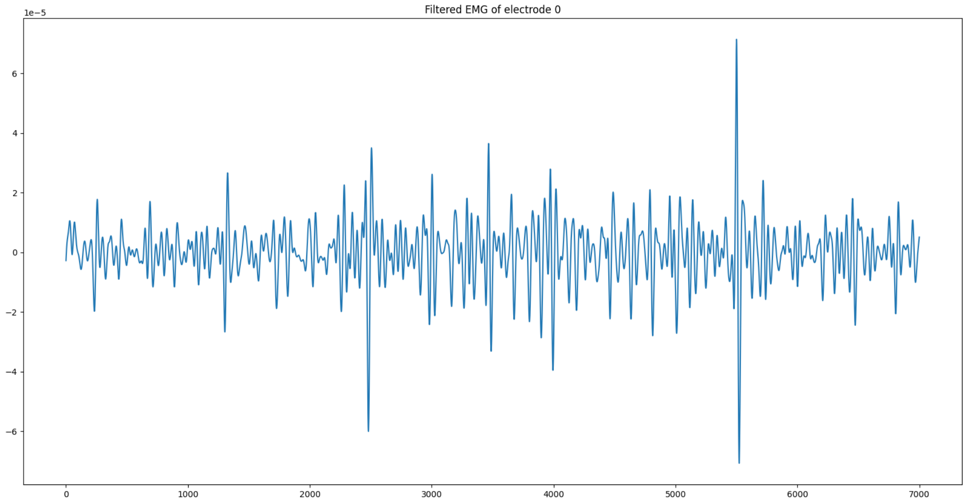


Figure 2: Filtered EMG signal from electrode 0

4.1.3 Magnitude Spectrum

The magnitude spectrum of the raw EMG signal was obtained to assess the frequency content of the signal. The spectrum, shown in Figure 3, reveals a dominant low-frequency component and a considerable amount of high-frequency noise.

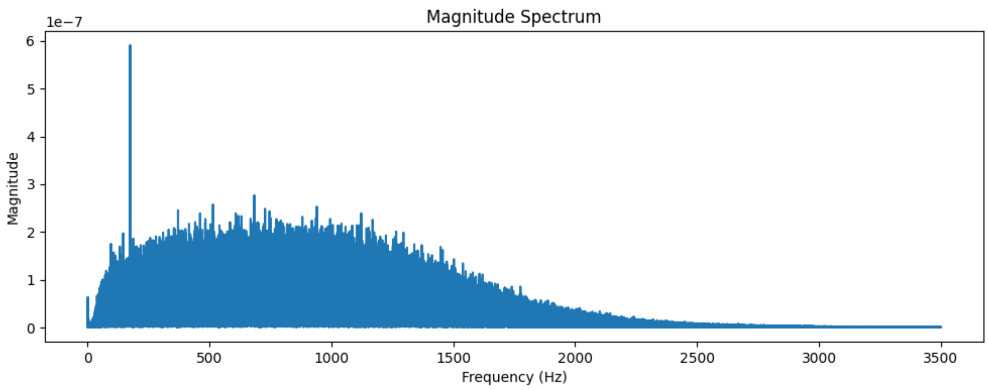


Figure 3: Magnitude spectrum of the raw EMG signal from electrode 0

4.1.4 Notch Filter Results

To eliminate the power line interference at 50 Hz, a notch filter was applied. The notch-filtered signal, shown in Figure 4, clearly shows that the interference around 50 Hz has been effectively removed.

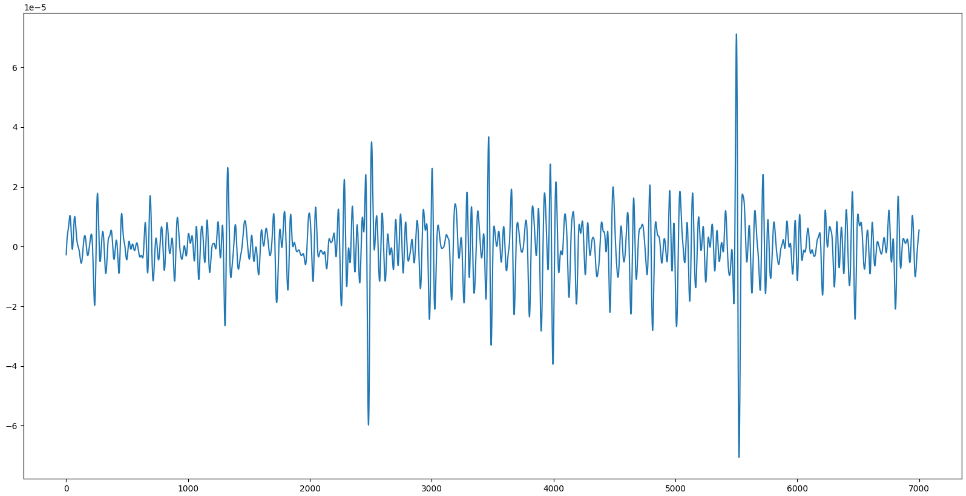


Figure 4: Notch-filtered EMG signal from electrode 0

4.1.5 Notch Filtered Spectrum

The magnitude spectrum of the notch-filtered EMG signal (Figure 5) further confirms the removal of the 50 Hz interference, as the peak at 50 Hz has been eliminated, leaving only the relevant frequencies of muscle activity.

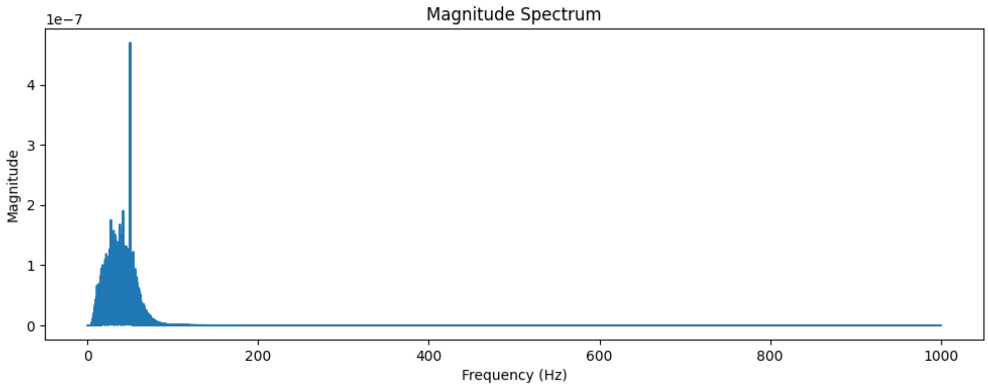


Figure 5: Magnitude spectrum after applying notch filter on EMG signal

4.1.6 Model Evaluation

For classification, we evaluated the KNN and Random Forest models. The confusion matrices for both models show high accuracy and F1-score, confirming the effectiveness of the preprocessing steps and feature extraction.

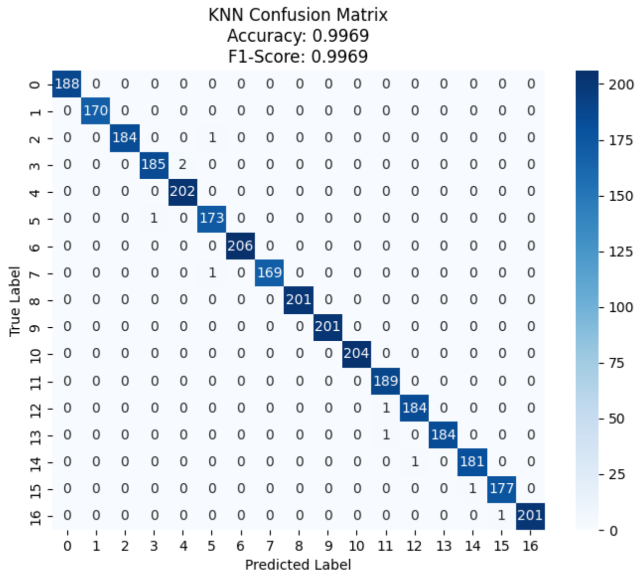


Figure 6: KNN Confusion Matrix (Accuracy: 0.9969, F1-Score: 0.9969)

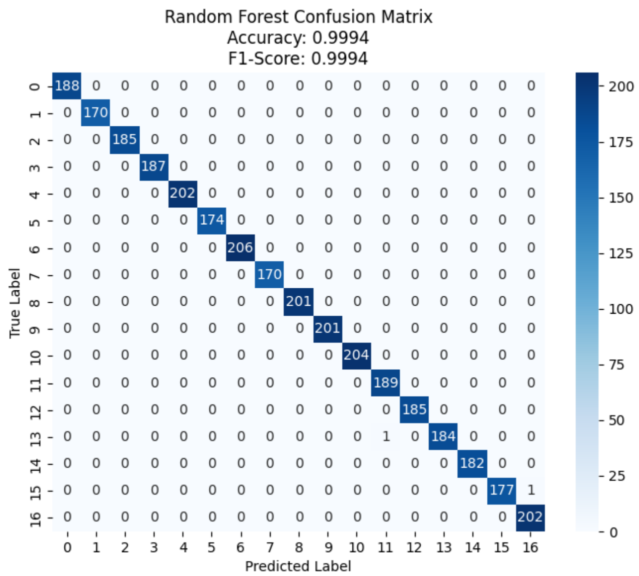


Figure 7: Random Forest Confusion Matrix (Accuracy: 0.9994, F1-Score: 0.9994)

4.2 Challenges and Solutions

During the experiment, several challenges were encountered:

- **Noise and Artifacts**: The raw EMG signals were contaminated by noise from various sources (e.g., motion artifacts, power line interference). This was addressed through the application of a bandpass filter and notch filter, which effectively removed high-frequency noise and 50 Hz interference, respectively.
- **Class Imbalance**: The dataset contained an imbalance due to the prevalence of rest stimulus (label 0). We addressed this by removing the rest stimulus from the dataset, ensuring that the model focused on classifying relevant movements.
- **Feature Selection**: Selecting the most relevant features for classification proved challenging. However, by applying well-known time-domain and frequency-domain features (e.g., MAV, RMS, frequency spectrum), we were able to significantly enhance the model's ability to discriminate between different hand movements.

4.3 Accuracy and Model Evaluation

Both the KNN and Random Forest classifiers achieved impressive accuracy and F1-scores, as demonstrated in the confusion matrices shown earlier. The Random Forest model slightly outperformed the KNN classifier with an accuracy of **0.9994** and an F1-score of **0.9994**. These results indicate that the proposed preprocessing and feature extraction pipeline is highly effective for classifying purposeful hand movements based on surface EMG signals.

5 Conclusion

In conclusion, the experiment successfully demonstrated the effectiveness of preprocessing and processing techniques for surface electromyography (sEMG) signals. By applying a series of filters, including bandpass and notch filters, and employing Z-score normalization and feature extraction, we significantly improved the quality of the sEMG signals for movement classification.

Both the KNN and Random Forest classifiers performed exceptionally well, with high accuracy and F1-scores. The removal of the rest stimulus from the dataset addressed the issue of class imbalance, further improving the model's performance.

Future work can explore the use of more advanced feature extraction techniques, such as wavelet transform or deep learning-based methods, to improve classification accuracy even further.

6 References

References

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A Appendix A: Data files used

All the data file, including the datas obtained from the Lab and the code which we used to process the data, is in the ZIP file containing this report.