Hardware and Software Design for ECG Signal Acquisition and Processing

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Abstract

This research report details an experiment designed to collect and analyze electrocardiogram (ECG) data through an integrated ECG acquisition module to monitor and assess heart health, the main point of which is the realization of automatic heartbeat measurement. At the same time, the influence of oversampling and undersampling on sampling accuracy, the interference of EMG to ECG signal, and the verification of Einthoven's law are also studied. The core goal of the experiment was to develop a graphical user an application that could capture ECG data in real time and de-noise the data, and alert when an abnormal heart rate was detected, while saving the data and generating reports after the test.

1 Introduction

An Electrocardiogram (ECG or EKG) is a medical test that records the electrical activity of the heart. It works by placing a series of electrodes on the surface of the body to capture and record the tiny electrical impulses produced with each beat of the heart. These electrical pulses are displayed on paper or on a screen as waveforms that reflect the electrophysiological state of the heart and can help doctors diagnose various heart conditions.

The main components of an electrocardiogram consist of a series of peaks and troughs, usually divided into P waves, QRS complex waves, and T waves: P wave: represents atrial depolarization, that is, the electrical activity of atrial contractions. QRS complex wave: Represents ventricular depolarization, that is, the electrical activity of ventricular contraction. Q wave, R wave and S wave are three parts of QRS complex wave. T-wave: represents ventricular repolarization, the electrical activity of ventricular diastole. An ECG can provide the following information:

Heart rate: The number of heart beats per minute. Rhythm: The regularity and evenness of the heartbeat. Conduction: Whether the conduction path of the heart electrical signal is normal. Myocardial ischemia: Whether the heart muscle is damaged due to insufficient blood flow. Myocardial infarction: Whether the heart muscle dies due to complete interruption of blood flow. Heart disease: such as cardiomyopathy, heart valve disease, etc. An electrocardiogram is a quick, painless, and non-invasive test that is essential for assessing heart health. It is commonly used in emergency rooms, hospital wards, clinics and heart monitoring. Ecg results need to be interpreted by a professional physician to ensure an accurate diagnosis.

Now the incidence of heart disease is increasing, this experiment is about the examination method of heart condition, the collection and processing of biological signals is the key technology to achieve precision medicine and patient monitoring. Electrocardiogram (ECG) signal is one of the important biological signals to monitor cardiac activity, and its collection and analysis are of great significance for the diagnosis and treatment of heart disease. In this experiment, we use USB-6009 data acquisition module to collect signals, use MATLAB software for processing and analysis, and design a graphical user interface to control the acquisition process and display the measurement results, and realize the ECG measurement, electrocardiogram drawing, and heartbeat speed calculation. The software will give an alarm when the heartbeat is too fast or too slow. At the end of the measurement, the software will export a data result.

2 Method and Material

2.1 Material

In this electrocardiogram (ECG) acquisition experiment, we utilized MATLAB software to design an application for data acquisition, analysis, and visualization of cardiac signals. The AD8232 single-lead heart rate monitor was employed to capture the ECG signals, widely recognized for its precision and ease of use in medical research. The signals were transmitted to the computer through the NI USB-6009/6002 data acquisition module, which supports rapid and efficient digital processing of signals. During signal acquisition, adhesive electrodes were used to measure the heart's electrical activity from leads I, II, and III on the subject's body.

2.2 Procedure1: Design GUI

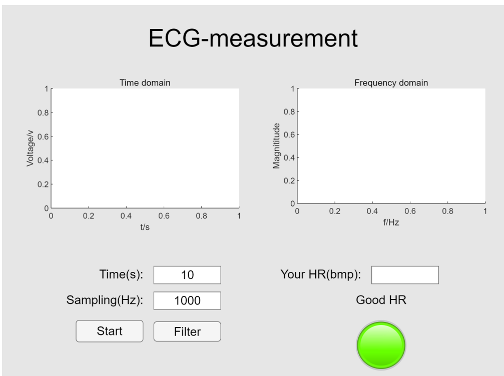

Fig. 1: Designed GUI

We designed the application interface, as shown in figure 1 shown, including a "Start" button that allows the user to enter acquisition time (default 10 seconds) and sampling frequency (default 1000 Hz) to initiate acquisition of an electrocardiogram (ECG) signal. The program uses Data Acquisition Toolbox of MATLAB for signal Acquisition. The collected ECG signals are displayed in the time domain on the first axis of the application and in the frequency domain on the second axis by Fast Fourier transform (FFT).

Additionally, we have developed a heart rate calculation feature. First, the ECG data undergo preprocessing where the signal average is subtracted to eliminate DC offset, enabling more accurate data analysis. Then, upon clicking the "Filter" button, the signal is processed through an ideal band-stop filter with cutoff frequencies set between 48-52Hz to remove the 50Hz power interference, with the frequency response shown in Figure 2. The processed signal is displayed on the application's coordinate axis. Using MATLAB's findpeaks function, we analyze the R-waves in the filtered time-domain signal, estimating the heart rate (including standard deviation) by calculating the intervals between R-waves, and displaying this rate in the "Your HR" edit box on the interface, the found R waves are also displayed on the time-domain signal, making it easier for the operator to check for errors. If the heart rate exceeds 120 beats per minute or drops below 60, the indicator light will change from green to red, and a text alert indicating the heart rate is too high or too low will be displayed at the bottom right of the interface, accompanied by an audible alarm. All collected information is automatically saved in the program folder, named by the time of collection.

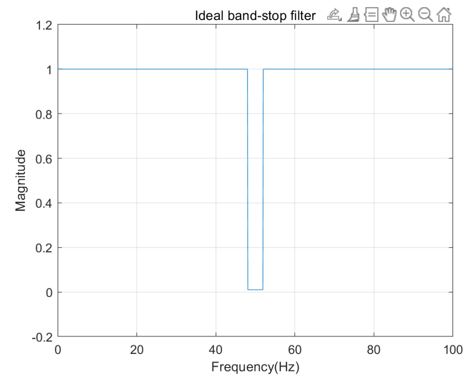

Fig. 2: Ideal band-stop filter

2.3 Procedure 2: System Detection and Further Research

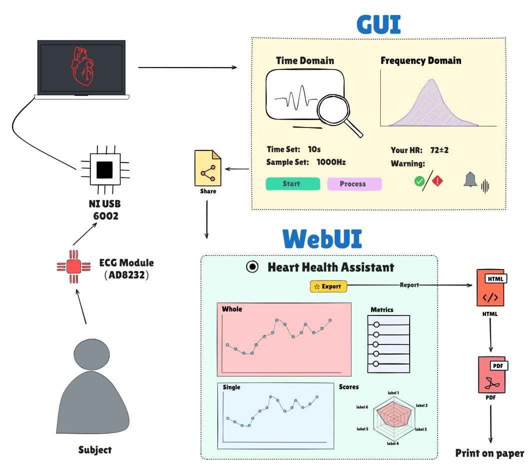

Fig. 3: System Design

To facilitate further diagnosis by specialized physicians, we have engineered a data transmission system(Figure 3) for online consultation. The raw data and parameters collected by the test instruments and a GUI are shared with other users via shared files. They are presented via a user-friendly web-based user interface (WebUI).

The WebUI is primarily developed based on the Django framework, with Python handling backend data processing and a combination of HTML and JavaScript for frontend display. Visualization is achieved through the Charts library. The system includes an independent data processing workflow (Figure 4), which begins with resampling to mitigate the effects of sampling frequency on filter performance, specifically redirecting to 444 Hz.

Heartpy, a Python library adept at ECG signal recognition and analysis, is utilized to provide the WebUI with a data panel that showcases metrics such as heart rate, R-wave intervals, and respiratory rate. At the same time, it can also be used to check whether our heart rate calculation results are accurate.

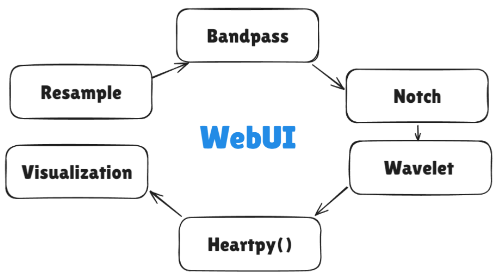

Fig. 4: WebUI Workflow Design

Additionally, we have incorporated the functionality to export health reports, which also supports the customization of report templates by developers for future use(Figure 3 right-bottom).

2.3.1 Bandwidth and Noise Analysis

To achieve noise reduction in the initial signal, we first conducted an in-depth analysis of the signal's frequency domain composition. Based on the frequency domain characteristics, we designed band-pass filters to eliminate interference such as electromyography and notch filters to mitigate electromagnetic power frequency interference. To further optimize the noise reduction, we also employed wavelet denoising methods and evaluated the effectiveness by comparing the amplitude spectrum and time-domain signals before and after denoising(Figure 4). To comprehensively demonstrate the noise reduction effects and study the impact of electromyography on ECG signal acquisition, we introduced the factor of forearm muscle exertion and collected a set of signals for in-depth research.

Additionally, we explored the impact of sampling frequency on signal waveform and information loss. We initially sampled at 1000 Hz to determine the upper frequency limit f_{upper}. Subsequently, we sampled at frequencies of 5 times, 2 times, 1 time, half, and a quarter of f_{upper}, and compared the degree of information retention at each sampling frequency.

Ultimately, we assessed the accuracy of our ECG acquisition system by using heart rate (HR) as an indicator. This was done by comparing the HR calculated from the R-wave period of the acquired signals with the HR based on pulse measurements. We also analyzed the changes in HR following muscle activity.

2.3.2 Verification of Einthoven's Law

We configured the USB - 6002 to capture signals from a single channel. During this process, the ECG data of leads I, II, and III in the resting state were successively collected. Then, statistical analysis of the amplitudes of the QRS waves is to be performed for the purpose of verifying Einthoven's Law, which examines the relationship between the amplitude of lead II and the combined amplitudes of leads I and III. Additionally, potential sources of error in this process are discussed and improvement suggestions are provided to enhance the accuracy of the verification.

3 Result

Time and frequency domain signals are obtained at a sampling frequency of 400Hz. As shown in Figure 6b,c, the blue signal is the original data source collected by the hardware system, and the red data is obtained after noise reduction. Select the appropriate block selection area (single ECG signal period, energy main distribution frequency band), and enlarge it to obtain the details of Figure 6e,f. R wave and T wave are very obvious in the long time series, and P wave, QRS wave group and T wave can also be clearly identified in the single period signal (Figure 6e).

From the perspective of frequency domain, the main energy distribution of ECG signal is below 25Hz (80% energy accumulation according to 5). According to the existing experience, the P-wave period of normal adults is about 0.1s, the QRS group is 0.06-0.1 s, and the T-wave period longer than the former two, indicating that the corresponding frequencies of these components are all below 110Hz. This is consistent with the results in Figure 5.

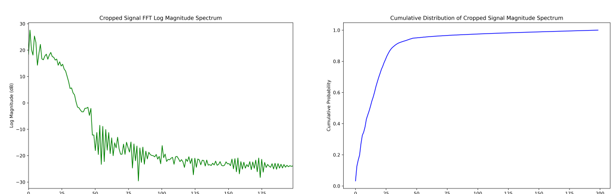

Fig. 5: Logarithmic amplitude spectrum and cumulative distribution of spectral energy in frequency domain of positive semi-axis

In addition, compared before and after noise reduction, it can be found that the 50Hz power frequency interference is greatly suppressed, while the effective information is fully preserved. The signal after noise reduction can be fully identified and resolved by Heartpy (Figure 6d).

In the resting state of the subjects, the heart rate data obtained through pulse counting, the self - developed heart rate (HR) algorithm, and the Heartpy heart rate algorithm are presented in Table 1. When compared within the same row, the results of these three methods are similar, and the difference is no more than 1. Based on the correlation degree of the three columns of data, the correlation matrix is calculated as shown in Figure 6a. Taking the pulse data as the benchmark, the Heartpy algorithm indeed outperforms our self - developed algorithm. However, the results of the Heartpy algorithm are highly correlated with those of our algorithm, indicating that the logic of calculating the heart rate in our method may be similar. Overall, both the self - developed algorithm and Heartpy exhibit relatively good heart rate resolution capabilities.

Table 1: HR(bpm) comparison by various methods

HR_Impulse	Custom	Heartpy()
76	75($\pm$3)	75.17
74	75($\pm$3)	74.72
76	76($\pm$2)	76.32

According to the spectral performance of the 1000Hz sampling result, take f_{upper} = 200Hz, so a group of sampling groups such as 1000, 400, 200, 100, and 50Hz are obtained. The influence of different sampling frequencies on the ECG signal is shown in Figure 7. High-frequency sampling retains some high-frequency information, and naturally retains the power-frequency interference of 50Hz. Note that **Sample 5**, that is, the result of 50Hz sampling, effectively suppresses the power-frequency interference. On the right-hand side of the spectrum, it's clear that the 50 Hz peak has been erased. But it also suppresses the effective signal, resulting in information loss. For example, in the second period of the right end of **Sample 5**, the peaks of R and T waves are very close, which is obviously abnormal.

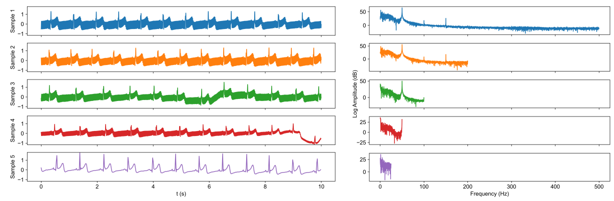

Fig. 7: Sample frequency's influence on ECG signal

It is noted that the sampling at 50Hz is still not enough to show the significant impact of low sampling on information loss, and the sampling results themselves are different in different environments. Here the results of 1000Hz sampling are down-sampled to 400, 200, 100, 50, and 25Hz. The results are shown in Figure 8. It can be found that the 50Hz signal eliminates most of the power frequency interference, and the R wave is also suppressed, which is the same as the previous discussion results. But in the case of 25Hz, the loss of information can be clearly found, which is manifested as the R wave and the T wave are flat. The reason is that the period of the T wave is higher than that of the R wave, etc., so it is less suppressed by low sampling than the latter.

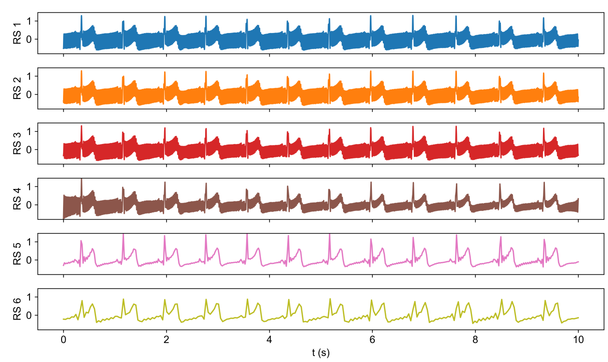

Fig. 8: Resample frequency's influence on ECG signal

In order to eliminate the influence caused by the asynchronous measurement of the three leads, the R wave peak value of each cycle and the average value of the adjacent R wave intervals are extracted to form the peak sequence (Figure 9). This can achieve the alignment of the R waves between the three leads. Further, the three leads are normalized here to eliminate the interference of different experimental environments on signal acquisition, especially signal drift. The deviation between the experimental data and the theoretical value of Einthoven is finally obtained as shown in Figure 9.

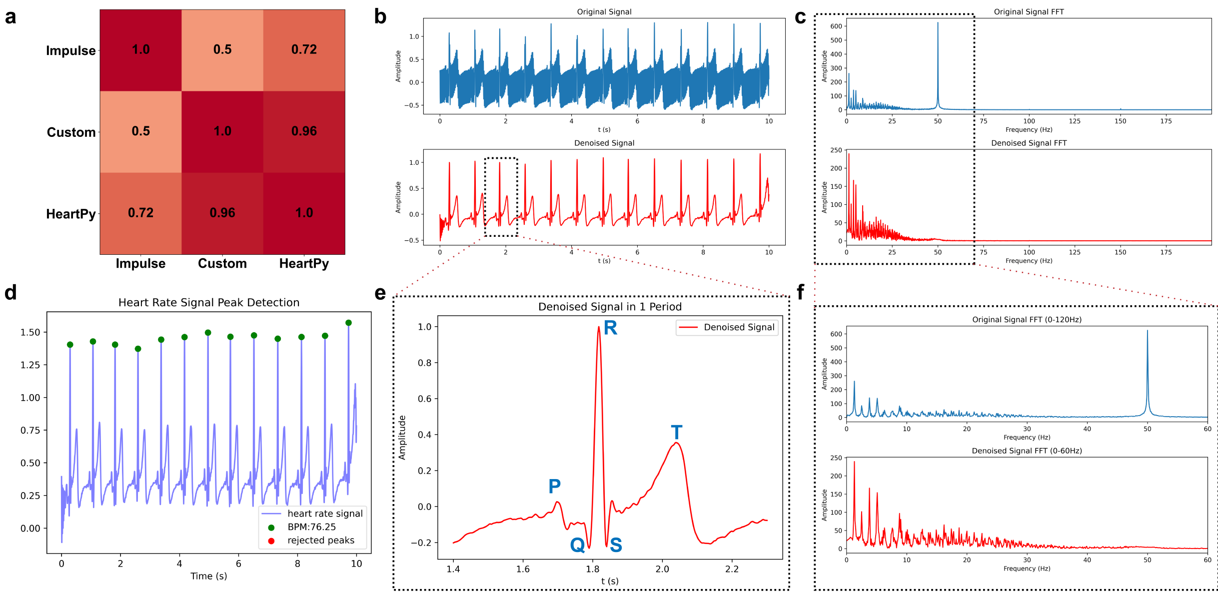

Fig. 6: Analysis Data: a. Correlation coefficient matrix heat map by the heart rates acquired through impulse, custom method and Hertpy library; **b.** Time-domain images of the original and processed signals at a sampling rate of 400 Hz; **c.** Frequency-domain images of the original and processed signals at a sampling rate of 400 Hz; **d.** Recognition and computed results from Heartpy library; **e, f.** Amplified region from b and c.

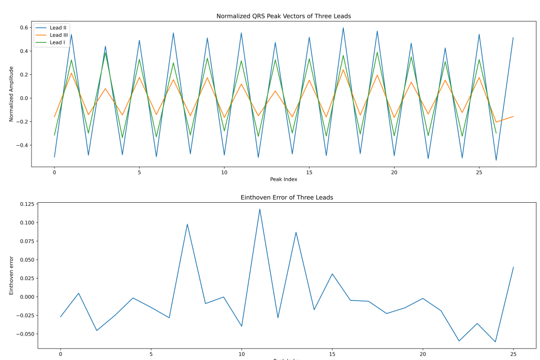

Fig. 9: Verification for Einthoven's law

less data fluctuation and more reliable results; the current standard deviation suggests that the data stability is at a certain level. To further improve the reliability of the results, it may be necessary to optimize the data acquisition or analysis methods.

Statistical indicators	value
t	-0.3690351513095924
p	0.715208649942736
μ	-0.003243567066511931
σ	0.04394658686308754

Table 2: Statistical analysis for the error data

In this verification analysis of electrocardiogram signal data and Einthoven's law, corresponding results as shown in Table 2 were obtained through processing and analyzing the collected data. At a significance level of 0.05, the p-value obtained from a one-sample t-test is about 0.72, the t-statistic is about -0.37, and the mean of the error sequence is about -0.003. This indicates that the mean of the Einthoven error sequence is not significantly different from 0. Overall, the actual measured data is relatively consistent with Einthoven's law. However, although the mean difference is not significant, there is still some fluctuation as seen from the standard deviation of the error sequence (about 0.044). A smaller standard deviation means

As shown in Figure 10, the introduction of electromyography (EMG) creates messy peaks that may bury the ECG signal. From the spectral point of view, EMG introduces more components above 30Hz, and from the cumulative distribution of the frequency domain, EMG introduces more energy in the high frequency region. There is a step in the original data source (blue), which is from the power frequency interference of 50Hz. The signal under EMG interference does not have this step, and it may be that the power frequency interference is buried in the EMG signal. Naturally, the measurement quality of HR has declined. However, it is worth noting that Heartpy still has relatively excellent HR resolution.

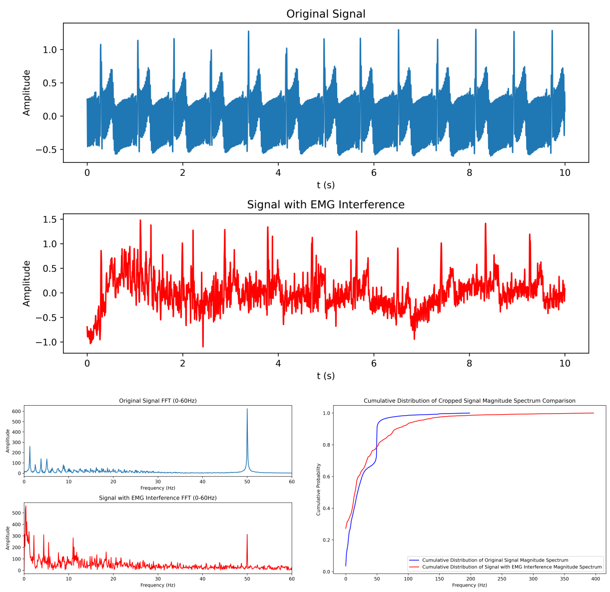

Fig. 10: EMG interference effect

Figure 11 shows the actual operation interface of the WebUI.

Fig. 11: WebUI interface snapshot

4 Discussion

In our designed filtering process, we applied an ideal band-stop filter because the performance of traditional Butterworth and Chebyshev filters is limited under conditions of high 50Hz power line interference. Although Butterworth filters have flat passbands and stopbands, their transition bands are wide, preventing sharp cutoff near the interference frequency, thus making it difficult to completely eliminate the interference. Chebyshev filters, offering steeper cutoff slopes, might lead to reduced output signal quality due to ripple in the passband and stopband, and their initial stopband attenuation may not be sufficient to handle extremely strong power line interference. In contrast, ideal band-stop filters can precisely block specific frequencies within a very narrowband. Although theoretically challenging to achieve perfectly, in digital signal processing, their effect can be approximated through algorithms, thereby effectively eliminating specific frequency interference.

We also discovered significant interference during muscle contraction activities due to active EMG signals. These myoelectric signals are generated from motor neurons that are a part of the central nervous system[1]. Since muscle tissues can conduct electric signals similar to the way nerves do, they can form muscle action potentials during muscle movements. Although the human body is electrically neutral, the nerve cell membranes are depolarized in the resting state due to differences in concentrations and ionic composition and thus form a potential difference between intra-cellular and extra-cellular fluids of the cell. This in turn stimilates muscle fibres and makes them depolarized[2]. The EMG signal shows the muscle response to neural stimulation and appears random which reduces the quality of ECG signals.

In the experiment of verifying Einthoven's law, the LII amplitude is almost identical to the sum of LI and LIII amplitudes despite negligible errors. These errors may the consequence of the following factors: inconsistent data from asynchronous acquisition, phase deviation during alignment, and hardware limitations. The three signals were not collected at the same time so there could be fluctuation in signals even though the subject was stable. The electrical components including resistors, capacitors and wires were not ideal and could also contribute to the deviations. Subsequent data processing could decrease but not completely diminish the errors. Improving the circuits to collect data synchronously from three leads may help further reduce the errors.

In the increasing digital age, countless data is measured and stored for later analysis. Biomedical data can reveal a person's physical and mental status and is a valuable resource for research in human activities. During data acquisition process, researchers and institutions should inform the test subject of the data usage and respect the test subject's will, and the experiment should be conducted under international and local regulations and the consent of the subject. Acquired biomedical data should be kept for research use only and not propagated on malicious purposes. Therefore, the test subject in our experiment was provided with an informed consent form and signed it with us. The consent form was attached in the appendix.

In the digital medical environment, there are many ethical considerations involved in deciding whether to adopt over- or under-sampling. Oversampling can improve the detail of data, but it can capture more high-frequency information such as EMG signal, reduce the specificity of diagnosis, and increase the risk of data privacy and security, it also violates the "Principle of minimum necessity" in medical ethics, which is to collect more data than is necessary. However, the lack of information may lead to inaccurate diagnosis, increase the risk of misdiagnosis or missed diagnosis, and impair the rights of subjects. Therefore, we need to select the appropriate sampling frequency, neither undersampling nor oversampling. In the case of electrocardiogram (ECG), the recommended sampling rate is usually about 400 Hz, which can balance data quality and processing requirements, and avoid ethical questions as much as possible.

5 Work Distribution

Sitian Zhong: Introduction and abstract
Yantong Liu: Matlab GUI Design and Method of procedure 1
Renjie Mei: WebUI Design and Code, Method and Result about Procedure 2
Ye Li: Discussion

6 Appendix

Informed Consent:
Separate documentation is also attached to the GitHub repository.

Code Acquisition:
The code for this study has been open-sourced and can be accessed and downloaded via the following GitHub link: https://github.com/MajorDionysus/IME_Expriment_I_Lab2.git

References

[1] V. Gohel and N. Mehendale. Review on electromyography signal acquisition and processing. *Biophysical reviews*, 12(6):1361–1367, 2020.

[2] M. B. I. Reaz, M. S. Hussain, and F. Mohd-Yasin. Techniques of emg signal analysis: detection, processing, classification and applications. *Biological procedures online*, 8:11–35, 2006.