

SIGNAL PROCESSING FOR ELECTROMYOGRAPHY

SIGNAL CONDITIONING

1st Author: Dr. Archana Bajirao Kanwade,

Associate Professor, Department of Electronics and Telecommunication Engineering, Trinity Academy of Engineering, Pune-411048

2nd Author: Dr. Sarika A. Panwar

Assistant Professor, Department of Electronics and Telecommunication Engineering, All India Shri Shivaji Memorial Society's Institute of Information Technology, Pune-411001

3rd Author: Dr Pankaj Magar

Associate professor, Department of Pulmonary Medicine, SKNMC and General Hospital, Narhe Pune 411041

4th Author: Dr.Mousami V. Munot (Corresponding Author)

Associate Professor, Department of Electronics and Telecommunication Engineering, SCTTR's Pune Institute of Computer Technology, Pune, India, PIN: 411043

Abstract: *In today's medical environment, technology is a crucial factor in the development of new treatments and cures. Diagnostics using biosignals have traditionally relied on bulky, high-priced equipment. Most individuals can't afford this kind of care. Current biosignal conditioning systems tend to be application-specific, whereas those that are generic need a huge number of different sensors, making them more costly as well as more labour intensive. As a result of this, there is a requirement for a signal conditioning circuit that can be used to measure any of the many biosignals created by our bodies with no modification. Researchers may substantially benefit from the use of MATLAB, which provides them with a great deal of versatility when it comes to analysing biosignals. It is also possible to utilise MATLAB on practically all computer systems, which is a huge plus for the software. MATLAB has been used to simulate the numerous filters needed to eliminate various sorts of noises that are present in a normal electromyography signal to obtain raw bio signal data.*

Keywords—Diagnosis, Signal Conditioning, Digital Processing, MATLAB, Electromyography.

I. INTRODUCTION

Bio potentials are generated by electrical activity in cells of neurological, muscular, or glandular tissue as a consequence of various biological processes. An ionic potential is what you're looking at. These cells are capable of conducting an action potential when they are sufficiently activated [1]. Biosensors detect this flow of charged ions (electrodes). Modern medicine places a high value on biosignals. Diseases that need bio signal processing for diagnosis include a wide range of conditions. We can make it easy for students and researchers to undertake sophisticated processing on Bio Signals by utilising MATLAB to produce exact results.

EMG signals may be used to diagnose a variety of muscle-related problems, including paralysis, dysphagia, and more [2]. A transducer may be likened to a motor neuron's function. [3] It turns brain signals into movement via molecular mechanisms [3]. Physiotherapy costs may be considerably reduced and muscle illnesses can be detected at an early stage if the ability to analyse and make conclusions about the condition of muscles is available without the need for costly equipment. Raw data may be obtained and evaluated on any computer, even if such capabilities are not available. Figure 1 depicts the overall organisation of the article.

II. RELATED WORK

A. Characteristics of noise associated with EMG Signals

We had to do a thorough investigation into the different sorts of sounds linked with biosignals to eliminate them from the EMG data.

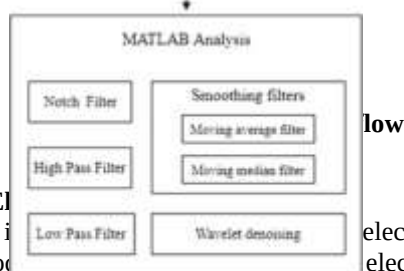
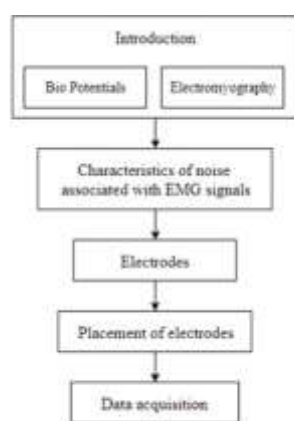
- **Inherent Noise:** Electronic equipment-induced noise in the signal. Because of their vast frequency spectrum and difficulty in eradicating them, The only method to reduce this kind of noise is to use well-designed circuits and high-quality equipment.
- **Electromagnetic Noise:** There is no way to avoid being exposed to electromagnetic radiations from the environment. Because they interfere with the signal and produce undesired electromagnetic noise, these radiations must be removed. Signals may be as strong as three times as strong as an EMG signal [4]. Electromagnetic interference is most often caused by power line interference (PLI). 50Hz is the frequency range in which they are most often seen.
- **Motion Artifact:** The gel layer presses on the electrodes, which results in motion artefacts. A frequency of 1-10 Hz and the same voltage as an EMG signal characterise these sensors. Motion artefacts induced by changes in potential between the skin's layers must be reduced. To eliminate this

form of motion artefact, such as skin abrasion, many approaches are applied.

- ECG Artifacts: Electrocardiographic (ECG) signals are generated by the beating of the heart. EMG signals are often muddled by these noises. Using common-mode rejection, the impact of these signals may be minimised. Electrodes placed along the heart's axis may be used to measure the signals. After then, the EMG signals are adjusted accordingly.
- Cross Talk: This is a reference to the fact that muscles that aren't being monitored might inject noise into the signal. The size of the electrodes and the distance between their placement may lessen these interferences. Mathematically, this background EMG activity may be shown (1).

$$T_b^2 = R_b^2 + T_i^2 + O_b^2 \quad (1)$$

T_b is the background EMG at the target.
 R_b is crosstalk from remote muscles.
 T_i is the intrinsic noise from the target.
 O_b is crosstalk from other muscles.



B. El

The i via electrode electrical impulses electronic circuits. The signal is more easily transmitted when electrons in the electrode interact with ions in the body [6]. Because of its low half-cell potential and low impedance, we employed silver/silver chloride electrodes in our work. These electrodes have properties that are very close to those of completely non-polarizable electrodes, which is a good thing. Noise levels are lower when using these electrodes than when using an analogous polarizable electrode. Silver chloride is applied to a silver chloride base on the electrode. Conductive gel is used to promote conductivity and lessen the chance of a short circuit [7].

Figure 2 shows. The electrode-electrolyte interface impedance is represented by R_d and C_d . R_s is a measurement of the electrical resistance of the electrode material and the electrolytic gel it is placed in a cell. In electrochemistry, E_{hc} refers to the electrode's half-cell potential (220mV) [6]. It is possible to express the effective impedance in this manner (2).

$$\frac{R_d}{1 + j\omega C_d R_d} + R_s \quad (2)$$

III. METHODOLOGY

A. Placement of electrodes

EMG measurements are performed with the use of three electrodes. Our test was conducted using the motion of squeezing the palms of our hands together. In the human arm, the flexor carpi radialis muscle is the most responsive to this movement. The EMG signals are measured using two of the electrodes, with the third electrode serving as a reference. The arm's elbow is where it's connected. This is due to the area's preponderance of bone, which acts as a more neutral conductor of electricity than muscle tissue does [8]. The Minimum Crosstalk Area (MCA) is established to limit the noise caused by crosstalk. Crosstalk vs co-contraction is at a minimum on this surface specified by Basmajian & Blumenstein.

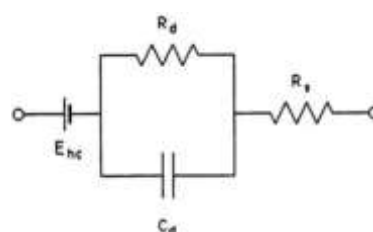


Figure 2: Representation of electrode electrolyte interface of biopotential electrode

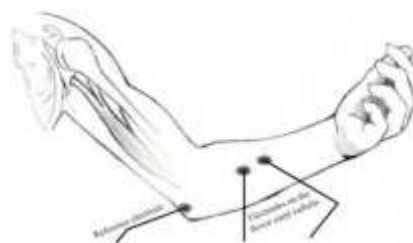


Figure 3: Placement of electrodes on the arm

A. Data acquisition

The EMG signals were retrieved using an AD8232 Module coupled to the electrodes attached to the arm. The analysis and filtering were conducted. The shareware CoolTerm was used to gather data from a computer's COM port. The resulting.txt file was created from the original.csv data. We also analysed raw data gathered from an online survey database. An EMG monitoring equipment from Medelec, the Synergy N2, was used to get this data. Finally, they were entered into the

MATLAB programme.

B. MATLAB Analysis

A matrix [Ai1 Bi2] defines the data. There are two columns in this table: Ai1, which represents the amplitude of the electrode voltage readings, and Bi2, which represents the equivalent time intervals between the two. The time-domain waveform of the EMG signal may be derived from this data. This is seen in Figure 4.

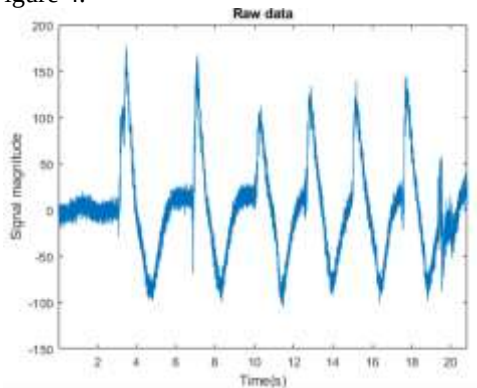


Figure 4: Raw data (Time Domain)

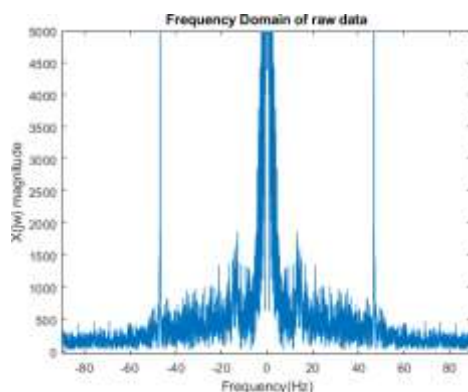


Figure 5: Raw data (Frequency Domain)

Frequency spectra may be computed with the help of the Fast Fourier Transform. A frequency-domain signal plot is created (Figure 5). It's difficult to see and distinguish noise components by eye examination since most of the noise components fall within the EMG signal's frequency and amplitude range. To accomplish this, a variety of filtering methods are used. The numerator and denominator coefficients are used to build a rational transfer function for a discrete-time filter's output. It is the filter's order that is determined by summing all the coefficients and dividing them by two. EMG-related sounds have been dealt with using a variety of filters.

1) Notch Filter

It can be observed from the frequency distribution of the signal (Figure 5) that there exists interference at

approximately the 50Hz range of the signal. External electromagnetic interference, notably Power Line Interference, is to blame for this problem. For many experiments, it was found that building a band-stop filter within the frequency range of 47 Hz was more successful than the standard 50 Hz bandstop filters used in popular literature on reducing PIL noise.

All frequencies between the two cutoff frequencies are blocked by a band stop or band-reject filter. A notch filter is used since our task necessitates the removal of just a limited subset of frequencies centred around 47 Hz. The stopband of a notch filter is very narrow and weakly attenuated. As an example of a common notch filter, consider (3).

(3)

Rejected bandwidth and the centre rejected frequency are both

$$y[n] = \frac{1}{a_0} \left(\sum_{i=0}^M b_i x[n-i] - \sum_{j=1}^N a_j y[n-j] \right)$$

where 42Hz and 52Hz are the stopband frequencies for IIR Notch filters. After notch filtering, the signal in the frequency domain is seen in (Figure 6). Infinite Impulse Response is the acronym for IIR. The formula for an IIR response may be found here (4).

(4)

Here, $x[n]$ is a feedforward signal, while $y[n]$ is a feedback signal.

2) High Pass Filter

Due to the intrinsic instability of neurons, noise with a frequency below 20 Hz is caused by motion artefacts and the random firing of motor neurons. High pass filters help to alleviate this problem. Those frequencies over the cut-off frequency are let through, while those below are reduced (Figure 7). IIR filters have a 20Hz cutoff frequency.

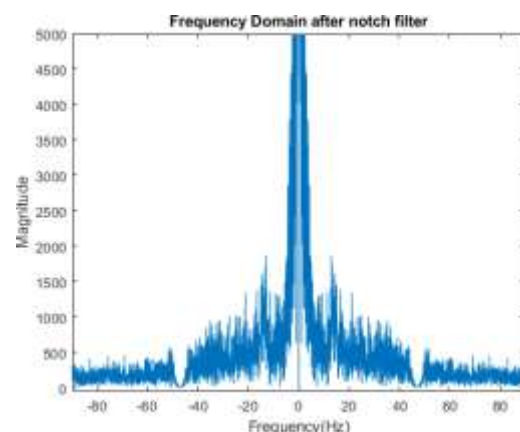


Figure 6: Signal after notch filtering (Frequency domain)

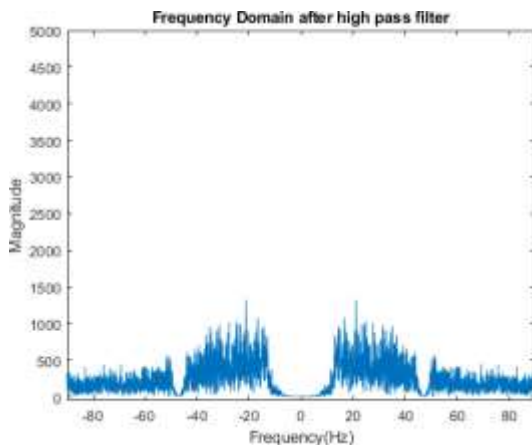


Figure 7: Signal after high pass filtering (Frequency domain)

There is a wide variety of frequencies in EMG signals. At contrast to this, most of the signal's usable components are located below 200 Hz, while noise is concentrated in the higher frequencies. We used a low-pass filter with a frequency of less than 100 Hz in our investigation to limit the amount of computing required. As seen in (Figure 8). With a lower passband frequency of 10 Hz and an upper passband frequency equal to the cut-off frequency of the low-pass filter, a band pass filter may also be used to accomplish the same result.

3) Smoothing Filter

Smoothing methods may also be used to minimise sudden changes in the signal as a result of undesirable movements. Filtering algorithms that use moving averages and moving medians are among them. These filters employ a window of predetermined size and move it along the data, calculating the average and median of data inside each frame. A simple moving average filter weights each sample equally. Figure 9 shows the results of this experiment. In a moving average filter with a window length of "WS," the output response is provided (5).

$$y(n) = \frac{1}{W_s} (x(n) + x(n-1) + \dots + x(n - (W_s - 1))) \quad (5)$$

For both filters, the window size is set to 4. The coefficients' values are set to $1/W_s$. Weighted average filters, on the other hand, use the binomial expansion of $[12 \ 12]^n$. Iteratively, the coefficients of this binomial filter $[12 \ 12]$ concatenate themselves n times. N is set to 2, which results in a window size of 4.

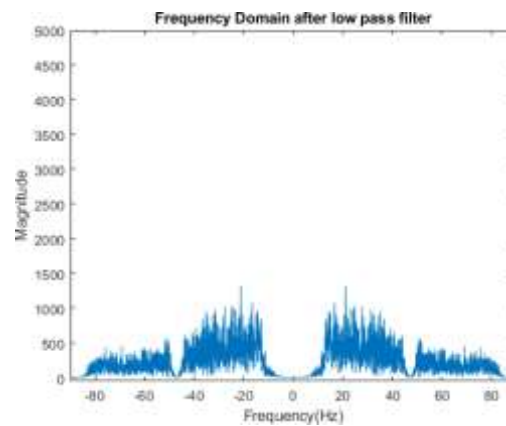


Figure 8: Signal after low pass filtering (Frequency domain)

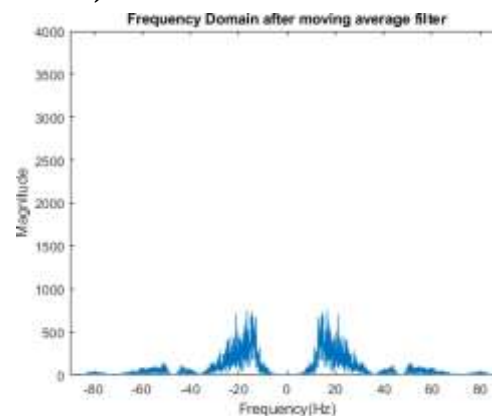


Figure 9: Signal after moving average filter (Frequency domain)

4) Wavelet Filtering

The signal may be broken down into time-varying frequency components using wavelets. Data characteristics are localised into distinct scales by them. It's possible to reduce the noise by focusing on the big magnitude wavelet coefficients, which include important signal components. [9].

Decomposition, thresholding, and rebuilding are all part of the denoising process. The signal is decomposed into M levels during decomposition. The coefficients at each of the aforementioned levels are multiplied by a predetermined threshold. Both the original coefficients from level M and the improved coefficients from levels 1 to M are used in the reconstruction. Sym4 wavelet (Figure 10) and thresholding approaches are used to derive the denoising output in our work.

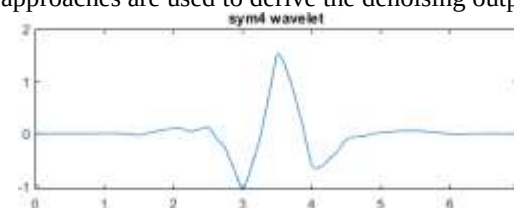


Figure 10: Sym4 wavelet

IV. RESULTS

A signal's MAV may be calculated using the convolution approach. To identify separate areas, K-means clustering is used with a clustering window of a predetermined size. The data is partitioned into two groups, one corresponding to the areas of contraction in the muscle and the other corresponding to the baseline without movement of muscles, using clustering. The ultimate result is shown graphically (Figure.11). Pulses may be seen in the output waveform anytime a muscle contraction occurs.

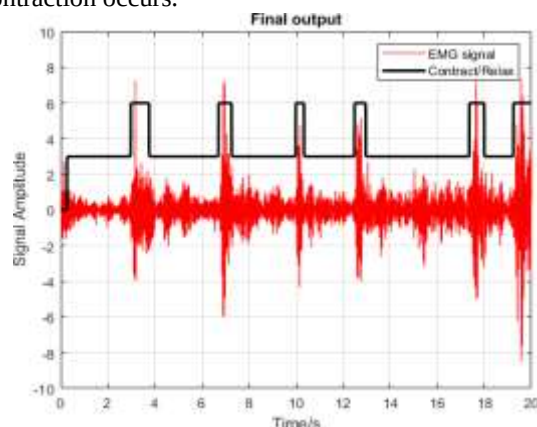


Figure 11: Final plot with pulses representing contraction (Time Domain)

V. CONCLUSION AND FUTURE SCOPE

Research on electromyography signals is described in this study, as well as the work we did to extract meaningful information from it using MATLAB. To improve the signal-to-noise ratio of a recording, various filtering techniques are used for each kind of noise. Raw signals are subjected to notch, high- and low-pass filtering, smoothing algorithms, and wavelet denoising. Muscle contractions and relaxations may be distinguished with great precision.

Because of the hardware limits, this technique has some drawbacks. The inherent noise in the acquisition circuit cannot be eradicated, even with the most advanced processing methods. In this article, we've spoken about the processing of data that has been collected and stored. However, it may be adapted to function in real-time. It is possible to send this sort of data to the cloud, where the doctor may see the patient's data online and make an appropriate diagnosis.

REFERENCES

- [1] J. W. Clark Jr., "The Origin of Biopotentials" in J. G Webster, "Medical Instrumentation", 4th ed, John Wiley and Sons, New York, pp. 126-87, 2010
- [2] C. Steele, "Applications of EMG in Clinical and Sports Medicine", InTech, Croatia, December 2011.
- [3] C. Heckman and R. M. Enoka, "Physiology of the motor neuron and the motor unit", pp. 119-147, 2004
- [4] M.B.I.Reaz, M.S Hussain, F. Mohd-Yasin, "Techniques of EMG signal analysis: Detection, processing, classification and Applications", 2006

- [5] H.W.Tam, J.G. Webster, "Minimizing electrode motion artifact by skin abrasion", IEEE Trans. Biomed. Eng., 1977
- [6] M. R. Neuman, "Biopotential Electrodes", in J. G Webster, "Medical Instrumentation": 4th ed, John Wiley and Sons, New York, pp. 189-240, 2010
- [7] G. J. Janz, D. J. G. Ives, "Silver, Silver Chloride Electrodes", 1968
- [8] Y. Blanc, U. Dimanico, "Electrode Placement in Surface Electromyography (sEMG) "Minimal Crosstalk Area" (MCA)", 2010
- [9] X. Zhang, Y. Wang, R.P.S. Han, "Wavelet transform theory and its application in EMG signal processing", Yantai, China, September 2010.