Electromyographic system for prosthetic arm.

Group DNAwesome : Janhavi Shedge, Mahesh, Adil CT.

Abstract
The prosthetic hand is a device used for the amputee to make them capable of doing daily life stuff. Losing upper limbs is not just a physical loss it also affects the way that person sees their life, they start feeling disabled all the time. To join hand to hand and to make more abled than disabled, prosthetic arm can be used.

In this report we have performed mathematical calculations of digital signal processing (DSP) such as the Fourier Transform or the design and application of digital filters to deduce information from the raw signal. This information can then be used in prosthesis by using characterization techniques.

1.Introduction

Worldwide, every year the number of amputees increases from 150,000 to 200,000, which are added to the existing four millions; 30% of these amputees have suffered from upper limb amputation, 60% of the arm amputations are found in people between 21 and 64 years old, whereas 10% of them are patients under 21. According to Amputee Coalition of America's National Limb Loss Information Center (NLLIC), 70% of amputations, due to a trauma or an accident, involve the upper limbs.

Therefore, it is important to provide the technology of prosthesis since it can offer those patients significant support so that they can normally practice their life activities and be involved in the community.

Different types of prosthetic hands have been developed, some of which are just for cosmetic purposes with no functions, known as the Passive Hand. Other types have some functioning abilities such as the Body-Powered Prosthesis, the Electrical Hand, and the Myoelectric Hand. The Body-Powered Prosthesis (so called mechanical prostheses) is operated with straps that commonly pass over the amputees' shoulders and is controlled by scapula abduction; the Electrical Hand is operated by a motor driven by microswitches; and the Myoelectric Hand is operated by a microprocessor and a motor which are controlled by electromyography signals (EMG). The EMG signals are biological signals that occur in the residual limb and can be collected with sensors to control the movement of the prosthesis.

2.Theoretical Background

Many of the amputees use prostheses which have a very few functionalities like hand shaped or like a hook shaped.These kind of (Body _powered) prostheses are most widely utilised, least priced, and widely available prostheses . However, the movement of such prostheses has a significant mechanical disadvantage.

Myoelectrically controlled prosthesis were first developed in the 1950s–1960s, with the prosthesis being controlled by reading and analyzing signals created by flexing the remaining muscles of a limb.Such kind of signals are called EMG signals.

Due to the mixing of numerous noise signals or artefacts, the identification of a real EMG signal that originates in the muscle is lost. The EMG signal's characteristics are influenced by the subject's internal structure, such as skin formation, blood flow velocity, observed skin temperatures, tissue structure (muscle, fat, etc.), measurement site, and more.
EMG signals indicate the electrical impulses induced by muscle contractions and activities, they are frequently employed in prosthesis research. Furthermore, because they may be collected by surface sensors, they are more appropriate and easy for amputees.The EMG signal is the total of all action potentials that happen in a muscle at the same moment. Standard electrodes can be used to record it on the skin's surface.
In comparison to other EMG electrodes, surface EMG is comparatively simple to use. This is why it is widely employed in the control of robotic devices in the pursuit of prosthesis. It is also commonly employed in recent EMG experiments by engineers because it does not require medical certification or experience to use. Its application in rehabilitative prostheses is advantageous since it causes no discomfort to the individual on whom it is used. When put into the subject's skin, other types of EMG electrodes (needle and thin wire) may generate a twitching feeling and cause him or her to move.

It is critical to have a thorough grasp of the muscles from which the EMG signal is taken in order to receive the best results from SEMG.
In most situations, two sensing surfaces (or EMG electrodes) are bipolarly implanted on the skin. The EMG electrode should be put in the right area and its direction across the muscle is critical in order to obtain the greatest possible signal.
Before moving on to the signal acquisition step, it's critical to familiarise yourself with both the EMG signal and the numerous problems and elements that impact its qualitative qualities.

The amplitude of the EMG signal ranges from 1 to 10 mV, making it a very faint signal. The signal has a frequency range of 0-500 Hz, with 50-150 Hz being the most dominating.

2.1 Electrode

Modern prosthetic sockets contain electrodes which detect subtle movements in stump muscles and convert them into movement of the prosthetic arm, leg, hand, or foot. They found that patients had far better control of their movements, and the prosthetics themselves followed instructions more reliably via their muscles.

Today's movable prosthetic arms have two electrodes attached to the prosthesis. When the amputee flexes a certain muscle in the stump of the amputated arm, the electrodes in the prosthetic arm detect the signal, which they then convert into a movement in the artificial hand.

2.2 sEMG

Since the discovery of surface electromyography (sEMG) in 1912, this noninvasive technique for the acquisition and analysis of myoelectric signals has contributed significantly to enhancing our understanding of the function and dysfunction of the neuromuscular system and has become an essential tool in modern musculoskeletal physical therapy. Surface EMG can be considered as a summation of tissue-filtered signals generated by a number of concurrently active motor units. Detection, recording, and analysis of myoelectric signals provides a reproducible means of determining disturbances in motor control in patients with musculoskeletal disorders. Surface EMG is typically applied in physical therapy for the assessment of disturbed motor control and for monitoring change with rehabilitation. The sEMG signal can be analyzed in various ways to provide the investigator or clinician with a multitude of information about the muscle/s being studied.

Examples of analyses include

1. detection of the onset or offset of muscle activity during tasks such as postural perturbations
2. assessment of myoelectric manifestations of muscle fatigue
3. evaluation of the magnitude of muscle activation
4. generation of tuning curves of the sEMG amplitude to relate the amplitude of the muscle response to the magnitude and direction of force
5. monitoring the spatial distribution of activity with high-density, two-dimensional sEMG.

These fundamental methods of EMG assessment are being explored as a means of evaluating neuromuscular impairment in patients with musculoskeletal disorders with a focus on two of the most common musculoskeletal complaints, namely, low back pain and neck pain.

2.3 Filters- band pass and band stop

Numerous publications have suggested optimal cutoff frequencies for EMG bandpass filtering for conductive EMG sensors. The significant power spectrum of EMG signals ranges from approximately 20–500 Hz. Low-frequency noise, such as movement artifacts, occurs predominantly in the range of 0–20 Hz. The recommended cutoff frequency *fC* for the high pass filter for attenuating these low-frequency artifacts is within the range of 5–30 Hz for conductive

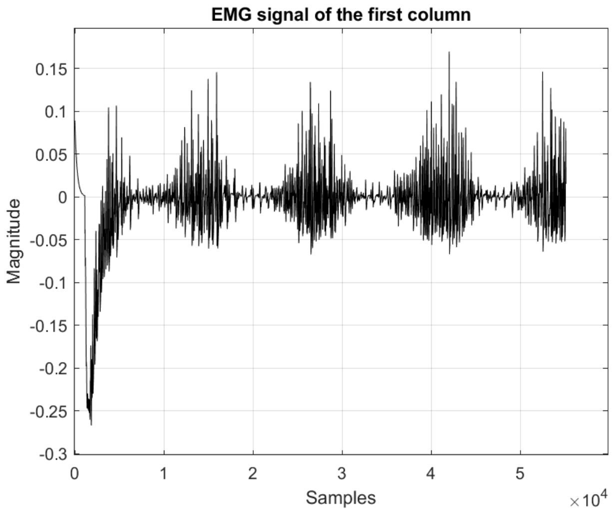
EMG sensors. A 400–500 Hz lowpass filter *fC* is recommended for filtering high-frequency noise while maintaining EMG signal power.

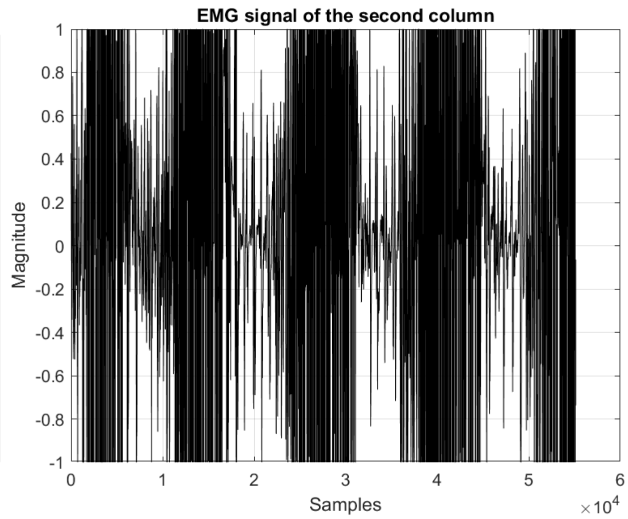
Digital filtering realized by programmable μC has various advantages over analog filtering. Active analog filters of second or higher order require many components, which must be matched exactly. Component accuracy and the resulting filter behavior is limited by manufacturing, temperature and aging tolerances. Providing various analog filters requires several active and passive low-noise high-precision electronic components, which increase power consumption and cost. One might argue that analog filters are faster; however, in the case of EMG at a sampling frequency in the kHz-range, the delay caused by the presented digital signal processing is negligible. The signal delay that is dominated by the time constant *T* of the lowpass filters does not depend on the realization of the filter. Anyway, an analog anti-aliasing filter upstream of the analog-to-digital conversion (ADC) to conform with the Nyquist–Shannon sampling theorem is indispensable. The digital filter algorithms can simply be adjusted. For example, the notch frequency for the power-line interference can be changed by one parameter from 50 Hz in Europe to 60 Hz. Furthermore, it allows the real-time implementation of additional algorithms like artifact suppression or dexterous prostheses control. Such adjustments require re-engineering and a new design of the sensor electronics at analog signal processing.

An offset-free control is one that drives the controlled outputs to their desired targets at steady state. In the linear model predictive control (MPC) framework, the elimination of steady-state offset may seem a little obscure, since the closed-loop optimization tends to hide the integral action. Theoretically, implementing a well-posed optimization problem and having unbiased steady-state predictions are sufficient conditions to eliminate the output offset. However, these basic conditions are not always achieved in practical applications, especially when state-space models are used to perform the output predictions.

3. Design and Results

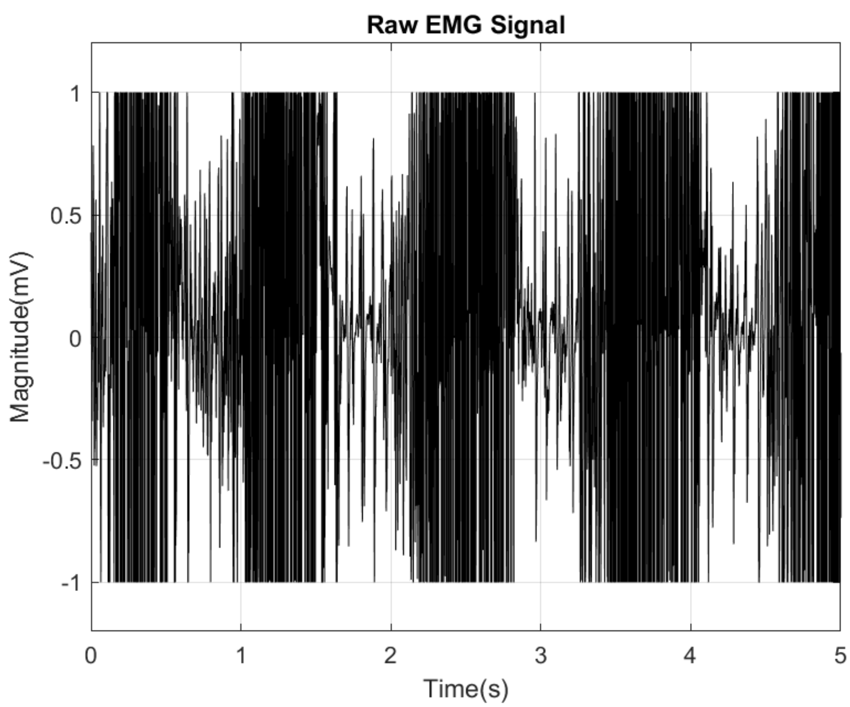
We used a pre- existing EMG signal file to then process it. Common mode rejection ratio filter, cascade configuration of the filters band-stop and bandpass. EMG variable had two column vectors corresponding to different EMG signals. Both signals are then plotted. We can see that the second EMG signal is more noisy as compared to the first EMG signal.



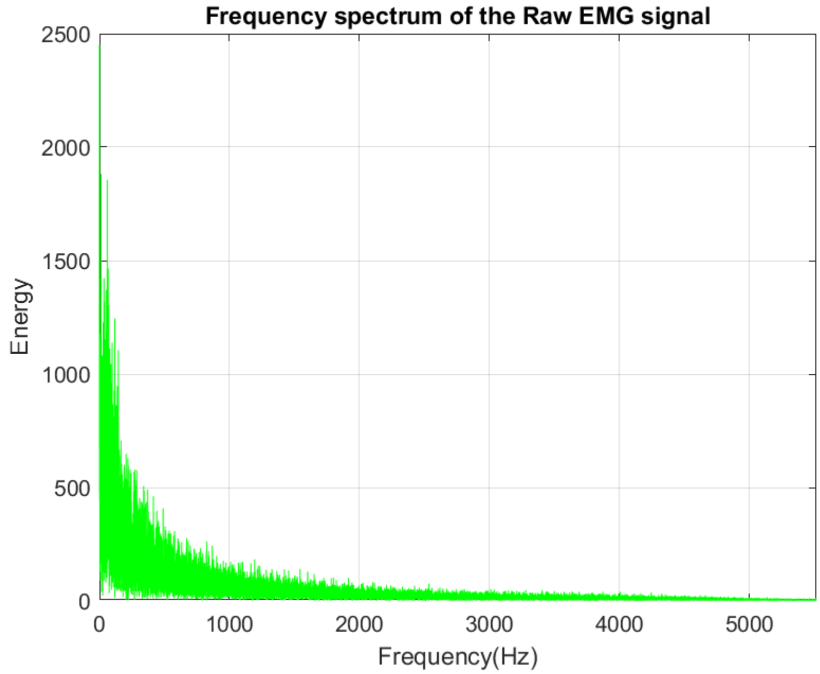


Intrinsic characteristics like time, magnitude and sampling frequency are determined for the raw EMG signal.
fm is the sampling frequency in Hz.
Sampling time: tm = 1/fm

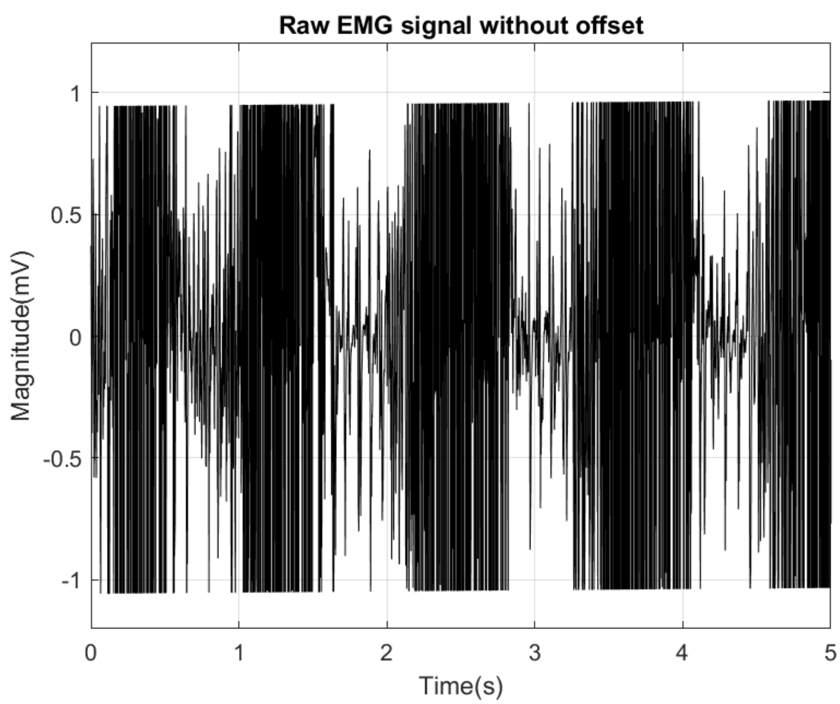
A graph of the raw EMG signal is plotted.



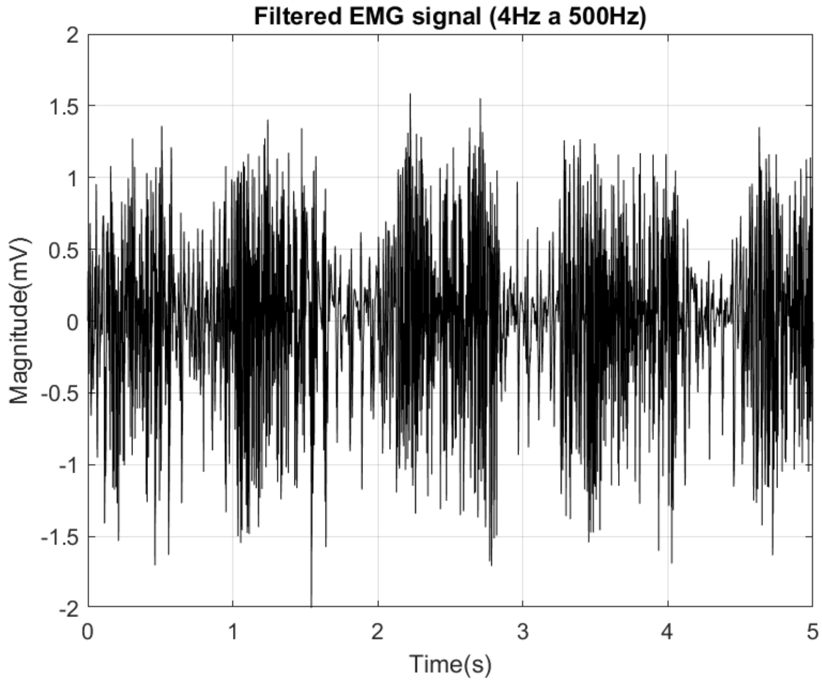
Fast Fourier Transform is then performed on the raw EMG signal and its frequency spectrum is plotted.

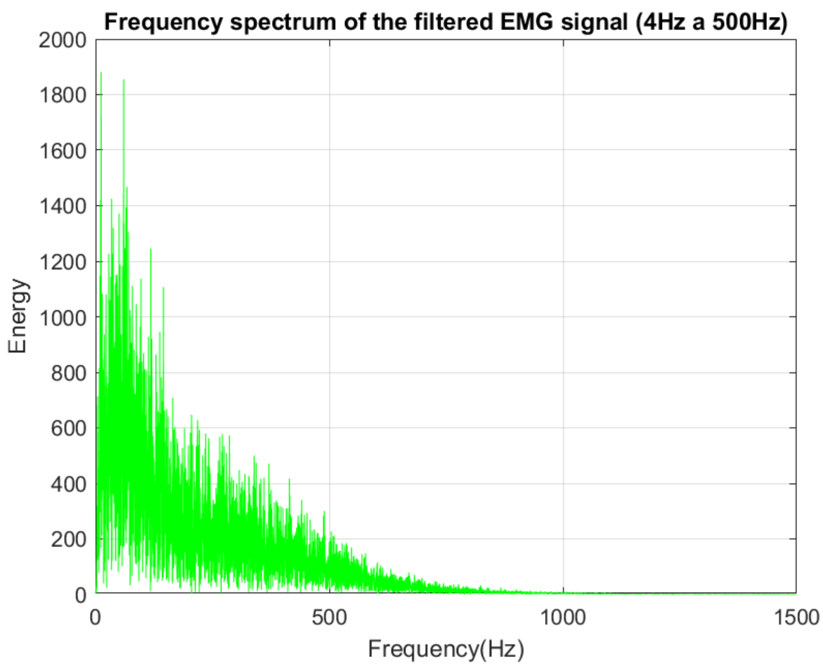


Offset elimination is an important step in the process. It is used to eliminate the offset or DC level on which the signal can be mounted.

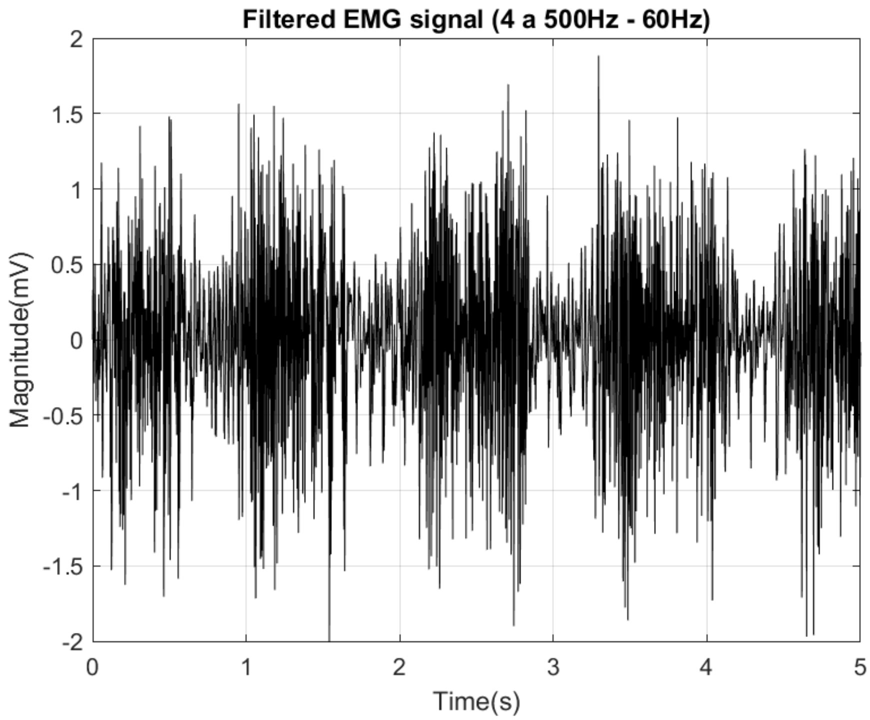


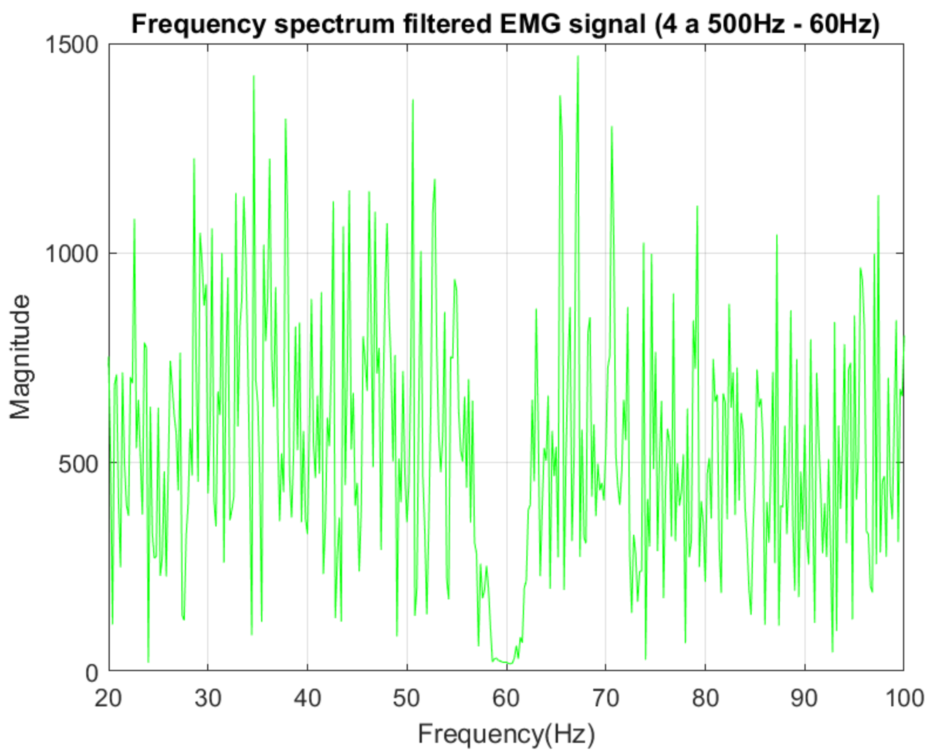
The signal is then filtered with the bandpass filter with Butterworth configuration and butter function is used. The filtered EMG signal as well as its frequency spectrum is the plotted. This helps us to see a more defined physiological behaviour which is similar to that of the muscle contractions.



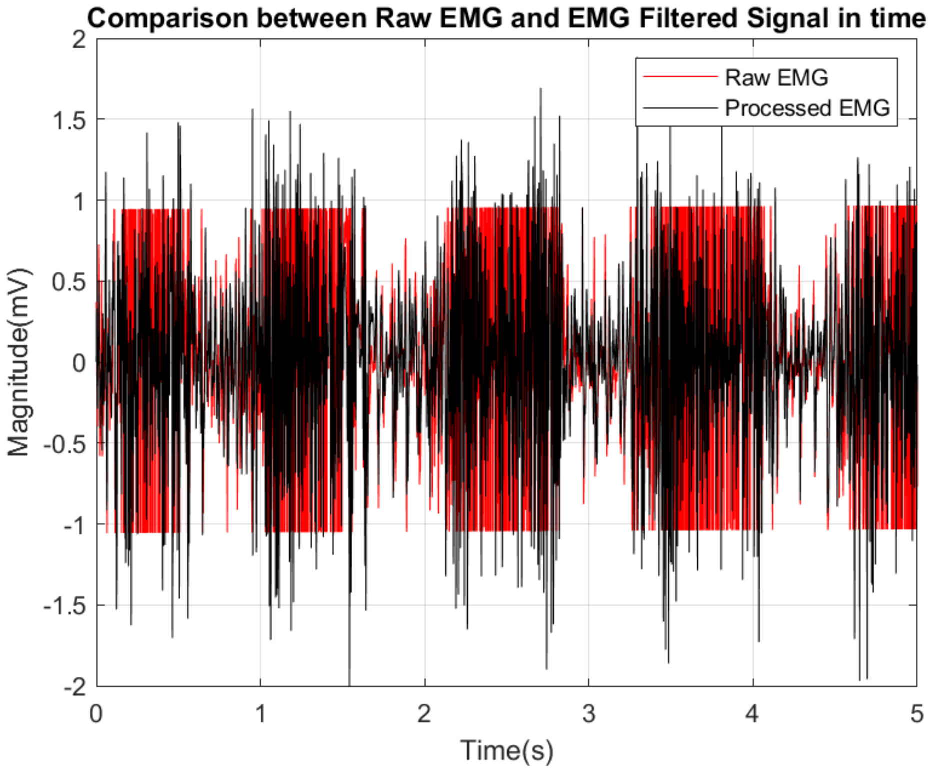


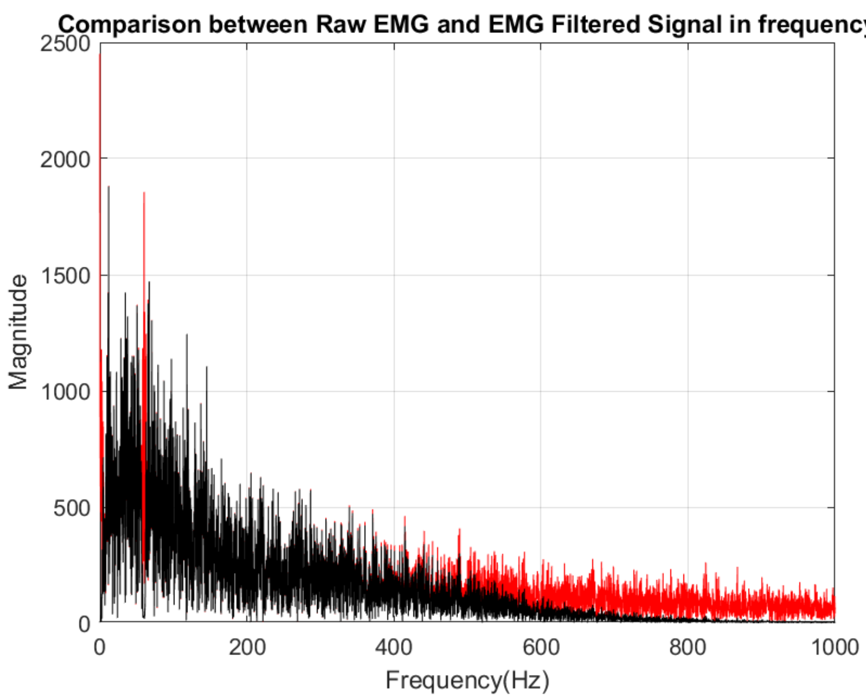
Another filter the band stop filter is then used with butter function and the graph and frequency spectrum of the filtered signal is plotted.





Upon comparison we can thus see the difference between the raw signal and the filtered signal.





After the conditioning of the signal characterization techniques are implemented. This expresses the information in a more smoothed way. Mathematical tools like effective value (RMS), the mean absolute value (MAV). or the sum of the absolute value (IAV) are used to achieve this.

The effective value or the root mean square (RMS)

$$EMGE_{\mathrm{RMS}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} EMG_i^2} = \sqrt{\frac{EMG_1^2 + EMG_2^2 + \cdots + EMG_N^2}{N}}$$

The mean absolute value (MAV)

$$\overline{\mathrm{EMG}E_{\mathrm{MAV}\,i}} = \frac{1}{N}\sum_{k=1}^{N} |\mathrm{EMG}_k|, \quad i = 0, \ldots, L-1.$$

The integral or sum of the absolute value (IAV)

$$\overline{\mathrm{EMG}E_{\mathrm{IAV}\,i}} = \sum_{k=1}^{N} |\mathrm{EMG}_k|, \quad i = 0, \ldots, L-1.$$

These characterization techniques have similar results.

These EMG signals can then be used to control the prosthetic arm by sending the signal required for a particular action or muscle movement.

4.Contribution

The research and design work was done as follows:
Prosthetic arm - Adil CT
Surface Electromyography and electrodes - Mahesh and Janhavi
Offset Elimination and Filters - Mahesh and Janhavi

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