B. TECH. PROJECT REPORT

On

Myoelectric Pattern Recognition System

(for emergency prediction)

BY

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DISCIPLINE OF MECHANICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

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Myoelectric Pattern Recognition System

(for emergency prediction)

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degrees

of
BACHELOR OF TECHNOLOGY
in
MECHANICAL ENGINEERING

Submitted by:
Sai Kiran Chowdarapu

Guided by:
Dr. Kapil Ahuja, Professor

INDIAN INSTITUTE OF TECHNOLOGY INDORE
May 2022

CANDIDATE’S DECLARATION

I hereby declare that the project entitled **“Myoelectric Pattern Recognition System”** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in ‘ Mechanical Engineering ’ completed under the supervision of **Dr. Kapil Ahuja, Professor, Department of Computer Science and Engineering,** IIT Indore is an authentic work.

Further, I declare that I have not submitted this work for the award of any other degree elsewhere.

Saikiran.ch / 27/05/2022

Sai Kiran Chowdarapu (180003015)

Date : 27/05/2022

CERTIFICATE by BTP Guide(s)

It is certified that the above statement made by the student is correct to the best of my knowledge.

KA

Supervisor
Dr. KAPIL AHUJA
Professor,
Indian Institute of Technology Indore
Date :

Preface

This report on "Myoelectric Pattern Recognition System" is prepared under the guidance of Dr. Kapil Ahuja.

Through this report, I have tried to give a detailed design of a wearable device that uses a pattern recognition system to analyze the bio-potential activity of an individual, and predict an emergency.

I have tried, to the best of my abilities and knowledge, to explain the content in a lucid manner. A simulation of the desired device is also built for illustration purposes.

Saikiran.ch / 27/05/2022

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Acknowledgements

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Abstract

The cases of molestation and kidnapping have been continuously increasing over the last 5 years.

The intention is to build a wearable device, that analyses the bio-potential activity and helps reduce the chances of molestation and kidnapping.

Any movement of the body is achieved by muscle contractions and is stimulated by the motor neurons. This process is called the Action Potential. Irrespective of whether an individual is free to perform the intended action or not, the action potential patterns remain the same. Electromyography(EMG) is the technique to measure these action potentials. The device uses the surface electromyography technique to measure the potentials.

A predefined sequence of actions is defined for the fingers. The acquired data is analyzed to determine if the previously defined sequence of actions is intended by the individual. In case of a match, the device informs the nearby police station about the emergency and also shares the location coordinates. The device tries to predict the motion intended by the digits(fingers).

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List of Abbreviations

ECG - Electrocardiography
EEG - Electroencephalogram
EMG - Electromyography
ECG - Electrocardiography
ECG - Electrocardiography
ECG - Electrocardiography
ECG - Electrocardiography
ECG - Electrocardiography
CNS - Central Nervous System
AP - Action Potential
MUAP - Motor Unit Action Potential
SEMG - Surface Electromyography
MVC - Maximum Voluntary Contraction
ADC - Analog to Digital Converter
TFD - Time-Frequency Domain
STFT - Short Time Fourier Transform
WT - Wavelet Transform
CWT - Continuous Wavelet Transform
DWT - Discrete Wavelet Transform

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Chapter 1

1. Introduction

The cases of molestation and kidnapping have been continuously increasing over the last 5 years.

The intention is to build a wearable device, that analyses the bio-potential activity and helps reduce the chances of molestation and kidnapping.

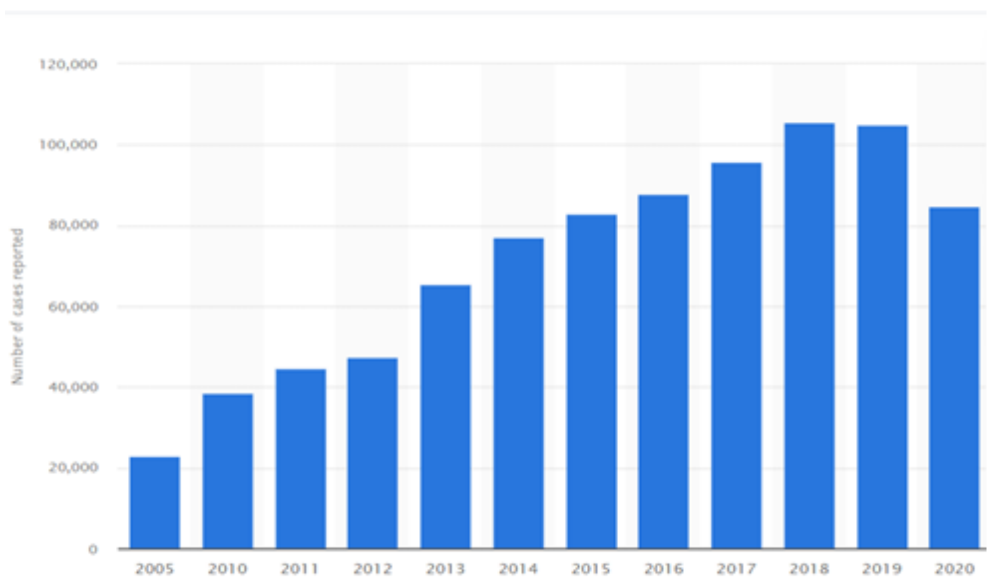


Figure 1 : Kidnapping and abduction cases in India

Due to the unavailability of the required hardware like the electrode setup etc., a simulation of the desired device is built.

As an overview of what the device does :

Any movement of the body is achieved by muscle contractions and is stimulated by the motor neurons, by altering the potential across the cell membrane of the muscle fiber. This process is called the Action Potential. Irrespective of whether an individual is free to perform the intended action or not, the action potential patterns remain the same. They are robust to any extreme situation taking place externally and can be analyzed to predict an emergency situation.

Electromyography(EMG) is the technique to measure these action potentials. The device uses the surface electromyography technique to measure the potentials[14].

A predefined sequence of actions is defined for the fingers. The acquired data is analyzed to determine if the previously defined sequence of actions is intended by the individual. In case of a match, the device informs the nearby police station about the emergency and also shares the location coordinates. The device tries to predict the motion intended by the digits(fingers).

The device mainly has 6 tasks to do:

1. Signal Acquisition
2. Signal processing
3. Data segmentation
4. Feature extraction
5. Classification
6. Response

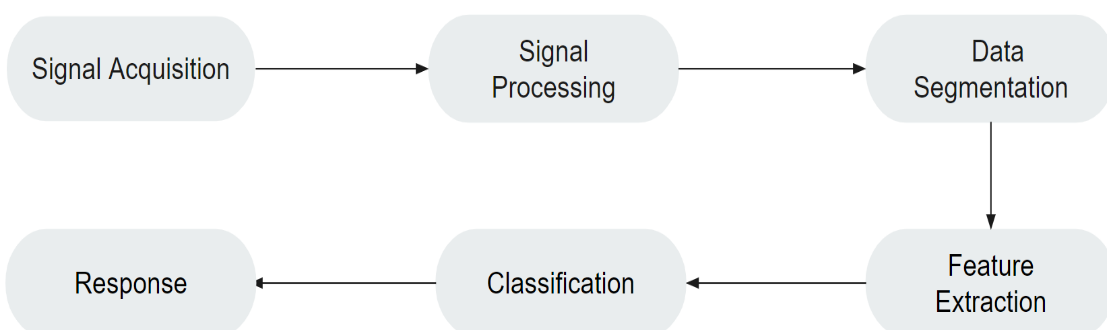


Figure 2 : Block Diagram

Hardware details

The device consists of 3 units :

1. Input unit
    a. Electrodes and amplifier circuit.
    b. For signal acquisition.
    c. 5 Ag-AgCl electrode pairs are used.

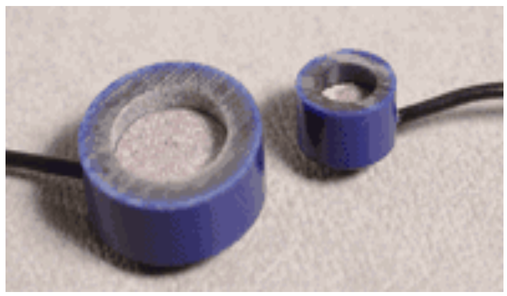


Figure 3 : Electrode pairs

2. Processing Unit
    a. A microprocessor.
    b. Performs signal processing, data segmentation, feature extraction, classification, and post-processing.
3. Response Unit
    a. SIM 868 Module.
    b. To share the location coordinates and make an emergency call.

Chapter 2

2. Signal Acquisition

For the device to predict if a person is at risk, the device has to analyze the actions of an individual. Two types of activities can be analyzed :

1. Physical Activity
2. Bio-potential Activity

In the case of physical activity, the person needs to be free to perform the intended action which might not always be possible in the scenarios considered. Whereas in cases of bio-potential activities, some of them are robust to the considered situation and can be analyzed for emergency prediction with a minimum number of false positives.
Hence the device analyzes the bio-potential activity of an individual to predict an emergency.

2.1 Biopotential Signals

Bio-potential signals(voltage vs time) are those produced due to various physiological processes occurring within our body[14].
There are 7 types of bio-potential activities :

1. Electrocardiography (ECG)
2. Electrodermal Activity (EDA)
3. Electroencephalography (EEG)
4. Electrogastrography (EGG)
5. Electromyography (EMG)
6. Electrooculography (EOG)
7. Impedance Cardiography (ICG)

Among the 7 biopotential activities ECG, EMG, and EEG are the most famous activities and are easy to acquire compared with others.

2.1.1 Electrocardiography(ECG)

These signals depict the contraction of the heart muscles wrt to time. The potential difference across the heart muscle fibers is measured.

ECG signals create a lot of false positives in our field of interest. The fluctuations in the contraction levels of the heart muscles might be due to various reasons like anxiety etc., Hence analyzing the ECG signals doesn't help in our case[14].

2.1.2 Electroencephalography(EEG)

These signals are to be acquired from the scalp and inspect a huge domain of actions.

Since the device is to be carried by the user round the clock, it has to be portable and the attackers should not be able to notice the device.

Considering the above hardware constraints and to make the prediction easier for the classification algorithm, EEG signals aren't used[14].

2.1.3 Electromyography(EMG)

There are 3 types of neurons in the human body :

1. Sensory
2. Motor
3. Autonomic

Among the three, motor neurons are responsible for stimulating any movement of our body.

A motor neuron is connected to 1000s of muscle fibers, through its axon terminals, which along with the respective neuron, are collectively called a motor unit[14].

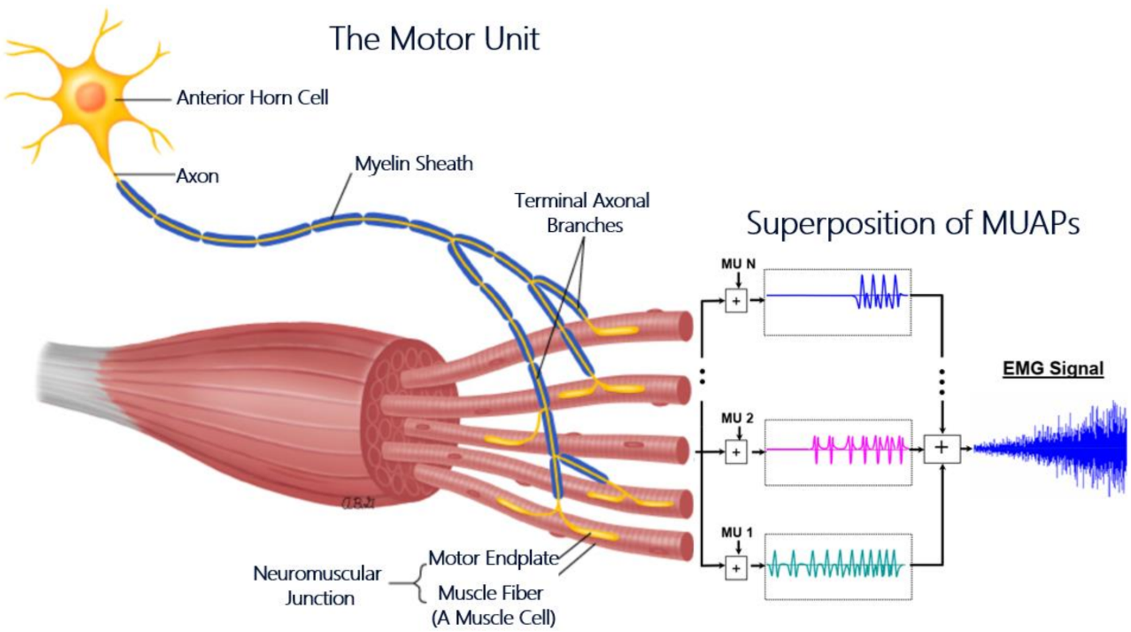


Figure 4 : Superimposition of multiple MUAPs

Any movement of the body is stimulated by these motor neurons by varying the potentials across the membranes of the muscle fibers present in the respective motor unit. This process is known as the action potential[15]. The potentials are varied by the electric signals generated within the neurons, which are transmitted to the muscle fibers through axon terminals.

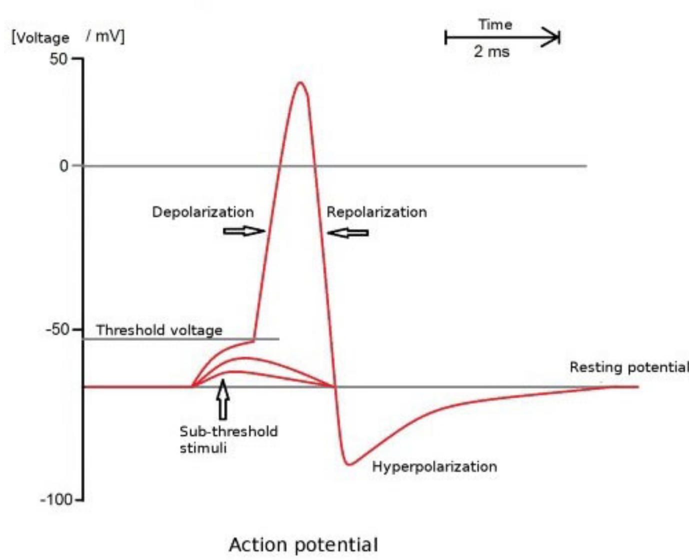


Figure 5 : Action Potential

EMG is the technique to measure these Motor Unit Action Potentials(MUAPs).
The advantage of these signals is that they remain the same irrespective of whether the person is free to perform the intended actions or not and depend solely on the force intended.

2.1.3.1 Types of Electromyography

Based on the type of electrodes used EMG is broadly classified into 2 types [10] :

1. Invasive
2. Noninvasive

Noninvasive electrodes do not invade the body while acquiring the data, whereas invasive electrodes are to be inserted into the body for data acquisition.
Surface electromyography is a non-invasive EMG technique.
The device uses the Surface electromyography technique to extract the EMG signals.

2.2 Body part chosen

The situation or the scenario considered is very sensitive and having minimal false positives is a major concern. For this reason and other constraints like the device having to be wearable, fingers are chosen for EMG analysis, as they have the highest number of egress of freedom i.e., the highest number of compound actions achievable.

2.3 Control Sites

Control sites are the spots where the electrodes are to be placed for data acquisition. The choice of control sites plays a major role in deciding the accuracy of the classifier. Choosing improper sites results in the greater superimposition of MUAPs making the task of discrimination difficult for the classifier. Since the electrodes are to be placed close to the body part in observation(fingers in this case), the electrodes are to be placed on the forearm. The control sites are to be chosen such that the superimposition of various MUAPs is minimized. To choose the appropriate control sites, the anatomy of the forearm is to be observed.

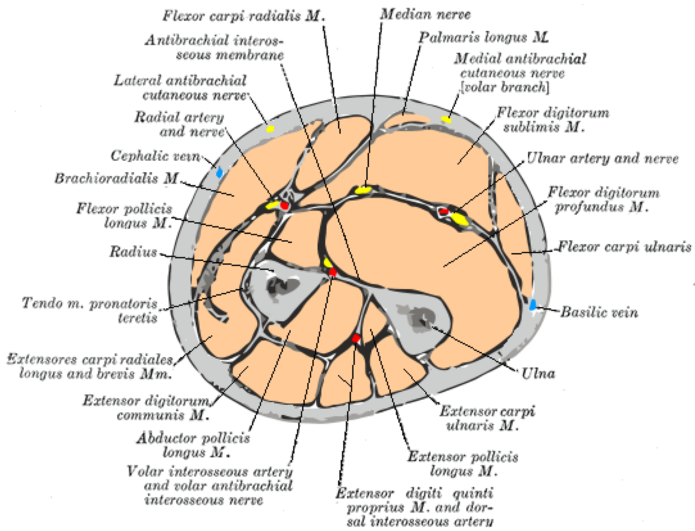


Figure 6 : Anterior compartment of Forearm

2.3.1 Muscles responsible for finger flexions

Since we are dealing with flexion/ contraction of fingers, the anterior compartment of the forearm where the flexor muscles are present is to be observed[18]. There are 8 flexor muscles in the anterior compartment and are broadly classified into 3 types based on the nerves innervating them. They are :

1. Superficial
2. Intermediate
3. Deep

Level	Muscle	Extrinsic/Intrinsic	Nerve
superficial	flexor carpi radialis	extrinsic	median
superficial	palmaris longus	extrinsic	median
superficial	flexor carpi ulnaris	extrinsic	ulnar
superficial	pronator teres	intrinsic	median
superficial (or intermediate)	flexor digitorum superficialis	extrinsic	median
deep	flexor digitorum profundus	extrinsic	ulnar + median (as anterior interosseous nerve)
deep	flexor pollicis longus	extrinsic	median (as anterior interosseous nerve)
deep	pronator quadratus	intrinsic	median (as anterior interosseous nerve)

Table 1 : Flexor Muscles

Among the 8 flexor muscles, 5 are responsible for digit flexion. They are :

Thumb finger	Flexor pollicis longus
Index finger	Flexor digitorum superficialis
Middle finger	Flexor carpi radialis, Palmaris longus
Ring finger	Flexor carpi radialis
Baby finger	Flexor carpi ulnaris

Table 2 : Muscles responsible for finger flexion

Choosing these 5 flexor muscles as control sites reduce the superimposition of MUAPs.

2.4 Hardware setup

5 Ag-AgCl electrode pairs are used for signal acquisition and are placed at the chosen control sites[12].

A velcro strap is used to hold the electrodes intact during the data elicitation, avoiding the relative motion over the skin.

Figure 7 : Velcro strap

2.5 Dataset

The control sites chosen for data acquisition weren't previously explored in the literature. But the advantage of EMG signals is that irrespective of the muscles under observation the action potentials of individual muscle fibers remain the same. Changing the elicitation sites by small distances does not alter these trends to a great extent. Using the put EMG database, where the electrodes were placed on the forearm itself but at different locations, the data was mimicked for the chosen control sites[13, 11]. The MUAPS of individual motor units were also simulated to check if the data was deviating too much from reality.

Compound actions like flexion of multiple digits aren't considered as they are complex and difficult to mimic due to various artifacts and high transient nature.

The dataset created consists of 5 classes each corresponding to a finger flexion, with 128 samples per class i.e., a total of 640 samples each of length 64ms are simulated.
Only steady-state signals, where the contraction level of a muscle fiber isn't changing, are considered for ease.

Though surface electromyography is safe, it has its disadvantages. The collected signals are a superposition of multiple MUAPs. Skin, midway muscle tissue, and other factors like motion, ECG artifacts, and muscle crosstalks attenuate the signal and introduce noise. The extracted raw EMG signals are to be processed to partly eliminate these defects.

Chapter 3

3. Signal Processing

Five signal processing techniques are to be applied to finetune the raw EMG signals[19] :

1. Amplification
2. Analog Band Pass Filtering
3. Signal discretization
4. Normalization
5. Rectification

3.1 Amplification

The obtained EMG signals are attenuated by various artifacts and are too weak to analyze, to predict a pattern. They are to be amplified for further analysis.
The EMG signals are amplified by a factor of **1000**.

3.2 Analog Band Pass Filtering

External noises hamper the actual patterns in the EMG signals complicating the task of motion prediction. These are to be eliminated to improve the quality of the signals. The quality of a signal is measured in terms of the signal-to-noise ratio(**SNR**).

Most of the EMG signals fall into the frequency range of 20Hz to 500Hz. Those with a frequency below 20Hz are mainly due to the motion artifacts like the relative movement of the device over the skin etc., and those above 500 Hz are due to other noises like muscle crosstalks, ECG artifacts, electromagnetic radiation, etc.,

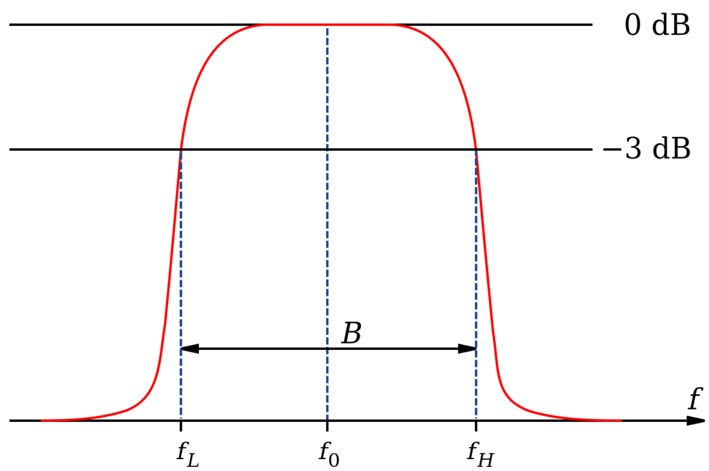


Figure 8 :   Butterworth bandpass filter

A bandpass filter performs both low pass and high pass filtering and takes two parameters lower cutoff frequency and higher cutoff frequency.

The lower cutoff frequency is to remove the DC component and other low-frequency noises, setting the mean to approximately 0.

The higher cutoff frequency is to remove high-frequency noises added due to other artifacts.

A 4th order Butterworth Bandpass filter in analog mode is used to remove the unwanted noises. Cutoff frequencies considered :

1. Lower cutoff frequency : 20Hz
2. Higher cutoff frequency : 500Hz

Analog filtering is computationally costly compared to digital filtering and is sensitive to noise. Though analog filtering has its disadvantages, it helps in our case as we don't miss out on the required data present near the cut-off frequencies, which might be eliminated considering it as noise in the case of digital filters. Moreover, digital filters might introduce some spurious high-frequency components while filtering the signal.

3.3 Signal Discretisation

Analog signals are continuous wrt time and range, whereas digital signals are discretized.

Digital electronics with memory constraints cannot afford to store the analog signals and hence are to be discretized. There are 2 major steps in the Analog to digital conversion process :

1. Sampling
2. Quantization

3.3.1 Sampling

Sampling is the process of discretizing the analog signal wrt to time i.e converting the continuous signal to a discretized time sequence.

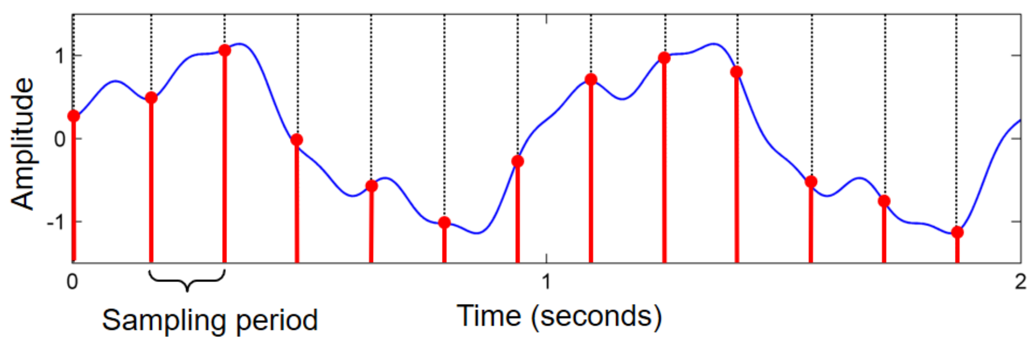


Figure 9 : Sampling the analog signal

Sampling rate : The frequency at which the Analog to Digital Converter samples the analog signal.

3.3.1.1 Sampling theorem

For the analog signal to be completely determined from its digital counterpart, the analog signals are to be sampled at a rate that is at least 2 times the highest frequency component present in the analog signal.

In the case of EMG signals, frequencies do not go above 500Hz. Hence to sample an EMG signal without any loss of information, the sampling rate needs to be at least 2*500 = 1000 Hz.

After numerous trials, a sampling rate of 5000Hz was found to be optimal. The analog signal obtained by interpolating the corresponding digital counterpart almost matched the actual analog signal. Moreover, the analog signals are sampled at a steady rate i.e at constant time intervals.

3.3.2 Quantization

Since analog signals are continuous over their range, they can assume infinitely many values, which makes the task of storing them difficult due to the memory constraint. Hence, we quantize the values to a particular number of discrete levels i.e the digital counterpart can assume only a particular set of discrete values. The number of discrete values depends on the number of bits in the ADC.

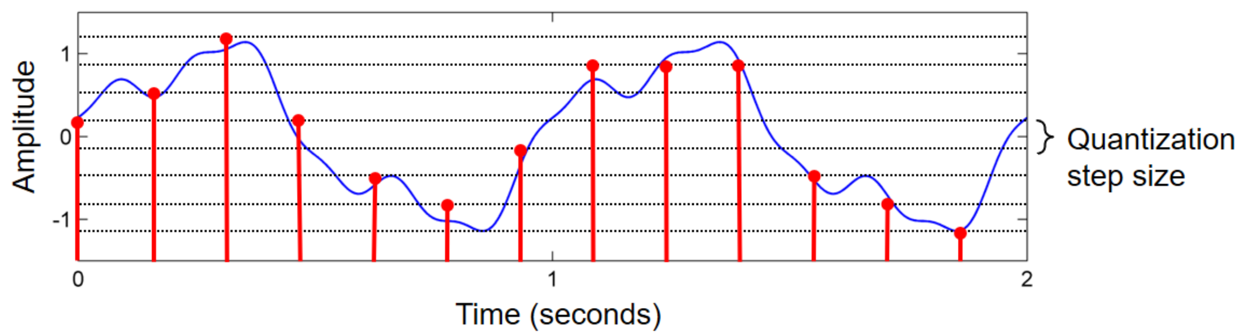


Figure 10 :   Quantisation

The device uses an 8-bit ADC i.e the final digital signals can assume 2^8 discrete values (32 values).

3.4 Normalization

Though the patterns of EMG signals remain almost the same(might vary with external conditions), the magnitude of variation in the signals, for stimulation, varies with the individual. The signals are to be normalized to avoid these differences, else the accuracy of the classifier will be greatly affected.

Maximum Voluntary Contraction(MVC) : The action potential corresponding to the maximum possible force or contraction achievable by an individual.

Maximum Voluntary Contraction is used as the base to normalize the raw EMG signals.

If normalization is done before rectification, generally the signals are normalized to a range of [-1,1]. To enhance the energy content in the signals, they are normalized to a new range of [-75,40] which is the approximate range of voltage values during an action potential, with the resting potential value at -65. Normalization is done before rectification to capture the negative range of values too.

3.5 Rectification

Only absolute values of the signals are to be considered to avoid the case of the mean turning to be 0 or the integral over the signal being 0. Now that the signal amplitudes belong to the range of [-75,40], the deviation of the signals from -65 (resting potential) is to be considered instead of the actual signal. This way it can be ensured that at the resting stage the muscles contain no energy. The absolute values of these deviations are considered in the further processing steps.

This helps in enhancing the difference between the feature values in further steps.

Chapter 4

4. Data Segmentation

Say the data is sampled at a rate of 5000Hz i.e, 5000 samples per sec. Passing a single sample as an input to the classifier doesn't help as it doesn't carry much information regarding muscle activity[4].

Hence we consider passing the data over a window of time as a single input and this process is called windowing or data segmentation.

There are 3 major parameters for data segmentation[1] :

1. Length of the segment
2. State of data
3. Windowing technique

4.1 Length of the segment

The length of the segment should be selected carefully such that the sum of segment length and response time is less than a particular threshold, so that it satisfies the real-time constraints, and is also not so small that it carries minimal information regarding the muscle activity and tampers the classification accuracy.

4.2 Windowing technique

There are 2 types of windowing techniques:

1. Adjacent windowing
2. Sliding/overlapping windowing

4.2.1 Adjacent windowing technique

In adjacent windowing, adjacent segments with a predefined length are used for feature extraction and are disjoint i.e do not overlap. A classified intended motion emerges after a certain processing delay. Since processing time is a small portion of segment length, the processor is idle during the remaining time of the segment length.

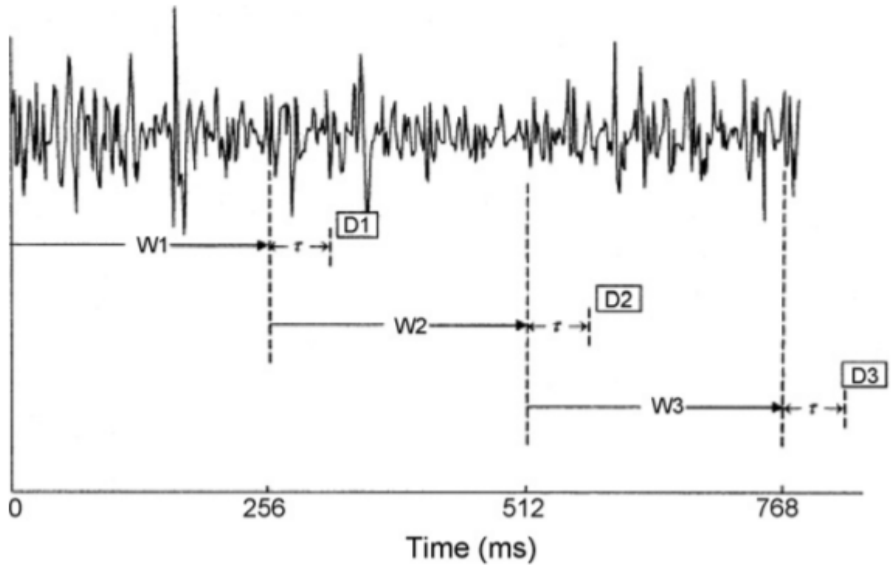


Figure 11 : Adjacent Windowing Technique

4.2.2 Sliding windowing technique

In the sliding window technique, the new segment slides over the current segment, with an increment time less than the segment length. This helps in reducing the ideal time but we need to ensure that the increment time is to be greater than the response time.

The sliding window technique introduces redundant data because of the overlapping windows. Post-processing techniques like Majority Voting etc., are to be used to maintain the desired accuracy.

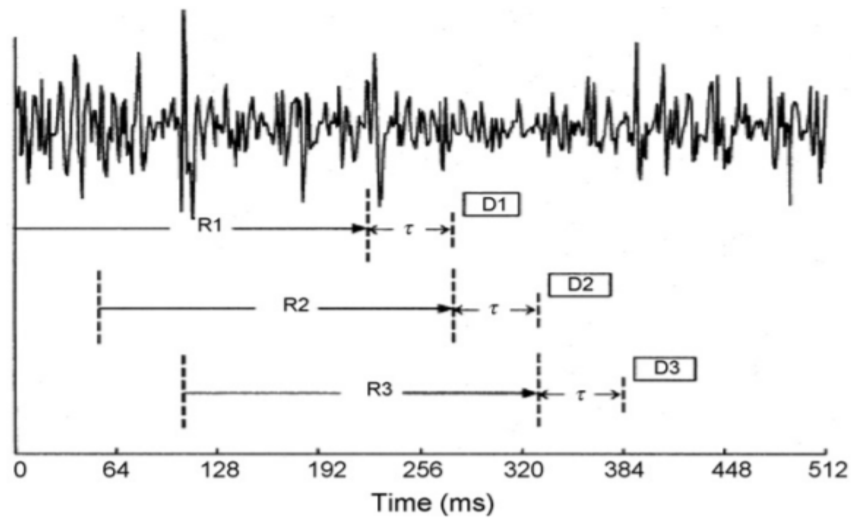


Figure 12 : Overlap Windowing Technique

Adjacent windowing with a segment length of 64ms is used in the device for data segmentation. Since the signals are sampled at a rate of 5000Hz each window consists of 320 samples.

Chapter 5

5. Feature extraction

The actual signal data (voltage vs time) is of large dimensions. Say we use 5 electrode pairs for data acquisition and sample the analog signals at a rate of 1000Hz. Considering a window of size 256ms, the size of each sample would be 256x5 which is huge. Moreover, due to the stochastic nature of EMG signals, the raw time sequence signal data do not carry much information and as a result, the classifier can't make accurate predictions. Hence we try to extract particular parameters called the features from each window that can represent the muscle activity[1].

The accuracy of the classifier greatly depends on the selection and extraction of features. The features can be selected from any of these 3 domains[1]:

1. Time Domain
2. Frequency Domain
3. Time-Frequency Domain

5.1 Time Domain

These features express the signals as voltages wrt time. They have no information regarding the frequencies of the signals involved[19].

Some of the important time-domain features are :

1. Mean Absolute Value(MAV)
2. Root Mean Square(RMS)
3. Zero crossings (ZC)
4. Slope sign changes(SSC)
5. Waveform length(WL)
6. Standard deviation(SD)

5.2 Frequency Domain

These features express signals as intensity vs frequency. They have no information regarding the time of occurrence of a data point[19].
Most important frequency domain features are extracted from the power spectral density (PSD).

5.3 Time-Frequency Domain

The features of this domain have all the required information about the EMG signals[19].
The signals are first decomposed into multiple child signals and each of them is then analyzed to extract the required features. Either Fourier or wavelet transform can be used to decompose the signals.

5.3.1 Short-Time Fourier Transform (STFT)

The Fourier transform represents signals frequencies and intensities but does not give any information regarding the point of occurrence of a particular data point. This is well suited for stationary signals. Since the Fourier transform cannot provide frequency information for a localized signal region in time, the short-time fourier transform is developed to overcome the poor time resolution problem. A time-frequency representation of the signal is obtained using the short-time fourier transform, unlike the fourier transform which gives only a frequency representation of the signals.

The STFT supposes that a fraction of the non-stationary signal is stationary and applies the Fourier transform over the localized piece of the signal. The Fourier transforms of various such fractions are added up to get the final result.

Now that the nonstationary signal is split into various stationary signal blocks, the frequency content in each portion is constant. STFT uses a moving window function, of fixed length, that slides over the signal from beginning to end and computes the Fourier transform over each stationary signal block. The windowing function is a rectangle with a particular constant value within the considered interval and is zero-valued outside the interval. Hence when the window function is multiplied with a particular stationary block, the signal turns out to be 0 outside the considered interval i.e signal is zero-values outside the considered interval. Only the signal or the waveform present within the considered interval remains unaltered. Fourier transform can now be applied to this stationary signal which is localized wrt time.

The major difference or the only difference between the Fourier transform and short-time fourier transform is the window function which helios in localizing the non-stationary signals.

However, now the output incorporates some temporal localization, whereas the transform merely supplied frequencies.

Consider a signal with 4 stationary sections of different frequencies. The output of the STFT will be the amplitude/intensity of the frequencies, the frequency, and then the time they occur in the signal, so four peaks are located at different times depending on when these stationary frequency components occur in the considered signal, and the other four peaks aren't included in the signal. Each stationary section has a peak, but they aren't singular definite peaks. They're time and frequency distributions, so there's some uncertainty in the frequency and time of the component's frequencies, as well as the time at which they exist in the signal.

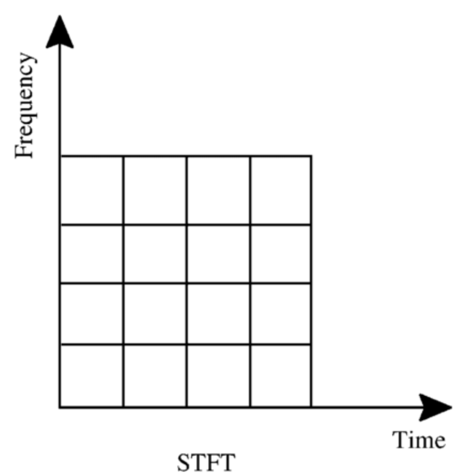


Figure 13 : Spectrogram of STFT

This is an issue. We face uncertainty, which leads to limits. The window function is finite, so the frequency resolution will decrease when compared to the fourier transform. The fixed length of the window means time and frequency resolutions will be fixed for the entire length of the signal. This is based on a fundamental principle in physics that we cannot know what frequencies exist at what time intervals, but we can know what frequency bands or frequency ranges exist at what time intervals, as shown by this equation Looking at the frequency-time plane for a short-time Fourier transform, we can see that at all increasing times and higher frequencies, the frequency and time resolution are fixed given by squares of equal area. A narrow window will give good time resolution but bad frequency resolution, while a wide window will give poor time resolution but good frequency resolution.

When we consider these two factors, we can see that low-frequency components of sound and signals generally last a long time, thus our time uncertainty is small. Because they last a long time, we need a high-frequency resolution to resolve this appropriately. High-frequency components, on the other hand, emerge as brief bursts and signals, necessitating more time resolution. The STFT fails miserably at this, while the wavelet transform succeeds. The wavelet transform divides a signal into multiple frequencies at different resolutions, which is known as multi-resolution analysis.

5.3.2 Wavelet Transform

Slowly moving trends or oscillations punctuated by transients are common in real-world data or signals. Smooth zones are broken up by edges or sudden contrast changes in images, on the other hand. These sudden changes are frequently the most fascinating aspects of the data, both in terms of perception and information. The Fourier transform is an effective data analysis tool. It does not, however, effectively reflect abrupt changes.

This is because the Fourier transform represents data as a sum of sine waves that are not the time or spatially localized. These sine waves continue to oscillate indefinitely. As a result, we need to apply a new class of functions that are well localized in time and frequency to accurately evaluate signals and images with sudden changes: This leads to the subject of Wavelets. A wavelet is a zero-mean, quickly fading wave-like oscillation. Unlike sinusoids, which have infinite duration, wavelets have a finite duration. Wavelets are available in a variety of sizes and shapes. Here are a few well-known examples. A fundamental strength of wavelet analysis is the large range of wavelets available.

5.3.2.1 Wavelets

Wavelets are a novel family of functions that are well localized in time and frequency and can be used to accurately assess signals with rapid changes. A wavelet is a zero-mean quickly fading wavelike oscillation. Wavelets only exist for a limited amount of time. Wavelets are available in a variety of sizes and shapes. A fundamental strength of wavelet analysis is the large range of wavelets available[7].

Wavelet has two main parameters: scaling and shifting. The process of stretching or shrinking a signal in time is known as scaling, and it can be described using this equation.

$$\varphi(\frac{t}{s})s > 0$$

where, the scaling factor, S, is a positive number that indicates how much a signal has been scaled in time. Frequency is inversely related to the scale factor. Scaling a sine wave by two reduces its initial frequency by half or an octave, for example. There is a reciprocal link between scale and frequency for a wavelet, with a proportionality constant. The "central frequency" of the wavelet is the proportionality constant. This is because, unlike the sinewave, the wavelet has a frequency domain bandpass feature. This equation is used to define the equivalent frequency mathematically.

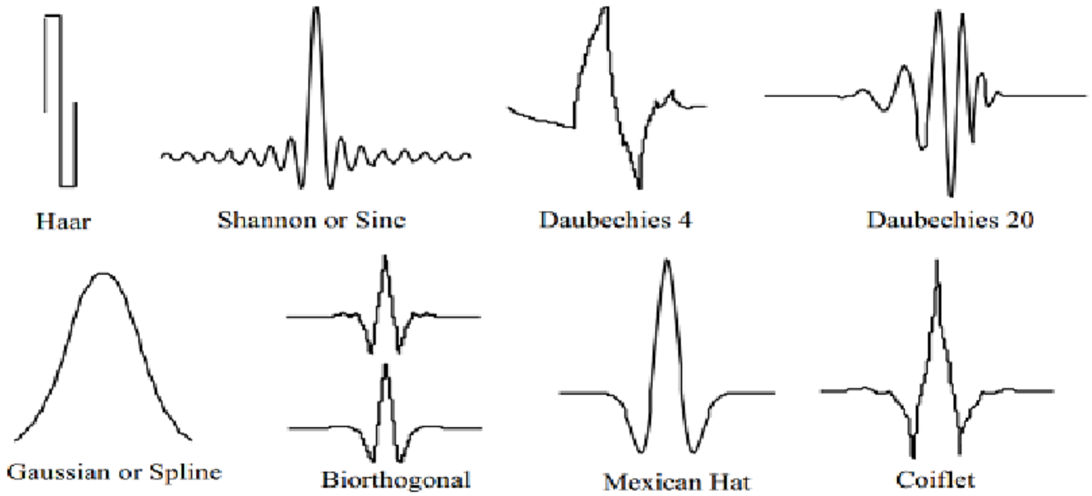
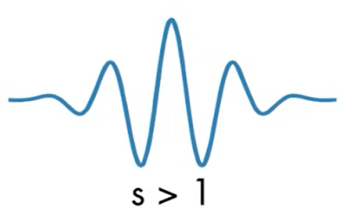


Figure 14 : Various wavelet functions

$$F_{eq} = \frac{Cf}{s\,\delta t}$$

The center frequency of the wavelets is Cf, the wavelet scale is s, and the sampling interval is delta t. As a result, when you scale a wavelet by a factor of two, the comparable frequency is reduced by an octave. A stretched wavelet with a higher scale factor correlates to a lower frequency. A shrunken wavelet with a reduced scale factor corresponds to a high frequency. A stretched wavelet captures the signal's slowly changing changes, whereas a compressed wavelet captures rapid changes[7]. As previously discussed, we can create alternative scales that inversely correlate to the comparable frequencies.



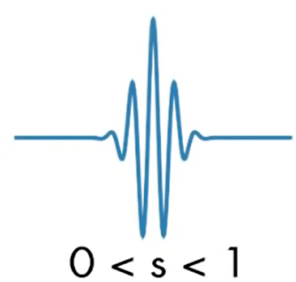


Figure 15 (a) : Wavelet scaling for s >1

Figure 15 (b) : Wavelet scaling for s <1

Shifting a wavelet essentially means delaying or advancing the wavelet's onset across the signal's length. The wavelet is shifted and centered at k in a shifted wavelet expressed by this notation (t - k). We need to tweak the wavelet to match the signal feature we're looking for.

Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) are the two major transformations in wavelet analysis.

The wavelets are scaled and shifted differently in these transforms. The scale and translation parameters are discretized differently in these two transforms.

5.3.2.2 Continuous Wavelet Transform

Time-frequency analysis and filtering of time localized frequency components are two key applications of continuous wavelet analysis. This transform can be used to get a simultaneous temporal frequency analysis of a signal. Because analytical wavelets do not include negative frequency components, they are best suited for time-frequency analysis. Some analytic wavelets that are suited for continuous wavelet analysis are Morse wavelets, Bump wavelets, and Analytic morse wavelets[7].

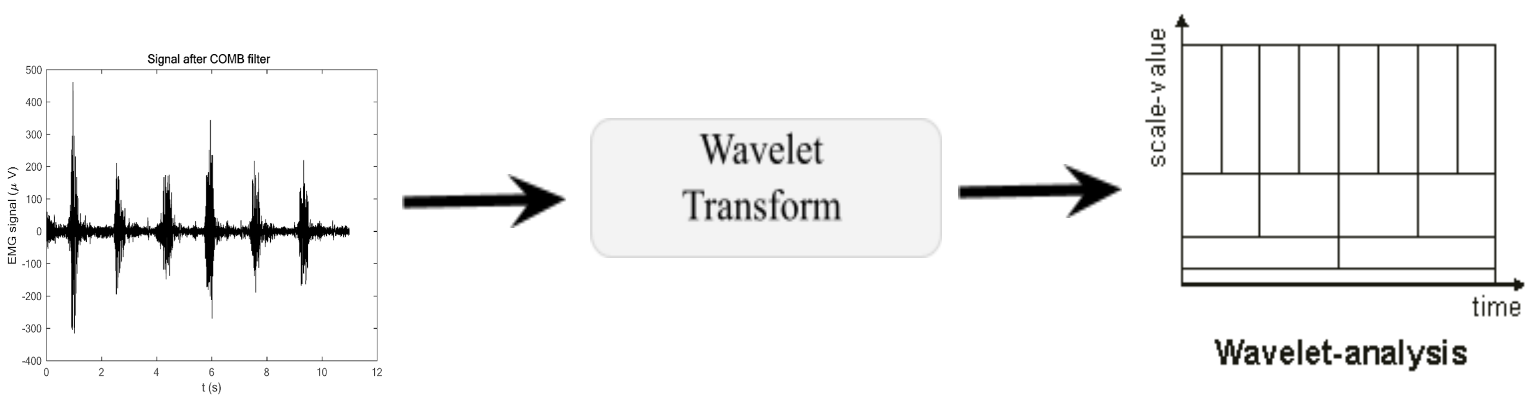


Figure 16 : Continuous Wavelet Transform

The signal properties can be described using a combination of wavelets. Each wavelet is based on the same "mother wavelet" function. These wavelets are a subset of the mother wavelet, which has been scaled and translated. The coefficients produced by CWT are a function of scale, frequency, and time. When we scale a wavelet by a factor of two, the equivalent frequency is reduced by an octave; however, with the CWT, we may evaluate the signal at intermediate scales within each octave (2^{jN} (j = 1,2,3, ….)). This permits fine-scale analysis. The number of scales per octave is the name given to this parameter (N). The scale discretization becomes sharper as the number of scales per octave increases. This parameter's typical values are 10, 12, 16, and 32. To establish a physical significance, the scales are multiplied by the signal's sampling interval.

Each scaled wavelet is compared to the original signal after being shifted in time throughout the entire length of the signal. This method can be repeated for all scales, yielding coefficients that are a function of the wavelet's scale and shift parameters. A signal with 1000 samples evaluated with 20 scales yields 20,000 coefficients. With the Continuous wavelet transform, we can better define oscillatory behavior in signals. The redundancy in coefficients is CWT's worst flaw.

5.3.2.3 Discrete Wavelet Transform

The discrete wavelet transform, often known as the DWT, is useful for denoising and compressing signals and images because it allows many naturally-occurring signals and images to be represented with fewer coefficients. This makes sparse representation possible. In DWT, the base scale is set to 2. By elevating this base scale to integer values represented in this fashion, you can get other scales. In this equation, the translation happens at integer multiples. Dyadic scaling (2j (j = 1,2,3...)) and shifting (2j m (m = 1,2,3...) are terms used to describe this operation.

Redundancy in coefficients is eliminated with this type of sampling. The transform's output produces the same number of coefficients as the input signal's length. As a result, it uses less RAM. Comparing a signal with discrete multi-rate filter banks is the discrete wavelet transform process.

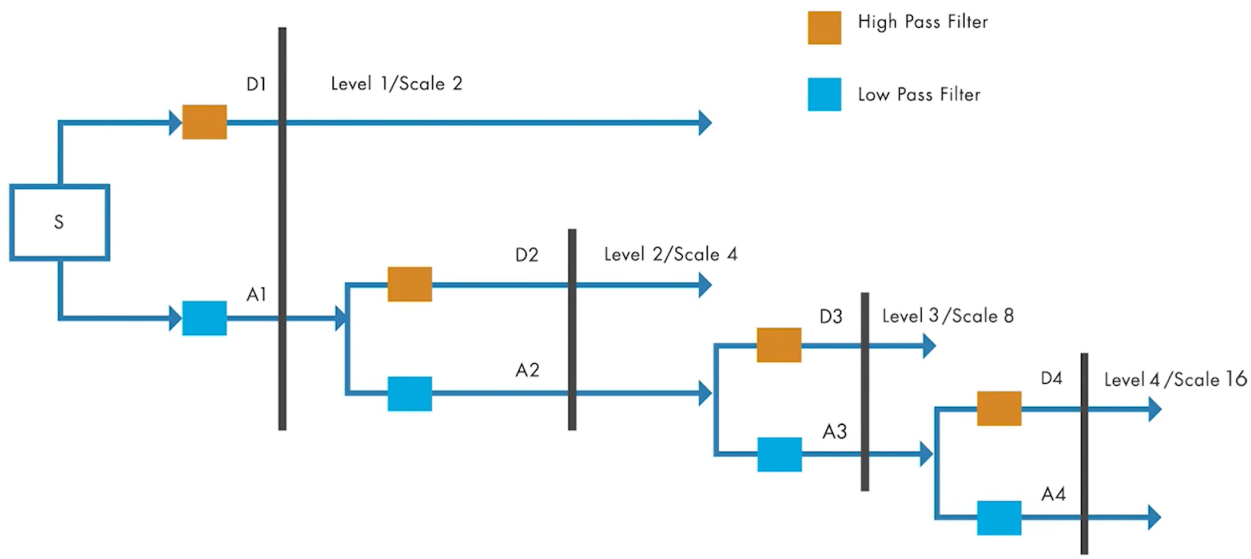


Figure 17 : Discrete Wavelet Transform

The signal S is initially filtered using a specific lowpass and highpass filter to produce lowpass and highpass sub-bands. These might be referred to as A1 and D1. After filtering according to the Nyquist criterion, half of the samples are deleted. Filters with a minimal number of coefficients often have superior computational performance. These filters can also recreate subbands while erasing any aliasing that occurs as a result of downsampling. The lowpass subband (A1) is iteratively filtered to create smaller subbands - A2, D2, and so on - for the next stage of decomposition. Each subband's coefficients are half the length of the previous stage's coefficients. You can capture the signal of interest with a few large magnitude DWT coefficients using this technique, while the noise in the signal results in smaller DWT coefficients. The DWT aids signal analysis at various resolutions by progressively narrowing subbands. It also aids in signal denoising and compression[3].

Scaling and translation are represented as a and b, respectively, in the equation. Scaling is the compression or dilation of the mother wavelet as a function of its frequency change. To keep the energy of the scaled wavelet equal to that of the mother wavelet, it is normalized by 1 / a. As a result, if (t) is the mother wavelet's function, a general term of wavelet with the positions of a and b can be represented as an equation.

$$\varphi_{b,a}(t) = \frac{1}{\sqrt{a}}\, \varphi\left[\frac{t-b}{a}\right] = \varphi(\text{ scale, position, t })$$

The valuable signal is in the low-frequency range, whereas the noise is in the high-frequency range. Following the wavelet transform, the low frequency and high-frequency components of the signal (S) are separated to provide approximate values (Ca) and detail values (Cd), as shown in Fig. 3. A one-dimensional wavelet is employed in the picture to split an original signal into four levels, which can be expressed in the equation.

$$S = Ca_3 + Cd_1 + Cd_2 + Cd_3 + Cd_4$$

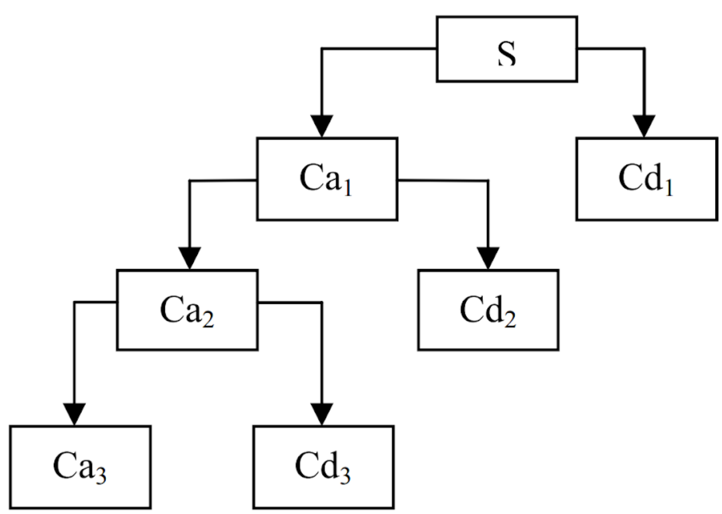


Figure 18 : Decomposition of the EMG signal into approximate and detail signals

Chapter 6

6. Classification

The extracted features are to be analyzed to determine the motion patterns. Since the EMG signals are stochastic, the feature values vary with time. Neural networks (eg. Multi-Layer Perceptron, Radial Basis Function Neural Networks, etc.,) can be used for the myoelectric classification because of their strength in predicting non-linear relationships[1].

Other approaches like fuzzy logic, which tolerates contradictions in data, and the probabilistic approach(Gaussian Mixture Model), etc., were also proved to perform well in this field.

6.1 Neural Networks

The literature has already recorded various neural networks that perform well in this field. Based on the type of features chosen, one model outperforms the other. Neural networks can predict non-linear relationships, crediting to their complex structure[1].

A neural network has multiple layers of neurons connected densely to each other. In order to predict the relationship among the data, these connections are to be tuned. Because of their complex structure, neural networks take a large amount of data to finetune their parameters.

Due to lack of data, shallow neural nets with 2to 3 hidden layers are considered for classifying the EMG signals.

Three neural networks were trained over 640 samples each of length 64ms i.e, 324 entries.

A five cross-validation is performed to test the accuracy.No data is left behind for testing purpose.

6.1.1 Neural network 1

Neural network 1 has one hidden layer with 10 hidden neurons. It uses the RELu activation functions and runs up to a maximum of 1000 iterations. An accuracy of 93.6% is achieved.

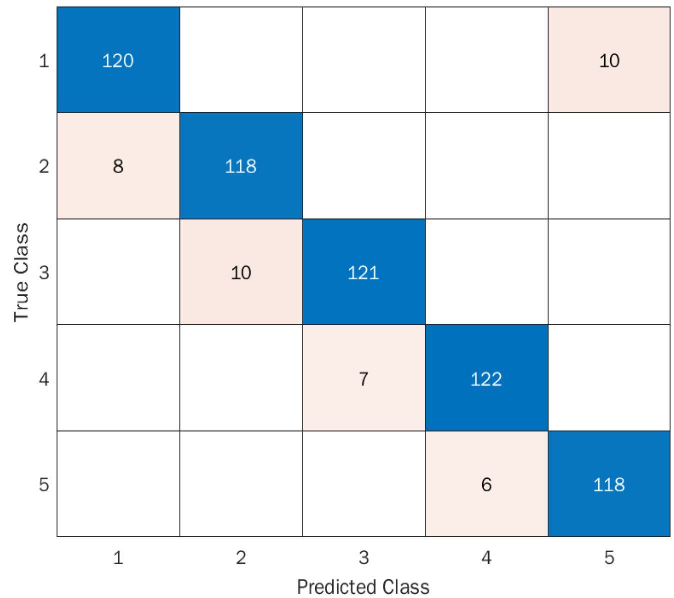
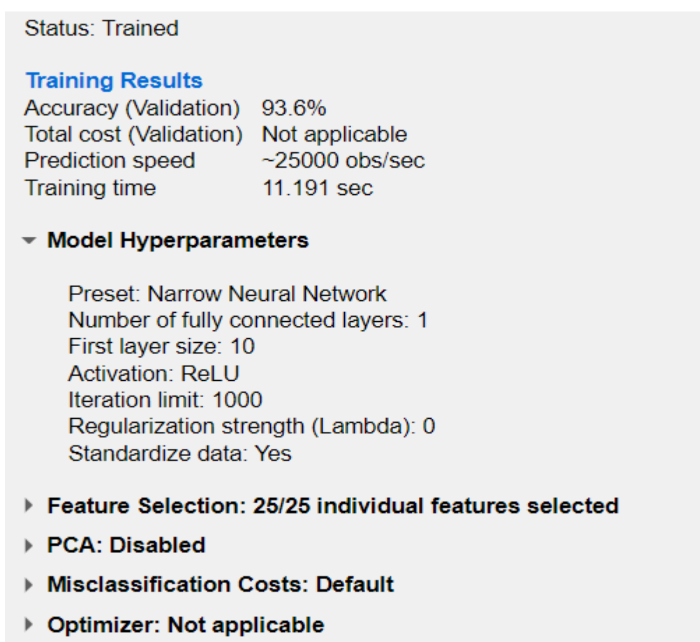


Figure 19 (a) : Confusion Matrix for Neural Network 1



Status: Trained

Training Results

Accuracy (Validation)	93.6%
Total cost (Validation)	Not applicable
Prediction speed	~25000 obs/sec
Training time	11.191 sec

Model Hyperparameters

Preset: Narrow Neural Network
Number of fully connected layers: 1
First layer size: 10
Activation: ReLU
Iteration limit: 1000
Regularization strength (Lambda): 0
Standardize data: Yes

Feature Selection: 25/25 individual features selected

PCA: Disabled

Misclassification Costs: Default

Optimizer: Not applicable

Figure 19 (b) : Model summary of Neural Network 1

6.1.2 Neural network 2

Neural network 2 has two hidden layers with each of 10 hidden neurons. It uses the TanH activation function and runs up to a maximum of 1000 iterations. An accuracy of 93.8% is achieved.

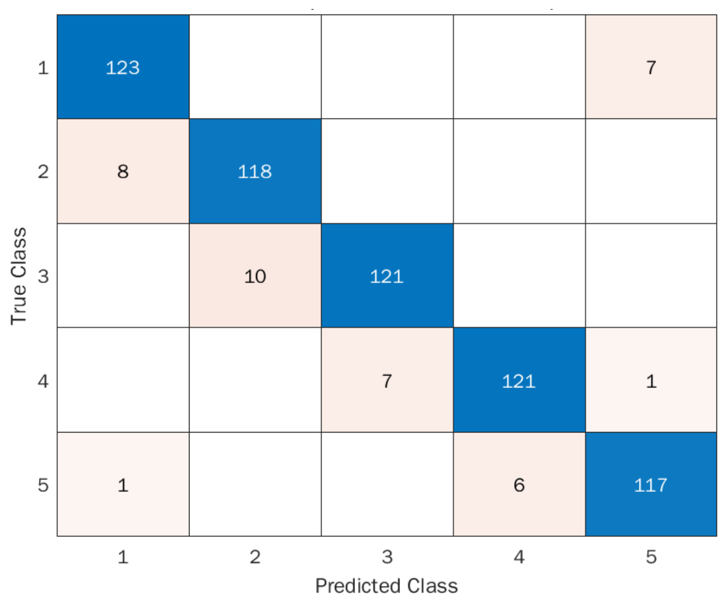
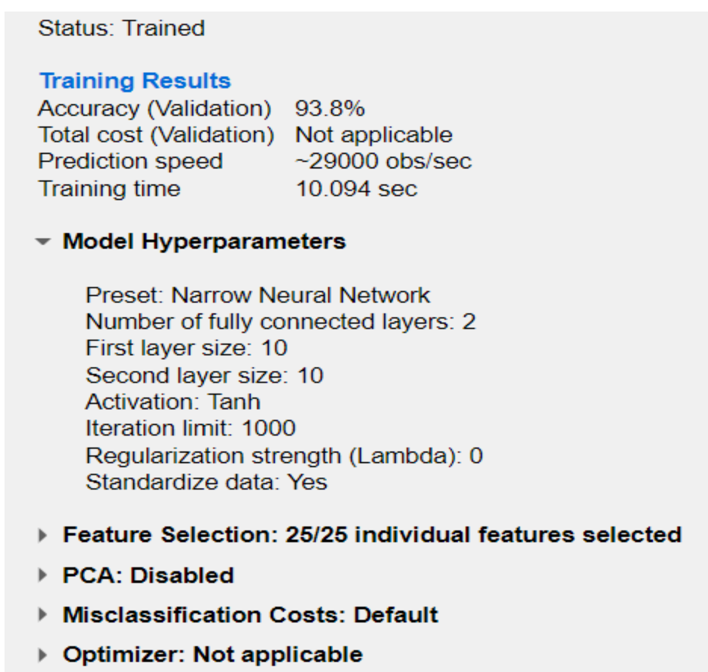


Figure 20 (a) : Confusion Matrix for Neural Network 2


Status: Trained

Training Results
Accuracy (Validation) 93.8%
Total cost (Validation) Not applicable
Prediction speed ~29000 obs/sec
Training time 10.094 sec

Model Hyperparameters

Preset: Narrow Neural Network
Number of fully connected layers: 2
First layer size: 10
Second layer size: 10
Activation: Tanh
Iteration limit: 1000
Regularization strength (Lambda): 0
Standardize data: Yes

Feature Selection: 25/25 individual features selected
PCA: Disabled
Misclassification Costs: Default
Optimizer: Not applicable

Figure 20 (b) : Model summary of Neural Network 2

6.1.3 Neural network 3

Neural network 3 has three hidden layers with each of 10 hidden neurons. It uses the sigmoid activation function and runs up to a maximum of 1000 iterations. An accuracy of 93.4% is achieved.

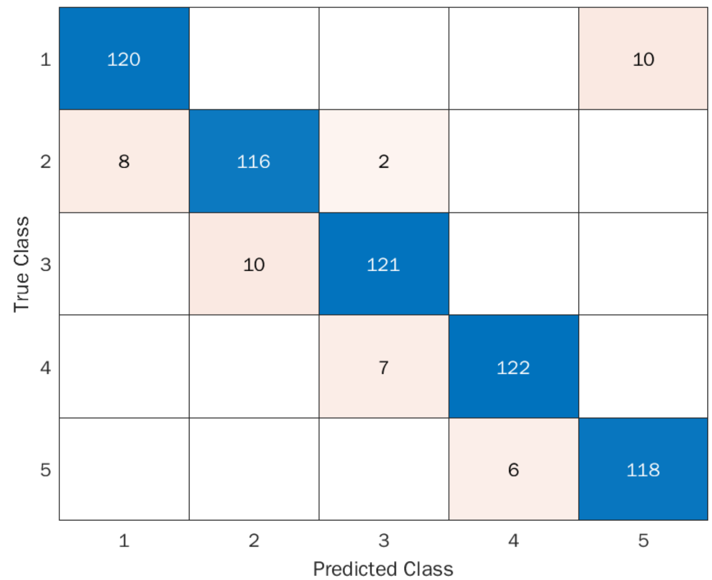


Figure 21 (a) :   Confusion Matrix for Neural Network 3

Status: Trained

Training Results

Accuracy (Validation)	93.3%
Total cost (Validation)	Not applicable
Prediction speed	~29000 obs/sec
Training time	11.277 sec

Model Hyperparameters

Preset: Narrow Neural Network
Number of fully connected layers: 3
First layer size: 10
Second layer size: 10
Third layer size: 10
Activation: Sigmoid
Iteration limit: 1000
Regularization strength (Lambda): 0
Standardize data: Yes

Feature Selection: 25/25 individual features selected

PCA: Disabled

Misclassification Costs: Default

Optimizer: Not applicable

Figure 21 (b) :   Model summary of Neural Network 3

Chapter 7

7. Response Unit : SIM 868E Module

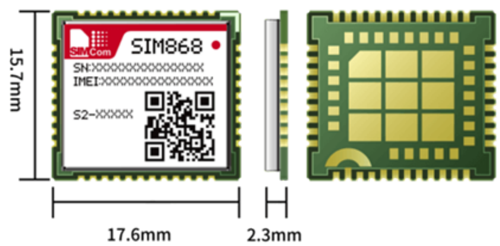


Figure 22 :   SIM 868E Module

In order to predict an emergency, we predefine a sequence of actions (which need to be a bit complex in order to reduce the false positives). Now that we have a stream of class labels, generated by the classifier, the processor checks if the predefined sequence was intended at any point in time. In case of a match, it is considered an emergency and the response unit will be informed. The response unit then makes a call to the emergency numbers and shares the location coordinates.

For this task, the SIM 868E module, which has the GSM, GPRS, GPS, and other related modules installed in it is used[17].

GSM module helps in making a call, GPRS is for internet connection and other modules are for location tracking[17].

Chapter 8

8. Simulation

Due to the unavailability of the hardware setup, a simulation of the desired wearable device was built in MATLAB. The simulated model does the first 4 tasks in the pipeline i.e Data acquisition, data processing, data segmentation, and feature extraction. The obtained feature vectors for each channel i.e for each electrode pair are concatenated together and are passed as a single feature vector to the trained classifier.

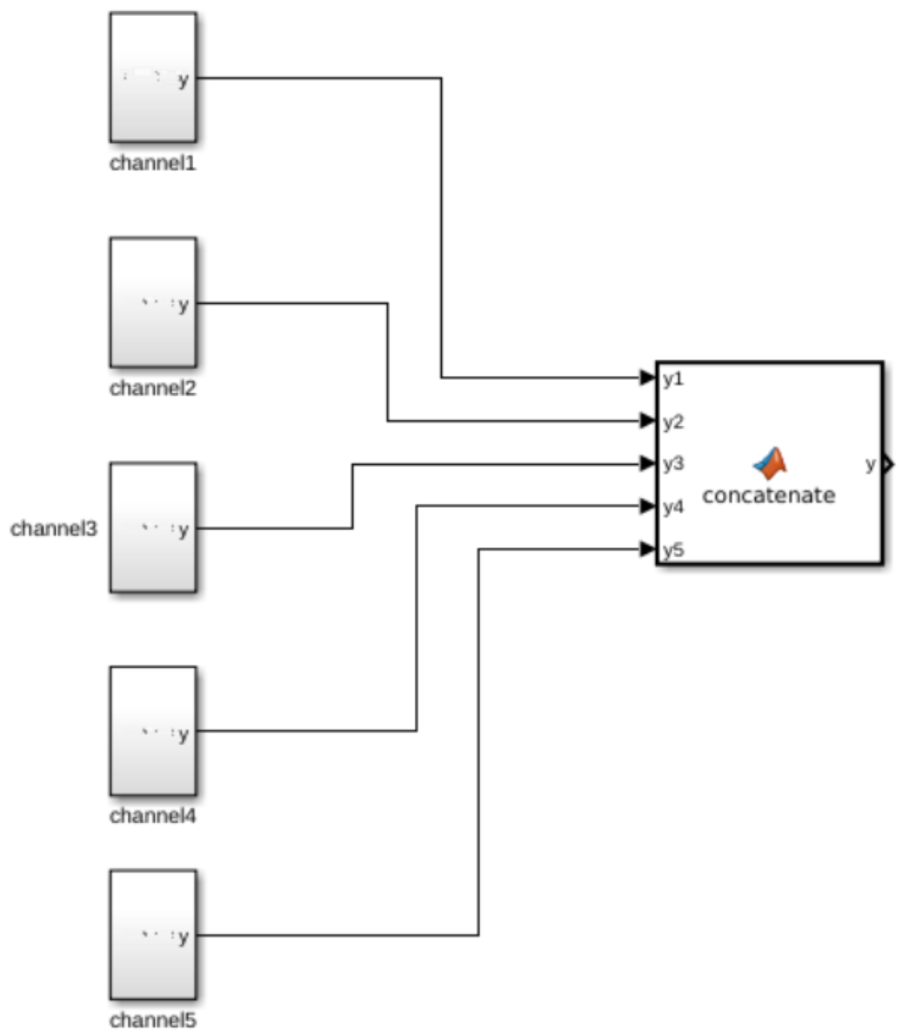


Figure 23 : Simulation model

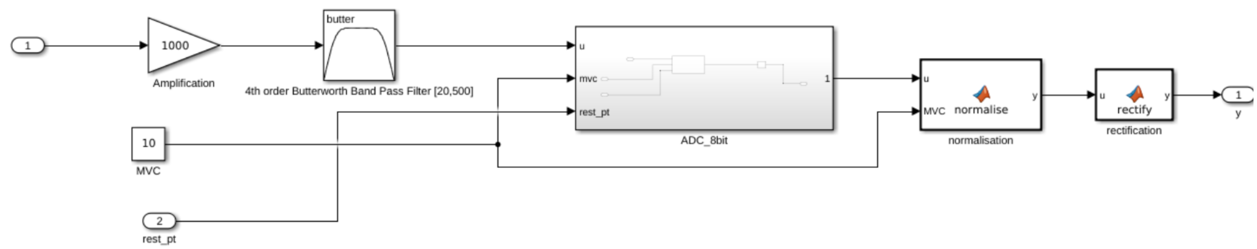


Figure 24 : pipeline in each channel

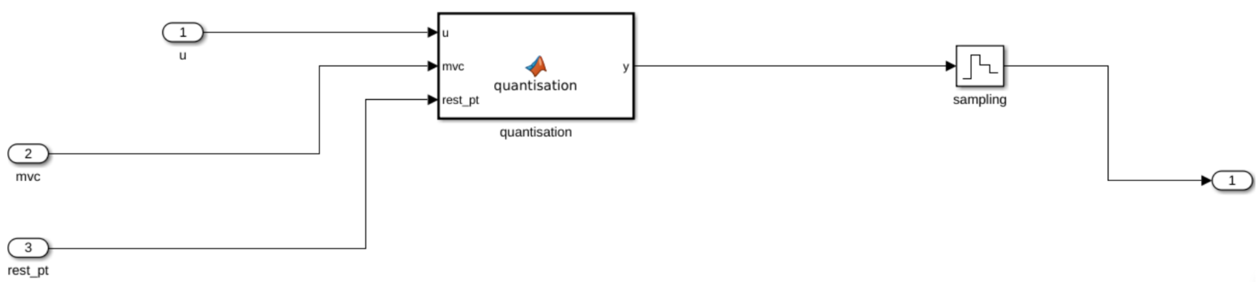


Figure 25 : pipeline for signal processing

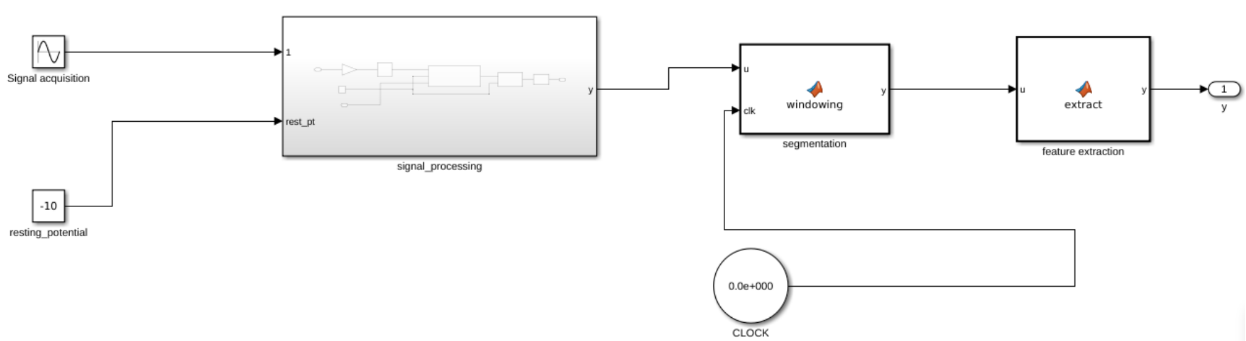


Figure 26 : Simulation model of an 8-bit ADC

Chapter 9

9. Future work

1. Acquire data experimentally from real-life subjects.
2. Develop the model to predict even complex actions and also handle the transient data.
3. Deploy a wearable device that helps in the time of emergency.

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