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NOVEL MACHINE LEARNING FILTER PROTOTYPING FOR ECG/EEG/EMG SIGNALS

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Abstract

The ECG/EEG/EMG monitoring system is a new type of medical technology that has emerged because of the convergence of mobile technology and the increased demand for healthcare management caused by an ageing population. The ECG/EEG/EMG signal detecting system makes it possible to carry out a dynamic medical diagnosis in a manner that is both quicker and accurate by giving accurate ECG/EEG/EMG signals throughout a varied range of physical activities. This study covers the installation of a prototype biomedical measurement system, which can be used to pedagogically evaluate the usefulness of specific modules for detecting electrical activity in the brain, heart, and muscles.

Keywords:

Filter, Band Pass, ECG, EMG, EMG

1. INTRODUCTION

Wearable medical devices are a new type of medical technology that has emerged because of the convergence of mobile technology and the increased demand for healthcare management caused by an ageing population [1]. It is now possible to prevent the emergence of diseases and protect persons from impending dangers to their health thanks to the capacity for continuous monitoring. Diagnostic techniques are increasingly making use of biosignals obtained from wearable medical devices [2]. Additional examples include one blood pressure and glucose levels in their blood. Electrocardiograms (ECGs) and electromyograms (EMGs) are created whenever there is a change in the electrical signal that is caused by the contraction of a muscle. Both categories of diagnostic procedures are utilised to a significant degree in the delivery of medical treatment [3].

Electrodes are connected to the patient skin to record the electrical activity created by the contracting and relaxing of the cardiac muscles. This is done during an electrocardiogram (ECG). The electrophysiologic rhythm of the heart muscle during each pulse generates the microscopic electrical change on the skin that is picked up by the ECG signal detection system. This change can be seen as a line on an ECG. The initial polarisation can be regarded of as having been inverted because of this alteration. The evolution of the ECG signal detecting system is targeted at miniaturisation, family use, and intelligence as people grow more health-conscious and as better diagnostic tools become accessible. ECG electrodes made of conductive fabric to carry out accurate ECG monitoring during physical exercise. The electrodes were sewn onto the shirt using conductive thread. A low-power wearable device based on a single-arm ECG with the goal of monitoring a subject heart rate while the subject is engaged in physical exercise. The device is designed to be worn by the subject. The wearable ECG monitoring device makes it possible to carry out a dynamic medical diagnosis in a manner that is both quicker and accurate by giving accurate ECG signals throughout a varied range of physical activities. This enables the device to improve patient care [4].

Electromyography is another method applied in the field of electrodiagnostic medicine. Its purpose is to analyse and record the electrical signal produced by the activity of skeletal muscles, and it is a technique that is utilised to analyse and record the signal. When the cells that make up a muscle are stimulated in any way, whether by electricity or by nerves, muscle potentials are formed. Muscle potentials can be either positive or negative. Human biomechanics, medical issues, and activation levels can all be observed and quantified thanks to modern scientific advancements [5]. EMG signal processing has been applied in an increasing variety of applications within the disciplines of healthcare and medicine. A configurable integrated platform for EMG recording to make gesture identification easier to accomplish. The controlled appropriateness of assistance devices by employing a dual-channel EMG biopotential amplifier and an artificial neural network to interpret and categorise EMG data. This allowed the researchers to investigate the controlled appropriateness of help devices. This is done to establish whether the assistive equipment is suitable for the individual. The feature analysis of an EMG signal has the potential to shed light on different characteristics of the activity of the muscles in the body [6]. These components include a person level of fitness, weariness, endurance, and gesture.

People who have suffered a stroke but have been able to survive it often face a challenging and protracted road to recovery that involves the utilisation of physical therapy. This is since strokes can cause significant damage to nerves and muscles, which can make the process of rehabilitation both sluggish and hard. Even though this type of service frequently falls short of the survivor requirements, those who have survived a stroke may benefit from the physiological exercise treatment that is delivered under supervision in rehabilitation centres. Trained workers routinely explained monitored physiological signals to improve rehabilitation procedures; nevertheless, a shortage of therapists and exorbitant consultation rates impede recovery for a major percentage of stroke survivors [7].

Robotics of the hand and wrist can be employed to restore function to the upper limbs, and patients may be able to use the devices on their own in the privacy and convenience of their own homes [8]. There has been no continuous detection work done on the great majority of the robot-assisted rehabilitation systems that are currently available on the market [9]. These systems have only been tested in the standard pre- and post-clinical settings. As a result of this, it is of the utmost importance to devise a monitoring system that can be comprehended with relative ease and offers a detailed explanation of the training progression in the here and now. Patients will have a much easier time understanding the exercise recovery process that is connected to their treatment because of this.

2. SYSTEM DESIGN

In applications like wear monitoring, it is preferable to employ a smaller number of electrodes in fixed installations rather than a larger number of electrodes. When monitoring an ECG, a configuration consisting of three electrodes is typically utilised. This consists of a third ground electrode that shields the patient from potentially dangerous current leakage and two active electrodes that serve as differential inputs to an amplifier. The patient is protected from potential harm by these electrodes [10].

An electrocardiogram, often known as an ECG, is a recording of the electrical activity of the heart. It is decided to use only two electrodes to monitor the ECG signal in this experiment because the two-electrode technique can build an isolated circuit to assure patient safety without adding ground.

It is decided to use only two electrodes to monitor the ECG signal. Because the procedure involving two electrodes can produce an isolated circuit, this is done. The connection between the printed circuit board and the electrodes that were safely fastened is made with the help of two snap fasteners. The fact that the printed circuit board dimensions are 20x65 mm makes it a fantastic option for use in applications that take place in the real world.

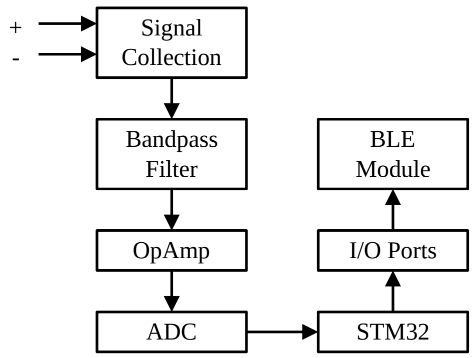

Fig.1. Overall architecture

Stable electrodes ensure a good signal effect, which suggests that a precise monitoring location and adequate contact between the electrodes and the skin are necessary for capturing an accurate ECG signal and limiting the amount of external noise or interference. This is because stable electrodes ensure a good signal effect. A reliable signal effect can also be ensured by using electrodes that are stable. Previous research has demonstrated that the side of the chest and the area around the lower right rib (10th rib bone) are ideal locations for stable and high-quality ECG signal detection because they require minimum pressure from clothing. This is since human respiration, movement, and the pressure that clothing puts on the body are less likely to influence certain sections of the body.

The microcontroller, signal processor, A/D converter, Bluetooth Low Energy (BLE), and power management module are all integrated onto the printed circuit board (PCB) (Fig.1). ECG signals were transmitted from the electrodes to a hardware filter. There, the signals were amplified with an operational amplifier, converted to digital value with an A/D converter read with an STM32 chip and transmitted to a smartphone or laptop via a BLE module in accordance with the communication protocol.

Another important consideration is the amount of power that is used, which has a direct bearing on the capabilities of radio chips and microcontrollers. This is since the usability criteria of the wearable monitoring system place an emphasis on the capability of the device to be worn. The integrated circuit that plays the role of the circuit most important component is designated as the STM32. The STM32is a microcontroller that has a low power consumption, a very small size, an abundance of peripheral connectors, and the ability to communicate with a BLE module through a serial connection.

The complex analogue front-end circuitry and the powerful digital signal processing structure allow it to be optimised for biosignal inputs in the microvolt (V) to millivolt (mV) ranges. This is possible because of the chip low power consumption. The microvolt range and the millivolt range are corresponding to these ranges, respectively. By combining high-pass filters with low-pass filters, it is feasible to build a bandpass filter that has a passband extending from 0.5 to 40 Hz. This bandpass filter would have a passband.

3. PHYSIOLOGICAL MONITORING SYSTEM

The ECG and EMG devices can fulfil their intended duties when the EMG electrodes are positioned on the necessary upper-limb muscles and the ECG electrodes are positioned on the appropriate chest muscles, respectively. After the internal BLE modules that are situated on the circuit boards of the wearable monitoring system have been enabled, the system will be able to begin the process of data collection and will be able to do so immediately. Using a programming tool, the initial calibration values were inserted into the registers of the STM32 microcontroller.

These types of data are obtained from patients. The software that is developed contains two built-in configuration choices that enable it to connect with the BLE modules of two separate devices and receive ECG and EMG data from each of those devices simultaneously. These options allow the programme to connect with the BLE modules of two different devices. Utilising a communication protocol is the first step that must be taken before reading the ECG or EMG measurements.

After the raw data have been processed and analysed with the appropriate mathematical techniques, the results of those processes are displayed on the screen in real time in the form of curves. These curves show the relationship between the raw data and the processed and analysed data. These charts show how heart rate and muscle activity change over the course of the experiment. To provide users of the physiological monitoring system with information regarding rehabilitation, a computer software and an application are built for the system.

To set the controller parameters, a link must first be made between the controller and a professional programme using the BLE module that is integrated right in. In addition to that, the controller makes use of a mode known as the fixed mode, in which the user can adjust the air pressure and working duration by rotating the knob on the box. The BLE module is shown in Figure 5c to be the component that oversees delivering the control strategy instructions from the physiological monitoring system to the control board. This demonstrates how the BLE module performs its functions.

The pump applies the appropriate amount of pressure to the robotic glove in accordance with the control strategy to make hand rehabilitation training more accessible. Differential pressure sensors are used to monitor pressure. These same sensors also provide the controller with input regarding the present pressure that is being measured.

The fact that electromyography (EMG) sensors assess the muscles in the upper limb makes this possible. It is chosen to conduct this research on a healthy individual whose hands would be held in their natural postures to ensure that the findings of the experiment on muscle activation could be relied upon and repeated. This is done since it is thought that this would be the best way to achieve these goals.

Filtering and processing the received EMG signal, which is a combination of the EMG potentials as well as the real-time noise and offset, is necessary to make use of the data obtained from the EMG sensor. Before the raw EMG data can be utilised for analysis, the features of the data must first be extracted from the raw data, and any noise that is not necessary must be filtered out.

Root mean square (RMS), mean absolute value (MAV), sign changes in slopes, zero crossings, and waveform duration are some examples of feature extraction approaches that have been used to evaluate human muscle activity in real time. Other techniques such as these have also been used. By applying the following equation, we can determine the value of the root mean squared for the EMG signal:

$$RMS = \frac{1}{N}\sum_{i=1}^{N} v_i^2 \tag{1}$$

where N is a constant number and v_i is the voltage that is sampled at the i^{th} point in time. The values of the root-mean-square, which are also known as RMS, were recovered from the original EMG signal so that the success of the strategy could be evaluated. It is feasible to utilise the estimated RMS values as a basis for attempting to define the activity level of the muscle based on the raw EMG signal.

The value of the root-mean-square could be a measure of how intense the physiological processes that are taking place in the motor unit now of the contraction are. This is because the root-mean-square is calculated after the contraction has taken place. Both types of weak muscle activity revealed a link between the degree of activity and the strength of the EMG signal that is comparable to one another. This is the case regardless of the type of weak muscle activity.

At high levels of muscular activity, the amplitude of the muscle activity signal gets saturated; thus, the same connection does not hold for such levels; hence, a different calculation strategy is necessary. This is since high levels of muscular activity led the signal to reach its maximum possible value.

However, because there is no baseline, it may be difficult to interpret the signal that is collected by the EMG module from the surface of the skin. This signal comes from the subject skeletal muscles. This is since variances between individuals may render it hard to compare the results. It is necessary to develop a method for normalising the EMG signal.

After determining the maximum RMS value (RMSM) of the EMG data before the rehabilitation programme, the strategy may utilise the normalisation methods to determine the nonnormalized RMS values. After acquiring the RMS value that is determined to be the greatest possible one, this step is taken. The formula for the equation can be stated in written form as follows:

$$RMSN=RMS/RMSM \tag{1}$$

where *RMSN*, *RMMS*, and *RMSM* each stand for the maximum *RMS* value of EMG, the normalised *RMS*, and the nonnormalized *RMS*, respectively. By physically moving the hand that is being tested into the most extreme posture, we were able to capture the largest root-mean-square (*RMS*) EMG value. We carried out the analysis three times, with the average value serving as the RMSM, to cut down on the amount of uncertainty that is brought about by the experimental measurements. This is done to limit the amount of uncertainty that is introduced by the measurements.

3.1 DESIGN OF ECG/EEG/EMG MODULES

3.1.1 Gain:

Due to the high common-mode rejection ratio and high level of precision that this amplifier possesses, it is ideally suited for usage with biomedical signals. This is because of the nature of these signals. When performing the calculation to determine the gain, the ratio that is used is the one that is provided.

$$G = 1+50\ \mathrm{k}\Omega R_G \tag{2}$$

The RL electrode is utilised by the ECG module to accomplish the task of establishing a driven right leg circuit. This circuit is vitally necessary for maintaining the safety of humans. It can stop unbalanced currents and correct for common-mode noise problems at the differential input of the instrumentation amplifier. Both functions are located at the same location. Figure 8 is a diagram that illustrates the method of acquiring an electrocardiogram signal by using the INA128P instrumentation amplifier.

3.1.2 60 Hz Notch Filter:

Utilising the UAF42 integrated circuit in each of the ECG, EEG, EOG, and EMG components allowed for the successful implementation of the Notch filter in each of these portions. This application-specific integrated circuit (ASIC) is a Sallen-Key-style second-order active filter that takes the values of six resistors (RF1, RF2, RZ1, RZ2, RZ3, and RQ) as inputs. The resistors are numbered from left to right: RF1, RF2, RZ1, RZ2, RZ3, and RQ. The following is the value for the frequency of the notch:

$$f_0=12\pi RF_C \tag{3}$$

$$R_Q = 25\ \mathrm{k}\Omega Q - 1 \tag{4}$$

$$Q=RZ3/RZ1=RZ3/RZ2 \tag{5}$$

A Notch filter that satisfies the requirements of the application bulletin is constructed by adhering to the procedures that have been detailed in previous sections of this article.

3.1.3 Band-pass Filter:

A band-pass filter that comprises of a first-order passive high-pass filter and a fifth-order active low-pass filter is intended for use with the ECG, EEG, and EOG modules. This filter is a band-pass filter. Utilising the parameters C_{11} = 1 μF and f_c = 0.15 Hz allowed for the creation of a first-order high-pass filter that has a value of R_{10} = 1 MΩ.

A low-pass filter with a cutoff frequency of 40 Hz and a unity-gain, fifth-order, Butterworth-optimized, Sallen-Key topology is utilised. The cutoff frequency is determined to be 40 Hz.

3.1.4 Cascaded Band-Pass Filter:

Cascaded second-order active high-pass and low-pass filters were used to construct a band-pass filter for the EMG module with a passband extending from 20 Hz to 500 Hz (see Figure 11). This filter is designed to create a band-pass filter for the EMG module.

The first filter is a Butterworth-optimized Sallen-Key high-pass active filter with a unity gain and a cutoff frequency of 20 Hz. The filter also had a Butterworth-optimized Sallen-Key low-pass active filter. Additionally, a Butterworth-optimized Sallen-Key low-pass filter is a part of this filter. By applying the following equations, we were able to ascertain the values of R7 and R6:

$$R_7 = 1/\pi f_c C_{a1} \tag{6}$$

$$R_6 = a/14\pi f_c C_{b1} \tag{7}$$

An active low-pass filter of order 2 is constructed, and it had a cutoff frequency of 500 hertz, a Butterworth-optimized gain of 1, and unity gain. Additionally, it had a Butterworth-optimized gain of 1. In addition to that, the filter had a gain that is equal to one. Because these high-pass filter coefficients are of the same type and order as the ones that came before them, they were used once again in the process.

3.1.5 Adjustable Gain:

At this stage, the total gain of each module is being fine-tuned in preparation for the initial 500 V/V amplification that is going to be planned. This preparation took place in preparation for the initial 500 V/V amplification. This is made possible because it is possible to construct the amplifier.

4. NOVEL MACHINE LEARNING

Since the beginning of the development of this technology, artificial neural networks (ANN) have patterned the accuracy of their computations after that of human thought. In the discipline of statistics, this item is referred to as a model for interpreting data that is non-linear. The most up-to-date technique for this machine learning model is known as multilayer perception (MLP), and it is implemented in artificial neural networks (ANN) to evaluate and forecast the statistical dataset.

The ANN model is a more advanced alternative to more standard statistical approaches, as it involves expertise with the structure of the input data as well as the kind of relationship that exists between variables (linear or non-linear). In addition, the ANN model requires knowledge of the kind of relationship that exists between variables (linear or non-linear). There are three distinct layers that make up the MLP technique that the ANN model uses.

These layers are the input layer, the hidden layer, and the output layer. In a data structure, the information is evaluated at the nodes of the hidden levels if the input layers are not sufficiently involved in the process. This is the case if the input layers are not sufficiently involved in the process. In this scenario, the output layer is linked to the input layers, which are made up of parts like the several GECFs and the gully erosion training sites.

Following this, the input and hidden layers will carry out a continuous function evaluation of the output, as well as create systematic predictions regarding the model structure of the input nodes. In the ANN model, the configuration of the input and output nodes is carried out in accordance with a preset set of criteria. The Boolean value of each pixel is denoted by the number of output nodes, which is either one or zero depending on the situation.

If the value is 1, then there is evidence of gully erosion, however if the value is 0, then there is no evidence of gully erosion. The utilisation of hidden layers makes it possible to perform calculations about model trials and errors.

4.1 GENERAL LINEAR MODEL (GLM)

GLM is a well-known statistical probability strategy that may be used to model a wide variety of natural disasters. An alternative to the general linear regression model, which is the model that is generally employed, is the GLM.

GLM is a technique for doing statistical analysis that is gaining in popularity due to the relative simplicity involved in putting it into practise. This statistical machine learning model operates on the presumption that there is a linear relationship between the dependent variable and numerous independent variables, and that the link function may either be identity or logistic.

This model assumes that the dependent variable is a continuous variable. In the scenario where the dataset has just true or false information, GLM is able to utilise a logistic regression model to convert the dataset into a binary data model. This is possible since the dataset contains only true or false information. When working with a dataset that only contains binary values, such as 0 and 1, the logit link function in GLM is used to simulate a fractional response. This is because binary values can only take on two possible states: either 0 or 1. The values 0 and 1 in binary are represented by the numerals 0 and 1, respectively.

$$Y = \Pr(y=1) = eC_0+C_1X_1+\cdots+C_nX_n \tag{8}$$

4.2 MAXIMUM ENTROPY (MAXENT)

The anticipatory model that is referred to as MaxEnt is built on the fundamental idea of maximising the amount of entropy. The maximisation of entropy is founded on the fundamentals of statistics and information theory, both of which are connected to the idea being discussed here. These principles serve as the foundation for the maximisation of entropy principle, which not only gives an appropriate approximation of an uncertain probability distribution, but also serves as the principle. It is argued that the MaxEnt model choose the probabilistic restriction that ends up producing the most entropy based on all the many possibilities that are accessible.

MaxEnt is a well-known model for machine learning that is generated with presence-only features. It is created by using these characteristics. The presence-only feature is important for the aim of the machine learning model since it is more dependable in locations that are difficult to access. There is an average MaxEnt result for an unknown target allocation and true distribution across all the pixels in the area x, which were all represented by pixel values of x.

This result is calculated for all the pixels in the region. This finding is discovered throughout the entirety of the region pixel data. During this investigation into the GESM modelling, the MaxEnt model is tasked with finding the probability distribution of gully occurrence at point x. This is done as part of the study of the GESM modelling. This equation is used to provide a quick statistical description of the model.

$$P(y=1|x) = P(x|y=1)/P(y=1)P(x), \quad (9)$$

where $P(y=1|x)$ represents the probability of the gully being present at the location of x, where $P(x|y=1)$ represents being at the site of given x, $P(y=1)$ is the overall prevalence, and $P(x)$ is the probability of picking the location x. The above equation can also be rewritten as follows:

$$P(y=1|x) = \pi(x)/P(y=1)|x|. \quad (10)$$

The calculation of $P(x)$ can also be done by the probability distribution of marginalizing, such as:

$$P(x)=\sum_y P(x,y)=P(x|y=1)/P(y=1)+P(x|y=0)/P(y=0). \quad (11)$$

The generative model basically deals with $P(x,y)$ and P(y). The equation for the equal probability of MaxEnt is as follows:

$$P(y=1|x)=P(x|y=1)P(x|y=1)+(P(x|y=0). \quad (12)$$

5. EVALUATION

The students were able to evaluate the effectiveness of each individual component that made up the measurement system because the prototype is designed in a modular fashion, which allowed them to do so.

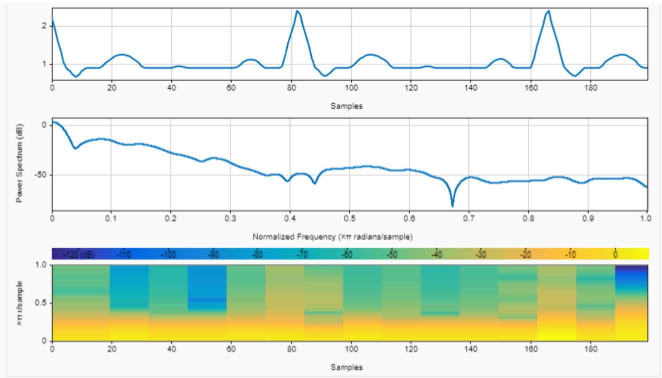

Fig.2. Noise Reduced ECG Signal using GLM

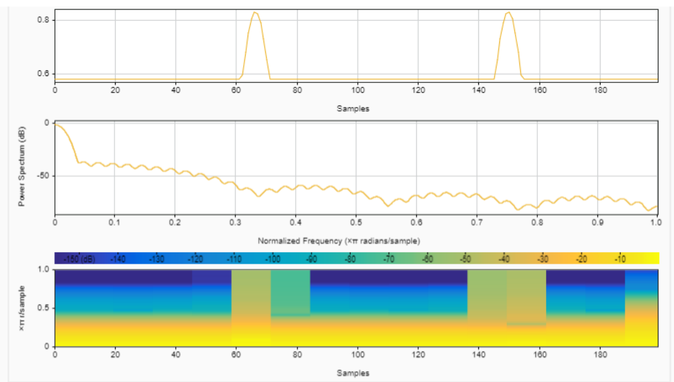

Fig.3. Noise Reduced EMG Signal using GLM

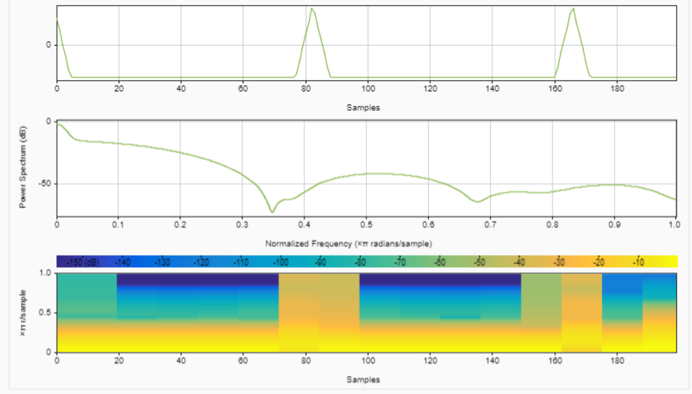

Fig.4. Noise Reduced EMG Signal using GLM

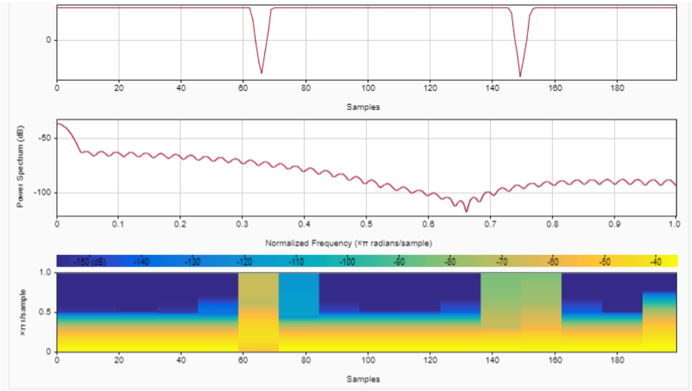

Fig.6. Noise Reduced ECG Signals using MaxEnt

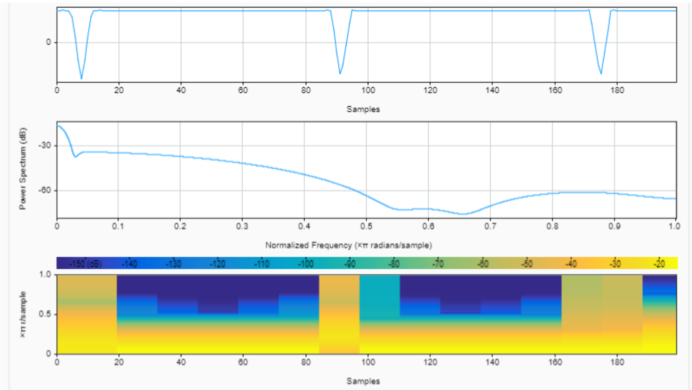

Fig.7. Noise Reduced EMG Signal using MaxEnt

This method allows for the investigation of all types of active filters, including band-pass, band-stop, high-pass, and low-pass filters, as well as their corresponding frequency responses.

The primary objective is to design a prototype that could simultaneously evaluate ECG, EEG, and EMG data, in addition to skin bioimpedance. The ECG module made it possible to evaluate 12 separate leads coming from various parts of the body in addition to the heart rate, and the exercises that were included in this unit provided the students with a better understanding of the phenomenon of electrical activity that occurs during the heart cycle.

In addition, the EOG module made it possible for us to interpret the electrical shift that occurred in the muscles that control eyeball movement. A comparable amount of effort is put into the testing portion of the EEG module to acquaint students with brain electricity. The EMG module allowed students to investigate the difference in electrical potential that occurs because of utilising a wide variety of different muscle motions.

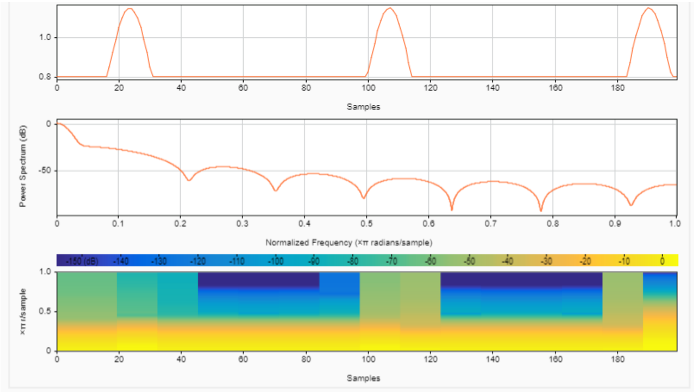

Fig.7. Noise Reduced EEG Signal using MaxEnt

6. CONCLUSION

Users can test theoretical hypotheses by evaluating each stage of the device on its own. This study covers the installation of a prototype biomedical measurement system, which can be used to pedagogically evaluate the usefulness of specific modules for detecting electrical activity in the brain, heart, and muscles. The results of such an evaluation can be used to inform future developments in the field. In conclusion, the bioimpedance module demonstrated how the bioelectrical impedance varies at different locations throughout the body. It is essential to highlight the fact that the EMG, EEG, and EOG subsystems all utilise the same quantity of input channels that were incorporated into the prototype.

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