Indonesian Journal of Electrical Engineering and Computer Science
Vol. 4, No. 3, Desember 2016, pp. 568 ~ 579
DOI: 10.11591/ijeecs.v4.i3.pp568-579

Identification of Brain disorders by Sub-band Decomposition of EEG signals and Measurement of Signal to Noise Ratio

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Abstract

In the case of medical science, one of the most restless researches is the identification of abnormalities in brain. Electroencephalogram (EEG) is the main tool for determining the electrical activity of brain and it contains rich information associated to the varieties physiological states of brain. The purpose of this task is to identify the EEG signal as order or disorder. It is proposed to enrich an automated system for the identification of brain disorders. An EEG signal of a patient has been taken as a sample. The simulation has been done by MATLAB. The file which consists of the signal has been called in and plotted the signals in MATLAB. The proposed system covers pre-processing, feature extraction, feature selection and classification. By the pre-processing the noises are ejected. In this case the signal has been filtered using band pass filter. The Discrete Wavelet Transform (DWT) has been used to decompose the EEG signal into Sub-band signal. The feature extraction methods have been used to extract the EEG signal into frequency domain and the time domain features. The SNR (Signal to Noise ratio) is obtained in this work is 1.1281dB.

***Keywords**: feature extraction, sub-band decomposition, EEG waves, MATLAB, wavelet transform, EEG etc*

1. Introduction

EEG detects the electrical activity of brain to monitor its states of infants, children and adult whether it is in normal or abnormal condition without any affliction. Several electrodes which are generally made up of small metal discs with thin wires are assembled over the scalp to measure these waves. After that, these electrodes send the collected to a computer to record and display the results. Physicians can identify the pattern of normal EEG. For this reason, they can try to reveal the patterns of seizures and other different brain complexities. Most of the time, physicians use EEG to diagnosis the seizure disorders. Whereas, EEGs can also be used to find out the reasons behind other brain problems like changes in behavior, sleep disorders, etc. There are two significant applications of EEG. One is for diagnosis brain disorders which are known as clinical application and the other one is Brain Computer Interface (BCI) technology in research application. Generally, in clinical application, this signal are used vastly to diagnosis brain disorders like epilepsy, tumors, stroke, brain death, sleep disorder, coma, drug intoxication, coups of the brain and Alzheimer. Moreover, it can be used in the treatment of depression, stress reduction, betterment of attitude and scoring intelligence of children with Attention Deficit Hyperactivity Disorder (ADHD) implementing neurofeedback methods. Neurofeedback or Neurotrapy is one kind of biofeedback that employs mostly the EEG measurements is generally supplied using video or sound. Usually, biofeedback therapy includes training patients with an aid of biofeedback therapist to control their unpremeditated physiological processes that can be recorded by the biomedical instruments like Electromyography (EMG), Electrodermograph (EDG), Electroencephalograph (EEG) and Electrocardiogram (ECG). So after observing these biopotential waves and trainings, patients can get the idea about the methods to control these unpremeditated processes towards the improvement. Almost 1% of people experience an expropriation at some time in their life [1]. The world requires more researches to understand the mechanisms which cause brain disorder

Received October 2, 2016; Revised November 11, 2016; Accepted November 29, 10, 2016

perfectly. To make sagacity into this comprehensive brain disorder, careful analysis of the Electroencephalograph (EEG) has no alternative. A disease is defined as an abnormal circumstance which affects the body of a creature. A characteristic set of symptoms and sign are used to identify any dislodgement from the unstrained construction of a body part or organ. Generally, we use EEG to identify the brain diseases. EEG is the process of recording the electrical activities of the brain from scalp. The main function of EEG is to calculate the voltage changeability which results from the flow of ionic current into the neurons of the brain. In general, diagnostic applications concentrate on the spectral content of neural oscillations from the EEG signal. EEG is that kind of measuring method which does not cause any affliction and injury. Even, it doesn't allow passing any electricity within the brain or body. Delta, theta, alpha, beta and gamma are the five EEG sub-bands on which the EEG signals are usually decomposed. The frequency range of alpha waves is from 8 to 12 Hz and these waves are rhythmic. Its amplitude is low. Although, the characteristic of alpha rhythm can be found from the every region of the brain, most of the times the occipital and parietal regions are chosen to record it. On the other hand, beta waves are irregular in type and its frequency range is from 13 to 30 Hz. Its amplitude is very low. Temporal and frontal lobe regions are the mostly used regions to record it. Moreover, 0.5 to 4 Hz is the frequency range of delta waves which are rhythmic. These waves have high amplitude. These waves generally recorded from occipital lobe. The slow waves having a frequency range of 5 to 7 Hz are called theta waves. It has a low-medium amplitude range. And, gamma waves are the waves with highest brainwave frequency which is greater than 30 Hz with the smallest amplitude. The locations, normal state and pathological of all bands are shown in Table 1.

Table 1. Different Bands of EEG Signal with Location, Normal State and Pathological

Band	Location	Pathologically	Normally
Delta	Frontally in adults, posteriorly in children	Sub crotical lesions diffuse lesions	Adult slow sleep in babies
Theta	Found in location not related to task at hand	Focal sub cortical lesions, Deep meedline disorder	Higher in young man idling
Alpha	Posterior regions of head, both sides, higher in amplitude on dominant side	Coma	Relaxed closing the eyes
Beta	Both sides, symmetrical distribution, most evident frontally	Benzodiazepines	Range span: active calm->intense -> stressed -> mild obsessive active thinking, focus
Gamma	Somatosensory cortex	A decrease in gamma band	Displays during cross-modal sensory processing Also is shown during short term memory

According to more recent papers argument, alpha rhythms intercept the areas of the cortex which are not employed or they play an important role in network coordination and communication alternatively [2]. Historically, they were assumed to exhibit the action of the visual cortex in a lethargic state. Due to have some attainments in humans for seizure suppression and treatment of depression, alpha wave biofeedback is explained further [3].

Sometimes after encountering a severe head injury or before heart or liver transplantation, EEGs are used to measure brain activity [4]. Table 2 represents the amplitude of EEG in the range of microvolt up to 200 μV with the frequency bands when it is taken over the scalp and in the range of milivolt when it is measured directly from the surface of brain (in open operation). Here, its frequency is approximately up to 100Hz.

Table 2. Characteristics of EEG Rhythms

State	Unconscious		Conscious		
Rhythm	Delta	Theta	Alpha	Beta	Gama
Frequency(Hz)	0.5-4	5-7	8-12	13-30	>30
Amplitude(μV)	20-200	10	20-200	5-10	5-10

In this proposed work, the EEG signals are given as input to the pre-processing. In the pre-processing, the discrete wavelet transform are used to take aside the noises and then the EEG signal are decomposed into five sub-band signals. After that, the non-linear parameters (time and frequency) were extracted from each of the six EEG signals (original EEG, delta, theta, alpha, beta and gamma). Then, these features are fed into a Support Vector Machine (SVM) to classify the data samples as epileptic or not epileptic. The fed features to the SVM are a set of four features for each sample data that we have extracted. Then, we can use the classifier to classify the given EEG signal as normal or abnormal.

The remaining of this task is settled as follows: The second section shows the related works. The third section gives the proposed system. The fourth section gives the simulation environments.

2. Related Works

Some literature survey has been focused for the pre-processing of EEG signals, feature extraction, feature selection and classification methods. To improve the classification accuracy of EEG signals, Siuly [5] has proposed a cross correlation based LS-SVM [8] [10]. The discrete wavelet transform is implemented by Sabeti M [6] for preprocessing [8] [13] and genetic algorithm to select the best features from the extracted features. SVM [8] and LDA are two such classifiers that can be implemented to classify the EEG signal abnormalities. Stevenson N J [7] has developed a system named as Automated Grading System for EEG abnormality in neonates. Multiple linear discriminate classifiers are implemented to classify the EEG abnormality in neonates. Time-frequency distributions of EEG signals have been presented by Marcus [9]. Here, we used the SVM to classify the epilepsy from EEG signals.

A classification of EEG signals according to the neural networks has been proposed by Nandish M [11]. Salih Gunes [12] has discussed the Fast Fourier Transform for pre-processing. The combination of KNN and Decision Tree classifiers are used to classify the EEG signals. Multilayer perception neural network for EEG signal classification has been focused by Umut Orhan [13]. Parvinnia E [14] has presented the adaptive method designated as weighted distance nearest neighbor algorithm is applied for EEG signal classification.

EEG waves hold a lot of useful information of brain functions and states. Although, this information is generally existed in the time domain, we cannot extract this information directly by observing only the time domain. So, we have to use signal processing techniques to analyze these waveforms. There are some methods of analyzing the EEG signals which can be applied in time domain, frequency domain and time-frequency domain. There are many new EEG machines which are capable of applying simple signal processing tools like the Fourier transform to perform frequency analysis and also equipped with some imaging tools to visualize the EEG topographies. Many methods have been proved favorable for various EEG characterizations. Fast Fourier transform (FFT) for spectral analysis of EEG signals have been used by many researchers in frequency domain. EEGLAB is used to process continuous and event-related EEG, MEG and other electrophysiological data which is an interactive MATLAB toolbox. Interactive Graphic User Interface (GUI) which is provided by EEGLAB allows users to process their high-density EEG flexibly and interactively. Moreover, it facilitates the users to use to Independent Component Analysis (ICA), Time-Frequency Analysis (TFA) and standard averaging methods [15] to process other dynamic brain data which are freely available. An EEG signal processing program based on EEGLAB has been developed by O. A. Padierna Sosa et al [16]. They resolved that EEGLAB is a program that provides an accessible solution to the EEG signal processing problem as its free allocation and great service diversity approves inexperienced users to become able to gather some knowledge while doing experimentation with EEGLAB. MD. Shahedul amin et al, have recommended spectral analysis of human sleep EEG signals using EEGLAB. They have deduced the delta band more particularly. According to their deduction, PSD at 1.8 ~ 2.0 Hz and at 2.7 ~ 2.9 Hz is good for discovering whether a person is in sleeping state or not. According to them, if the person is in sleeping state then there would be a sharp change at these frequency ranges [17]. S. Deivanayagi and her group have worked on spectral analysis of EEG Signals at the time of Hypnosis. They have found the spectral analysis of EEG during hypnosis represents the frequency bands in theta and alpha ranges. From that analysis, they have derived that the frequency bands received from the scalp falls in the higher theta and smaller alpha waves at the time of hypnosis [18]. In this paper, we have used FFT for detecting the location of alpha rhythm in subjects with closed and open eyes.

But fast Fourier transform (FFT) suffers from having large noise sensitivity. Parametric power spectrum estimation methods like autoregressive (AR) lessen the spectral loss problems and provide better frequency resolution. But, the parametric methods are not compatible for frequency decomposition of these signals because the EEG signals are non-stationary.

Spectrum analysis which is indicated as frequency domain analysis or spectral density estimation is an eminent method in biomedical signal analysis. Spectral analysis is the technical process for decomposing a complex signal into simpler branches where the various amounts are quantified against frequency. Those amounts can be in state of amplitude, power, intensity or phase. The frequency spectrum of a time-domain signal is a visual representation of that signal in the frequency domain. A fourier transform of the signal is used to generate the frequency spectrum, and then the resulting values are usually represented as amplitude and phase where both the values are plotted against frequency [19]. EEG signals are best portrayed as a sum of many individual frequency components. So, a powerful method named as the wavelet transforms (WT) was proposed to perform time-scale analysis of signals. This method provides an established framework for different techniques that have been developed for various applications. Since the WT is suitable for analyzing the non-stationary signals and represents a major benefit over spectral analysis, it is well suited to locate the transient events which may occur during brain disorders. Transient features are exactly received and localized in both time and frequency context through wavelet decomposition of the EEG records. As this mathematical microscope is capable to explore different scales of neural rhythms, it can be recommended as a potential instrument for inquiring small-scale oscillations of the brain signals.

3. Proposed System

The main purpose of this work is to analyze the EEG signal for the identification of brain disorders. This proposed system includes the process such as EEG signal pre-processing, feature extraction, feature selection and classification. The modules of this system are:

1) Pre-processing
2) Feature extraction
3) Feature selection
4) Classification

The first block includes with the EEG signal pre-processing concept. It is used to eject the noises from the signal. The next step sucks the features of the EEG signal from the decomposed signal. Then the consequential features are chosen from the sucked features. The inputs of the classification process are taken from the chosen features. The classification method is mainly used to for analyzing the EEG signal classification method is mainly used. It classifies the signal into order or disorders. The Figure 1 shows frame work for analysis of EEG signal. This work is performed using MATLAB.

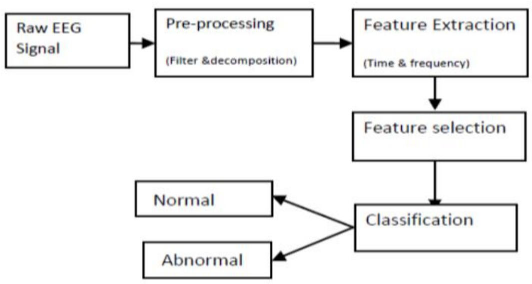

Figure 1. The Whole Simplified Process for Analyzing EEG Signal

EEG DATABASE

The raw EEG signal has been collected from the physionet database. (http://www.physionet.org/cgi-bin/atm/ATM)

3.1. Methodology for Finding Signal to Noise Ratio (SNR) and Sub-Band Decomposition

Primarily the EEG signal is loaded and plotted into MATLAB then we define a sampling frequency for the band pass filter. Then the band pass filter has been defined. After getting the filtered signal we define several band frequencies for alpha, beta, theta, delta & gamma. Besides those signals are compared with the basic signals. The comparison between actual signal and filtered signal gives us SNR which is 1.1281dB. Figure 2 shows the methodology for analysis of EEG signal. This work is implemented by using MATLAB.

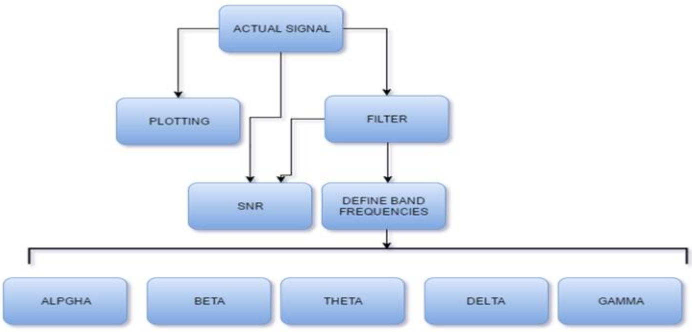

Figure 2. Methodology for finding Signal to Noise Ratio (SNR) and Sub-Band Decomposition

3.2. Analysis of Discrete Wavelet Transform (DWT)

The DWT decomposes the signal into a well upholstered assumption and explicit information to analyse the signal at different frequency bands with different resolutions. Two sets of functions named as scaling functions and wavelet functions which are respectively associated with low pass and high pass filters are employed by DWT. By successive high pass and low pass filtering of the time domain signal, the decomposition of the signal into different frequency bands is obtained. At first, the original signal, x[n] is took across a half band high pass filter, g[n] and then across a low pass filter, h[n]. The filtering and sub sampling will come to half the number of samples (hence, the time resolution will be halved) and half the frequency band spanned (hence, the frequency resolution will be doubled) at every level.

Haar, Meyer and Shannon are some examples of orthogonal wavelets. There is another orthogonal wavelet which is named as the Daubechies wavelet can be used to extract the features of EEG. Multi Resolution Analysis (MRA) is a feature of WT which is used to express the given signal by dilates and translates of a wavelet function at multiple scales but at one particular scale (depends on the characteristic of signal being analyzed) at a time.

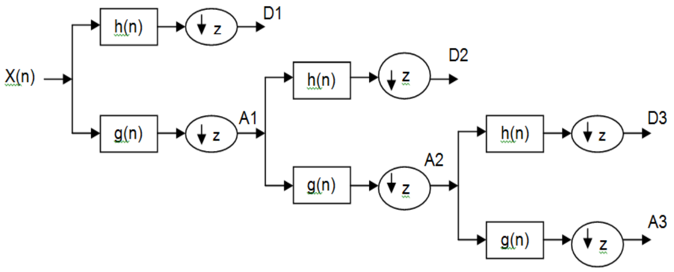

Figure 3. Sub-Band Decomposition

If, the operators h and g please the following orthogonality conditions, then they can be designated as perfect reconstruction or quadrature mirror filters (QMFs):

$$G(z)G(z^{-1})+G(-z)G(-z^{-1})=1 \quad (1)$$

Where, G(z) indicates the z-transform of the filter, g.

After the first high-pass and low-pass filtering, the down sampled outputs provide the detail, D1 and the approximation, A1, respectively. Then, the first approximation, A1 is again decomposed and this process is continued as shown in Figure 3. As the EEG signals do not possess any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 5. Thus, the EEG signals were decomposed into details D1–D5 and till the final approximation, A5. Daubechies wavelet of order 4 (db4) has a special feature called smoothing feature which made it more perfect to detect the deviations of EEG signals. Hence, the wavelet coefficients were computed using the db4 in this paper. A compact representation provided by the extracted wavelet coefficients exhibits the energy distribution of the EEG signal in time and frequency. Table 3 represents frequencies corresponding to different levels of decomposition for Daubechies wavelet of order 4. We have extracted four sets of features for the data after sub-band classification, these features are:
1) Mean of the wavelet coefficients in each sub-band
2) Standard deviation of the wavelet coefficients in each sub-band
3) Minimum of the wavelet coefficients in each sub-band
4) Maximum of the wavelet coefficients in each sub-band

These coefficients are then fed to the SVM to classify the data samples as disorder or not.

Table 3. The Values of Decomposed Signal after the Decomposition of Sub-Band by Daubechies Wavelet

Decomposed signal	Range of frequency(Hz)
Non-Useful Frequency(Noise)	43.7-87.0
Gamma(D1)	21.9-43.6
D2 Beta(D2)	11.0-21.8
Alpha(D3)	5.6-10.9
Theta(D4)	2.9-5.5
Delta(A4)	0-2.8

3.3. Feature Extraction

To decrease the dimensionality of the features, the extraction methods are used. The characteristics of original signal without superfluity are represented by the extracted features. The features can be extracted from the EEG signal in two different domains such as Time Domain Features (TDF) and Frequency Domain Features (FDF).

3.3.1. Time Domain Features

Time domain analysis forms of statistical calculations. Mean, Median, Mode, Standard deviation, Maximum and Minimum are the features of time domain. These features are measured for the rebuilt EEG signal amplitude and time duration.

1) Mean: Mean fits to the center of a set of values. Using the following equation, the Mean is calculated for each and every sub-band signals.

$$Mean = \frac{1}{N}\sum_{i=1}^{n} X_i \quad (2)$$

2) Standard deviation: Standard deviation is a simple measurement of the variability of a data set. The Standard deviation is the root-mean-square (RMS) deviation of its values from the mean value.

$$Std = \sqrt{\frac{\sum_{i=1}^{n}(x_i - x)^2}{N-1}} \quad (3)$$

3) Maximum and Minimum: The maximum and minimum values are used to describe the range of look-out in the reconstructed signal.

3.3.2. Frequency Domain Features

The power values of each channel from the frequency band are defined as the frequency domain features. Band power, fractal dimension and energy are some of those. Band power narrates the way the power of a signal or time series is allotted with frequency. Fractal dimension is used to assume the dimension of a signal.

3.4. Feature Selection

To pick the relevant features, feature selection method is used where the features with little or no vatical information are eliminated. It is very helpful to find out a feature subset which increases the classification accuracy and lessens the training time. SVM algorithm is the perfect algorithm to elect the relevant features. It initiates with the initial population of individuals representing the probable key to optimization problems. Selection, crossover, and mutation rules controlled the evolution process. The mutation and crossover operators take care of the variety of the population. SVM algorithm is the perfect algorithm for an efficient dealing with the large search space.

3.5. Classification

Classification is a method of data mining which is used to allot data in a gathering of target categories and classes. The main objective of classification is to presume the dockets for each class in the data correctly. In the proposed system, we used the selected features as inputs to the k-means classifier. Then, the signals are classified as order and disorder according to the selected features vector. It will abate the training time and enhance the performance of classifier.

Algorithmic steps for k-means clustering:

Let,

The set of data points, $X = \{x_1, x_2, x_3, \ldots\ldots, x_n\}$

And, the set of centers, $V = \{v1, v2, \ldots\ldots, v_c\}$.

1) To initialize the process, elect ‘c’ data points as cluster centers.
2) Measure the distance between each data point and cluster centers.
3) Find out the minimum distance and assign that data point to the cluster center.
4) Use the following equation to update the new cluster center,

$$V_i = \left(\frac{1}{C_i}\right) \sum_{j=1}^{C_i} X_i \qquad (4)$$

where, c_i is the number of data points in i^{th} cluster.

5) Again, calculate the distance between each data point and the newly updated cluster centers.
6) Go to step 3 and continue the process until the cluster centers have no longer move.

4. Simulation Environments

4.1. Actual EEG Signal

The signal has been collected from online which is a dat file (http://www.physionet.org/cgi-bin/atm/ATM).

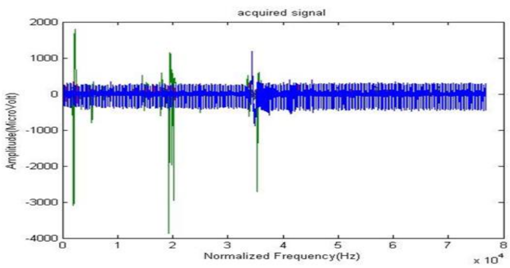

Figure 4. Patient’s Actual Signal

The actual EEG signal for a normal people is collected from a patient which is available in ‘eeganalysis’ [20]. From the Figure 4 it is understood that the signal is noisy and needed to be filtered. Here the x-axis defines normalized frequency while y-axis defines amplitude. From Figure 5 it is clear that the patient's signal is noisier then the actual signal for a normal people.

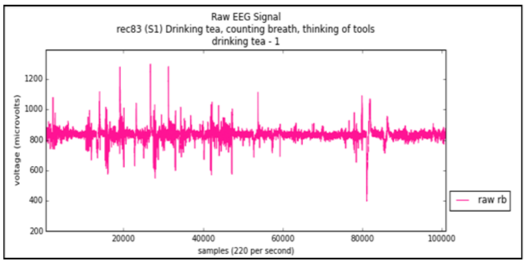

Figure 5. Actual Signal of A Normal People

4.2. Filtered Signal

The band pass filter has been used to filter the noisy signal. Here the sampling frequency is 8000Hz. We have tried it by several sampling frequencies for the signal but the sampling frequency 8000Hz is working best. The stop band frequency is 0.1Hz. Besides of this, three stop band frequencies have been identified. The filtered signal is also include a little noise, as shown in Figure 6 and 7.

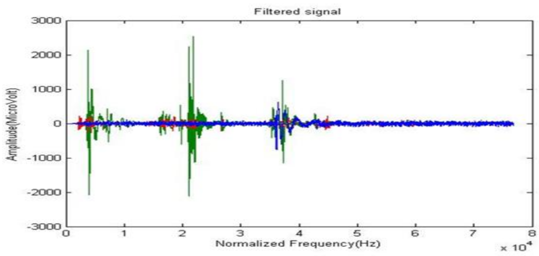

Figure 6. Patient's Filtered Signal

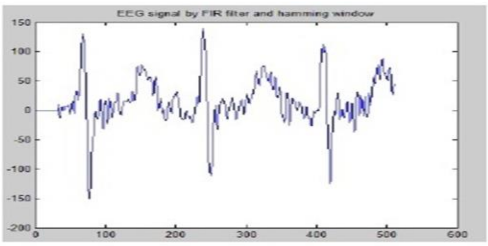

Figure 7. Filtered Signal of A Normal People

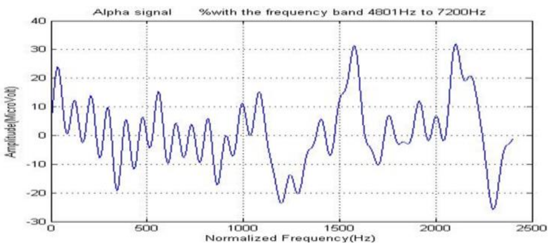

Figure 8. Decomposed and Filtered Alpha Signal

4.3. Alpha Signal

Here for getting the Alpha signal , the band frequencies are defined from 4801Hz to 7200Hz. It is seen that our filtered alpha signal has the less ripple then the alpha signal of people in case of closed eyes (Figure 9).

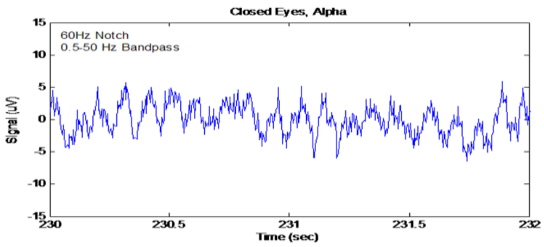

Figure 9. Alpha Signal in Case of Closed Eyes

4.4. Delta Signal

To obtain the Delta signal the band frequencies are defined from 8205Hz to 9000Hz. Both delta signals are almost the same but our obtained decomposed and filtered delta signal has the long amplitude for a certain time and this abnormal case.

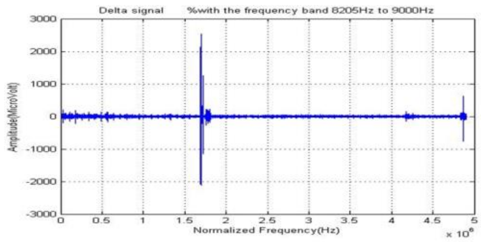

Figure 10. Decomposed and Filtered Delta signal

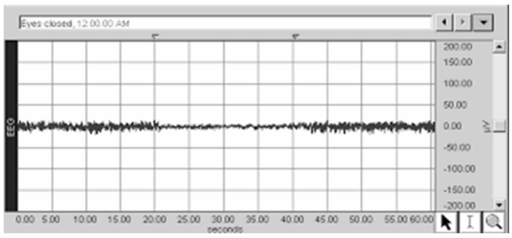

Figure 11. Delta Signal for A Normal People

4.5. Beta Signal

The frequencies for the beta signal are defined from 2400Hz to 4800Hz. Though the frequency and amplitude are different for both beta signal but their shape almost similar.

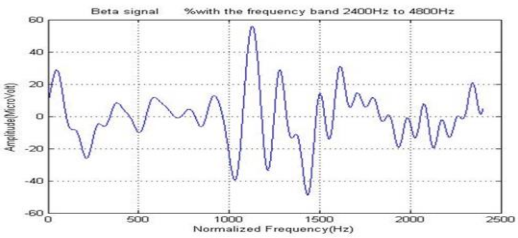

Figure 12. Decomposed and Filtered Beta signal

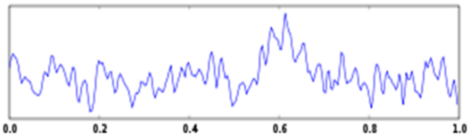

Figure 13. Beta Signal for General Condition

4.6. Theta Signal

To get the Theta signal the band frequencies are defined from 7301Hz to 8000Hz. It is seen that the shape of both theta signal is almost the same but the frequency and amplitude are different.

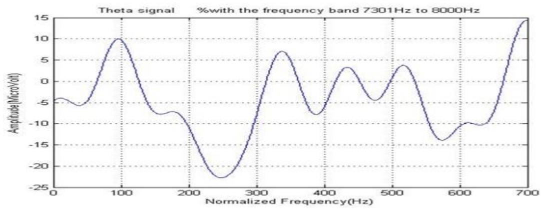

Figure 14. Decomposed and Filtered Theta Signal

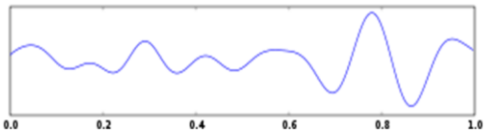

Figure 15. Theta Signal in General

4.7. Gamma Signal

To get the Theta signal the band frequencies were defined from 1Hz to 2400Hz. In case of gamma signal the patient and the general gamma signal are different due to some abnormal reasons.

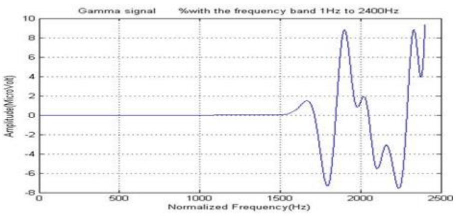

Figure 16. Decomposed and Filtered Gamma Signal

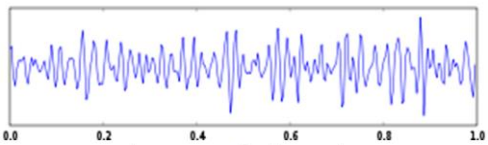

Figure 17. Gamma Signal in General

4.8. SNR

Signal-to-noise ratio is a measure used in science and engineering that compares the level of a desired signal to the level of background noise. It is defined as the ratio of signal power to the noise power, often expressed in decibels. The SNR we have got in this task is 1.1281dB.

4.9. Designed GUI

As shown in the Figure 18 Designed GUI;

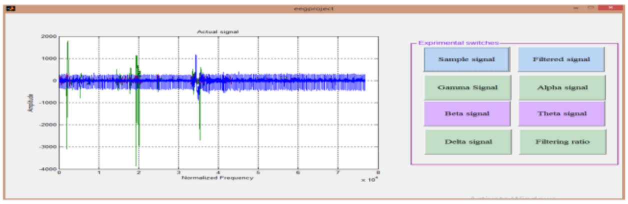

Figure 18. Designed GUI

5. Conclusion

The identification of brain disorders by analyzing EEG signal is a tough process. For this reasons the automatic system is essential for the identification of brain disorders. Our developed task may be an effective tool by studying abnormal and normal patients. In this paper a method has been developed to separate the different band frequencies of a raw EEG signal and to classify the order and disorder of EEG signal with the help of a intelligent algorithm, SVM and also to measure SNR of that signal. The frequency and time domain features have been extracted. The highest accuracy is achieved by the alpha band to classify the order and disorder of the EEG signals. Furthermore, this idea can be used to develop “Mind controlled wheel-chair” for the disabled peoples. Besides HCI (Human Computer Interaction) and machine learning can be combined to make better in future.

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