WAVELET BASED EEG SIGNAL ANALYSIS ON SMALL ABNORMALITIES FOR EMERGENCY MEDICATION APPLICATION

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APPROVAL

This Project titled **"Wavelet Based EEG Signal Analysis On Small Abnormalities For Emergency Medical Application"** submitted By Md. Habibullah Pappu, Kabir Hossain Tutul and Md. Mahim Bin Firoj to the Department of Electronics and Telecommunication Engineering (ETE), Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Electronics and Telecommunication Engineering and approved as to its style and contents. The presentation was held on May, 2018.

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DECLARATION

We hereby declare that this project is our own work and effort under the supervision of **Prof. Dr. A.K.M. Fazlul Haque, Professor, Department of Electronics and Telecommunication Engineering and Associate Dean, Faculty of Engineering,** Daffodil International University, Dhaka. It has not been submitted anywhere for any award. Where other sources of information have been used, they have been acknowledged.

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ABSTRACT

The Electroencephalogram (EEG) is a very crucial and effective tool for brain monitoring system as well as detection of various abnormalities on behalf of both regular checkup and in case of any emergency. This project aims to show an improved and more effective way of monitoring the brain and its disruptions. It also gives an enormous opportunity to analyze the brain signal more deeply considering the different environments. The project is divided into two parts as the EEG data reading and the signal processing. The EEG data reading part is responsible to extract the EEG signal from the body and eradicate the high frequency components and power line noise. The signal processing part can work to filter the signal to eliminate the background noise. As the current analyzing technologies are not sufficient enough to deal with the sudden abnormalities or even very small abnormalities, the proposed method provides an effective way of analyzing the data more accurately. The system has been developed using the wavelet tool in MATLAB. Because of the availability of statistical information of the EEG data, the system can detect the smallest possible abnormalities even in the harsh conditions. Extracting various statistical parameters along with the other processing techniques including filtering, the proposed method can monitor the brain as well as detect any type of abnormalities in a more accurate and effective way.

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INTRODUCTION

1.1 Overview

Brain diseases are one of the burning issues and new concerns in worldwide, and the importance of the electroencephalogram (EEG), which helps to monitor as well detect the small abnormalities in the brain is remarkable since epilepsy or other seizure disorder, head injury, brain tumor, stroke, dementia, sleep disorders, encephalitis (inflammation of the brain), encephalopathy (brain dysfunction that may have a variety of causes) diseases constitute one of the real reasons for mortality on the world. As reported by World Health Organization (WHO), almost 6.2 million people died due to brain diseases [1] [2]. Brain diseases are now growing as a serious health threat in the third world countries like Bangladesh.

And electroencephalogram (EEG) is the process adapted to detect the small electrical movement of the brain. The brain cells are communicating through electrical impulses. And the EEG here to be used to detect influential difficulties associated with this action in each time of arising [3]. The Electroencephalogram traces and notes the brain wave arrangements. And the small flat of metal discs are known as electrodes and those are appended to the human scalp through cables. The electronic movements (impulses) are considered by the electrodes and sends the signs to a computer which stored the outcomes [3]. The recorded electrical movements looks near a wavy channels with crests and valleys. Those channels enable specialists to rapidly survey if there finds any irregular examples. Any irregularities might be an indication of seizures either auxiliary issues in brain or various other reasons [4]. In most of the cases, small changes of the signal that come from the brain cannot find out and that’s why in crucial moments proper treatment cannot be made, which could lead into even more critical situation. EEG is the area where we can study about the smallest changes of the signal and implement into emergency medication application. That’s why we grow an interest to work in this field. But it’s not very easy to find the smallest changes or abnormalities in brain and we cannot take the necessary steps in proper time. But, by using wavelet, it can be possible to detect the smallest abnormalities or changes which will give a great advantage to take the proper treatments in case of heart attack, cardiac arrest and brain strokes.

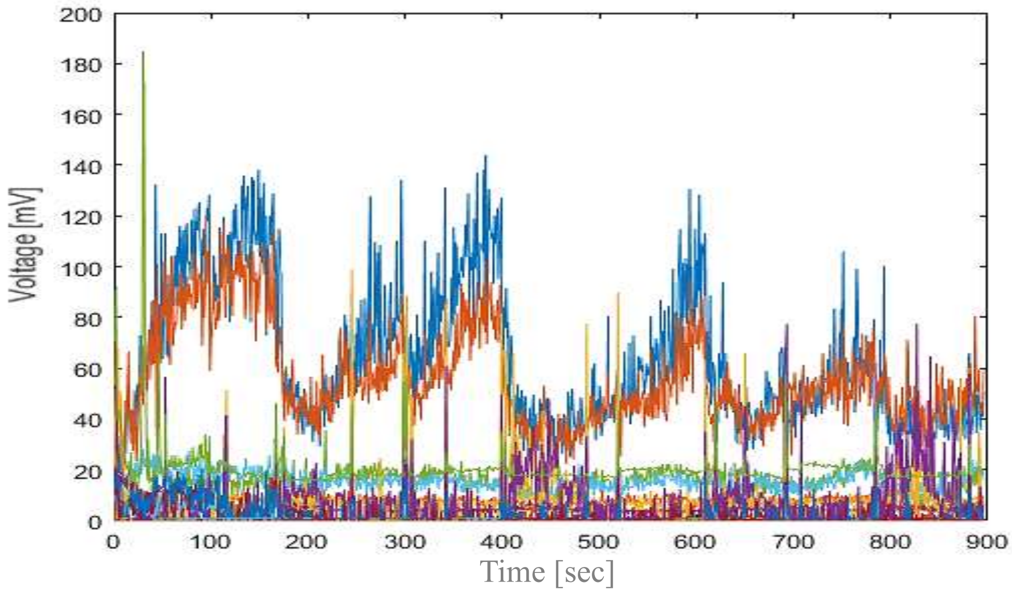


Figure 1.1: Recorded EEG Signal of Subject (A)

The various statistical parameters of the wavelet tool in MATLAB helps in monitoring the brain signals (EEG) and also offers the detection of small abnormalities in brain in emergency conditions. And figure 1.1 is the presentation of brain signal (EEG) of subject (A). It carries the brain signal information as for time (x-axis) as well as voltage (y-axis).

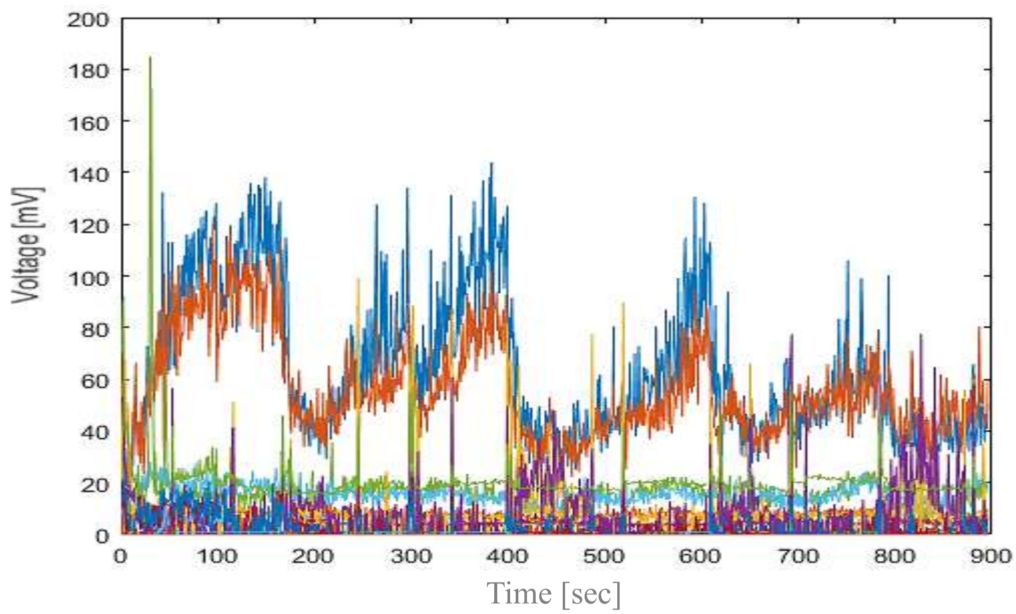


Figure 1.2: Recorded EEG Signal with Noise of Subject (A)

And figure 1.2 represents the same subject (patient), but in this case, figure 1.2 have some small abnormalities or changes compared with figure 1.1 due to noise or other brain problems. But normally these small abnormalities cannot be detected, eventually by using the First Fourier Transform (FFT) or other popular methods, it cannot be possible to detect the changes. And this project will clarify that by using wavelet, it can easily differentiate the smallest changes in the brain signal [5]. And which will surely help to take immediate action at the crucial moments. The methodology and statistical analyses will be discussed in the later portion of this work.

1.2 Literature Review

Brain signal analysis is a hot issue in the area of biomedical and signal processing. In last 30 years, many researchers are worked in this field and added a good numbers of information about the EEG but considering the importance of the brain signal in the case of emergency medication and small abnormalities detection, the information are not still good enough. In a research paper, Berdakh et al discussed about the brain activities, but it did not seems to clear to all about the brain functionalities and behavior of the brain in hash conditions [6].

Sheik et al clarified the classification of the electroencephalogram (EEG) signal and its feature extractions [7], but the brief discussion about the EEG did not focused on the small abnormality monitoring or detection. M. Akin's deep research based on the EEG on the wavelet transform and First Fourier Transform (FFT) also over loop the importance of the small abnormalities [8]. Subasi also dealing with the classification stage based on wavelet spectral [1]. Irijanti et al's paper was focusing on the neural network [3], the spotlight of the research also not touch the small abnormality issue. But Lee et al's narration was slightly touch the brain activity monitoring issue, but abnormality monitoring or detecting related such important issues were also disgusted in that paper [9].

Comparing with other research papers, which are dealing with the electroencephalogram (EEG) signal, Thakur et al's paper focused the time-scale based signal analysis which gave a better idea about the signal variation during difficult condition of the brain [10]. Saadat et al saw in headache patients appear to propose a conceivable physiological association between rest, hyperventilation and headache [11]. The investigation of such relationship may reveal new insight into headache psychopathology.

Most of the recent research on electroencephalogram (EEG) did not consider the brain signal monitoring in emergency conditions and did not tell about the small abnormalities on the brain signals (EEG) which causes various serious brain diseases. The aim of this project is to monitor the brain activity and detect the smallest abnormalities of the brain signal (EEG) based on wavelet transform which provides a statistical presentation of the brain signals that can help to monitor the brain activity in regular basis or in the case of emergency medication.

1.3 Motivation of the Project

Brain diseases is a great threats and major concern for our modern civilization. Sometimes the brain may not work properly due to various types of abnormalities and goes to sleep (simply called Coma). In the case of bloodless tissue, migraines, encephalitis (swelling of the brain), epilepsy or other seizure disorder, head injury, brain tumor, stroke, dementia, sleep disorders, encephalitis (inflammation of the brain), encephalopathy (brain dysfunction that may have a variety of causes), knowing the movement of the human brain interface is very important and the correct impulse collecting is a great problem and also hampered the proper treatment. And Wavelet based EEG signal analysis is the best way to evaluate the proper information of the brain interface and diagnose abnormal impulse of the brain. However, commercial machines are still beyond the reach of proper brain information. For example, in 2017, there are 6.2 million people who were died only for brain diseases and more than 21.6 million people are suffering by different brain diseases in every year [7]. And EEG data collection from the brain is a very easy processes nowadays. And the wavelet analysis can easily detect the small changes in the data and helps to take necessary steps. We hope that this project will help to find the way to analyzing the EEG data and monitoring or detecting the smallest abnormities of the brain signals, which will be helpful in regular and in the case of crucial moments.

1.4 About the report

This is an organized report which contains 6 chapters. The very first chapter provides the overview of the project. The physiological origin and properties of EEG signal are discussed in Chapter 2. It describes the principle of generation of an EEG signal. Chapter 3 concentrates on EEG data generating, noise and factors. It gives clear ideas of procedure of extracting the EEG signal from the human body. Chapter 4 depicts the EEG signal processing. It provides an apparent view of procedure of the signal processing of EEG records. In Chapter 5, the results and analysis are given. And finally the chapter 6 concludes the outcome of the project.

CHAPTER 2

PHYSIOLOGICAL ORIGIN AND CHARACTERISTICS OF THE EEG SIGNAL

To understand the specifications of the EEG signal, we have to know the features of Electroencephalogram signal. Section 2.1 depicts the working of the Brain and explains the origin of the EEG signal.

2.1 Origin and properties of the EEG (i.e. Electroencephalogram) signal

The presence of the electrical action of the cerebrum (i.e. the EEG) was found over a century back by Caton. EEG comprises of the aggregated electrical exercises of populaces of neurons, along with an unassuming commitment from glial cells. And the neurons are edgy cells with specific intrinsic electrical properties also their action produces electrical and also attractive fields. And these fields might be noted by methods for electrodes at a small separation from sources (the nearby Electroencephalograms) otherwise from cortical surface– else at longer separations, even from the human scalp (in the greater portion widely recognized sense). Neurons create time-changing electric currents when initiated. These ionic flows are produced at the cellular membranes levels, as it were, they comprise of transmembrane ebbs also the flows. It can recognize two fundamental types of neuronal enactment [8] [9], the quick depolarization of the neuronal layers, which brings about the activity potential intervened by the Kallium (potassium) and Natrium (sodium) voltage-subordinate ionic conductance's gK and gNa (DR). In addition, the variations in film potential are slower because of synaptic initiation, as interceded by a few neuro-transmitter frameworks. The activity potential comprises of a fast change in layer potential with the end goal that the intracellular potential sudden bounce towards positive from negative, and rapidly (within 2 ms) comes back to the process of resting intracellular pessimism. Thusly, a drive is created that owns the wonderful property of engendering along with axons and dendrites of human brain with no loss of plentifulness. As to slower postsynaptic possibilities, two primary sorts must be acknowledged: the EPSPs (excitatory potentials) and the IPSPs (inhibitory potentials). They rely upon the sort of neurotransmitter. And relating receptor with their cooperation's, which has strictly specified ionic channels and additional intracellular second emissaries. In EPSP's case at the level of a synapse, the current which is transmembrane is beard by inwards travelling positive ions (i.e. Na+). On the contrary, in IPSP's case, it is bearing by inwards travelling negative ions (i.e. Cl^-) or outwards travelling positive ions (i.e. K^+). Therefore, the positive electrical current is fixed to the medium of outer cell in the case of an EPSP as well as it is fixed from the inner side of the neuron to the outer side in the occurrence of an IPSP (Figure 2.1).

As an importance of these flows, an active sink is produced in the medium of outer cell at the level of an excitatory synapse, whereas active source occurs in the case of an inhibitory synapse. The compensating extracellular currents flows depend on the local tissue's electrical properties. Glial cells dwell a significant part of the space between neurons and the gap junctions coupled them one another [10]. The conductivity of the latter is very sensitive to variations in pH and extracellular Ca^{2+} and K^+, and it's possible therefore be modulated under various physiological and pathological conditions. Moreover, the capacity of the extracellular space might change under a number of physiological in addition pathological state of affairs, which will as well be reflected in fluctuations in nerve conductivity.

Meanwhile there is not at all accrual of charge wherever in the medium, the transmembrane currents which flow in or out of the neuron at the active synaptic sites are compensated by currents that flow in the reverse direction somewhere else along the neuronal membrane. Therefore, in the term of an EPSP, moreover the active sink at the stage of synapse, here are scattered passive sources along the soma-dendritic membrane. The reverse arises in the instance of an IPSP: moreover, the active source at the stage of the synapse, scattered passive sinks are formed along the soma-dendritic membrane. In this way, we can express that synaptic movement at a particular site of the soma-dendritic film of a neuron causes a sink source configuration in the extracellular medium around the neurons. With regards to the present dialog, we have to think about the geometry of the neuronal origins of electrical action. To be sure, the neurons that mostly add to the EEG are those that shape "open fields" [10], i.e. the pyramidal neurons of the cortex, since the last are formatted in palisades with the apical dendrites balanced oppositely to the cortical surface. Pyramidal neurons, when established with a particular level of synchronous, deliver sound electric/appealing fields.

Accordingly, these neurons are much the same as "present dipoles", the activity of which can be recognized by terminals set at modestly little detachments.

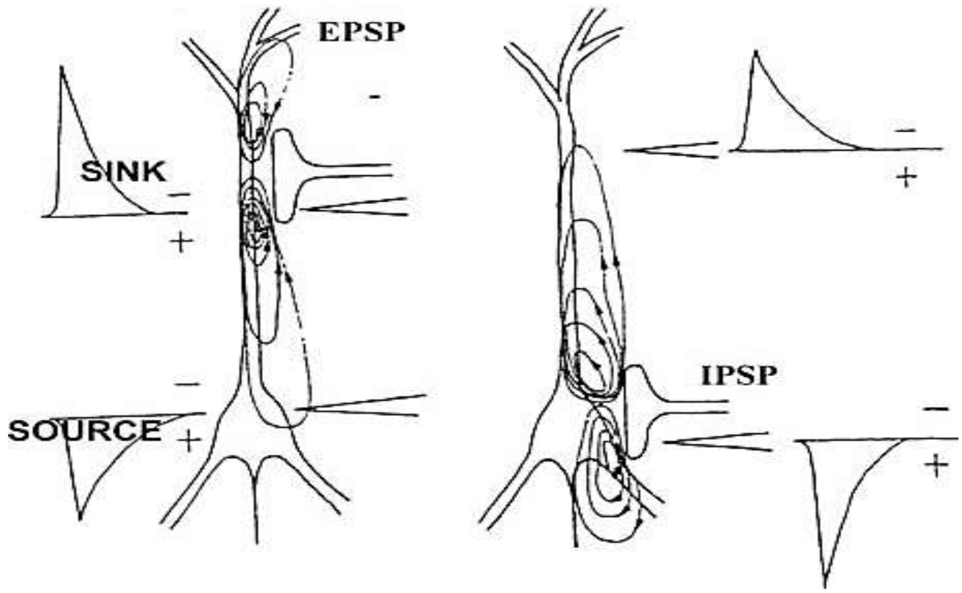


Figure 2.1: Scheme of a cortical pyramidal cell

The intracellular current is spoken to by a vector amount Q. The general extent of Q for the action of one pyramidal neuron of layers V and II/III is on the request of 0.29 pA – 0.90 pA, an esteem that is of an indistinguishable request of greatness from that evaluated for hippocampal pyramidal neurons [11]. Expecting a Q of 0.2 pA for each cortical pyramidal neuron, a populace of 55,000 synchronously dynamic cells would create a field with a size of 10 nA. As indicated by the last mentioned, the normal estimation of the volume current thickness of cerebral cortex is 175 nA/mm2 (or nA mm/mm3) for typical foundation movement.

Expecting a cortical thickness of 3 mm, the normal estimation of the relating surface current thickness is 525 nA/mm, and the normal estimation of the dipole minute mi(t) related with a neuronal populace I of surface si is M = si × 525 (nA mm) [11] [12]. This will come back to these ideas while examining volume conduction and source estimation.

2.2 Frequency Components

EEG (i.e. Electroencephalogram) is the estimation of electric possibilities at the human scalp because of currents coursing through scalp tissue. And the quality and dissemination of currents (accordingly possibilities) mirrors the power and position of action in the basic neural tissue. Electroencephalogram signal is estimated among two electrodes, the situation of which decides the noted brain zone. Numerous electrodes are commonly set in standard layouts that covers the whole human scalp and enable specialists to watch the action of the whole brain all the while.

EEG is regularly noticed as a period arrangement of potential contrasts, which can be assessed outwardly, or dissected frightfully, or using source limitation strategies. What's more, the primary frequencies leaving the electroencephalogram waves patterns of human are: theta, delta, alpha, beta and gamma. Numerous investigations have similar changes in different spectral segments of electroencephalogram to particular intellectual capacities and clinical situations.

2.2.1 Delta

Delta Wave has a recurrence of 3 Hz or underneath. It has a tendency to of being the most noteworthy in adequacy and the slowest of waves. This particular wave is typical as the predominant cadence in newborn children echo are aged up to 12 months and in stages 3 and 4 of rest. It might happen centrally with subcortical sores and by and large dispersion with diffuse sores, metabolic encephalopathy hydrocephalus or profound midline sores.

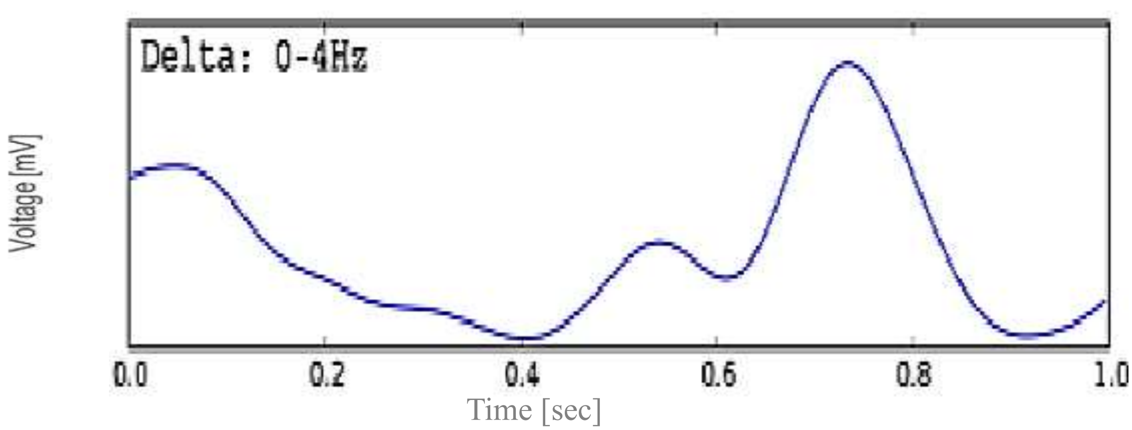


Figure 2.2: EEG Tracing in Delta waves

It is generally most conspicuous frontally in grown-ups (e.g. FIRDA) and posteriorly in kids e.g. OIRDA - Occipital Intermittent Rhythmic Delta) [13] [14].

2.2.2 Theta

Theta wave has a recurrence of 3.5-7.5 Hz and is delegated "moderate" movement. It is consummately ordinary in youngsters up to 13 years and in rest however anomalous in wakeful grown-ups.

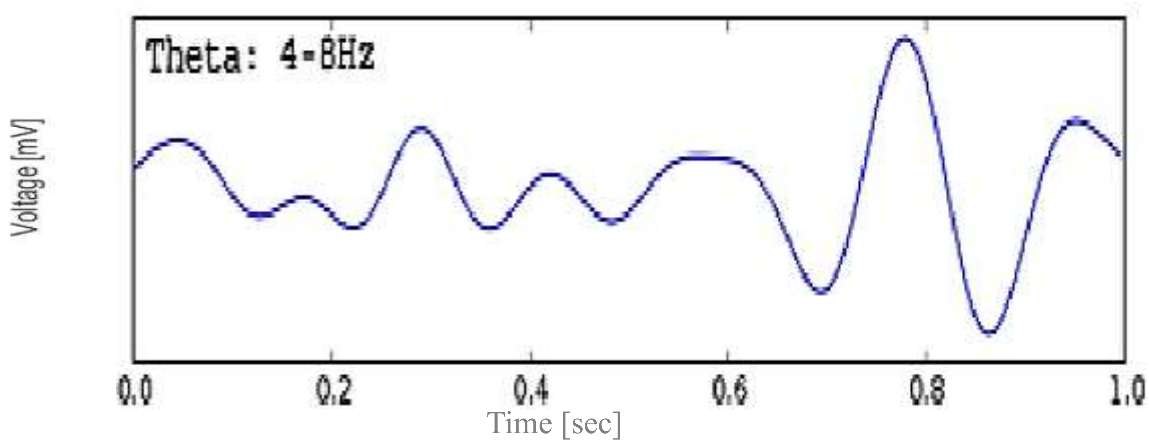


Figure 2.3: EEG Tracing in Theta waves

It can be viewed as an indication of central subcortical injuries; it can likewise be seen in summed up conveyance in diffuse clutters, for example, metabolic encephalopathy or a few occurrences of hydrocephalus [14].

2.2.3 Alpha

It has a recurrence in the vicinity of 7.5 and 13 Hz. Is typically best found in the back locales of the human head on both sides. It is usually higher in abundance on the prevailing side. It shows up when shutting the eyes and unwinding, and vanishes when eye-opening or cautioning by any system (considering, computing). It is a significant beat that is found in ordinary loose grown-ups [14] [15].

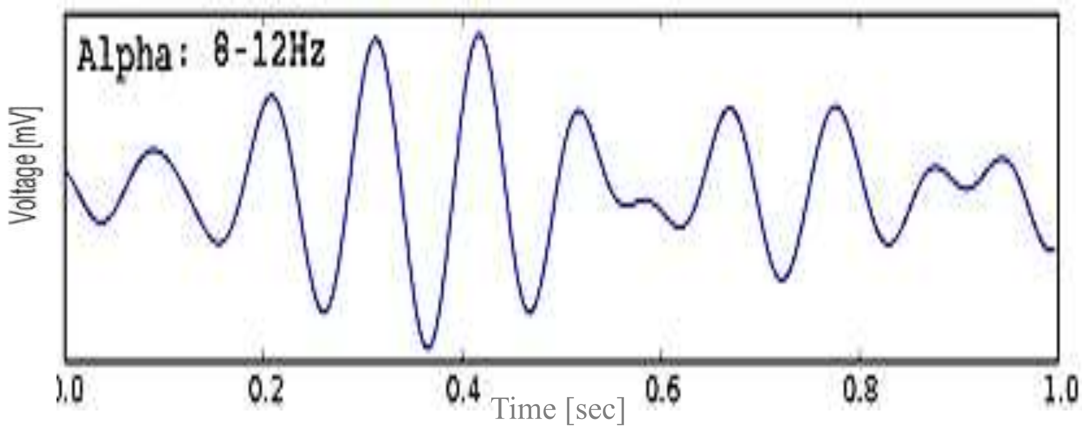


Figure 2.4: EEG Tracing in Alpha waves

2.2.4 Beta

Beta action is "quick" action. This wave has a recurrence of 14 and more prominent Hz. It is generally observed on both sides in symmetrical dissemination and is mostly clear in the front. And it is emphasized by narcotic entrancing medications particularly the benzodiazepines and the barbiturates.

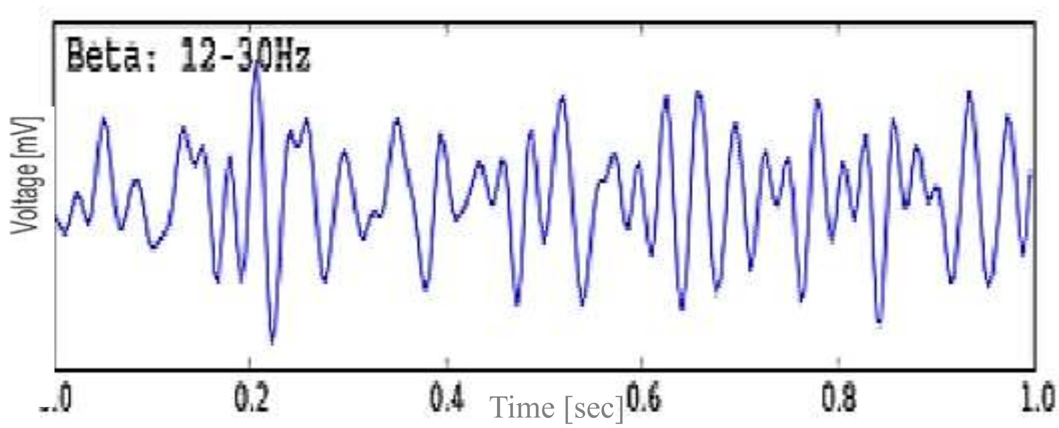


Figure 2.5: EEG Tracing in Beta waves

It might be truant or diminished in regions of cortical harm. It is for the most part viewed as an ordinary beat. It is the overwhelming cadence in those patients who are alarm or on edge or have their eyes open [15] [16].

2.2.5 Gamma (γ) Waves

In neuroscience, the most recent discovery is gamma (γ) waves, in this way the comprehension of how they work is always developing. To date, it's realized that Gamma (γ) waves are engaged with handling more intricate errands notwithstanding solid intellectual capacity.

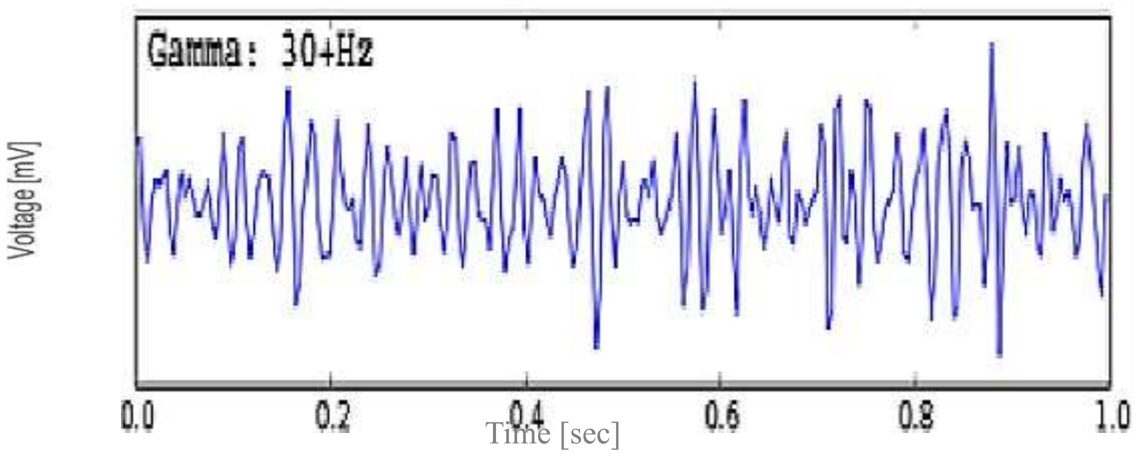


Figure 2.6: EEG Tracing in Gamma waves

Gamma (γ) waves are observed to be critical for memory, learning and preparing and those are utilized as a coupling device for our faculties to process new data. In individuals with mental incapacities, Gamma (γ) action is recorded in lower levels. All the more as of late, individuals have discovered a solid connection among reflection and Gamma (γ) waves [16].

2.3 Variables used to classify EEG activity

Frequency and voltage are two crucial variables used in EEG signal analysis to classify or clarify the signal activity. The rhythmic, arrhythmic and dysrhythmia characteristic of the frequency can classify the EEG whereas constriction, hyper synchrony and paroxysmal properties of the voltage can also clarify the EEG activity.

2.3.1 Frequency

Frequency alludes to rhythmic dreary movement (parameter: Hz) [13]. The Frequency of EEG action have diverse properties including the following:

- **Rhythmic.** EEG action comprising in rushes of roughly consistent recurrence.
- **Arrhythmic.** In this EEG action, no steady rhythms are available.
- **Dysrhythmia.** Rhythms and the examples of EEG movement that typically show up in understanding gatherings or once in a while or mostly seen in sound subjects.

2.3.2 Voltage

Voltage alludes to the normal voltage or pinnacle voltage of EEG movement. Qualities are reliant, partially, on the chronicle system [17]. Enlightening terms related with EEG voltage are included in following list:

- **Constriction (equivalent words: concealment, despondency).** Lessening of adequacy of EEG action coming about because of diminished voltage. At the point when movement is lessened by incitement, Scientists say that it have been "blocked" or it is demonstrating "blocking".
- **Hyper synchrony.** We usually see it as an expansion in voltage (V) and normality of cadenced action, or inside the alpha, beta, or theta go. The term infers an expansion in the amount of neural components adding to the beat. (Note: term is utilized as a part of interpretative sense however as a descriptor of progress in EEG).
- **Paroxysmal.** Action that rises up the out of foundation with a fast beginning, coming to (as a rule) very high voltage and consummation with a sudden come back to bring down voltage movement [17]. Though the fact that the term does not straightforwardly infer anomaly, much strange action is paroxysmal.

2.4 Morphology

Morphology is a term which alludes to state the waveform. The condition and characteristics of a wave or an EEG design is dictated by the frequencies that together form the waveform and by their stage and voltage connections. Wave examples can be depicted as being:

- **Monomorphic.** Particular EEG movement seeming, by all accounts, to be made out of one predominant action

- **Polymorphic**. Particular EEG movement made out of different frequencies that join to shape a perplexing waveform.
- **Sinusoidal**. Waves taking after sine waves. Monomorphic movement for the most part is sinusoidal.
- **Transient.** A confined wave or example that is unmistakably not the same as foundation movement.
    a) **Spike:** Spike is a transient which has a pointed pinnacle and a length from 20 to under 70 msec [18].
    b) **Sharp wave:** Sharp wave is a transient which has a pointed pinnacle and span of 70-200 msec [18].

2.5 Synchrony

Synchrony alludes to the synchronous appearance of cadenced or morphologically particular examples over various areas of the head, either on a similar side (one-sided) or the two sides (reciprocal) [19].

2.6 Periodicity

Periodicity alludes to the dispersion of examples or components in time (e.g., the presence of a specific EEG action at pretty much standard interims) [20]. The action might be summed up, central or lateralized.

CHAPTER 3

EEG DATA GENERATING, NOISE AND FACTORS

To understand the recordings of the EEG data, it is first necessary to understand the process of the EEG data recordings. Section 3.1 depicts the process of the EEG data generation and explain the working principle of the data processing.

3.1 EEG data reading

EEG traces and notes the brain wave arrangements. And the small flat of metal discs are known as electrodes and those are appended to the human scalp through cables. The electronic movements (impulses) are considered by the electrodes and sends the signs to a computer which stored the outcomes [9]. The recorded electrical movement's looks near a wavy channels with crests and valleys. Those channels enable specialists to rapidly survey if there are finds any irregular examples. Any anomalies might be an indication of seizures either auxiliary issues in brain [14].

3.1.1 EEG electrodes

Little metal plates typically made of stainless tin, steel, silver or gold secured with the help of a coating of silver chloride (AgCl) [21]. Those are set onto the human scalp in positions which are unique.

Figure 3.1: EEG cables [21]

EEG cables demonstrates the plate of electrodes on which the gel of electrode is connected and added on the human scalp.

This individual positions are determined to utilizing the International ratio: 10/20 framework. Every electrode's position is named with the combination of a number and a letter [21].

Figure 3.2: Data recording cap

Figure 3.3: Inner-side of recording cap

And the letter alludes to the territory of cerebrum fundamental of the terminal e.g. T-Temporal and F-Frontal flap projection. Indeed, even numbers indicate the right portion of human head and uneven numbers represent the left half of the head. And it can take the help of an electrode-embedded cap. It provides us with the advantages of recordings even when high-dense pack of electrodes are essential or when contrasting between recording sites. Figure 3.3 refers to the inner portion of a cap [22].

3.1.2 Electrode gel

It goes almost like a pliant expansion of electrode. In consequence, the development of the electrode cables are more averse to create antiquities.

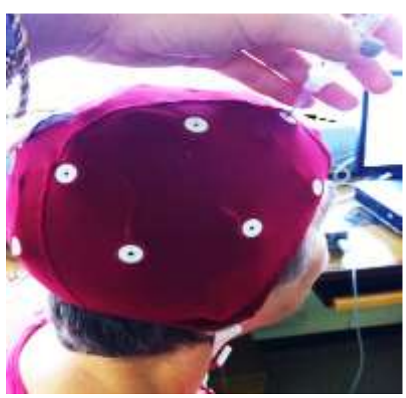


Figure 3.4: The process of electrolytic gelling

The gel amplifies contacts with human head’s skin and takes into account a low-protection recording within the skin. Every cavity in infused with electrolytic gel until the point of opening the mouth. Measuring the descending pressure directly, the syringe which includes a limit needle is quickly shaken front and forth.

3.1.3 Impedance

The measurement of impediment to substituting present’s signs, which is estimated in ohms and when frequency is given. Bigger numbers represent higher protection from current flows. Higher impedance terminal represents littler abundance of electroencephalogram (EEG) signal. In EEG considerations, should to be at keeping in mind that 100 Ω or less and close to 5 K Ω [22].

3.1.4 The positioning system of Electrode (10/20 system)

The institutionalized position of the scalp electrodes as a traditional EEG (Electroencephalogram) recording has turned out to be normal since the appropriation of 10/20 framework. The pith of this framework is the separation in rates of the 10/20 territory among settled focuses and Nasion-Inion. These focuses are set apart as like the Frontal post (Fp), Parietal (P), occipital (O), Central (C) and Temporal (T) [9].

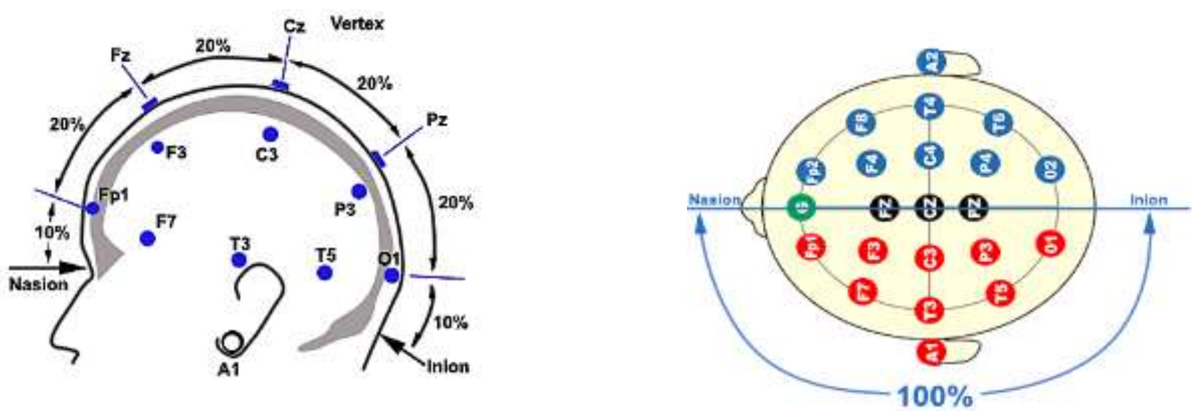


Figure 3.5: Electrode positioning (a) & Electrode positioning (b)

The subscript z sets apart the midline electrodes, which remains for zero. And the uneven numbers are utilized like subscript for focuses on the left half of the globe, and even numbers over the right. And the behavior of the brain is then recorded in a hard disk (computer). It is now very easy to read the brain movement but the final analysis of the brain is a difficult task, because noise and the coefficient factors are a great issue in this work.

3.2 Mathematical Representation of EEG Signal

To investigate the brain signals, it has to comprehend the properties of electroencephalogram (EEG) signals, for example, amplitudes, frequencies and inner and outside impacts that alters the state of these signs. Numerous gadgets are utilized to process different sorts of bio signals. For example, EEG to analyze sicknesses [17]. These gadgets utilize the sensory system that comprises of a substantial number of edgy associated cells named as neurons that quickly and particularly speak with various portions of human body using electrical signs. The sensory system comprises of three fundamental parts: the mind, the spinal line, and fringe nerves. It capacities to take over the human body and conveys through electric signs [18]. The cerebrum signals are obtained utilizing the terminals mounted straightforwardly on the human scalp. Equation (1) is delineated the mix of these signs [23] [24]:

$$X(t) = [X_1(t), X_2(t), \ldots, X_m(t)]^T \qquad (1)$$

In this point, X(t) is noted the electroencephalogram signal, "T" signifies transposition and where as "m" is the quantity of channels. And the lines of the information grid are electroencephalogram signals noted at various electrodes, though the sections speak to the varieties in the signs at various time focuses. Prior to the electroencephalogram signal is shown or put away, it can be prepared to wipe out low-recurrence or high-recurrence commotion and other conceivable ancient rarities. The client is often keen on the abundance of the signal; consequently, basic focuses in its handling need cautious treatment to lessen ancient rarities that pollute signals that can prompt wrong outcomes and conclusions. Condition (2) demonstrates the model that speaks to the noted blended EEG (electroencephalogram) signal X(t) with time, differing source signal s(t) with blending grid. An additional to the outside noise n(t). Considering just

X(t) is accessible, a few suspicions are expected to assess the network signal s(t) [24]:

$$X(t) = As_m(t) + n_m(t) \tag{2}$$

3.3 Noise Affected and Factors Affected Electroencephalogram Signal Bands

The dynamic scopes of the Electroencephalogram signal are typically ±100 μV back enhancement. Numerous sorts of noise is procured by these signs when they go through various tissues.

3.3.1 Noise Affected Electroencephalogram Signal Bands

The qualities of the noise influence the state of the Electroencephalogram signals [25]. And these are grouped into the accompanying sorts:

- **Inherent commotion**: The electronic gear creates noise which covers with the noted EEG signal. The noise may be disposed by superb electronic parts of the Electroencephalogram recorder.
- **Ambient commotion:** Radiation from EM gadgets is the primary wellspring of the Noise. The surrounding noise has more notable amplitudes compare with EEG signal. A protected room might be dispense with this sort of commotion.
- **Motion curios**: When these antiques cover with the electroencephalogram signal, the data signal is transverse and sporadic. The motion curios have numerous sources: electrode link; Electrode interface; visual antiquities; gulping; sweating; and relaxing. Movement relics can be diminished by acceptably outlining the electronic hardware and utilizing a keen program that isolates and expels these ancient rarities from the electroencephalogram signals.
- **Inherent signal flimsiness:** The sufficiency of the electroencephalogram signal is normally arbitrary. EEG curios influence the EEG signal particularly the plentifulness of the EEG signal changes amid the distinctive phases of anesthesia. EEG curios happen in light of the cardiovascular electrical field which effects of surface potential close to the scalp [14] [25].

3.3.2 Factors Affected EEG Signal Bands

Numerous factors influence the noted EEG signal. The elements are classified as takes after:

- **Causative Factors:** The factor specifically influences the noted EEG signals are named takes after:
    a) **Extrinsic:** The factor is because of the electrode structure and arrangement. For example, the state of electrode, identification surface, remove between terminal recognition surfaces, and area of electrodes concerning the volume of the scalp.
    b) **Intrinsic**: Biochemical, anatomical and physiologic components caused by the quantity of dynamic engine units, nerve write structure, blood pressure, nerve distance across, profundity and area of dynamic nerve as well as the measure of tissue among the terminal and the surface of the scalp.
- **Intermediate Factors:** This type of factor are physical and physiologic wonders impacted by at least one causative elements. Obstruction from close-by nerve is a case of a middle factor.
- **Deterministic Factors**: This type of factor are affected by middle of the road factors. The quantity of mechanical collaboration and dynamic engine units among nerves directly influence the data in the electroencephalogram signal and noted power [18].

Profundity of brain is difficult to dole out, as expanding the centralization of the mind is related with the different wonders, for example, loss of subjective capacity and amnesia, the marvels are adjusted against the serious excitement that surgical incitement can initiate. The difficulties and challenges of EEG securing amid in the nature of the information. Actually, the recorded EEG information are affected by outer or inner wellsprings of EM waves as it specified previously. This is the primary explanation behind the restricted estimation of crude EEG notes to screen the profundity of the brain.

CHAPTER 4

EEG SIGNAL PROCESSING

General signal preparing techniques are utilized to process Electroencephalogram signals. EEG signal investigation experiences four phases as takes after: Bi spectral Index (BIS), de-noising, feature extraction, classification. Figure 4.1 shows the abridged form of the procedures, where every stage is talked about in detail. And the usage of the stages must have to be successive, beginning from the chronicle stage to arrangement organize. At every single stage, a few activities ought to be done before throwing the signal to the following next.

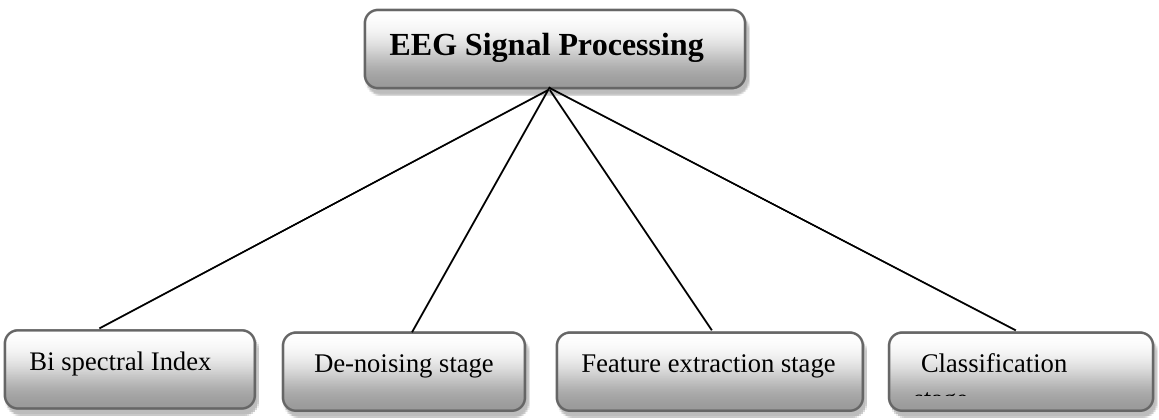


Figure 4.1: Basic stages of processing of Electroencephalogram signal

4.1 Bi spectral Index (BIS)

BIS is a measurable record in light of a mix of frequency domain, time, and high-arrange unearthly sub parameters. Extensive volumes of the clinical information are used to create a solitary variable in view of the dissimilarity of electroencephalogram signal; the uniqueness corresponds the conduct of trance and sedation. BIS fields from 100-00 (when patient is conscious) [26] [27]. For the most part, the bi otherworldly list is registered in two stages:

- Finding the First Fourier transform-(FFT) coefficients.
- Computing the bi spectrum.

$$B(f_1, f_2) = X(f_1) \times X(f_2) \times X * (f_1 + f_2) \quad (3)$$

In this point, B(f1, f2) is complex bi spectrum and X(f) is mind boggling Fourier change at frequency f of the Electroencephalogram signal x(n). The bi coherence is used to discover the connection between power at f1 and f2 in the EEG signal; bi coherence can be registered independently for every electrode.

Loss of cognizance happens at values in the vicinity of 70 and 80. And the qualities that reflect sufficient mesmerizing impact are 40-60. BIS records under 30 speak to profound abnormalities (quiet in danger). Consequently, the anesthesiologist must change likewise to expand this esteem. BIS is helpful for modifying the dose of sedatives; this modification keeps any aggravations in the patient's circumstance (mindfulness or stifle EEG signal).

4.2 De-noising Electroencephalogram Signal Stage

The Electroencephalogram signals are noted with a great deal of noise produced from the earth or ancient rarities. Advanced channels are used as a part of underlying phase of EEG information preparing to evacuate control frequency from the watched signal and lessen unfortunate recurrence segments. The electrical line clamor was expelled straightforwardly from the Electroencephalogram motion by the chain of high-pass and low-pass channels [23] reproduced and detailed that the EEG signal determined to have the computerized channel in time area normally includes cross-increasing each unfiltered information point and the neighbors with an arrangement of weights.

And antiquity is the second kind of noise, which show up as sharp spike-waves, spikes and waves in the electroencephalogram signal in view of developments of electrodes, eyes, and head. Ancient rarities may show up in view of automatic activities, for example, sweating, breathing, muscle movement, pulse, and eye flickers. Each channel ought to be handled and de-noised independently from others, as appeared in Figure 4.2, which delineates de-noising stage for every EEG channel.

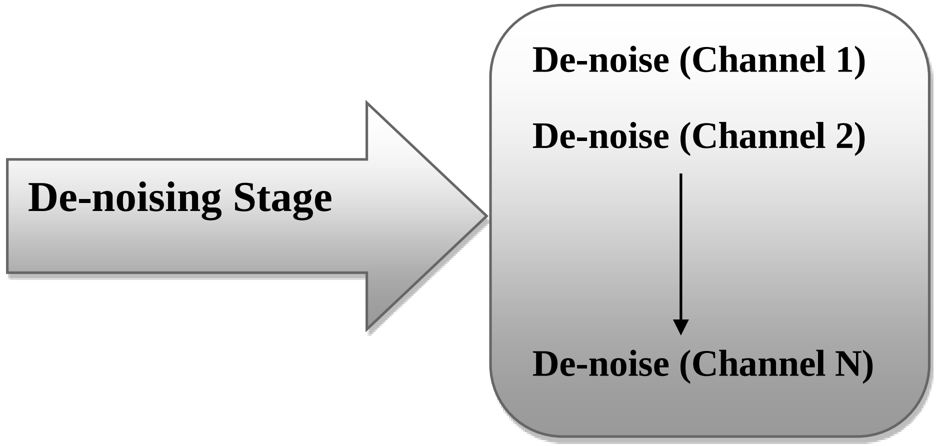


Figure 4.2: De-noising stage of Multi-channel to the noted EEG signal

The wavelet Transform (WT) expels different ancient rarities, for example, ocular artifacts, motion artifacts and inherent noise, which are utilized to show the level of variety in the EEG signal and mirror the impact of sedative medication [14].

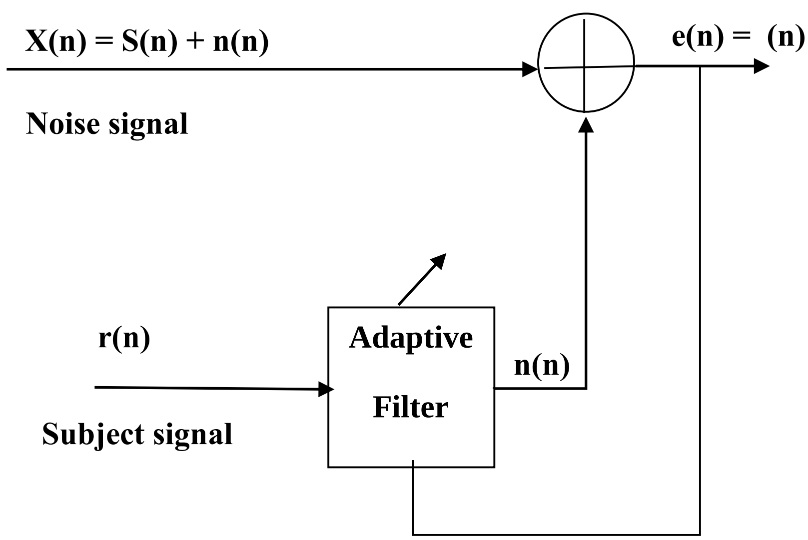


Figure 4.3: De-noising with Adaptive noise abolisher

With the reasonable decision of wavelet level smoothing strategy, antique noise can be evacuated to confirm and break down the EEG signal. Mother wavelet is especially viable in portraying different sides of non-stationary signals, for example, the discontinuities and rehashed examples of the noted EEG signal.

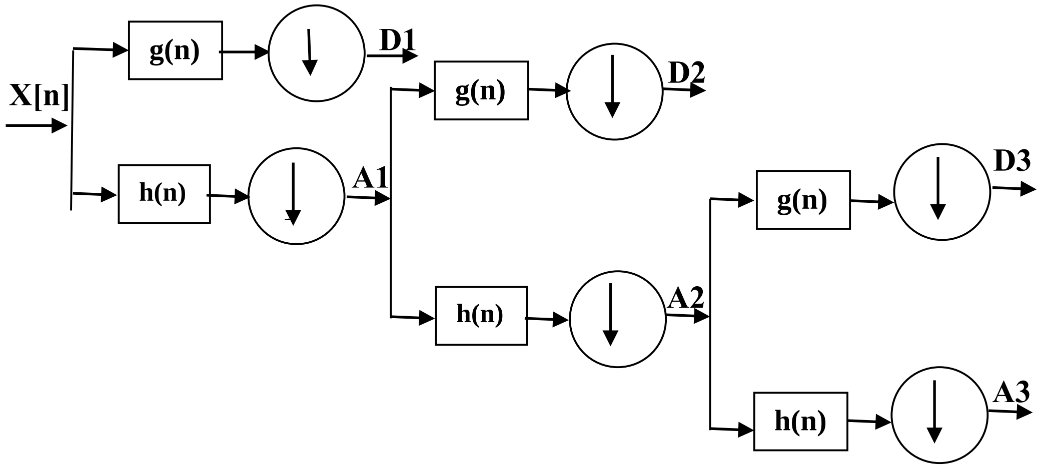


Figure 4.4: N-level Wavelet De-nosing

Wavelet Transform is accomplished by a progressive chain of high-take and low-pass a break space (versatile channel). Figure 4.3 demonstrates the guideline versatile channel used to separate commotion from the EEG signal. The information signal x[n] has gone through the high-pass channel with drive reaction h[n].

A similar info is gone at the same moment through low-pass channel with the drive reaction g[n]. The itemized coefficients are chosen from high-pass channel y high[n] and guess coefficients are chosen from low-pass channel ylow[n], as appeared in Figure 4.4. The yield channels (convolution) are given chosen in Equations (4) and also from (5):

$$y\ low[n] = \sum k = - \infty\infty\ x[k]g[2n-k] \qquad (4)$$

$$y\ high[n] = \sum k = - \infty\infty\ x[k]h[2n-k] \qquad (5)$$

Wavelet transform got a fundamental equation, which may be utilized as mother wavelet work. To utilize this change viably, precise points of interest of the particular application ought to be viewed as and the reasonable mother wavelet capacity ought to be picked entirely. The last recipe of the wavelet articulation in respect to mother wavelet ψ(t) and scaling capacity φ(t) of the signal x(t) [24].

$$x(t) = \sum kcj0k\varphi j0k(t) + \sum j = j0\sum kdjk\psi(t) \qquad (6)$$

The initial segment in the Equation (6) speaks to the estimation at the discretionary beginning scale j0, in order that the 2nd part portrays the junction of the subtle elements. Along these lines, the exact mother wavelet work is picked by its similarity with electroencephalogram signal, the capacity of processing of the signs into biomedical applications. And determination of exact channels decides likelihood of reproduction and the state of wavelet. And wavelet work is dictated through high-pass channel, which delivers the particular coefficients of wavelet decay.

The scaling capacity is fundamentally the same as the wavelet work, yet is dictated through the low-pass channel, which is related with the guess coefficients of wavelet deterioration. The outcomes demonstrate that the approach is reasonable for wiping out curios caused through eye developments and has upsides of simple usage, strength, and small computational cost [25].

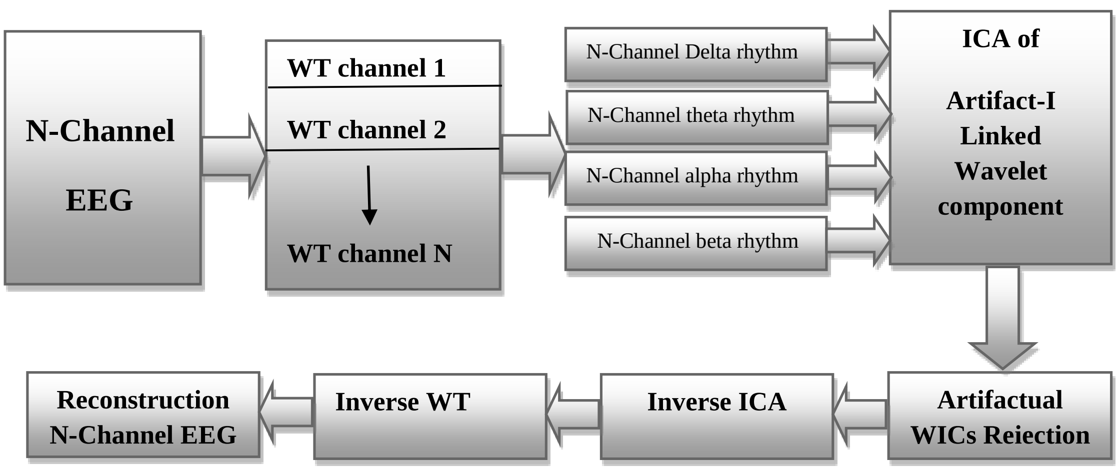


Figure 4.5: The combination structure among WT and ICA

Another strategy to expel the artifact from Electroencephalogram (EEG) signal; these analysts consolidated WT and autonomous segment investigation (WICA) [26][27], as appeared in Figure 4.5. The proposed method displayed the best relic division execution for each sort of antique and permitted insignificant data misfortune. Another strategy used to expel visual antiquities and muscle curios (EMG) implanted with the noted Electroencephalogram signals is programmed ancient rarity evacuation. SOBI was utilized to evacuate EOG curios, though standard relationship examination was utilized to expel muscle relics [27].

4.3 Feature Extraction of the Electroencephalogram Signal Stage

To distinguish and screen EEG varieties, numerous highlights of EEG signal were recognized to give a programmed framework that would bolster doctors amid conclusion. The arrangement organize can't acknowledge the recorded signal specifically as a result of the immense measure of information that ought to be prepared at the one time, which backs off the order framework.

The element of each channel differs as indicated by the area of the anode on the human scalp. The component extraction organize is outlined in Figure 4.6, where these highlights are masterminded as a cluster. The cluster can subjected to numerous capacities to produce another exhibit that speaks to the eventual fate of each channel.

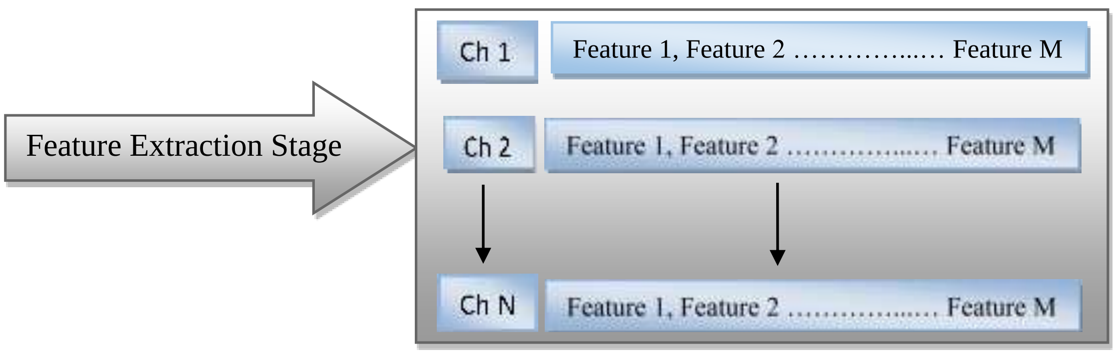


Figure 4.6: Multi-channel feature extraction stage

We utilize the office of wavelet strategy in investigating the frequencies of mind flags and extricating various highlights. The EEG signal is deteriorated into various sub-groups as indicated by the disintegration level, and afterward the vitality of tests is figured by each level. The strategy was requested to extricate the helpful highlights through the recorded Electroencephalogram (EEG) signals.

And Wavelet transform deteriorates an EEG motion into numerous frequencies in groups, in this manner, it is a powerful instrument for portraying these signs. Power of EEG and the frequencies change continually at every level inside particular groups; the connection between the varieties in recurrence band can be utilized for portray the DOA (Section 4.4 said this) [15].

Two sorts of highlights are utilized to identify the variety in Electroencephalogram (EEG) signal: and first relies upon varieties range power range and second relies upon varieties in signal at frequency-time space. What's more, Isoflurane caused dual peaks; where α go is the first one and δ run is the second one. Expanding the centralization of isoflurane is 0.3%-1.5% will move the α top recurrence (10.6 Hz) to bring down frequencies (9.5 Hz). In a similar setting, in regards to the critical α crest that was stage coupled in the moderate δ waves, bigger groupings of isoflurane moved this pinnacle (10.6 Hz) to bring down frequencies (7.6 Hz) [21] [28] [29].

The great criteria for assessing the different highlights are by computing mean squared blunder (Equation (7) shows) and Equation (9) shows signal-to-noise proportion. These qualities are computed from the first EEG (Electroencephalogram) signal x(n) and de-noised Electroencephalogram (EEG) signal x̂(n) [27] [28]:

$$MSE = 1N\sum n = 1N[x(n) - x\hat{}(n)]2 \quad (7)$$

$$SNR = 10\log |\sum nx\hat{}2(n) \sum n[x(n) - x\hat{}(n)]2 \quad (8)$$

These qualities can be ascertained at specific frequencies and contrasted with those amid mindfulness with exhibit the varieties in values as per the DOA. The total power range (control entropy) at particular frequencies (alpha, beta, delta and theta) was utilized to locate most extreme and least power estimations of the examples and additionally the proportion of frequencies of delta/beta and delta/alpha to screen the varieties in the electroencephalogram (EEG) signals [30]. We utilized standardized otherworldly entropy to describe the examination levels. This ghastly entropy was ascertained for every EEG age inside the productive recurrence scope of mind signals.

We utilized a short area (just 1s) to screen precisely the adjustments in electroencephalogram (EEG) signal [19]. AE (Approximate entropy) and PE (Permutation entropy) are requested to gauge the impact of breaking down medications utilizing a surge of EEG information. These highlights uncover the impacts of sevoflurane on cerebrum movement. AE depends on the similarity of occasions in stage space and is a suitable technique to characterize the arbitrariness of the framework.

AE relies upon three parameters: m, the implanting measurement, N, the quantity of tests; and r, the clamor limit. PE depends on the Shannon entropy (SE) and is ascertained utilizing Equation (9) [31]:

$$Hp(m) = - \sum j = 1JPjlnpj \tag{9}$$

At this point, P is likelihood dissemination of the particular images, which are characterized as pj,………, pl; and m is a stage; and J should be not as much as m. Both Approximate entropy and Permutation entropy perceive the two grades (anesthetized and wakeful) with high connection each other. And the expectation probabilities demonstrate that Permutation entropy has a more grounded ability for separating among the two grades.

The outcomes demonstrate that Permutation entropy gauges the impacts of sevoflurane higher viably than approximate entropy. This strategy can be connected to plan another EEG observing framework for evaluating the impacts of sevoflurane [32].

4.4 Classification of the Electroencephalogram Signal Stage

The last stage in handling and investigation of EEG (Electroencephalogram) signals is the grouping stage. The highlights of EEG (Electroencephalogram) signals are extricated amid the crude signal "include extraction arrange" and the repetitive data has been lessened by "dimensionality diminishment" in the past stage. Recognizing diverse classifications among the procedure is important by linking a classifier. The following figure 4.7 clears up the grouping stage for different channels that can be utilized like a controller either marker for DOA. A few procedures are utilized to characterize EEG signals, for example, NN (neural systems) classifier, straight discriminator examination bolster vector machine and classifier. These classifiers must diverse calculations and exactness rates. And the calculations rely upon the strategies used to instruct the classifier, in the point precision relies upon the clearness of the information, measure of the information, and the sort of highlights that utilized as a part of the classifier.

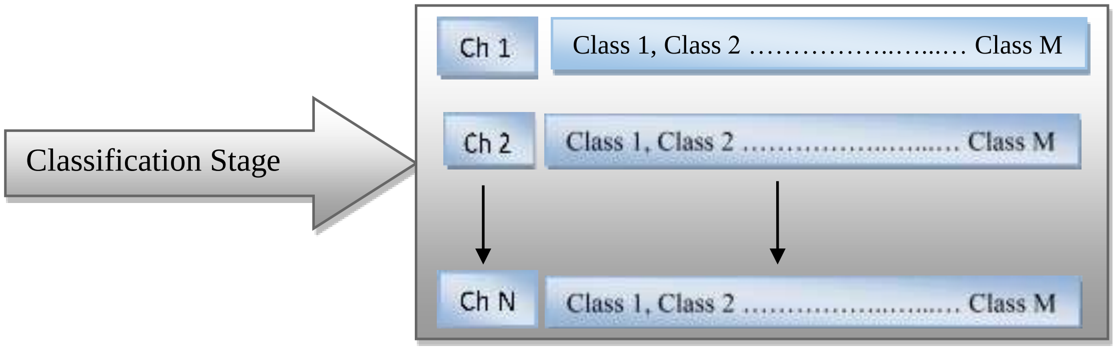


Figure 4.7: The classification stage for Multi-channel

The vast majority of the classifiers should be considered commonly before they are utilized thusly, be that as it may, the learning techniques contrast among classifiers. The information ought to be isolated in three sections: the primary dataset is being preparing the system and producing the shrouded layer; and second of the dataset is being trying the execution based on the classifier; furthermore, the third dataset is being finding and perceiving the outcomes.

The most well-known technique for distinguishing DOA is the neural system (NN) classifier in light of its effectiveness, exactness, and materialness, with numerous gatherings of specialists perceiving the precision of DOA framework in light of a fake NN [27] [28].

Artificial NNs are grouping frameworks that comprise of an extensive number of basic high interconnected handling components called hubs or simulated neurons. And this particular classifier is developed like the arrangement and activity of the organic sensory system. And neural systems classifier picks up by an uncommon calculation called "preparing."

Many composes and designs of NNs stand on a very basic level unique in relation to each other, contingent upon the system preparing technique. Extra middle of the road (shrouded) handling layers ought to be utilized to tackle the issues of nonlinearity and multifaceted nature. Figure 4.8 demonstrates the run of the mill structure and general phases of NN calculations [31] [33].

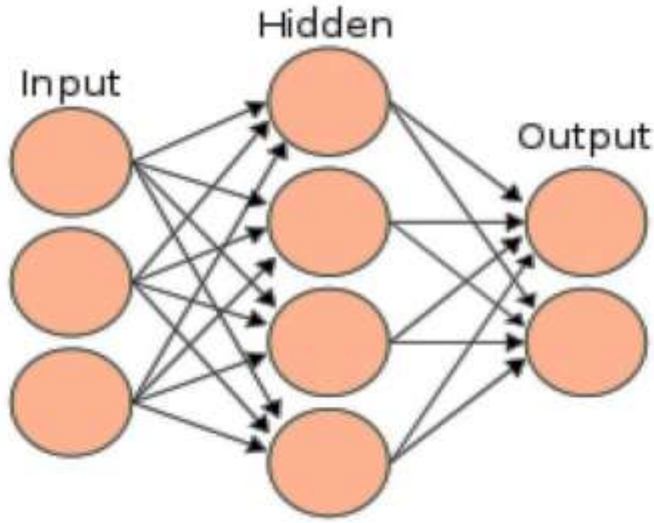


Figure 4.8: The correlations of neural system with the gathering of nodes [31].

Numerous specialists presented essential methodologies for planning MLNN (multilayer NN) classifier models. And the design of the classifier builds with at least two layers. The particular two layers comprise of an info layer consisting of the information factors, which talk to the highlights removed from EEG (Electroencephalogram) signals and this yield layer consisting of arrangement of the issue [31] [33]. The cost capacity of MLNN is characterized as takes after:

$$\varepsilon(n)=12\sum i=1Nei(n)2 \tag{10}$$

$$e_i\,(n) = d_i(n) - y_i(n) \tag{11}$$

In this point, di(n) as well as yi(n) which are the coveted and real yield of ith yield hub of a system, individually. Back propagation calculations are utilized to compute the hub weights. To ascertain the contribution to NN, mean esteem is deducted from the information signal and isolated with standard deviation. It can be utilized NNs to dissect EEG signs to quantify the DOA list, which one is as educational as the BIS.

Examinations affirm that while breaking down EEG information utilizing NN accomplishes great separation amongst anesthetized and alert patients with great dismissal of counterfeit signs is accomplished [11].

And RNN (Repetitive NN) is a compelling gadget for portraying and exhibiting EEG (Electroencephalogram). RNN comprises of various direct computational units with subjective interconnections and delayed criticism associations. In this calculation, all the neurons in a single layer are associated with all the neurons are in the following layer. These input associations give RNN an inborn case and the capacity to learn errands that look at memory [13] [14].

The Elman RNN is additionally used to evaluate the DOA that gives non-straight models to complex frameworks, for example, EEG (Electroencephalogram) signals, where informative signs are excessively mind boggling, making it impossible to be separated by exemplary calculations. Numerous scientists utilize the office of the fluffy strategy in characterizing the frequencies of mind amid anesthesia. These scientists joined fluffy rationale and neural system to make a versatile neuro-fluffy demonstrative module. The proposed system showed a generous connection amongst hypovolemia and anesthesia amid surgery [15].

4.5 Signal Processing

This section is contracted the signal processing of the recorded EEG. EEG data loading, coding and plotting of the signals in various respected form to investigate the EEG for the detection purpose.

4.5.1 EEG data loading

For processing the EEG signal in MATLAB, first of all, we need to load the EEG data set in the MATLAB tool. For this purpose, in this project, saved the EEG data set in .text (Dot text) format and saved the file in the same location where the MATLAB software is installed. Then run the MATLAB software and at first opened the command window. In command window, the following command was written: Load Data.txt.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
92.13	27.85	26.59	28.43	25.44	26.59	43.22	46.33	43.19	52.31	57.50	61.70	68.85	67.84		80.91	67.84	68.85	57.50	61.70	68
90.79	50.21	47.04	24.84	34.79	47.04	30.43	66.07	27.88	29.19	51.27	60.45	61.67	33.20	112.93	71.09	33.20	61.67	51.27	60.45	61.67
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	84.16	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	13.60	15.83	16.75	8.95	15.83	8.46	21.61	18.31	12.26	20.37	21.51	16.03	18.70	0.00	20.92	18.70	16.03	20.37	21.51	16.03
0.00	0.00	12.70	15.55	7.89	12.70	16.20	17.44	20.37	17.20	23.47	22.73	25.51	26.64	18.72	22.00	26.64	25.51	23.47	22.73	25.51
0.00	0.00	0.00	1.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	19.41	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	1.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23.55	27.18	7.40	8.90	23.56	7.40	6.94	9.69	9.92	7.20	7.98	7.19	5.80	8.79	0.00	9.59	8.79	5.80	7.98	7.19	5.80
55.08	67.84	9.21	7.75	35.82	9.21	8.20	0.00	16.03	11.17	10.46	9.84	10.58	0.00	7.29	9.53	0.00	10.58	10.46	9.84	10.58
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	8.95	2.41	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.22	0.00	0.00	0.00	0.00	0.00	0.00
20.27	14.69	7.27	7.06	8.82	7.27	4.67	8.37	6.91	8.30	6.27	4.55	5.80	4.96	0.00	4.39	4.96	5.80	6.27	4.55	5.80
21.33	15.30	5.25	5.30	14.00	5.25	4.92	5.95	5.66	0.00	4.65	5.37	7.88	4.61	4.85	4.85	4.61	7.88	4.65	5.37	7.88
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.58	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
37.22	14.11	4.33	4.99	10.13	4.33	5.19	6.53	6.84	0.00	5.49	4.97	5.02	4.58	0.00	4.55	4.58	5.02	5.49	4.97	5.02
36.83	12.92	6.00	6.37	6.42	6.00	5.41	4.36	5.96	4.78	4.57	5.18	4.71	4.60	4.45	4.56	4.60	4.71	4.57	5.18	4.71
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.19	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
0.00	0.00	0.00	1.00	0.00	0.00	0.00	2.00	1.00	0.00	0.00	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	1.00	1.00
0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00

Figure 4.9: Recorded EEG data

After loaded the data, we have been needed to run the data. In the workspace window, the data has been stored and by double clicking in the data name, the data will be run. That time the EEG data was arranged in the table, and the matrix of the data can easily be noted. The 1st stage of signal processing is done with the data loading and running process. The next task is that to write a MATLAB code to plot the data and generating the EEG signal.

4.5.2 MATLAB coding

For our project purpose and to generating the EEG data, we build a MATLAB code to run our data. In editor window, first of all, we determine x-level and y-level for original and added noisy signal, then we determine a noise variance and make a low pass FIR filter for the signal. After filtering we have plotted the original and noisy signal with the power spectral density. After coding we saved it.

4.5.3 EEG Signal Plotting

Run the program and plot the data in graphical form. Figure 4.10 is the EEG signal plotting of the respected data loaded in the MATLAB.

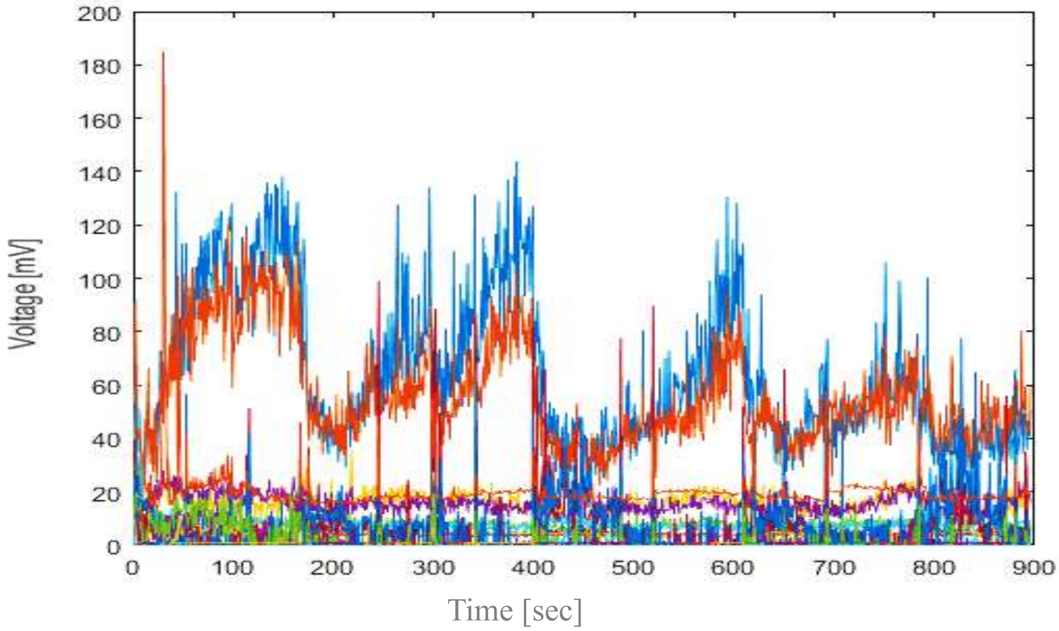


Figure 4.10: EEG Signal plotting

In x axis it represents time in second (sec) and y axis represents voltage in mv. Figure 4.10 is subject data signal for this project. With respect of this signal plotting, the abnormalities can be detected. The Basic EEG signal is shown in figure 4.11.

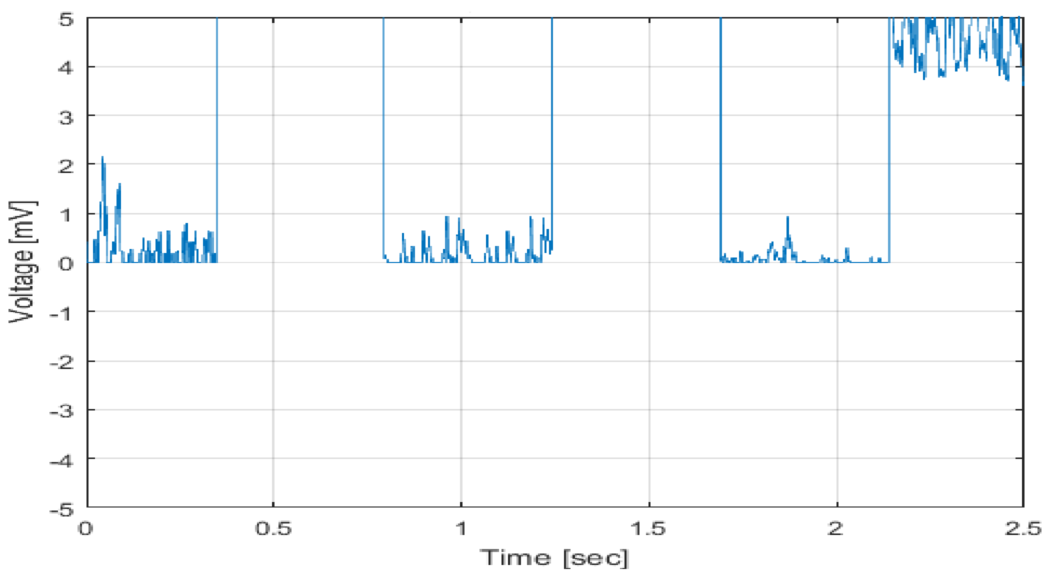


Figure 4.11: Basic EEG Signal

In EEG, Heartbeat signal pattern can also be monitored. Figure 4.12 is the heartbeat signal distracted from the EEG data which was collected from various subjects (patient). This project proposed a monitoring system, by which the detection of monitor of the EEG may be more efficient.

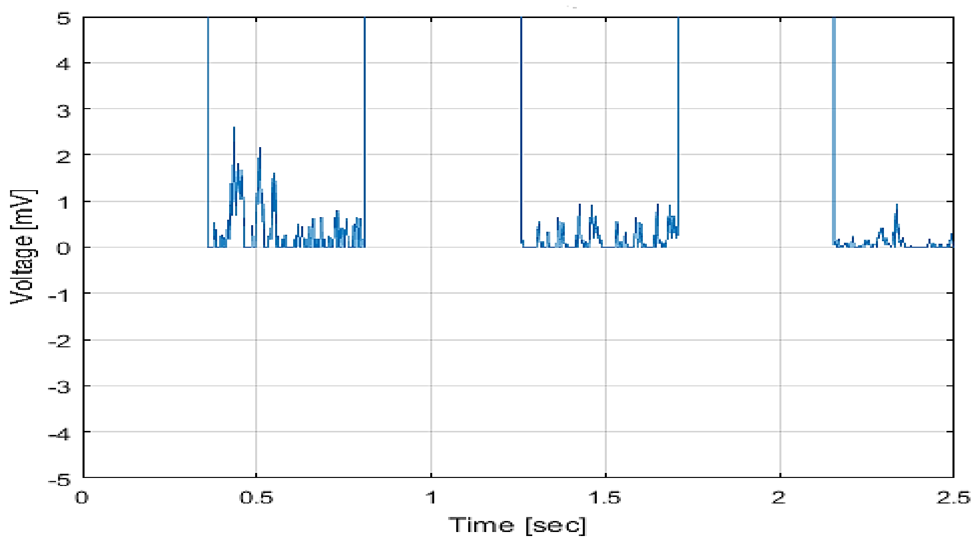


Figure 4.12: EEG Heartbeat Signal

There were background noises such as power line noise and high frequency components when the EEG circuitry was interfaced to the sound port of the PC. The power line noise eradicated by the software implemented of the MATLAB code and the high frequency components also removed by processing in the same technique. The output of the EEG circuitry is shown in the figure 4.13 before filtering:

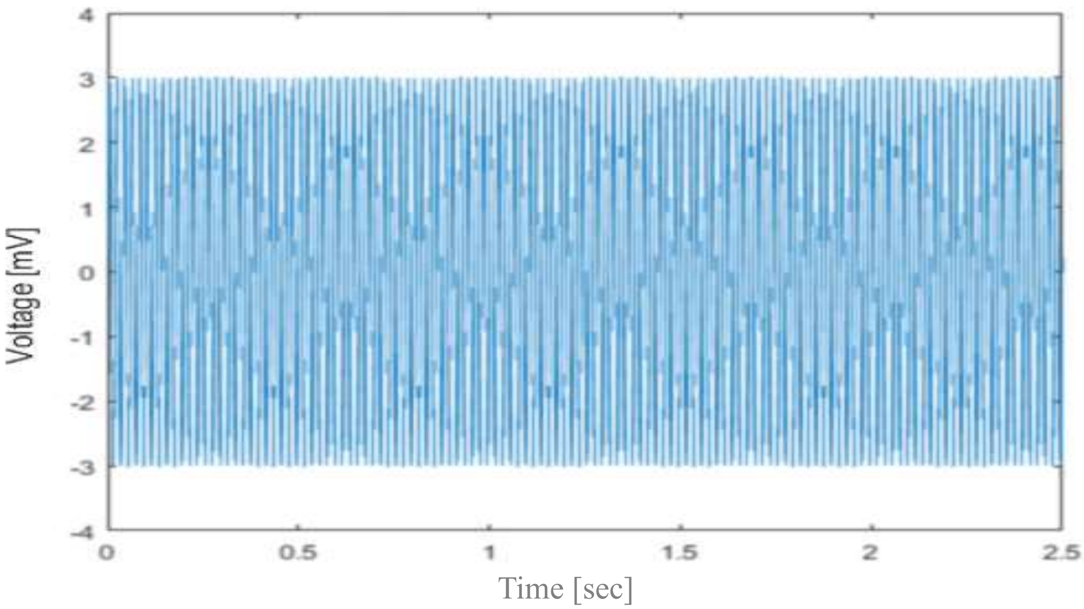


Figure 4.13: Noisy time domain signal

After realization of the fact of back ground noise, the EEG signal has further filtered for removing the power line and high frequency noises. Figure 4.16 shows the signal before filtering.

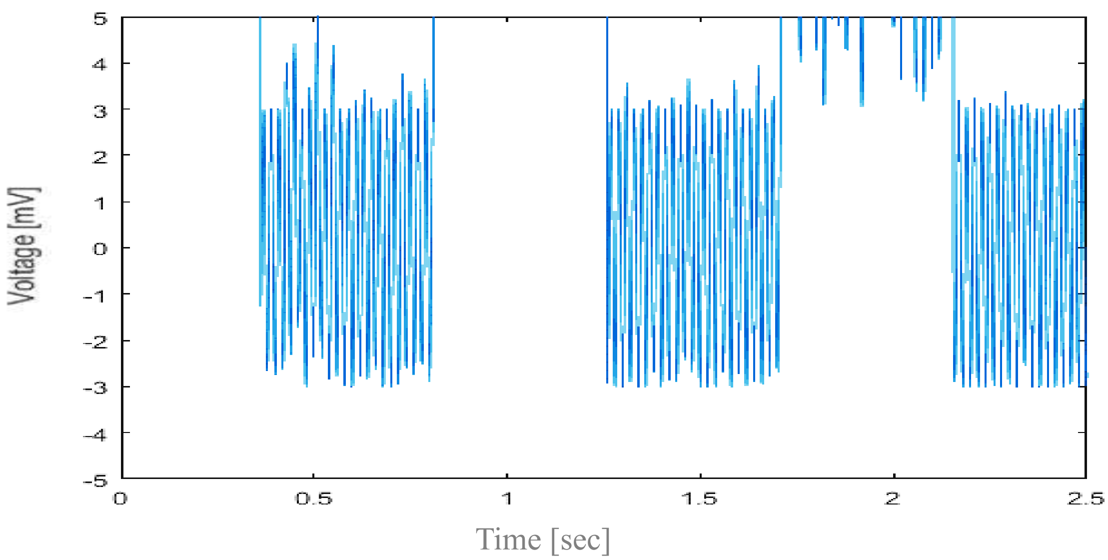


Figure 4.14: Signal + Noise

The aim of this project is to detect the noise or small changes or small abnormalities carrying with the original brain signal (EEG). Figure 4.15 shows the original information carrying signal and also the error signal.

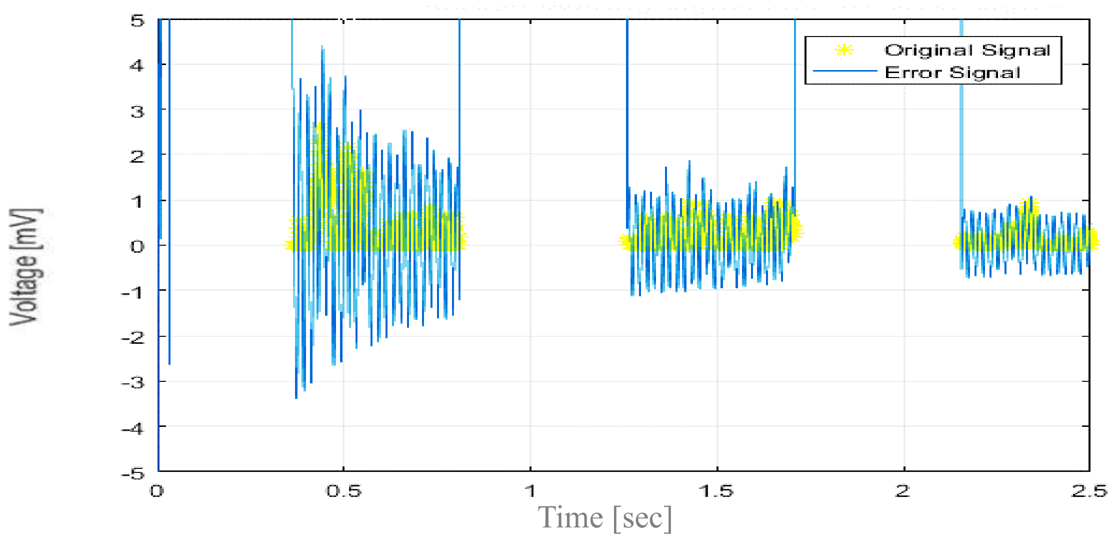


Figure 4.15: Original information carrying signal and also the error signal.

And extracting various statistical parameters along with the other processing techniques including filtering, the proposed method of wavelet based EEG signal analysis can monitor the brain as well as detect any type of abnormalities in a more accurate and effective way.

CHAPTER 5

RESULTS AND ANALYSIS

The results and analyzing outcomes of this project is discussed in this chapter. The two most popular methods of signal analyzing or monitoring techniques with real life experiments are described in this section to clarify that the proposed method in wavelet based EEG signal analysis of this project determines the smallest changes or abnormalities in the brain signals (EEG) that helps for emergency medication.

5.1 First Fourier transform (FFT)

Going into frequency domain and analyzing EEG spectra using First Fourier transform (FFT) is a first step, but in most cases it's not enough, as a relatively weak Mu (μ) peak in the spectra can be overshadowed by the stronger alpha at the neighboring frequency. Figure 5.1 and figure 5.2 are two EEG signals, using the same dataset.

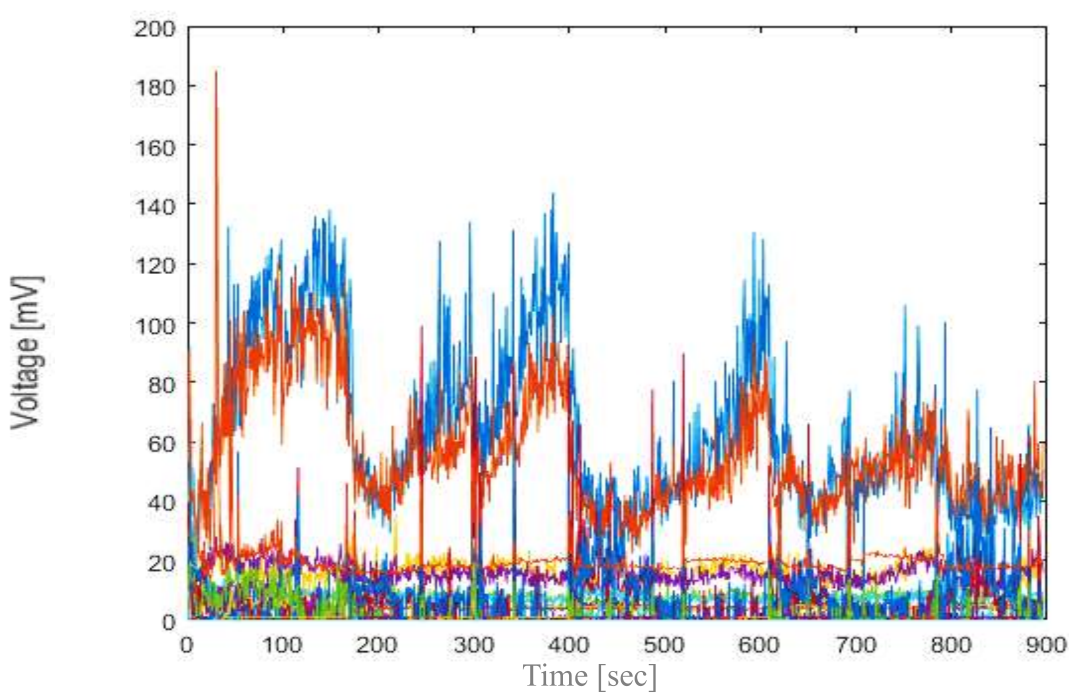


Figure 5.1: EEG Signal output of Subject A

But there are same changes or error or abnormality between figure 5.1 and figure 5.2. By using First Fourier Transform (FFT), we cannot detect the change and that's why proper treatment or necessary steps cannot be taken in proper time.

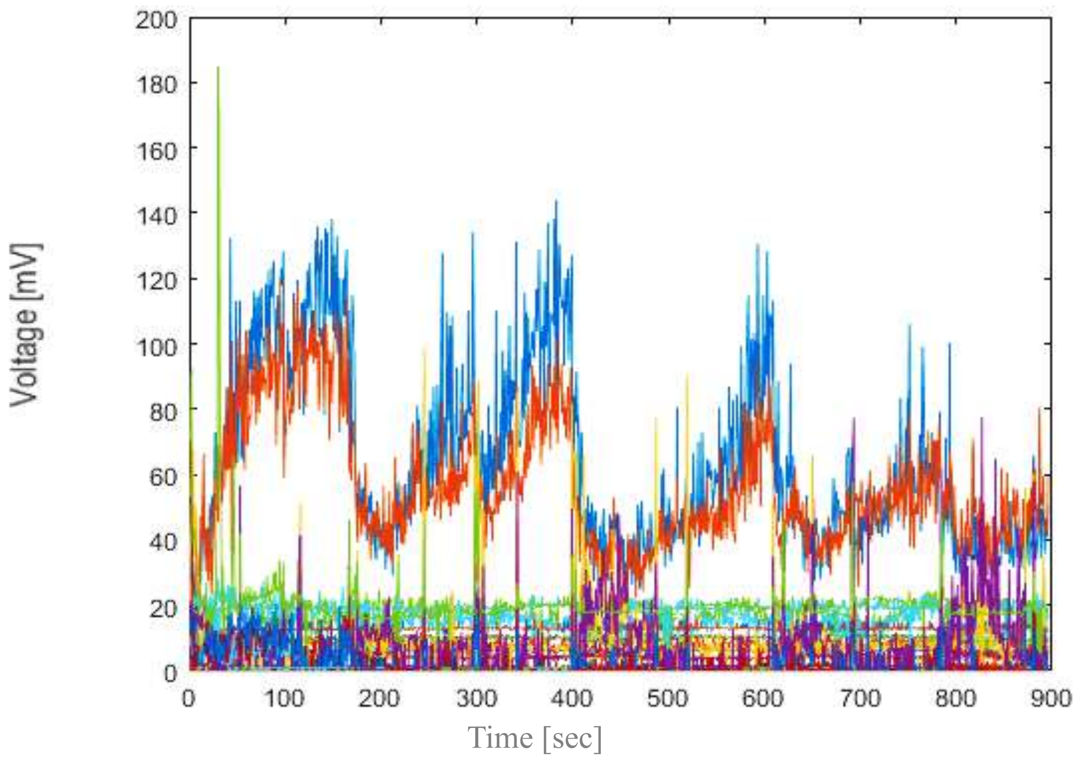


Figure 5.2: EEG Signal output with error of Subject A

Fourier Transform convert signal from time domain to frequency domain and provides two dimensional information about any signal that what various frequency component made up the signal and what are their respective amplitudes. And it has zero-time resolution and very high frequency resolution. But EEG (i.e. Electroencephalogram) signals are generally non stationary and it cannot monitor or detect the spectral analysis of such huge lengths of EEG data.

5.2 Calculation of Power Spectral Density (PSD)

Power Spectral Density (PSD) is one of the conceivable component extraction techniques to recognize contrasts in the cerebrum electrophysiological handling in youngsters with dyslexia. Known to be a neurological issue, dyslexia cause learning inadequacies for the most part identified with perusing, despite the fact that examination has demonstrated that written work issues additionally postures noteworthy test and is a decent marker to recognize a youngster to be dyslexic.

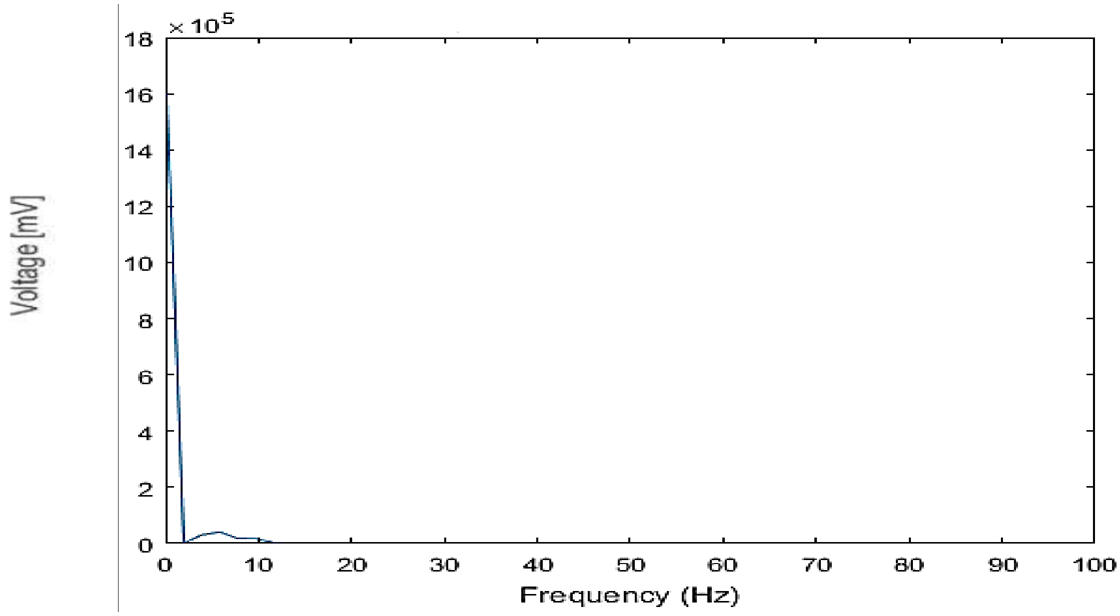


Figure 5.3: Power Spectral Density (a)

Electroencephalogram (EEG) signal power spectrum density (PSD) is shown in figure 4.16. It signifies the power sharing of electroencephalogram in frequency dominion to assess the abnormalities from the norm of the brain. In x axis it signifies frequency in hertz whereas y axis signifies voltage in mv.

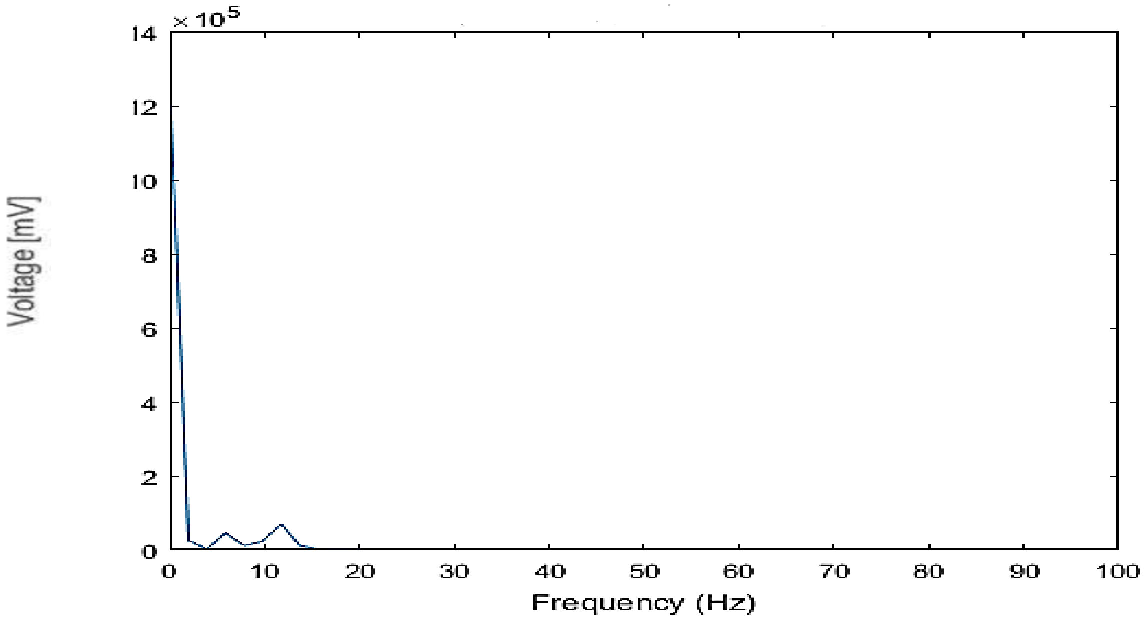


Figure 5.4: Power Spectral Density (b)

Power Spectral Density (PSD) is the regularity response of an irregular or occasional signal. It discloses to us wherever the normal power is spread as the component of the frequency.

- The Power Spectral Density is deterministic, in addition to certain varieties of irregular signals is autonomous of time. And this is beneficial because the transformation in Fourier form of an irregular time signal remains itself irregular, and for that reason of slight use computing transfer relations.
- The Power Spectral Density of an irregular time signal x(t) be able to expressed in unique of dual techniques that are comparable to them self.
    a) The Power Spectral Density is the normal transformation of the Fourier analysis of magnitude square off, over an enormous time interim.

$$S_x(f) = \lim_{T\to\infty} E\left\{ \frac{1}{2T} \left| \int_{-T}^{T} x(t) e^{-j2\pi ft} dt \right|^2 \right\}$$

    b) The Power Spectral Density is a Fourier change of auto-relationship work.

$$S_x(f) = \int_{-T}^{T} R_x(\tau) e^{-j2\pi ft} dt$$

$$R_x(\tau) = E\{x(t)x^*(t+\tau)\}$$

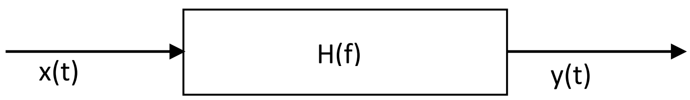
- The power may be considered from an irregular signal over the certain band of frequencies such as follows:

  a) Complete Power in x(t): $$P = \int_{-\infty}^{\infty} S_x(f)df = R_x(\mathbf{0})$$

  b) Power in x(t) in series of f_1 - f_2: $$P_{\mathbf{12}} = \int_{f_1}^{f_2} S_x(f)df = R_x(\mathbf{0})$$

This signal must be stationary, which implies that measurements don't change as an element of time.

- If an irregular signal x(t) is delivered through an invariant channel with frequency reaction H(f), the subsequent signal y(t) has a Power Spectral Density as takes after:



$$S_y(f) = S_x(f)|H(f)|^2$$

Figure 5.5: Irregular Gaussien noise signal

Two irregular signals $x_1(t)$ and $x_2(t)$ of 10 seconds period are formed as takes after:

```
» xl=randn(1,10000);              % signal 1
» x2=randn(1,10000);              % signal 2
» t=linspace(0,10,10000);         % time series
» dt = t(2)-t(1);                 % time increment
» subplot(2,2,1),plot(t,x1)       %plot of x1
» subplot(2,2,2),plot(t,x2)       %plot of x2
```

The example frequency is 1 kilo hertz. The First Fourier of both of these signs is ascertained shape

```
» X1=fftshift(fft(x1));           % FFT of signal 1
» X2=fftshift(fft(x2));           % FFT of signal 2
» Df=1/dt;                        % fequency span
» f=linspace(—Df/2,Df/2,10000);   % frequency series
» subplot(2,2,3),plot(f,dB(X1));  %plot of FFT of x1
```

» subplot(2,2,4),plot(f,dB(X2));   %plot FFT of x2

The plot beneath demonstrates a 0.1 second preview of two irregular time capacities x1(t) and x2(t) and the initial 10 Hertz of the FFT of these signs.

This demonstrates the frequency reactions of these irregular signs are commonly unique, despite the fact that they appear to have a typical normal level, and have comparative in general "haphazardness", which would be shown in whatever is left of the range if we somehow managed to indicate it.

Maybe what should be performing is considering at the normal Fourier transform instead of just a single sample of Fourier transform this is, more or less, what the PSD is; it is the average Fourier transform squared taken over a very long time interval.

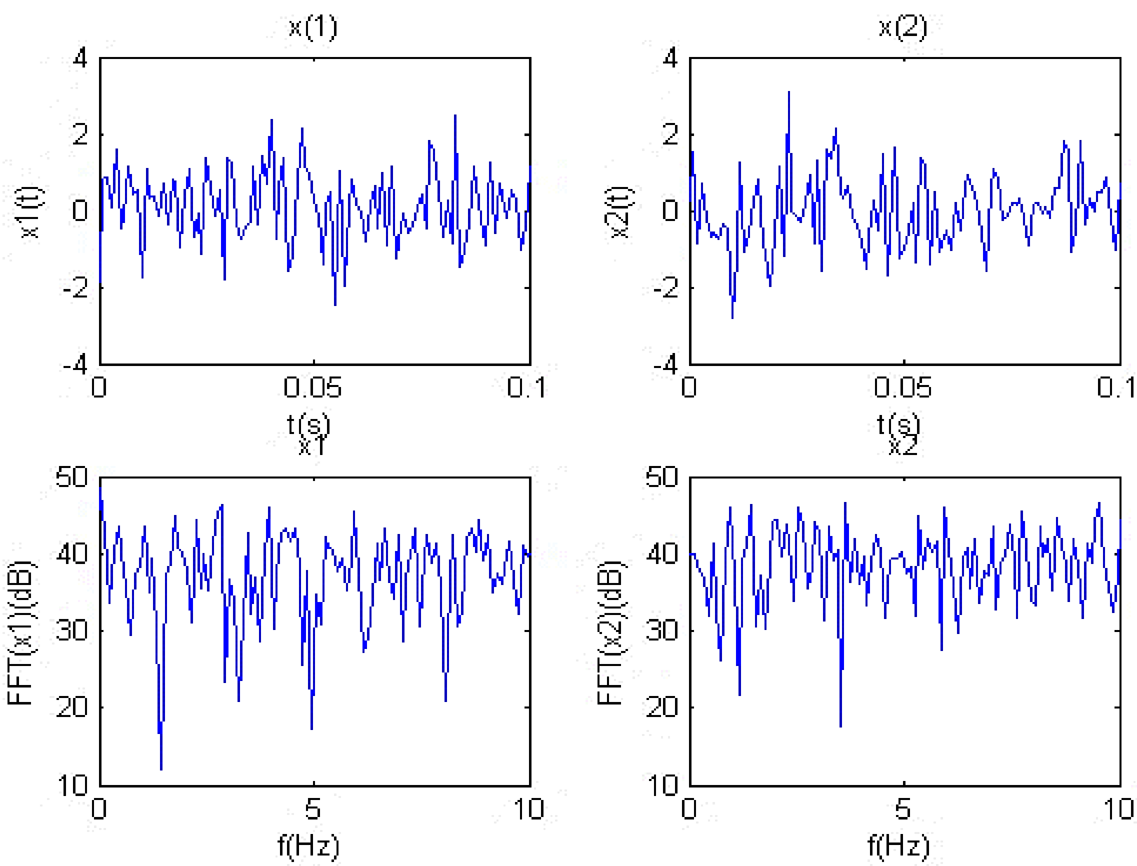


Figure 5.6: Frequency responses of random signals

Now compute and plot the original time series $x_1(t)$ and $x_2(t)$'s Power Spectral Density.

```
» x1=randn(1,10000);                  % signal 1
» x2=randn(1,10000);                  % signal 2
» t=linspace(0,10,10000);             % time series
» dt = t(2)-t(1);                     % time increment
» Df = 1/dt                           % fequency span
» subplot(2,2,1),plot(t,x1)           % plot of x1
» subplot(2,2,2),plot(t,x2)           % plot of x2
» Sx1=psd(x1,1024,1000);              % PSD of x1
» Sx2=psd(x2,1024,1000);              % PSD of x2
» f=linspace0,Df/2,length(Sx1));      % frequency series
» subplot(2,2,3),plot(f,db(Sx1));     % plot of PSD of x1
» subplot(2,2,4),plot(f,db(Sx2));     % plot of PSD of x2
```

The Power Spectral Density for each signal aspects less or more flat through the frequency band. This kind of noise is mentioned as white, and if it had taken an infinitesimally slight time growth, it would be seen this flatness through the whole frequency band.

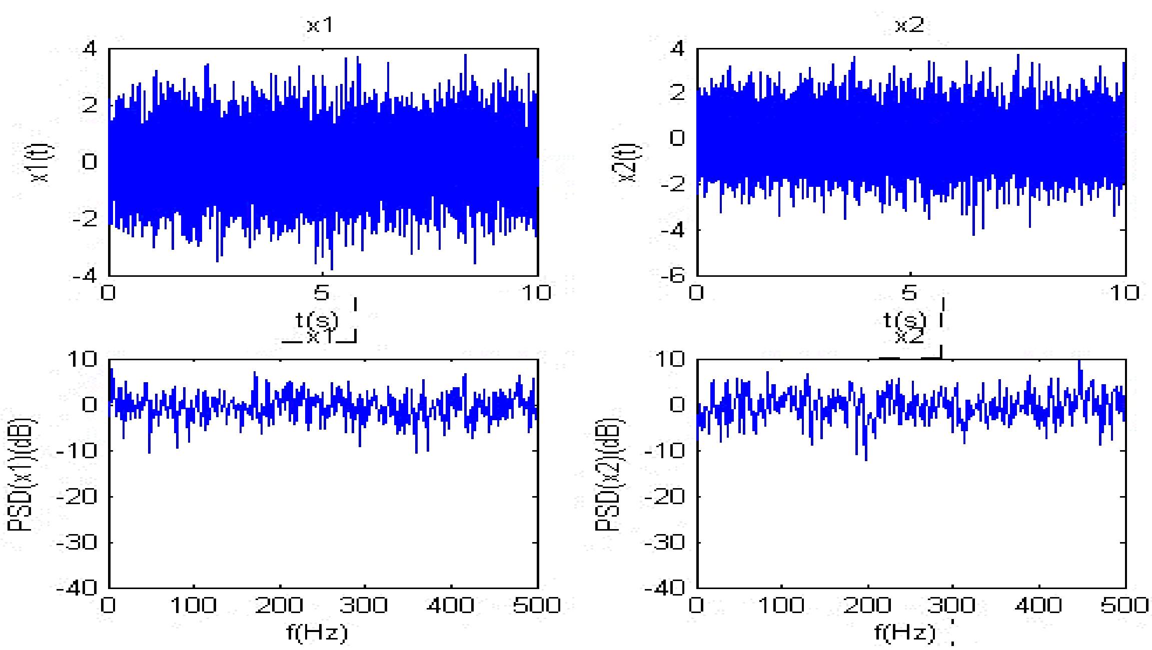


Figure 5.7: Power Spectral Density (PSD) of the original time series

The motive that there is certain difference about the persistent level is that didn't takings a large sufficient (i.e. infinite) time order of irregular numbers to calculate the Power Spectral Density from. The estimation of the Power Spectral Density (as considered in MATLAB) develops more precise as the model size develops infinite. The mean of the Power Spectral Densities of xl as well as x2 fit out to be precisely near to 1.

» mean (Sxl) % = 1.0137

» mean (Sx2)% = 1.0241

This is speaking that the regular rate of MATLAB Power Spectral Density, which is the variance, is near to unity. Currently let's consider pass through a filter of the Gaussian noise. At first scheme a high demand Butterworth filter that cuts off at half the Nyquist frequency (500 Hz)

»[b,a]=butter(40,0.5);   %n=40th order,fc=0.5 nyquist

Now plotting the frequency reaction, normalized to the nyquist frequency (just makes the thorough going frequency be 1)

» freqz (b,a) % plotting the frequency and phase reaction

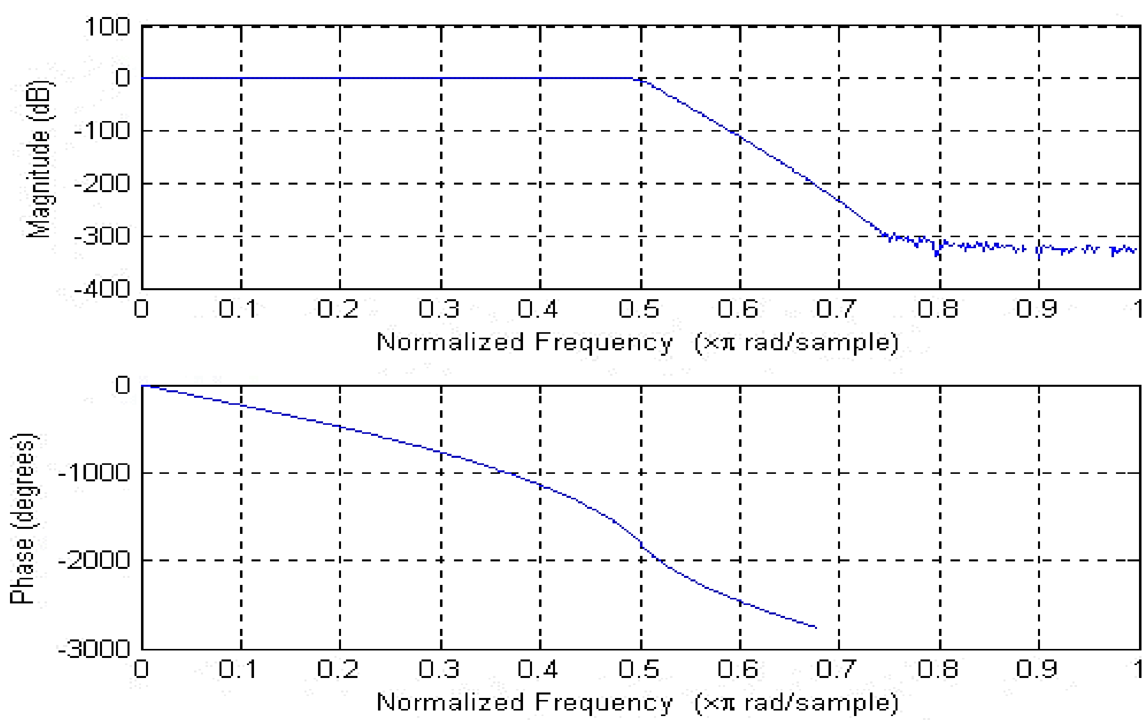


Figure 5.8: Frequency and phase response plotting

Now produce different noise samples $y_1(t)$ as well as $y_2(t)$ by passing through a filter $x_1(t)$ and $x_2(t)$.

```
» y1=filter(b,a,x1);                  %filter x1
» y2=filter(b,a,x2);                  %filter x2
» Y1=fftshift(fft(y1));               %calculate frequency response of y1
» Y2=fftshift(fft(y2));               %calculate frequency response of y2
» subplot(2,2,1),plot(t,x1)           %plot of y1
» subplot(2,2,2),plot(t,x2)           %plot of y2
» subplot(2,2,3),plot(f,dB(X1));      %plot of FFT of y1
» subplot(2,2,4),plot(f,dB(X2));      %plot FFT of y2
```

We get that the interval series is flatter (it has been filtered), but the First Fourier Transform remains irregular. The difference of the filtered noise is abridged to roughly 0.5.

```
» var (y1) % = 0.4895
» var (y2) % = 0.4956
```

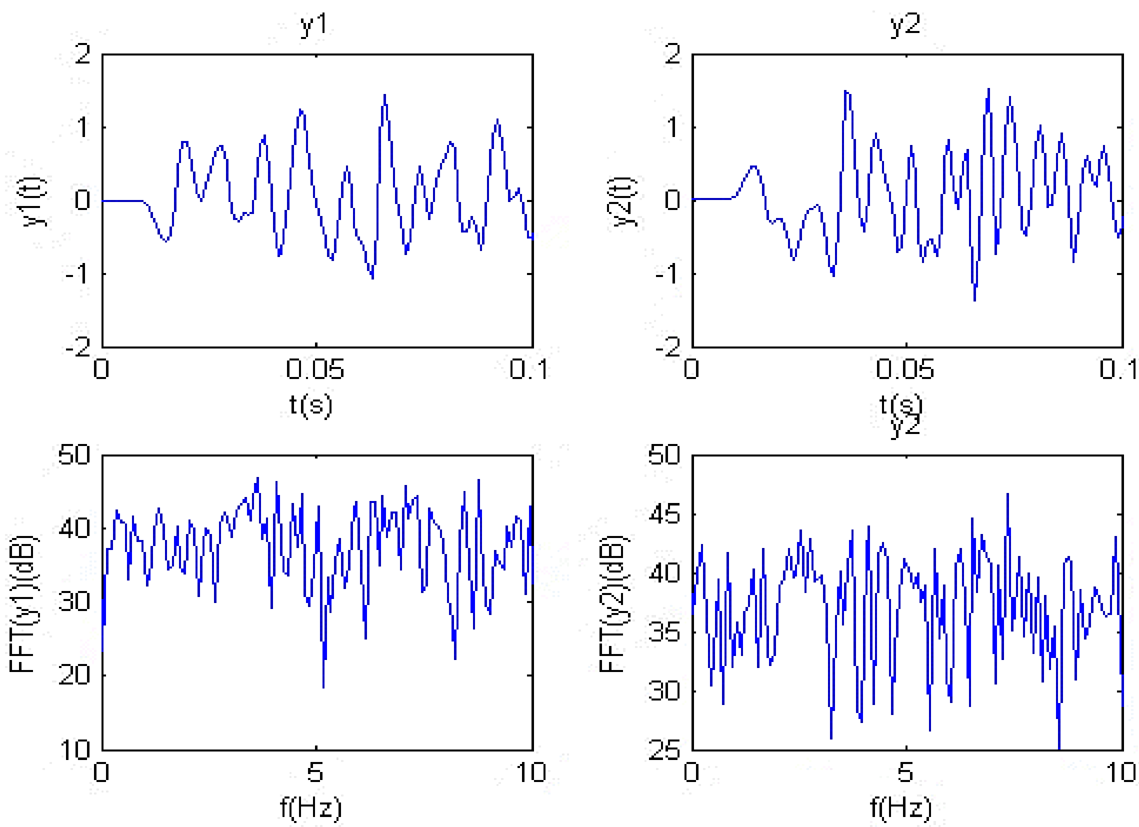


Figure 5.9: Noise samples

Considering the Power Spectral Density of the filtered noise

```
» Sy1=psd(y1,1024,1000);              %PSD of y1
» Sy2=psd(y2,1024,1000);              %PSD of y2
» f=linspace(0,Df/2,length(Sx1));     % frequency series
» subplot(2,2,1),plot(t,x1)           %plot of y1
» subplot(2,2,2),plot(t,x2)           %plot of y2
» subplot(2,2,3),plot(f,db(Sy1));     %plot of PSD of x1
» subplot(2,2,4),plot(f,db(Sy2));     %plot of PSD of x2
```

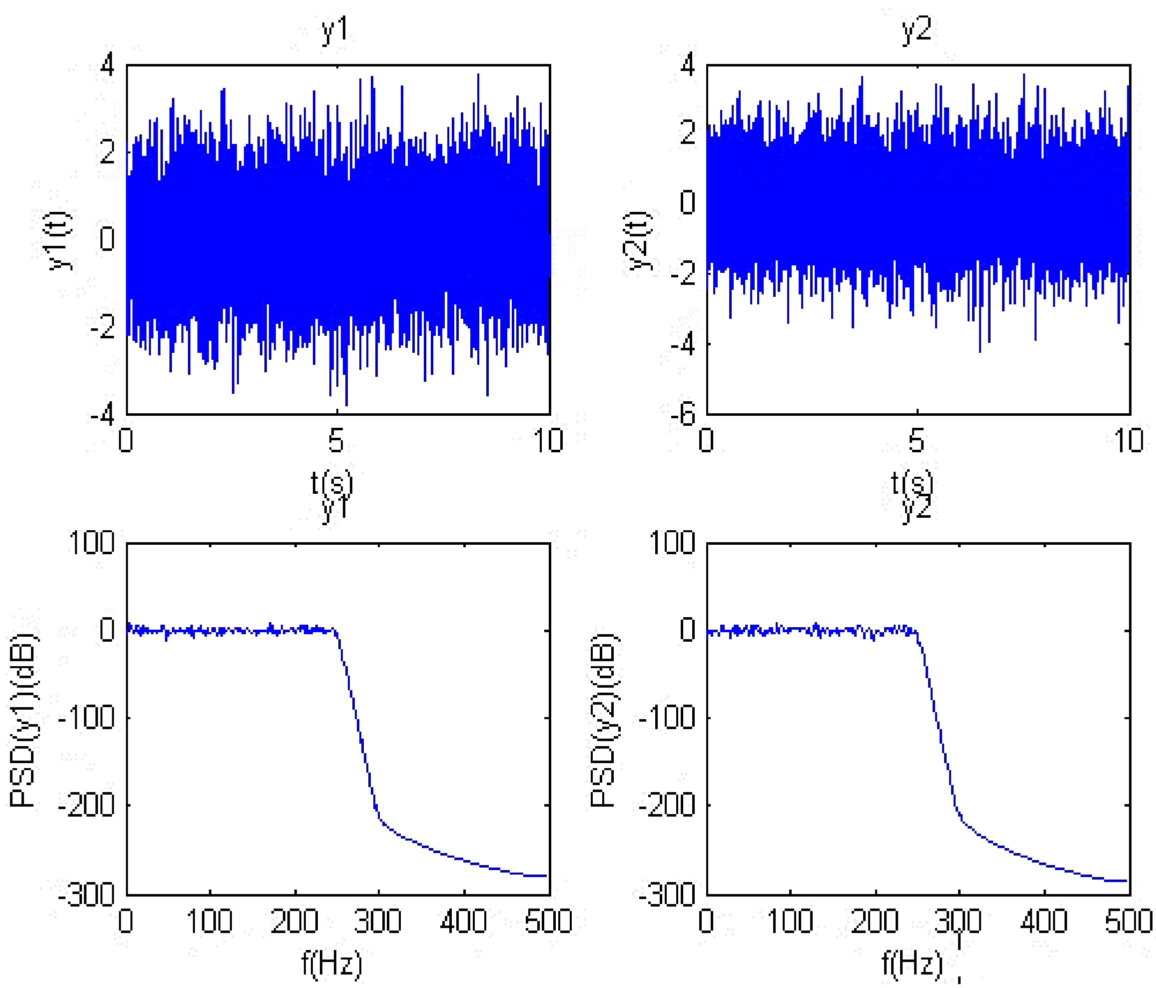


Figure 5.10: PSD of the filtered noise

Mostly what have completed here is filtered white noise. The Power Spectral Density of the filtered noise to takings on the form of the filter frequency reaction, and is the similar (within investigational variation) for every autonomous noise signal.
Computing the difference of the filtered noise outcomes in

»mean (Syl) % = 0.4851

»mean (Sy2) % = 0.4910

The means of the outcomes are together closer to the 0.5. Not remarkably, cutting out partial the noise with a vertical high demand Butterworth filter has abridged the total difference by roughly 0.5. The difference for the flat Power Spectral Density with amplitude S_x (Watt per Hertz) and entire positive in addition to negative frequency extent Δf is established by

$$(\sigma_x)^2 = S_x \Delta f.$$

In MATLABs computation of Power Spectral Density, Δf is normalized to 1, therefore $(\sigma_x)^2 = S_y = 1$. Intended for the filtered signal, S_x is 1 on behalf of half of Δf and 0 for the additional half of Δf, therefore

$$(\sigma_x)^2 = S_y/2 = 1/2.$$

In commonly, when the Power Spectral Density is not simple formed as in the above patterns, it will must to integrate the Power Spectral Density to discover the difference. In MATLAB, this is equal to simply resulting the mean of the Power Spectral Density.

5.3 Wavelet Transform (WT)

Wavelet transform is as of late turned into an extremely prominent with regards to examination, de-noising and pressure of signs and pictures. This area depicts capacities used to perform multilevel Wavelet Transforms and single.

5.3.1 Original Electroencephalogram Signal analysis using Wavelet Transform

Wavelet transform gives a complete three dimensional information about any Brain signal i.e. what distinguish between frequency components are present in any signal and what their respective amplitudes are and at time axis where the different frequency component exits. For this project analysis, we using the wavelet tool in MATLAB and generating the signal.

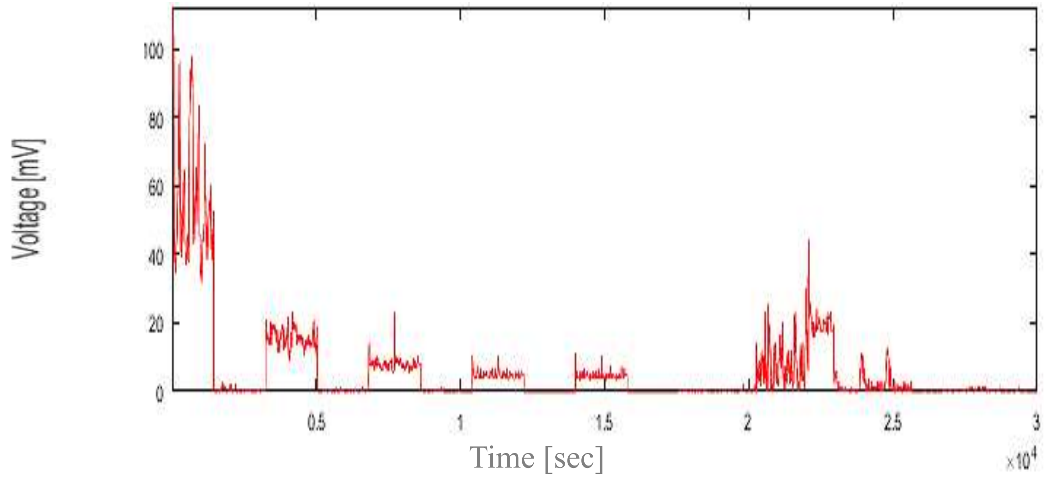


Figure 5.11: Raw EEG signal by using Wavelet Transform

Wavelet Transform has high time determination and also high frequency determination as well as frequency and time resolution can also be changed. Decomposition of Electroencephalogram (EEG) signal in wavelet tool is shown in figure 5.12.

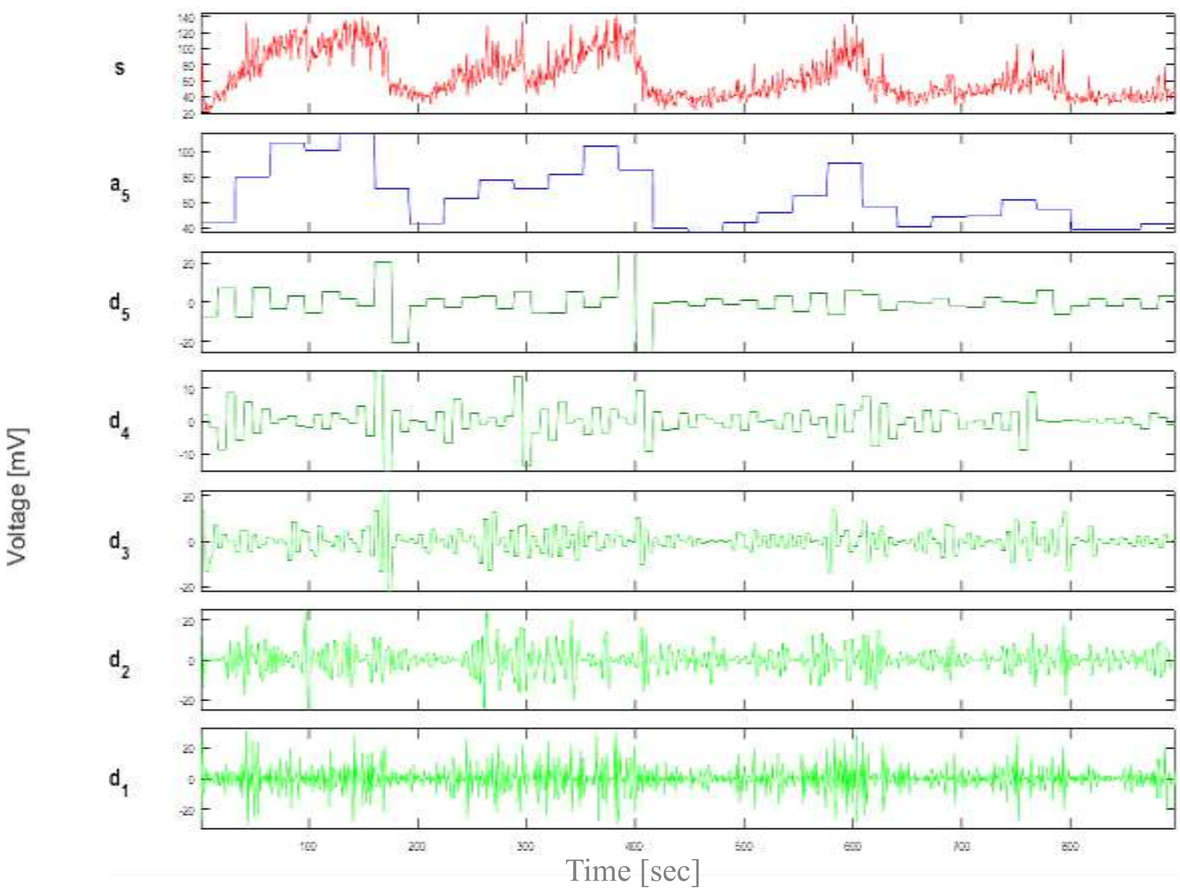


Figure 5.12: Decomposition of the electroencephalogram signal in wavelet tool

The 3D representation of the wavelet transform (WT) of signals have a great feature to represent the signals as amplitude, frequency and time domain form. The 3D representation of the signals is more convenient for pathological cases.

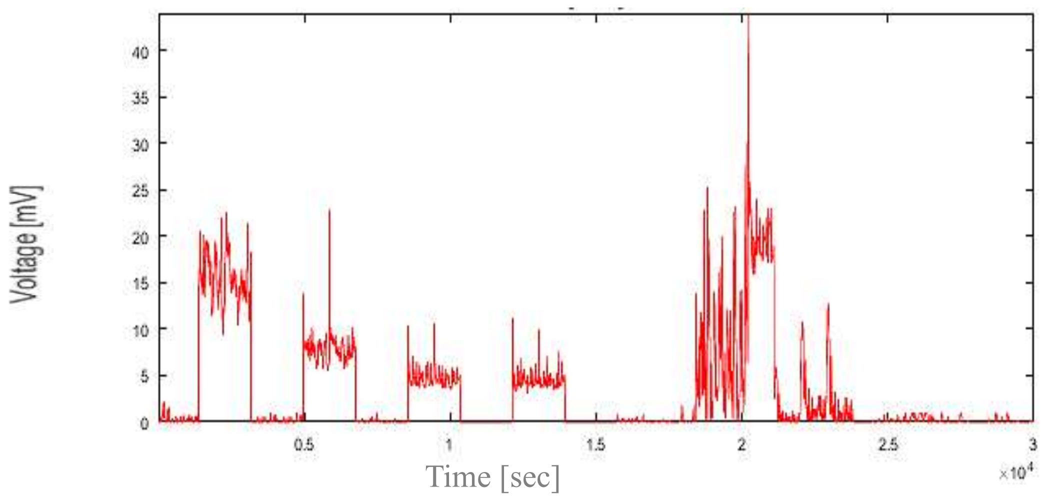


Figure 5.13: Statistical EEG signal analysis in wavelet

The investigation of this project clarify that the 3D representation of the signals in wavelet based analysis, statistical representation of the parameters and spectral analysis helps to fulfil the aim of this work. Wavelet transform is suitable for stationary and non-stationary signal. It helps to study the local signal's behavior, for example discontinuity or spikes. The statistical analysis through the wavelet tool helps to detect the changes. It shows the smallest values of each parameters.

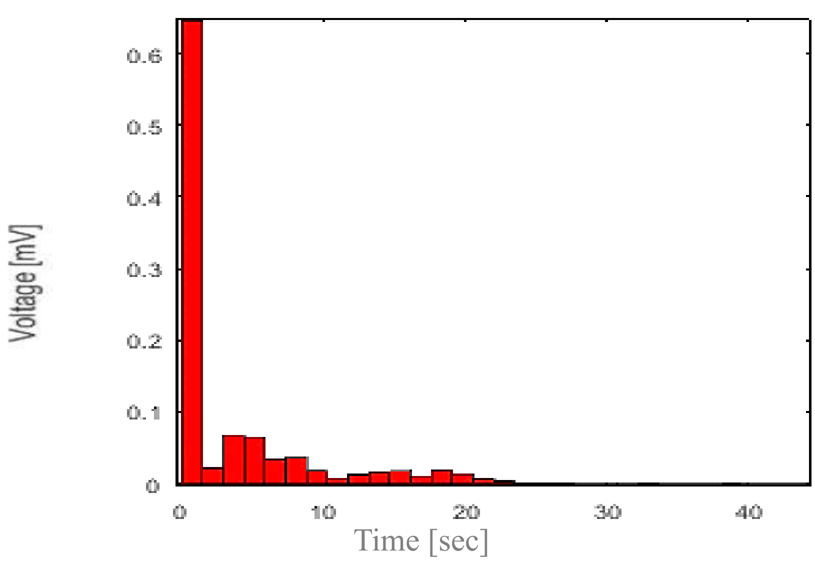


Figure 5.14: Statistical EEG signal analysis in wavelet (Histogram)

The statistical parameters along with the other processing techniques including filtering, makes the wavelet spectral analyzing techniques more effective also almost error free monitoring system and detection of the smallest abnormalities in the brain signals in sudden conditions. This project clarify that the small abnormalities can be determined through the helps of those statistical parameters in monitoring the EEG signals and take the proper steps in regular or emergency conditions. Figure 5.16 is the cumulative form of the EEG signal in wavelet spectral analyzing method.

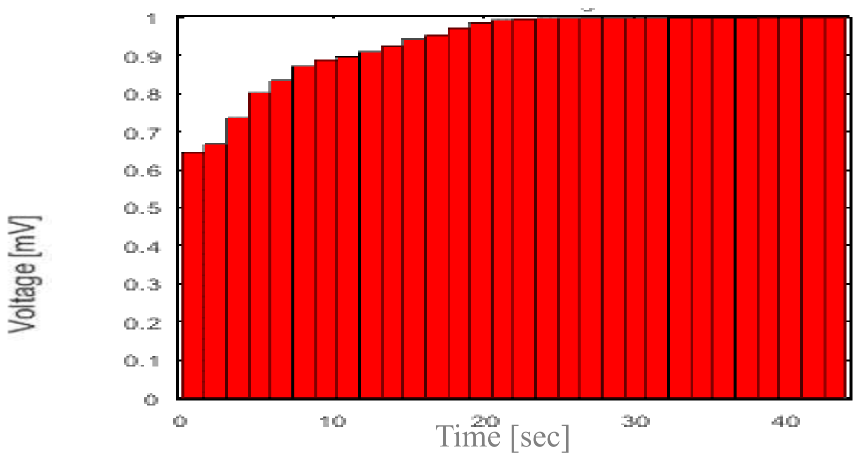


Figure 5.15: Statistical EEG signal analysis in wavelet (Cumulative)

In wavelet analysis the signal is converted into translated and scaled version of mother wavelet which is very irregular and helps to detect smallest changes. The mother wavelets are more suitable for predicting the local behavior of the signal for example irregularities and spikes. This is another wavelet's feature spectral analysis technique of this project.

Table -1: Statistical analysis of the original EEG signal in wavelet tool

Parameter	Value	Parameter	Value
Mean voltage	3.275	Standard Dev.	5.515
Median frequency	0.1933	Median Abs. Dev.	0.1933
Mean frequency	0.7734	Mean Abs. Dev.	4.086
Maximum	44.01	L1 norm	9.826e+04
Minimum	00	L2 norm	1111
Range	44.01	Max norm	44.01

Table -1 is the summery of the statistical values of brain (EEG) signal based on the wavelet spectral analysis. From this table, it seems very clear to all that the smallest changes or any kind of abnormality in the brain can effortlessly be identified and with the help of this monitoring, any emergency medication of the subject (Patient) might be provided.

5.3.2 Noisy EEG (Electroencephalogram) Signal analysis by Wavelet Transform

Brain is human body's sensitive part and Electroencephalogram (EEG) detect or sense the changes of human brain by signal analyzing. So it is a hard possible task to determine the small changes in brain. As the current analyzing technologies are not sufficient enough to deal with the sudden abnormalities or even very small abnormalities, the introduced method provides an effective way of analyzing the data more accurately. The system has been created using the wavelet tool in MATLAB. Because of the availability of statistical information of the EEG data even in noisy conditions, the system can determine the smallest possible abnormalities even in the hunched conditions.

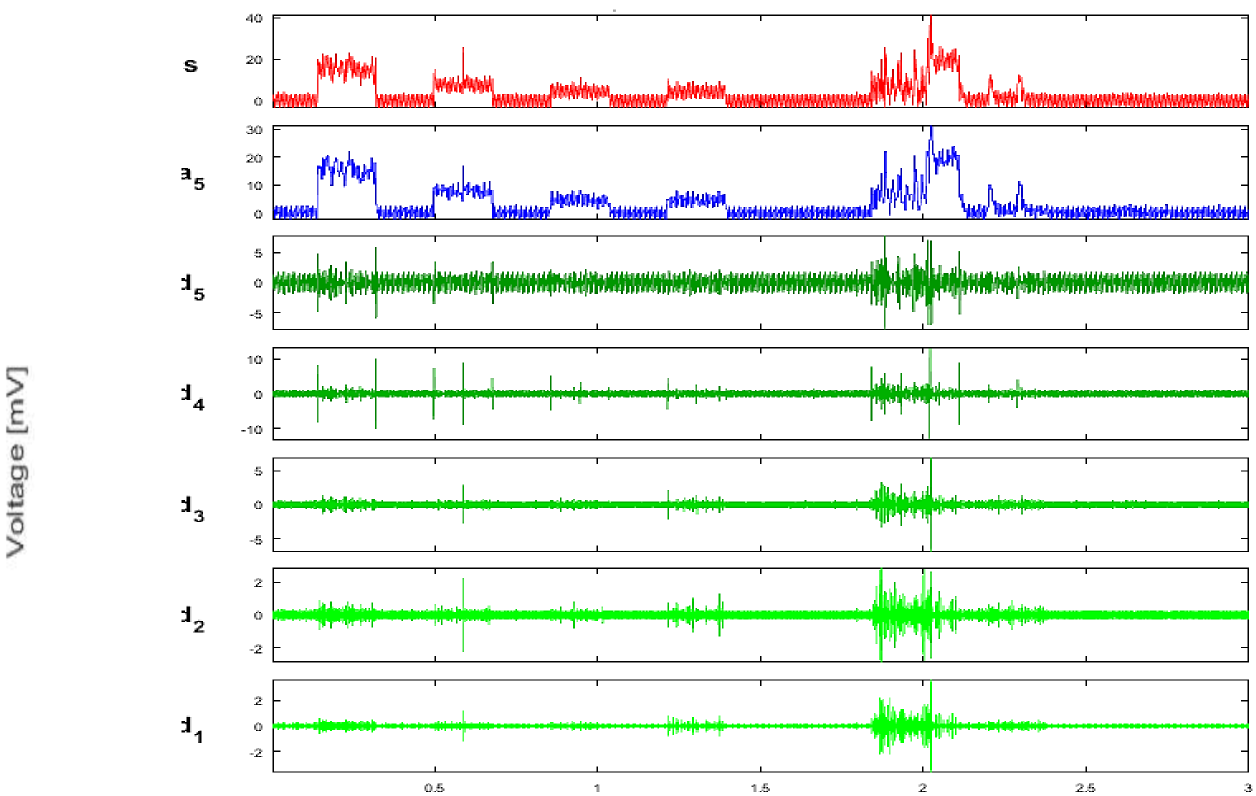


Figure 5.16: Decomposition of the noisy EEG signal in wavelet tool

The small changes or abnormality detection is very much important issue in neuroscience and proper detection of the abnormality helps for proper medication. Figure-5.8 is the demonstration of an EEG signal where noise or abnormality is detected.

Wavelet transformation is one of the best possible way to find the smallest changes in the brain as discussed earlier, the statistical properties in the MATLAB Wavelet tool helps to identify the small changes and parameter basis analyzing facility which makes the detection familiar in EEG analysis.

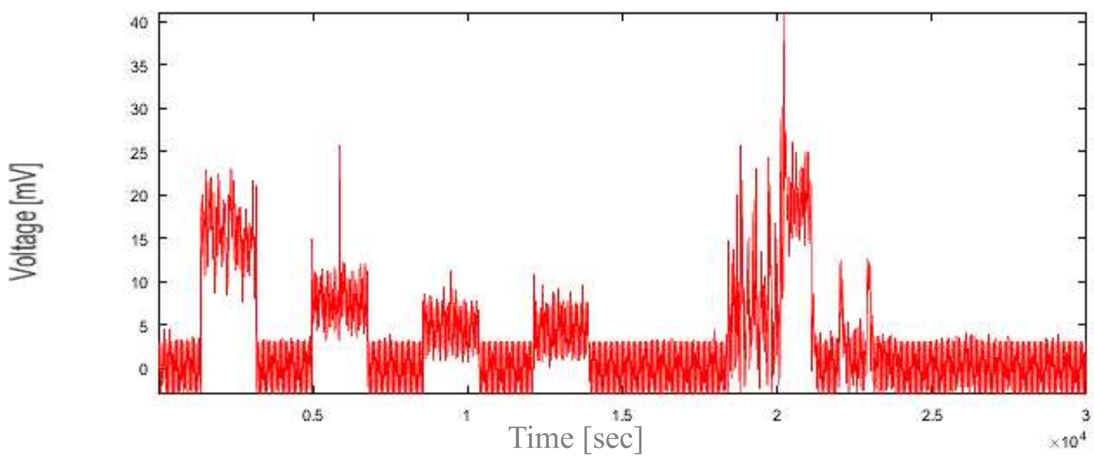


Figure 5.17: Statistical noisy EEG signal analysis in wavelet

Figure 5.17 is the representation of the Decomposition of the noisy EEG signal in wavelet tool. By this figure, the signal decomposition can be clarifies and can be observed without any problems.

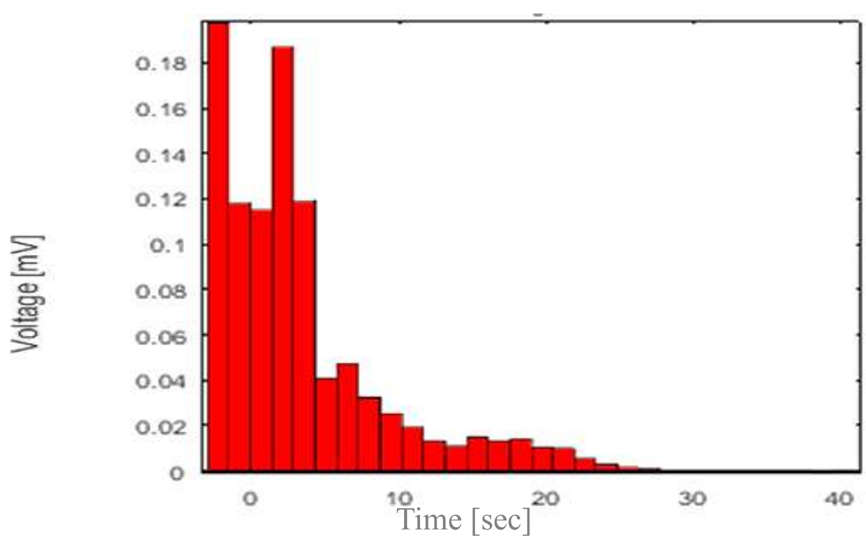


Figure 5.18: Statistical noisy EEG signal analysis in wavelet (Histogram)

In wavelet analysis the signal is converted into scaled and translated form of mother wavelet which is very irregular and helps to detect smallest changes. The mother wavelets are more suitable for predicting the local characteristic of the signal such as irregularities and spikes such as histogram presentation (figure 5.18) and cumulative (figure 5.19), which helps to detect the small abnormalities.

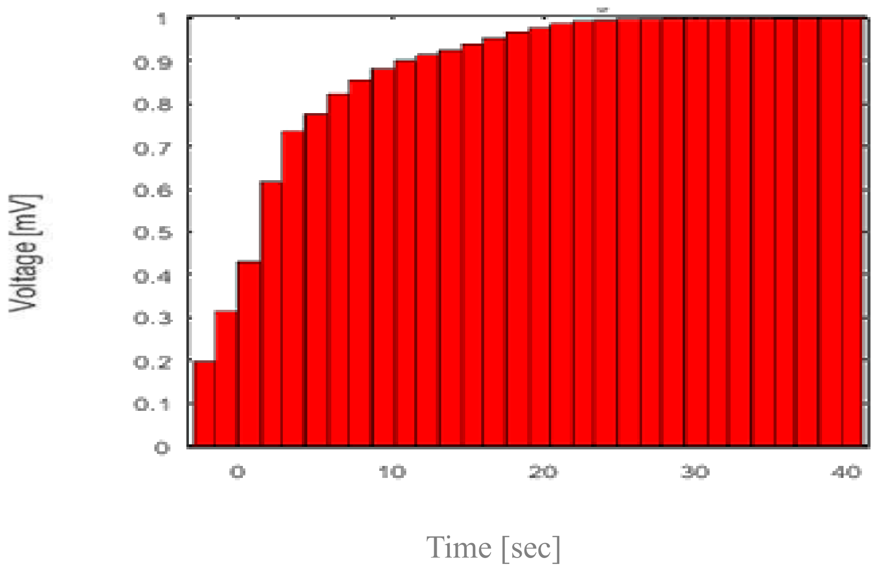


Figure 5.19: Statistical EEG signal analysis in wavelet (Cumulative)

The statistical table of the EEG signal where noise or small changes are noticed will helps a doctor or technician to detect the abnormalities. It could help the patient to take proper treatment or further steps.

Table -2: Statistical analysis of the noisy EEG signal in wavelet tool

Parameter	Value	Parameter	Value
Mean voltage	3.276	Standard Dev.	5.919
Median frequency	2.039	Median Abs. Dev.	2.887
Mean frequency	-2.268	Mean Abs. Dev.	4.248
Maximum	41.04	L1 norm	1.328e+05
Minimum	-3.002	L2 norm	1172
Range	44.04	Max norm	41.04

5.4 Comparison between Original EEG Signal and Noisy EEG Signal

First of all, First Fourier transform (FFT) convert signal of time sphere into frequency sphere signal. It provides two dimensional information regards to any signal that what different frequency component present in a signal and what are their respective amplitude. Whereas Wavelet transform gives a complete three 3D about any signal i.e. what different frequency components has created any signal and what are their respective amplitudes and at time axis where the different frequency component exits.

Table -3: Comparison between Original EEG Signal & Noisy EEG Signal

Parameter	Original EEG Signal	Noisy EEG Signal
Mean voltage	3.275	3.276
Median frequency	0.1933	2.039
Mean frequency	0.7734	-2.268
Maximum	44.01	41.04
Minimum	00	-3.002
Range	44.01	44.04
Standard Dev.	5.515	5.919
Median Abs. Dev.	0.1933	2.887
Mean Abs. Dev.	4.086	4.248
L1 norm	9.826e+04	1.328e+05
L2 norm	1111	1172
Max norm	44.01	41.04

And from the data comparison, it seems clear that wavelet can detect the smallest changes in EEG signal what is a great advantage that have not exist in FFT or other methods. It helps to anyone to observe the abnormalities of the brain signal through the wavelet properties.

CHAPTER 6

CONCLUSION

Every year lot of people around the world are dying by various brain diseases. EEG (Electroencephalogram) signal extraction is considered as a vital part to detect most of the brain diseases. Brain disease affected patients will be benefited most when EEG signal will offer the best analyzing report. There is no doubt that First Fourier Transform (FFT) has a great feature in frequency division signal analysis but it cannot ensure the detection of small abnormalities in the EEG signal data. As it is the issue of dealing with the most sensitive part of the human body, FFT does not provide the best way in the detection method. In this project, a method is proposed to monitor and detect the smallest changes or abnormalities in the brain signals with the help of wavelet based EEG signal analysis. It can be served as an innovative tool for both regular and emergency issues. This project is undertaken to justify that wavelet based EEG signal analysis is one of the best methods for brain signal monitoring and detection. In wavelet based signal analysis, this project determines smallest changes or abnormalities of brain signals that helps for emergency medication as well as future risk factors. The graphical analysis and statistical presentation of this project have shown that wavelet based EEG signal analysis is associated with better error detection feature which will help in any kind of medical application. The wavelet based EEG signal analysis shows the smallest changes in some signal parameters of the brain signal through the ability of statistical information of the EEG signal in wavelet transformation, eventually the smallest abnormalities which cannot be detected through other methods, can be detected easily by using the wavelet transform.

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APPENDIX

Acronyms:

AE	Approximate Entropy
Bior	Biorthogonal
Bip	Biphasic
CG	Complex Gaussian
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
ECoG	Electrocardiogram
EEG	Electroencephalogram
ERNN	Elman RNN
FFT	First Fourier Transform
FT	Fourier Transform
HOS	Higher Order Spectra
ICA	Independent Component Analysis
MLNN	Multilayer NN
NN	Neural Systems
PE	Permutation Entropy
PSD	Power Spectrum Density
RNN	Repetitive NN
WHO	World Health Organization
WPD	Wavelet Packet Decomposition
WPT	Wavelet Packet Transform

WT Wavelet Transform

Recorded EEG data sample:

38.27 35.05 0.00 0.00 19.62 22.15 0.00 0.00 0.00 13.20 0.00
0.00 16.17 18.05 0.00 0.00 29.75 28.02 0.00 0.00 0.00 0.00
3.00 39.58 52.28 70.82 8.67 15.25 11.25 1.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
92.13 90.79 0.00 0.00 0.00 0.00 0.00 0.00 23.55 55.08 0.00
0.00 20.27 21.33 0.00 0.00 37.22 36.83 0.00 0.00 0.00 0.00
0.00 26.05 53.00 90.71 9.84 20.25 18.50 1.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
47.53 50.75 0.00 0.00 12.37 0.00 0.00 0.00 24.21 61.98 0.00
0.00 25.34 21.30 0.00 0.00 27.94 27.39 0.00 0.00 0.00 0.00
0.00 21.62 41.81 58.57 4.69 11.25 19.75 1.00 0.00 0.00 0.00
0.00 0.00 0.00 0.00
27.85 50.21 0.00 0.00 13.60 0.00 0.00 0.00 27.18 67.84 0.00
0.00 14.69 15.30 0.00 0.00 14.11 12.92 0.00 0.00 0.00 0.00
0.00 11.20 18.17 39.25 7.73 8.50 12.25 1.00 0.00 0.00 0.00
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18.79 42.09 0.00 0.00 17.49 0.00 0.00 0.00 26.56 35.33 0.00
0.00 13.49 11.97 0.00 0.00 11.74 10.44 0.00 0.00 0.00 0.00
0.00 0.00 0.00 41.63 0.00 0.00 13.75 1.00 0.00 0.00 0.00
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33.02 42.92 0.00 0.00 15.77 10.73 0.00 0.00 28.15 51.17 0.00
0.00 14.39 17.66 0.00 0.00 8.64 7.60 0.00 0.00 0.00 0.00
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0.00 13.00 17.23 0.00 0.00 9.97 7.71 0.00 0.00 0.00 0.00

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29.42 29.94 0.00 0.00 15.68 16.31 0.00 0.00 7.31 7.49 0.00
0.00 7.90 7.60 0.00 0.00 5.38 4.58 0.00 0.00 1.00 0.00
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72.71 74.78 0.00 0.00 22.43 24.79 0.00 0.00 7.83 8.86 0.00
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0.00 7.23 0.00 14.86 5.86 10.75 10.00 0.00 0.00 1.00 0.00
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77.92 65.06 0.00 0.00 21.21 24.00 0.00 0.00 9.09 13.94 0.00
0.00 5.21 5.14 0.00 0.00 4.80 4.56 0.00 0.00 0.00 0.00
0.00 6.75 8.81 16.81 4.92 2.25 10.00 0.00 0.00 1.00 0.00
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68.85 61.67 0.00 0.00 16.03 25.51 0.00 0.00 5.80 10.58 0.00
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0.00 7.06 8.56 17.52 4.45 10.00 14.50 0.00 0.00 1.00 0.00
0.00 0.00 0.00 0.00

MATLAB Code:

```
x1 = load('A1.txt');
y1 = sgolayfi(kron(ones(1,13),x1),0,21);
n = 1:20000;
del = round(2500*rand(1));
signl= y1(n + del);
t = 0.00065:0.0025:7.5;
```

```
%subplt(3,2,1);
fig ;
plt(t,signl);
axiss([0 2.5 -5 5]);
grid;
xlabl('Time [sec]');
ylabl('Voltage [mV]');
titl('a) EEG Signal');
nvr  = 0.5;                  % Noise variance
%noise = rand(size(signal))*nvr;
nois=3*sin(2*pi*50*t);
%subplt(3,2,2)
fig.
plt(t,noise);
axiss([0 2.5 -4 4]);
titl('b) Noisy time domain signal')


nfil  = fir1(31,0.5);             % 31st order Low pass FIR filter
noise = filter(nfilt,1,noise);    % Filtering the noise
d  = signl+noise;
%subplt(3,2,3)
fig.
plt(t,d);
axiss([0 2.5 -5 5]);
titl('c) Signal + Noise')


D = ft(d,512);
Py = D.* conj(D) / 512;
f = 1000*(0:4256)/512;
```

```
%subplt(3,2,4);
fig.
plt(f(1:50),Pyy(1:50))
titl('d) Power spectral density')
xlabl('Frequency (Hz)')



M = 32;                    % Filt order
lam = 1;                   % Exponent weighting factor
w0 = zeros(M,1);           % Initial  weight vector
Zi = zeros(M-1,1);         % filter initial states

Haapt = adtfilt.rls(M,lam,P0,w0,Zi);
[y,e] = filt(Haapt,noise,d);
H = ab(frqz(Hadapt,1,64));
H1 = ab(frqz(nfilt,1,64));

%subplt(3,2,5);
fig.
plt(t,signal,'* Y',t,e); grid;
legend('Signal','Error Signal');
axiss([0 2.5 -5 5]);

E = fft(e,512);
PYY = E.* conj(E) / 512;
plt(F(1:50),PYY(1:50))
xlabl('Frequency (Hz)')
```