Sudan University of Science and Technology

College of Graduates Studies

Epilepsy Signal Analysis_and Classification

تحليل وتصنيف إشارة الصرع

Submitted in partial fulfillment of the requirement of

M.Sc Degree in Biomedical Engineering

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DEDICATION

TO the soul of my father

To my great mother

To my beloved sisters and lovely husband and children who suffered a lot during the preparation of this study.

With love, faith and respect

ACKNOWLEDGEMENTS

I would like to express my sincere thanks to my supervisor Dr. Mohammed Yagoub Esmail for his continuous guidance, generous advice, encouragement and co-operation throughout the study.

Thanks are sent to my husband and sisters encouraged me so much and to everyone who helped me throughout this study.

I am grateful to my daughter (Mayar) and small son (yassin) who suffered during examinations and during end these research.

ABSTRACT

Brain signals are important in diagnosing various disorders and abnormalities in the human body. These signals are recorded by scalp electrodes and are called as EEG signals. EEG signals are a mixture of signals from different brain regions which contain artifacts along with original information. EEG has several limitations; most important is its poor spatial resolution. EEG is most sensitive to a particular set of post-synaptic potentials. For this reason selected 25 samples (epilpsey) A computer program (Matlab) used for makining processing to remove noise from EEG signal and then estimating the EEG parameters for calculating the statistical parameters(mean,median,root mean square, standard deviation). The aim of this study is to classify the EEG signal as normal or abnormal. It is proposed to develop an automated system for the classification of brain abnormalities. The proposed system includes pre-processing, feature extraction, feature selection and classification. In pre-processing the noises are removed. The discrete wavelet transform is used to decompose the EEG signal into sub-band signals. The feature extraction methods are used to extract the time domain and frequency domain features of the EEG signal ,finally classification by using the table obtained from time and frequency domain features then calculated the Euclidean distance, calculated eucsum and the value was rounded

Finally it found that the accuracy is equall 84%,sensitivity 86.66%,specificity 80%,positive protective value 86.66% and negative protective value 80%.

المستخلص

تعتبرإشارات الدماغ مهمة في تشخيص الاضطرابات المختلفة وتحديد الحالة الصحية للمريض. يتم تسجيل هذه الإشارات من فروة الرأس باستخدام اقطاب تخطيط كهربية الدماغ، وإشارات تخطيط كهربية الدماغ هي مزيج إشارات من الخلايا الدماغية المختلفة والتي تشكل وتكون المعلومات الأصلية، ولكن هذه الاشاره لديها قيود تحد من صلاحيتها وهي ضعف جهودها الكهربية وقلة ترddاتها مما يجعلها عرضة للتداخل مع اشارات اخري غير مرغوبة.
في هذه الدراسة تم اختيار 25 عينة من اشارات تخطيط كهربية الدماغ من النوع (epilpsey) حيث تم استخدام برنامج المحاكاة (ماتلاب) لمعالجة وازالة الاشارات غير المرغوبة من الإشارة المعنية، ومن ثم تم استخلاص الخصائص المميزة لهذه الاشارات كالخصائص الإحصائية (الوسط الحسابي والوسيط، جذر متوسط مربع،الانحراف المعياري). وذلك بغرض التصنيف الي حالات سوية وغير سوية وفق مطابقة الخصائص.
تم تنفيذ وتطوير النظام في المراحل الاتية: المعالجة الاولية، واستخلاص الصفات الميزة للاشارة، ومن ثم اختيار الصفة الميزة بغرض التصنيف. في مرحلة المعالجة الاولية للإشارات، تمت تنقية اشارات تخطيط كهربية الدماغ من إشارات الضجيج بإستخدام المويجات المتقطعة والتي شكلت الإشارات لمستويات فرعية ، ثم إستخلصت وشكلت الخصائص الإحصائية والأشكال المميزه للإشارات في المجالين الزمني والترددي وذلك في مرحلة تشكيل خصائص الإشارة. أخيرا قورنت خصائص الإشارات التي يراد تصنيفها مع خصائص الإشارة المرجعية بإستخدام الEuclidean distance التقريبية وذلك بغرض التصنيف.

تم التحقق من نتائج النظام حيث وجد أن الدقة هي 84٪، والحساسية86.66٪ والنوعية 80٪، والنوعية للقيمة الوقائية الإيجابية 86.66٪ وللقيم الوقائيةالسلبية 80٪.

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Abbreviations:

AP :	Action potential
ANN:	artificial neural network
CNS:	Central nerves system
CT:	Computerized tomography
DFT:	Discrete Fourier transforms
DWT:	Discrete wavelet transforms
ECG :	electrocardiogram
EEG :	electroencephalogram
EGG:	Electrogastrogram
EOG :	electrooculogram
EMG.	Electromyogram
EUC:	Euclidean distance
FP:	false positive
FN:	false negative
ICA:	Independent component analysis
MATLAB:	Matrix laboratory
MEG:	Magnetoencephalogram
MRI:	Magnetic resonance imaging
NPV :	negative predictive value
PET:	Positron emission tomography
PPV:	positive predictive value
REM**:**	rapid eye movement
SPET:	Single photon emission tomography
SVM:	Support vector machine

TN :	true negative
TP :	true positive
WT:	Wavelet transformation

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Introduction

1.1 General view:

The electroencephalogram (EEG) is a non-invasive measure of brain electrical activity recorded as changes in the potential difference between two points on the scalp [1]
EEG measures voltage fluctuations resulting from ionic the brain normally produce tiny electrical signals that come from the brain cells and nerves which send messages to each other. These electrical signals can be detected and recorded by the electroencephalograph (EEG) machine [2] . There are five major brain waves distinguished by their different frequency ranges [3]
Delta waves lie within the range of 0.5 to 4 Hz, Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V, Alpha with a rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude, Beta, the rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μV . Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems and finally the Gamma waves which lie within the range of 35Hz and up. It is thought that this band reflects the mechanism of consciousness [4] .
The electroencephalogram (EEG) is widely used clinically to investigate brain disorders. EEG measurement is widely used as a standard procedure in research including sleep studies [1], epileptic abnormalities [5–7], and the diagnosis of other disorders [8,9].
It is believed that from this early stage and throughout life electrical signals generated by the brain represent not only the brain function but also the status of the whole body. This assumption provides the motivation to apply advanced digital signal processing methods to the electroencephalogram (EEG) signals measured from the brain of a human Activity. EEG waves (alpha, beta, delta and theta) show different characteristics during different daily physiological brain activities. The EEG signal is closely related to the level of consciousness of the person. As the activity increases, the EEG shifts to higher dominating frequency and lower amplitude. When the eyes are closed, the alpha waves begin to dominate the EEG. When the person falls asleep, the dominant EEG frequency decreases. In a certain phase of sleep, rapid eye movement called (REM) sleep, the person dreams and has active movements of the eyes, which can be seen as a characteristic EEG signal. In deep sleep, the EEG has large and slow deflections called delta Waves.

An effort toward its diagnosis and treatment are of great importance. Method techniques that describe the application of an artificial neural network (ANN) technique together with a feature extraction technique, viz., the wavelet transform, for the classification of EEG signals. Some literature survey has been focused for the pre-processing of EEG signals, Feature extraction, Feature selection and classification methods.

1.2 EEG background:

(EEG) is a recording of the voltages generated by brain activity. Electrodes placed at predefined locations on a patient's scalp allow clinicians to measure brain activity by registering the potential differences between certain pairs of electrodes and plotting the signals called electroencephalogram, or EEG signals—over time [10].

In order to investigate nervous system and brain, many research fields related to neuro-biological signals have been developed. Neuro-biological signals contain electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG), and electromyogram (EMG).

1.3 History

The history of human EEG recordings goes back to Hans Berger (1873–1941), professor of psychiatry at the University of Jena, Germany. Following the work of Richard Caton (1842–1926), a surgeon from Liverpool who successfully recorded the electrical activity of exposed cerebral hemispheres from monkeys and rabbits in 1875, Hans Berger was the first one able to record electrical activity from the human scalp in 1924. The importance of Berger's work was not recognized until 1934 when Lord Edgar Adrian (1889–1977), at Cambridge, confirmed his results .The first frequency Berger encountered was the 10-hertz range, which at first was called the Berger rhythm, currently called Alpha rhythm brain wave. In 1929, he published the first report on human EEG. In that report, he described and defined the alpha and beta waves. He recorded EEG not only in normal subjects but also in the brain-injured, thereby laying the foundation for the application of the technique to clinical technology.

A significant slowdown in EEG research resulted as a consequence of the introduction of other methodologies for measuring brain activity, in our days, EEG recordings are generally used for clinical diagnoses, like head injuries, brain tumors, and epilepsy. Neuroscientists also study different types of EEG activity during controlled behavior in human subjects and animal [11].

1.4 Problem statement

Detection and diagnosis of disease is hard, however, symptoms are often dismissed as normal consequences of aging and also diagnosis is usually performed through a combination of extensive testing and eliminations of other possible causes, especially in epilepsy most cases the cause is unknown, so that discovery and diagnosis are so difficult, EEG signals in general are represented in high dimensional features space and it is very difficult to interpret.

Also feature extraction and classification of signal components belong to very common problems in various engineering, economical and biomedical applications. Spectral analysis of the EEG signals produces information about the brain activities. Visual analysis and diagnosis of EEGs is a very time consuming and it is difficult to evaluate gradual changes and long-term trends

1.5 Objectives

The goal of the present work was to developed system for EEG signal analysis and classifies the EEG signal as normal or abnormal. It is proposed to develop an automated system for the classification of brain abnormalities

1.5.1 General Objectives:

The main objective of this study is to extract sub-signals from EEG signal using MATLAB ,wavelet techniques in order to compare their efficiency and give support to medical doctors in decision making and improve the diagnosis of epilepsy

1.5.2 Specific objectives:

Information content of EEG signals is essential for detection of many problems of the brain. Improve the accuracy of classification and disease detection. To explore a new automatic EEG spike detection algorithm for epilepsy diagnosis.

1.6 Methodology:

Spectral presentation of EEG measurements were used for the primary description of EEG artifacts.

EEG signals in general are represented in high dimensional features space and it is very difficult to interpret. Machine learning methods are helpful for interpreting high dimensional feature sets and analyze the characteristics of brain patterns. Wave let is one of the popular Machine Learning methods for classifying EEG signals and has the ability to indicate signal which localized in time or frequency domain.[12]

Over the past 30 years, a number of automatic spike detection methods have been developed, such as artificial neural network [13], [14], [15], wavelet analysis [16], [17], support vector machine [18], Kalman filter [19], [20], independent component analysis [21], [22],.

Various advanced methods have been applied to detect and remove artifacts in EEG signals, such as independent component analysis (ICA) 23]-[24] ,wavelet analysis [26]. These methods were appropriate for offline analysis.

The method of EEG analysis involves many steps, grouped in two parts: Feature extraction and Knowledge based expert system

All automatic analysis systems for neuro-biological signals consist of four stages: (1) data acquisition; (2) pre-processing; (3) main processing and (4) results and information obtained for right decisions.

1.7 Thesis layout:

Chapter one discusses the briefly introduction, background, EEG signals, problem statements and objectives.

Chapter two discusses a literature reviews (scientific papers) was included

Chapter three discusses the methodology of the project was written including introduction ,data set ,how to get the signal , pre-processing, feature extraction and classification and the code description and raw data description that used in the simulation

Chapter four the results and discussions

Chapter five the conclusions and recommendations of thesis.

Theoretical Background

2.1 Anatomy and physiology of the brain

The CNS generally consists of nerve cells and glia cells, which are located between neurons. Each nerve cell consists of axons, dendrites, and cell bodies.

2.1.1 Neural Activities

Nerve cells respond to stimuli and transmit information over long distances. A nerve cell body has a single nucleus and contains most of the nerve cell metabolism especially that related to protein synthesis. The proteins created in the cell body are delivered to other parts of the nerve. An axon is a long cylinder, which transmits an electrical impulse and can be several metres long in vertebrates (giraffe axons go from the head to the tip of the spine) as in figure (2.1). In humans the length can be a percentage of a millimetre to more than a metre. An axonal transport system for delivering proteins to the ends of the cell exists and the transports system has ‘molecular motors’, which ride upon tubulin rails.Dendrites are connected to either the axons or dendrites of other cells and receive impulses from other nerves or relay the signals to other nerves. In the human brain each nerve is connected to approximately 10,000 other nerves, mostly through dendritic connections.The activities in the CNS are mainly related to the synaptic currents transferred between the junctions (called synapses) of axons and dendrites, or dendrites and dendrites of cells. A potential of 60–70 mV with negative polarity may be recorded under the membrane of the cell body. This potential changes with variations in synaptic activities [28].

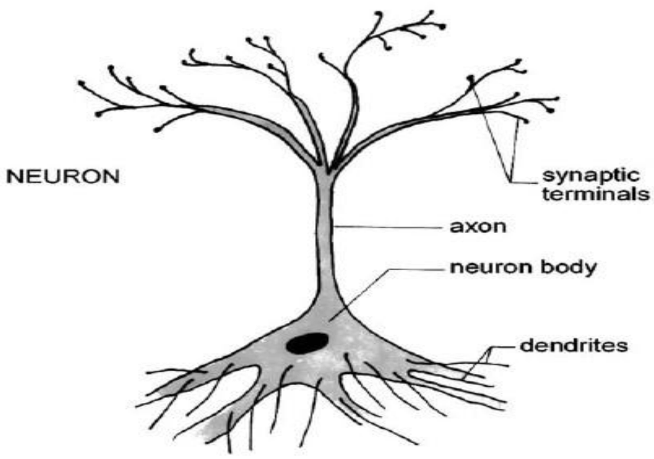

Figure (2.1) Neuron, Synaps

2.1.2Action potentials

The information transmitted by a nerve is called an action potential (AP). APs are caused by an exchange of ions across the neuron membrane and an AP is a temporary change in the membrane potential that is transmitted along the axon. It is usually initiated in the cell body and normally travels in one direction. The membrane potential depolarizes (becomes more positive), producing a spike. After the peak of the spike the membrane repolarizes (becomes more negative). The potential becomes more negative than the resting potential and then returns to normal. The action potentials of most nerves last between 5 and 10 Milliseconds as shown in figure (1.2) . The conduction velocity of action potentials lies between 1 and 100 mz/s. APs are initiated by many different types of stimuli; sensory nerves respond to many types of stimuli, such as chemical, light, electricity, pressure, touch, and stretching. On the other hand, the nerves within the CNS (brain and spinal cord) are mostly stimulated by chemical activity at synapses.

A stimulus must be above a threshold level to set off an AP. Very weak stimuli cause a small local electrical disturbance, but do not produce a transmitted AP. As soon as the stimulus strength goes above the threshold, an action potential appears and travels down the nerve [28]

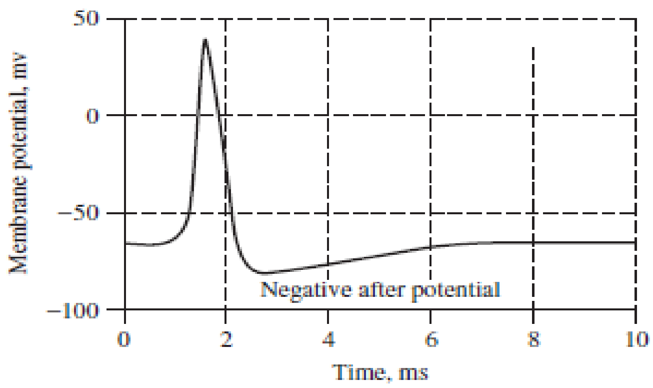

Figure (2.1): Action potential

2.2 Generation of EEG:

When brain cells (neurons) are activated, the synaptic currents are produced within the dendrites. This current generates a magnetic field measurable by electromyogram (EMG) machines and a secondary electrical field over the scalp measurable by EEG systems.

Differences of electrical potentials are caused by summed postsynaptic graded potentials from pyramidal cells that create electrical dipoles between the soma (body of a neuron) and apical dendrites, which branch from neurons. The current in the brain is generated mostly by pumping the positive ions of sodium, Na^+, potassium, K^+, calcium, Ca^{++}, and the negative ion of chlorine, Cl^-, through the neuron membranes in the direction governed by the membrane potential.

2.3Basic Principle of EEG Diagnosis:

The EEG signal is closely related to the level of consciousness of the person. As the activity increases, the EEG shifts to higher dominating frequency and lower amplitude. When the eyes are closed, the alpha waves begin to dominate the EEG. When the person falls asleep, the dominant EEG frequency decreases. In a certain phase of sleep, rapid eye movement called (REM) sleep, the person dreams and has active movements of the eyes, which can be seen as a characteristic EEG signal. In deep sleep, the EEG has large and slow deflections called delta Waves. No cerebral activity can be detected from a patient with complete cerebral death. Examples of the above-mentioned waveforms are given in the shown on figure (2.3).

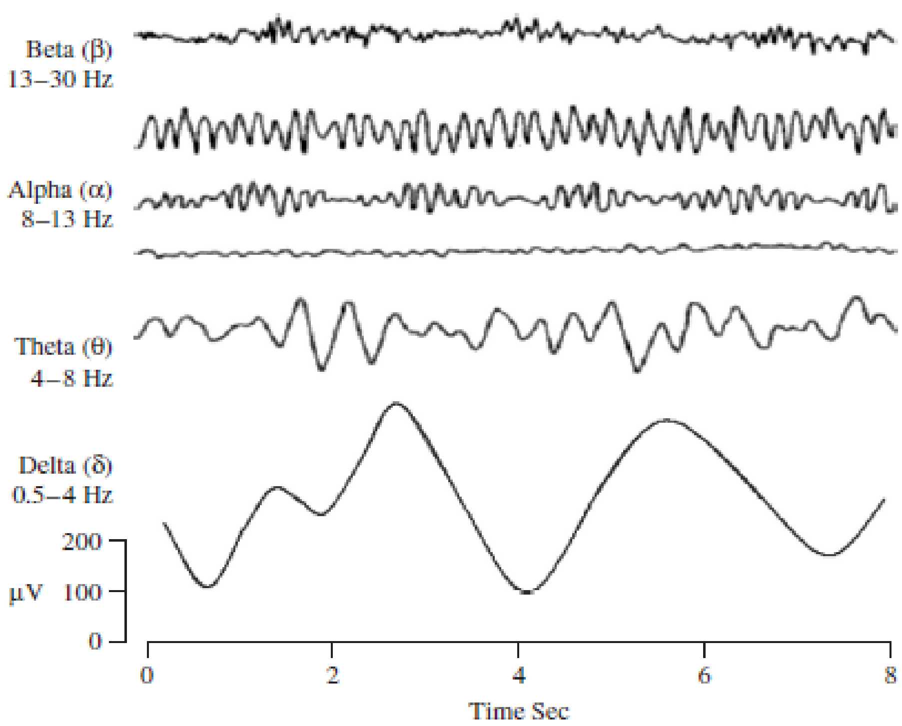

Figure (2.3) EEG activity wave form

There are five major brain waves distinguished by their different frequency ranges [1]: Delta waves lie within the range of 0.5 to 4 Hz, Theta waves lie within the range of 4 to 7 Hz, with an amplitude usually greater than 20 μ V, Alpha with a rate of change lies between 8 and 13 Hz, with 30-50 μV amplitude, Beta, the rate of change lies between 13 and 30 Hz, and usually has a low voltage between 5-30 μV . Beta is the brain wave usually associated with active thinking, active attention, focus on the outside world or solving concrete problems and finally the Gamma waves which lie within the range of 35Hz and up. It is thought that this band reflects the mechanism of consciousness [3]

2.4 EEG Recording and Measurement

Acquiring signals and images from the human body has become vital for early diagnosis of a variety of diseases. Such data can be in the form of electro biological signals such as an electrocardiogram (ECG) from the heart, electromyogram (EMG) from muscles, electroencephalogram (EEG from the brain, magnetoencephalogram (MEG) from the brain, electrogastrogram (EGG) from the stomach, and electroocclugram (or electrooptigram, EOG) from eye nerves. Measurements can also have the form of one type of ultrasound or radiograph such as sonograph (or ultrasound image), computerized tomography (CT), magnetic resonance imaging (MRI) or functional MRI (fMRI), positron emission tomography (PET), and single photon emission tomography (SPET).

2.5 EEG Electrodes Placement System

Several types of electrodes may be used to record EEG. These include Pad and Stick electrodes, Silver plated cup electrodes and Needle electrodes. EEG electrodes are smaller in size than ECG electrodes. They may be applied separately to the scalp or may be mounted in special bands, which can be placed on the patient's head.

In either case, electrode jelly or paste is used to improve the electrical contact. If the electrodes are intended to be used under the skin of the scalp, needle electrodes are used. They offer the advantage of reducing movement artifacts. The system is flexible and assures symmetrical, electrode placements on the scalp. Exact measurements are needed to determine placement of each electrode. Measurements are best made with a metric measuring tape of cloth or plastic. The standard set of electrodes for adults consists of 21 recording electrodes and one ground electrode. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front–back or right–left distance of the skull. Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for frontal, temporal, central, parietal, and occipital lobes, respectively. There exists no central lobe; the "C" letter is only used for identification purposes only. A "z" (zero) refers to an electrode placed on the midline. Even numbers (2, 4, 6, 8) refer to electrode positions on the right side, whereas odd numbers (1, 3, 5, 7) refer to those on the left side. In addition, the letter codes A, Pg and Fp identifies the earlobes, nasopharyngeal and frontal polar sites respectively as shown in figure (2.4). Two anatomical marks are used for the essential positioning of the EEG electrodes) first, the nasion which is the distinctly depressed area between the eyes, just above the bridge of the nose; second, the inion, which is the lowest point of the skull from the back of the head, and is normally indicated by a prominent bump, (Niedermeyer & da Silva, 2004). Measurements are made in a sequence of five steps.

Step 1: the distance between nasion and inion is measured along the midline. Along this line, the frontpolar point, Fp, is marked at 10% above the nasion. Frontal (Fz), central (CZ), parietal (Pz) and occipital (O) points are marked at intervals of 20% of the entire distance leaving 10% for the interval between O and inion.

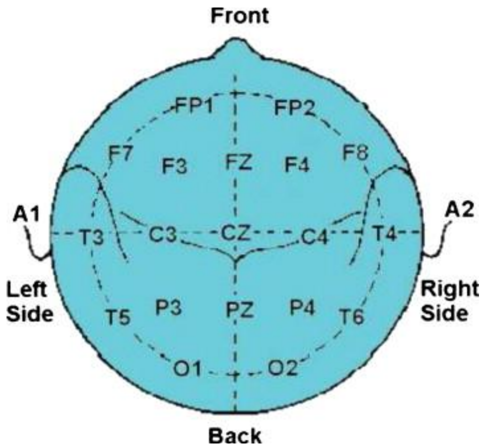

Figure (2.4):10-20 international electrode placement system

Step 2: the distance between the two preauricular points across CZ is measured. Along this line, the transverse position for the central point's C3 and C4 and the temporal points T3 and T4 are marked 20% and 40% respectively from the midline

Step 3:the circumference of the head is measured from the occipital point (O) through the temporal points T3 and T4 and the frontpolar points Fp. The longitudinal measurement for the Fp1 is located on that circumference, 5% of the total length of the circumference to the left of Fpz. The longitudinal measurements for F7, T3, T5, O1, O2, T6, T4, F8, Fp2 are at distances of 10% of the circumference.

Step 4: the longitudinal distance from Fp1 and Fp2 through C3 and C4 to O2 is measured on each side. The mid-points of these distances give the longitudinal coordinates of C3 and C4. The midpoints between Fp1 and C3 on the left, and Fp2 and C4 on the right give the longitudinal coordinates for F3 and F4. The midpoints between C3 and O1 on the left, and C4 and O2 on the right give the longitudinal coordinates for P3 and P4.
Step 5: Measurements from F7 to F8 through Fz define the transverse coordinates for F3 midway between F3 and Fz, and for F4 midway between Fz and F8. Measurements from T5 to T6 through Pz define the transverse coordinates for P3 midway between T5 and Pz and for P4 midway between Pz and T6.
Electrodes are placed at Fz, CZ and Pz, at all lateral points designated above, on or near both ears in positions called A1 and A2

2.6 Artifacts of EEG

Electrical signals detected along the scalp by an EEG, but that originate from non-cerebral origin are called artifacts. EEG data is almost always contaminated by such artifacts

2.6.1 Biological artifacts

The amplitude of artifacts can be quite large relative to the size of amplitude of the cortical signals of interest. This is one of the reasons why it takes considerable experience to correctly interpret EEGs clinically. Some of the most common types of biological artifacts include:

- Eye-induced artifacts (includes eye blinks, eye movements and extra-ocular muscle activity)(0.1-10Hz)

- ECG (cardiac) artifacts(60Hz)
- EMG (muscle activation)-induced artifacts(5-500Hz)[29]

2.6.2 Environmental artifacts:

In addition to artifacts generated by the body, many artifacts originate from outside the body. Movement by the patient, or even just settling of the electrodes, may cause electrode pops, spikes originating from a momentary change in the impedance of a given electrode. Poor grounding of the EEG electrodes can cause significant 50 or 60 Hz artifact, depending on the local power system's frequency. A third source of possible interference can be the presence of an IV drip; such devices can cause rhythmic, fast, low-voltage bursts, which may be confused for spikes.[28]

2.7 Abnormal EEG Patterns:

Variations in the EEG patterns for certain states of the subject indicate abnormality. This may be due to distortion and the disappearance of abnormal patterns, appearance and increase of abnormal patterns, or disappearance of all patterns.[29]

2.7.1 Epilepsy

Is a group of long-term neurological disorders characterized by epileptic seizures. These seizures are episodes that can vary from brief and nearly undetectable to long periods of vigorous shaking. In most cases the cause is unknown, although some people develop epilepsy as the result of brain injury, stroke, brain cancer, and drug and alcohol misuse, among others. Epileptic seizures are the result of excessive and abnormal cortical nerve cell activity in the brain.[30]

2.7.2External Effects

EEG signal patterns may significantly change when using drugs for the treatment and suppression of various mental and CNS abnormalities. Variations in EEG patterns may also arise by just looking at the TV screen or listening to music without any attention. However, among the external effects the most significant ones are the pharmacological and drug effects [28].

2.8 Background studies:

In December 2000 C.Guger, H. Ramoser, and G. Pfurtscheller r demonstrates that tmethod of common spatial patterns can be used to analyze the EEG in real time in order to give feedback to the subject. The method was utilized to give fast, continuous, and accurate feedback during left- and right-hand movement imagination[30].

In 2003, Deon Garrett, David A. Peterson, Charles W. Anderson, and Michael H. Thaut, reports the results of a linear (linear discriminate analysis) and two nonlinear classifiers (neural networks and support vector machines) applied to the classification of spontaneous EEG during five mental tasks, showing that nonlinear classifiers produce only slightly better classification results. An approach to feature selection based on genetic algorithms is also presented with preliminary results of application to EEG during finger movement.

In 2005,Rakendu Rao and Reza Derakhshani are processed Multichannel recordings of EEG data during various mental tasks using two popular methods, independent component analysis (ICA) and matching pursuit (MP). The results are fed to a time delay neural network (TDNN) for classification of each mental task. Based on the results of the test sets, we analyzed the effectiveness of ICA and MP methods for use in EEG preprocessing and TDNN classification[32].
In 2007 Ali Bashashati, Mehrdadpresents the comprehensive survey of all BCI designs using electrical signal recordings published .

In 2009, Aleˇs Proch´azka, Martina Mudrov´a, Oldˇrich Vyˇsata, Robert H´ava, and Carmen Paz Su´arez Araujo,The paper is devoted to application of Signal analysis of multi-channel data form a specific area of general digital signal processing methods for electroencephalogram (EEG) signal processing including signal de-noising, evaluation of its principal components and segmentation based upon feature detection both by the discrete wavelet transform (DWT) and discrete Fourier transform (DFT). A special attention is paid to comparison of the efficiency of feature extraction using signal segments properties estimated both by the FFT a DWT transforms. Cluster compactness is evaluated by the proposed criteria function. Signal components are then classified by the self-creating neural network structures)[33].

In 2010, Grega Repovš, give an overview of the most EEG recording, including elimination common sources of noise and review methods for prevention and removal of noise in of noise sources, signal averaging, data rejection and noise removal, along with their key advantages and challenges. Noise can present a significant challenge in analysis and interpretation of EEG data, necessitating efficient strategies for noise prevention and removal. A large amount of noise can be avoided by taking care of the appropriate recording environment and care full planning of experiments and recording sessions. Additionally, a number of methods and algorithms can be employed to reject noisy data, remove noise signal and improve signal-to-noise ratio of the data[31].

In 2011, Jing Zhou, describes several approaches to detecting and classifying epileptiform transients (ETs), including Bayesian classification (with Gaussian Assumption), artificial neural networks (Back propagation Feed Forward Network) various features were extracted, including the shape, frequency domain and wavelet transform coefficients. The long term goal of this research is to determine the required size of a dataset to obtain clinically significant machine classification results. The immediate goal is to identify a reasonable feature set which can achieve acceptable classification performance with reasonable computational complexity. Have implemented various feature sets and classification methods. They evaluated the results using different methods. So far the performance of the machine classifiers we have explored is probably insufficient for clinical application[34].

In 2012 YI Fang, LIHao and JIN Xiaojie demonstrates that the method of common spatial patterns can be used to analyze the EEG in real time in order to give feedback to the subject. The method was utilized to give fast, continuous, and accurate feedback during left- and right-hand movement imagination [34].

In 2013, S. D. Bhagwat, Vinod Jain, This paper studies wavelet transforms for EEG data processing. It is possible to expand the signal in a series of wavelets. Then join the advantages of the wavelet transform with the atomic decomposition of signal. Essentially, it is a successive decomposition of the signal in different scales. At each step, the corresponding details are separated, providing useful information for detecting and characterizing short time phenomena or abrupt changes of energy.The fundamental idea how to estimated human state is based on the measuring of dynamic changes of various psychological measures such as EEG, ECG, EMG, etc. by means of medical equipment such as polygraph, and then processing the characteristic (parameterization) of these measured signals to estimate various kinds of human state such as temporal level of mental workload. Naturally, the EEG signal involves the biggest amount of information considering human behavior[35].

In 2013, Dipti Upadhyay , EEG signals were used to extract the information and classify with different mental task. EEG data was collected. This data contains recording of 5 subjects in different mental task conditions (Resting, math, letter composition, geometric figure rotation task). EEG Signals were pre-processed and filtered. EOG artifacts were removed by visual inspection. For classification of these mental tasks wavelet was used to extract the features. Second order Daubechies mother wavelet has been used to get the wavelet coefficients for the selected EEG epochs. Mean, maximum, minimum and standard deviations values of wavelet coefficients for the EEG epochs were selected as inputs for the training the network and to classify mental tasks. This architecture of ANN was also found effectively differentiating the EEG from different mental tasks conditions Resting (98%) multiplication (92%), Letter composition (92%) and rotation (96%)[3]

Methodology

3.1 Introduction:

Brain Computer-Interfacing is a methodology that provides a way for communication with the outside environment using the brain thoughts. The success of this methodology depends on the selection of methods to process the brain signals in each phase .EEG signals will be generally represented in high dimensional features space and it is very difficult to interpret. Machine learning methods are helpful for interpreting high dimensional feature sets and analyze the characteristics of brain patterns. Wave let is one of the popular Machine Learning methods for classifying EEG signals and has the ability to indicate signal which localized in time or frequency domain [35]

The main goal of proposed work is to analyze the EEG signal for the detection of brain abnormalities. This system involves the process such as EEG signal pre-processing, feature extraction and classification. The modules of the proposed system are:

1. **Pre-processing**
2. **Feature extraction**
3. **Classification**

The first module deals with the EEG signal pre-processing method. It is be used to remove the noises from the signal. The next module extracts the EEG signal features from decomposed signal.

Feature extraction and classification algorithms commonly used in the literature are examined. Some of the studies with a high rate of classification accuracy

To analysis EEG signal we need a row data to import it in Matlab, after that we need to do some preprocessing to remove noise from it. Then extract feature from this signal and select the best of this feature. Now the signal is ready to classify as shown in figure (3.1). It can explain this method by details.

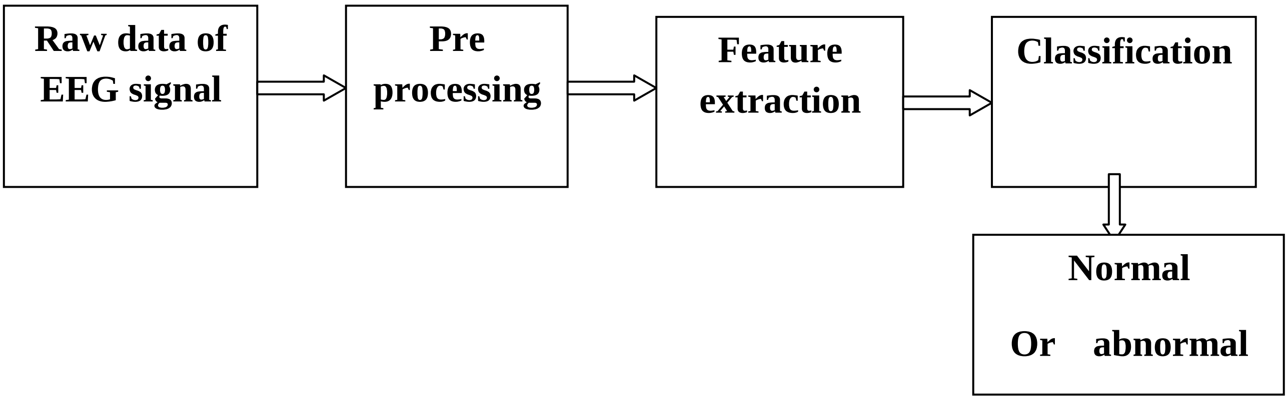

Figure (3.1) Basic steps applied in EEG data analysis

3.2 Method:

Matlab was used in pre processing, feature extraction by using wavelet method and classification by using the EUC (Euclidean distance) of the power spectrum and the conditional (IF).

3.2.1MATLAB

MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by Math Works, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and FORTRAN.
Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing capabilities. An additional package, Simulink, adds graphical multi-domain simulation and Model-Based Design for dynamic and embedded systems. In 2004, MATLAB had around one million users across industry and academia.[37] MATLAB users come from various backgrounds of engineering, science, and economics. MATLAB is widely used in academic and research institutions as well as industrial enterprises.

3.3 Raw Data:

Raw data brought from website (www.bci competition)(2 May 2015 at 4 PM), firstly made download to the signal and then import to Matlab environment for processing 10 data were normal and 10 were abnormal.

3.4 Pre-processing:

The process involves filtering that portion of the signal that is more important for signal classification. For example the alpha band is more important as far as the motor actions are concerned. Preprocessing also includes the removing the artifacts that creep into the signal due to various reasons like eye blinking or muscular activity. These often include the application of filters. The raw EEG signal contains some noises that occur due to eye blinking, muscle artifacts and breathing deeply at the testing time. These noises affect the edge function of the EEG signals and the structure of the wave form. The noises are removed by the discrete wavelet transform which decomposes the full-band signal into sub-band signals. The process of the discrete wavelet transform is as follows:

a) The EEG signal is processed with the deubechies wavelet which is used to remove the noises and decompose the signal into sub-bands signals.

b) Based on the frequency range the sub-band signals are separated as delta, theta, alpha, beta and gamma.

c) After the decomposition, the noises are reduced then the Error rate is calculated.

3.4.1 Filter:

Filters are fundamental to many circuit designs and they exist for analog and digital applications. Applications include noise reduction in communication systems, band-limiting of signals before sampling them, [37].

3.4.1.1 Band-pass filters

Is a device that passes frequencies within a certain range and rejects (attenuates) frequencies outside that range. Optical band-pass filters are of common usage.

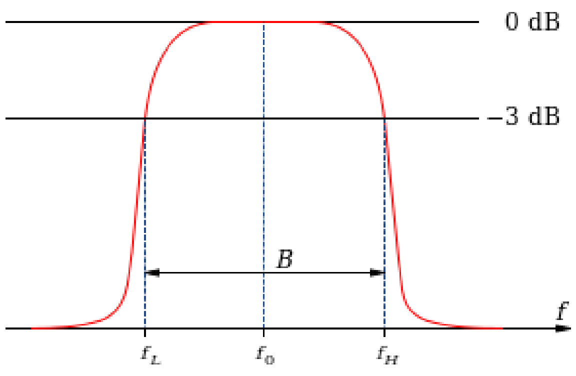

Figure (3.2) transfer function for band pass filter.

A band-pass filter can be characterized by its Q-factor. The Q-factor is the inverse of the fractional bandwidth. A high-Q filter will have a narrow pass band and a low-Q filter will have a wide pass band. These are respectively referred to as narrow-band and wide-band filters. [34]
In order to apply band pass filter in EEG signal, we need to determine the cut off frequency and filter order. In this research the cutoff frequency is (fc1=0.5HZ ,fc2=40HZ) so the rang of band is (0.5- 40 HZ) depend on data use.

3.5 Feature extraction:

The extraction methods are used to reduce the dimensionality of the features. Extracted features represent the characteristics of original signal without redundancy. The features can be extracted from the EEG signal in two different domains such as Time domain features (TDF) and Frequency domain features (FDF).

3.5.1 Time domain features:

Time domain analysis process consists of statistical calculations. The time domain features are: Mean, Median, Root mean square, Standard deviation. These time domain features are calculated for the reconstructed EEG signal amplitude and time duration.

3.5.1.1 Mean:

Mean corresponds to the centre of a set of value. The Mean is calculated for each and every sub-band signals.

$$M= \sum_{i=1}^{n}(x/n). \qquad (3.1)$$

Since: M=mean, x variable, n=number of variable

3.5.1.2 Median:

In statistics and probability theory, the median is the numerical value separating the higher half of a data sample, a population, or a probability distribution, from the lower half. The median of a finite list of numbers can be found by arranging all the observations from lowest value to highest value and picking the middle one. The median can be used as a measure of location when a distribution is skewed.[37]

3.5.1.3 Root mean square

In mathematics, the root mean square (abbreviated RMS or rms), is a statistical measure of the magnitude of a varying quantity. It is especially useful when variants are positive and negative. It can be calculated for a series of discrete values or for a continuously varying function. Its name comes from its definition as the square root of the mean of the squares of the values.[36]

$$\text{RMS}=\sqrt{(M.\hat{}2)} \qquad (3.2)$$

3.5.1.4 Standard deviation

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

The standard deviation is a parameter closely associated with the mean. It refers to the dispersion of values in a mammographic image around the mean. Standard deviation is given as:

$$\text{SD}=\sqrt{(mean)}^2 \qquad (3.3)$$

3.5.2 Frequency domain feature

3.5.2.1 Power Spectral density

In statistical signal processing, statistics, and physics, the spectrum of a time-series or signal is a positive real function of a frequency variable associated with a stationary stochastic process, or a deterministic function of time, which has dimensions of power per hertz (Hz), or energy per hertz. [36] The power spectral is one of the most important features can extract for signal. The power spectral gives a row of values. In order to get one value we compute a total power spectrum.

3.6 Feature selection

A feature selection is optional and is used in the case if a large number of features found and one is needed or more to be studied. Statistical methods can be applied such as principal component analysis, Calculated all statistical value by wave let

3.6.1 Wavelet transformation

Wavelet transformation is a time-scale analysis method and has the capacity of representing local characteristics in the time and scale (frequency) domains. In the low frequency, it has a lower time resolution and high frequency resolution, the high frequency part has the high time resolution and lower frequency resolution, it is suitable for detection of the normal signal, which contains transient anomalies and shows their ingredient [40]

3.6.2.1 Deubechies wavelet

Daubechies(1988) discovered an important and useful class of such filter coefficients. The simplest set has only 4 coefficients (DAUB4), and will serve as a useful illustration. Consider the following transformation acting on a data vector to its right .The discrete wavelet transform proceeds by the pyramid algorithm. the last N/2 elements of the transformed vector, and another transform of the N/2 smooth components is performed to provide a detail vector and a smooth vector each of length N/4. Then the detail at this level is stored and another transformation of the N/4 smooth vector is performed. This continues until only one smooth coefficient and one detail coefficient remain, at which point N coefficients of the transformed coefficient vector have been obtained. We can illustrate this process with an initial vector of length N=8[40].

3.7 Classification:

The classification process is divided into the training phase and the 5testing phase. During training, the features are extracted from the signal is known.

The distance (error) of PSD is calculated between reference signal (data 11 normal signal) and sample signal (tested) by using Euclidean distance, which means the distance between two points, determines by

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(pi - qi)^2} \qquad (3.4)$$

Where $d(p,q)$ is Euclidean distance, and are arrays of PSD in this study [39].

Step 1: calculated the different of power spectrum between the reference signal (data11) and (data1-data10) all these data s are abnormal

Step2: calculated the different of power spectrum between the reference signal (data11) and (data11-data20) all these dates are normal

Step 3: calculated eucsum and the value was rounded

Step 4: if loop, if eucsum minimum or equal to (2) output of signal is normal, otherwise abnormal

Finally, the accuracy, sensitivity, specificity of the classification is depends on the efficiency of the training

3.8 Test work

In order to test our work we calculate accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV). Using four categories output which are true positive (TP), false positive (FP), true negative (TN) and false negative (FN).

3.8.1 Accuracy

The accuracy of a measurement system is the degree of closeness of measurements of a quantity to that quantity's actual (true) value

$$\text{Accuracy} = (TP + TN) / \text{The number of data} \qquad (3.5)$$

3.8.2 Sensitivity

The sensitivity tells us how likely the test is come back positive in someone who has the characteristic. Among all people that have the characteristic, what proportion will test positive?

$$\text{Sensitivity} = TP \text{ by } (TP+FN) \qquad (3.6)$$

3.8.3 Specificity

The specificity tells us how likely the test is to come back negative in someone who does not have the characteristic. Among all people without the characteristic, what pro-portion will test negative?

$$\text{Specificity} = TN / (FP+TN) \qquad (3.7)$$

3.8.4 Positive predictive value

The positive predictive value tells us how likely someone is to have the characteristic if the test is positive. Among all people that test positive, what proportion truly has the characteristic?

$$PPV = TP / (TP+FP) \qquad (3.8)$$

3.8.5 Negative predictive value

The negative predictive value tells us how likely someone is to not have the characteristic if the test is negative. Among all people that test negative, what proportion truly does not have the characteristic?

$$NPV = TN / (TN+FN) \qquad (3.9)$$

RESULTS AND DISCUSSIONS

4.1 Introduction:

Firstly import data set into Matlab then started pre-processing, feature extraction and then feature extraction selection. The output of each stage was shown below step by step.

4.2 Results

Row data consist of 15 signals (data1-data15) abnormal signal (epilepsy) and 10 data (data16-data25) normal signal open eyes there were three figures for each data.

4.2.1 Data Set and pre-processing

Figure (1) described EEG signal, band pass filter, Figure (2) described wavelet function (A8, D1, D2, D3, D4, D5, D6
D7).figure (3) shows the original signal and power spectrum from each data from 1-15
Firstly, imported data 16 and made it as reference signal .

Data16:

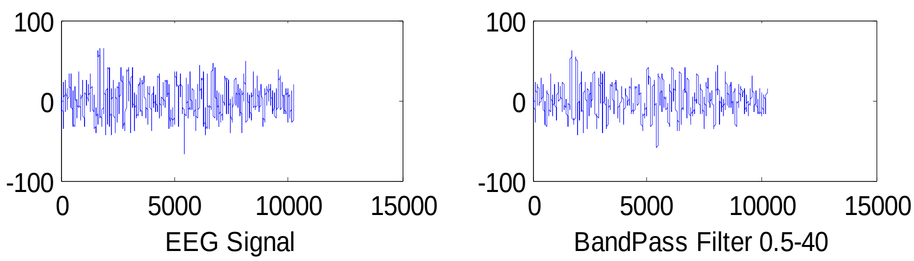

Figure (4.1)EEG signal,EEG signal after, (band pass filter)

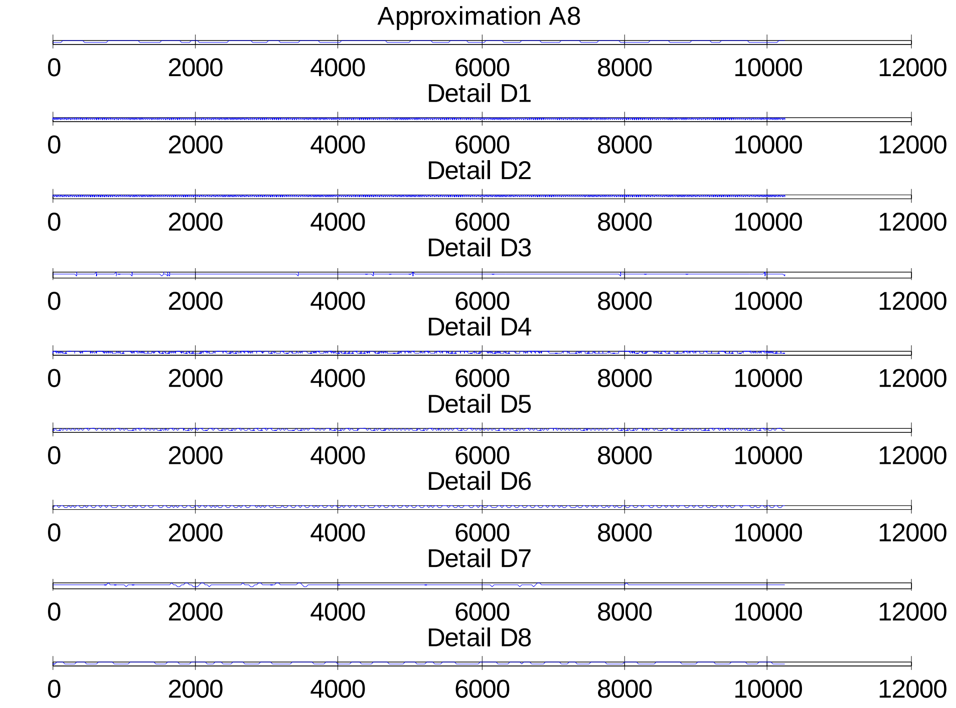

Figure (4.2) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

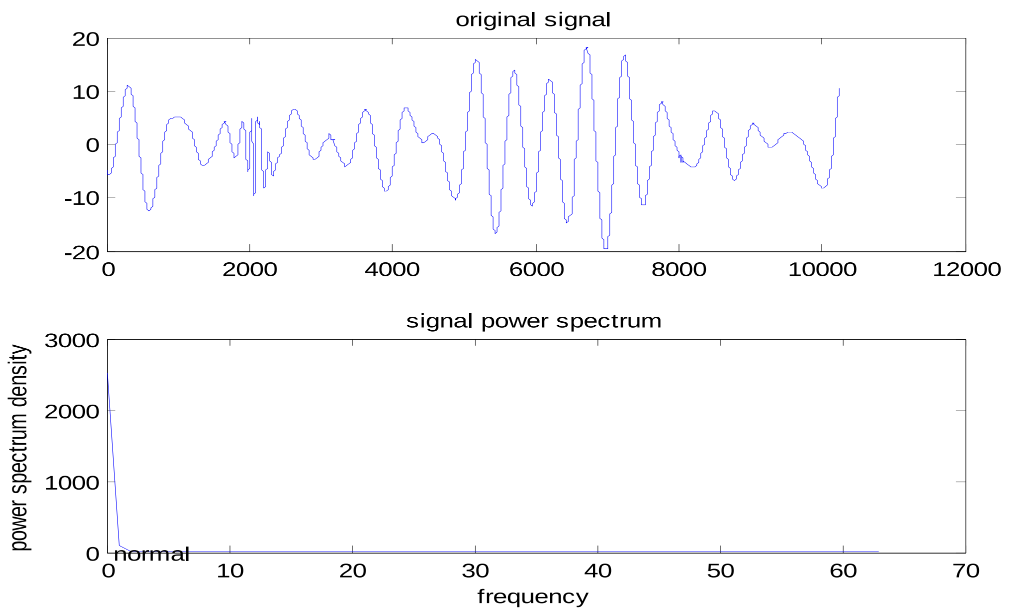

Figure (4.3) (original signal of EEG,power spectrum of EEG signal)

Data 1:

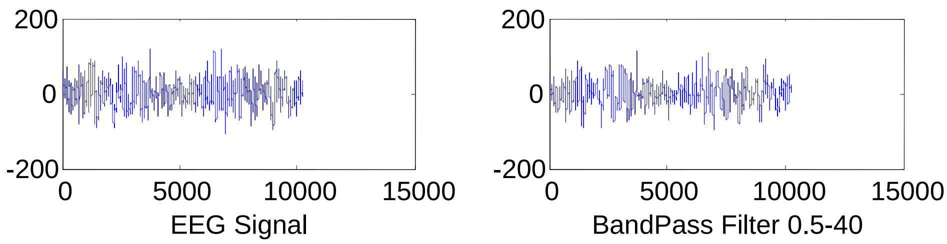

Figure (4.4) EEG signal,EEG signal after, (band pass filter)

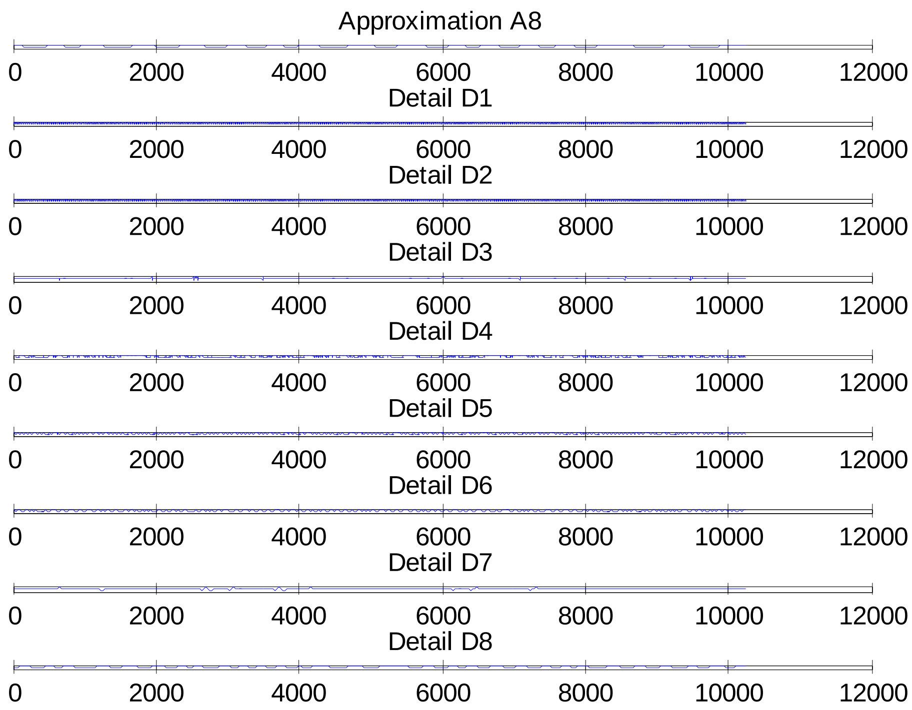

Figure (4.5) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

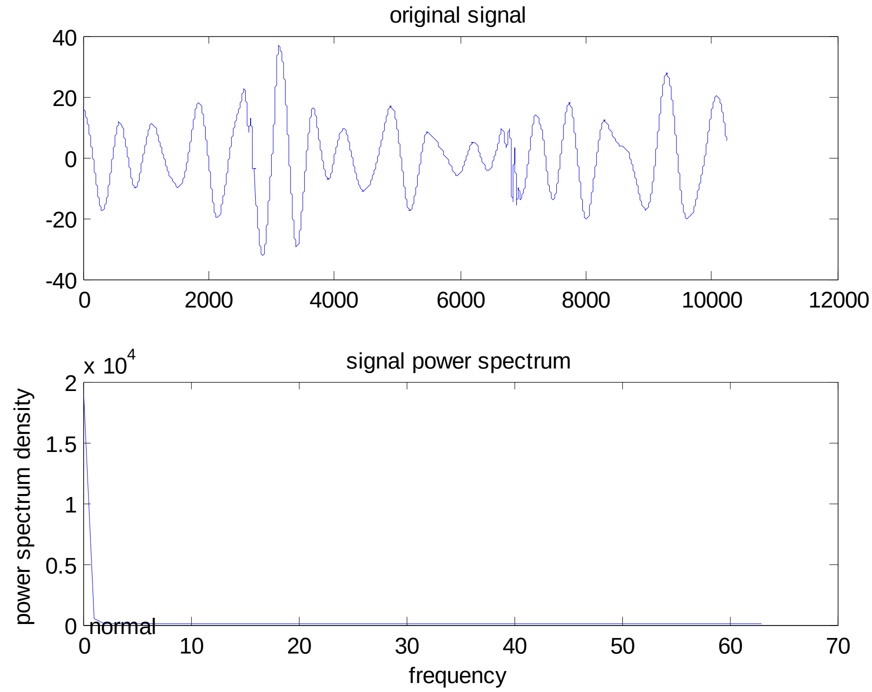

Figure (4.6) (original signal of EEG, power spectrum of EEG signal)

Data 2:

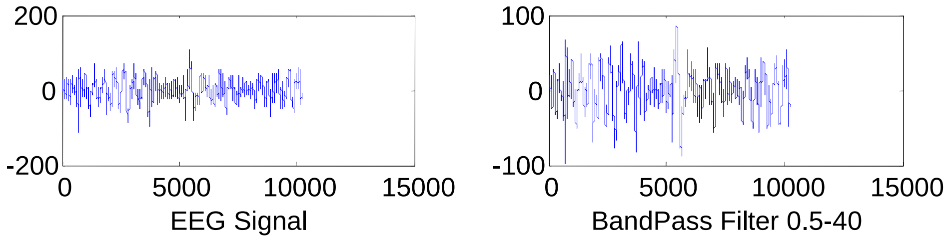

Figure (4.7) EEG signal,EEG signal after, (band pass filter)

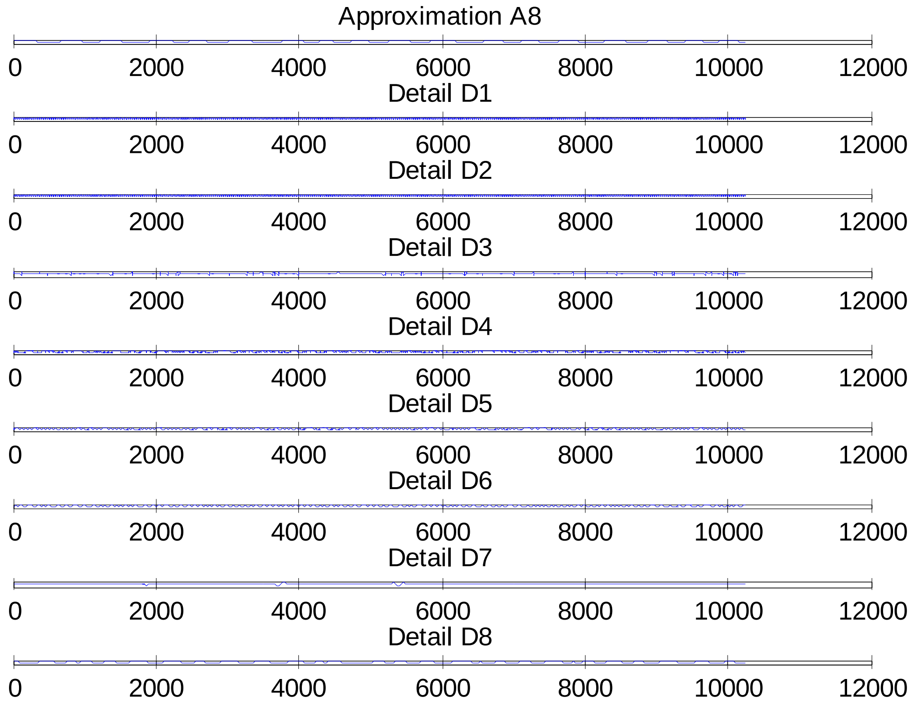

Figure (4.8) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

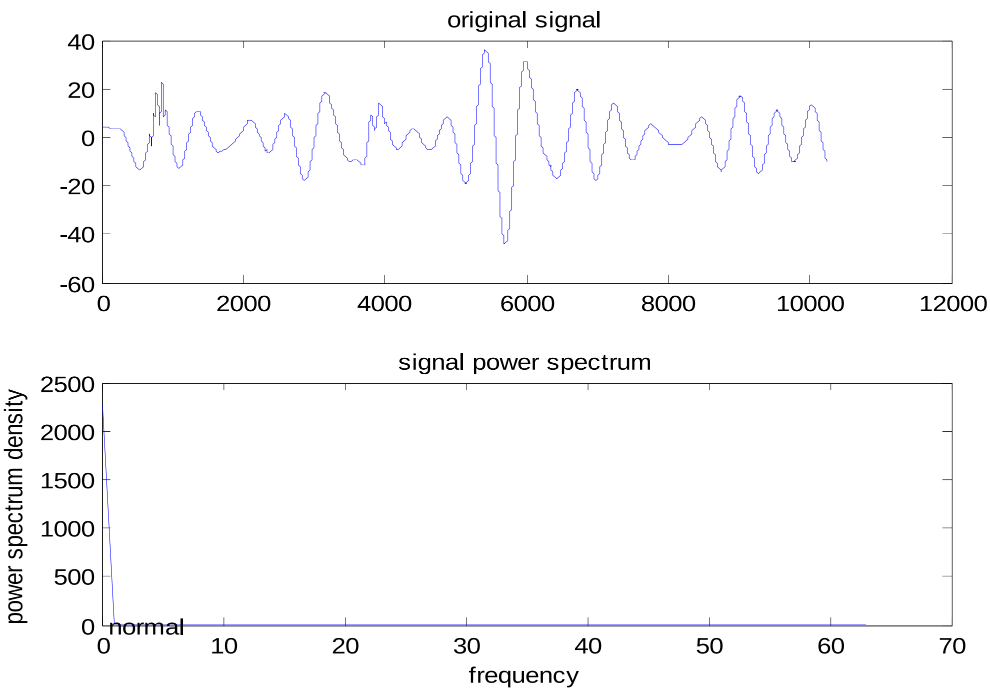

Figure (4.9) (original signal of EEG, power spectrum of EEG signal)

Data 3:

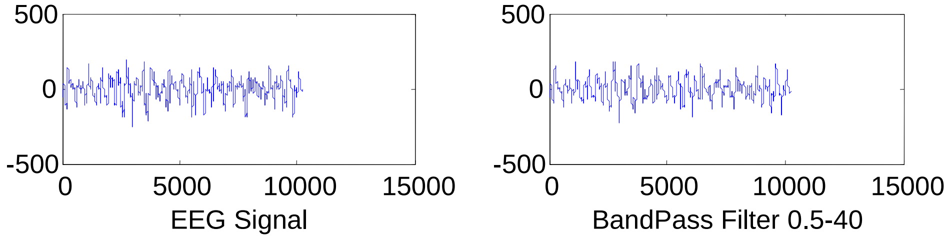

Figure (4.10) EEG signal,EEG signal after, (band pass filter)

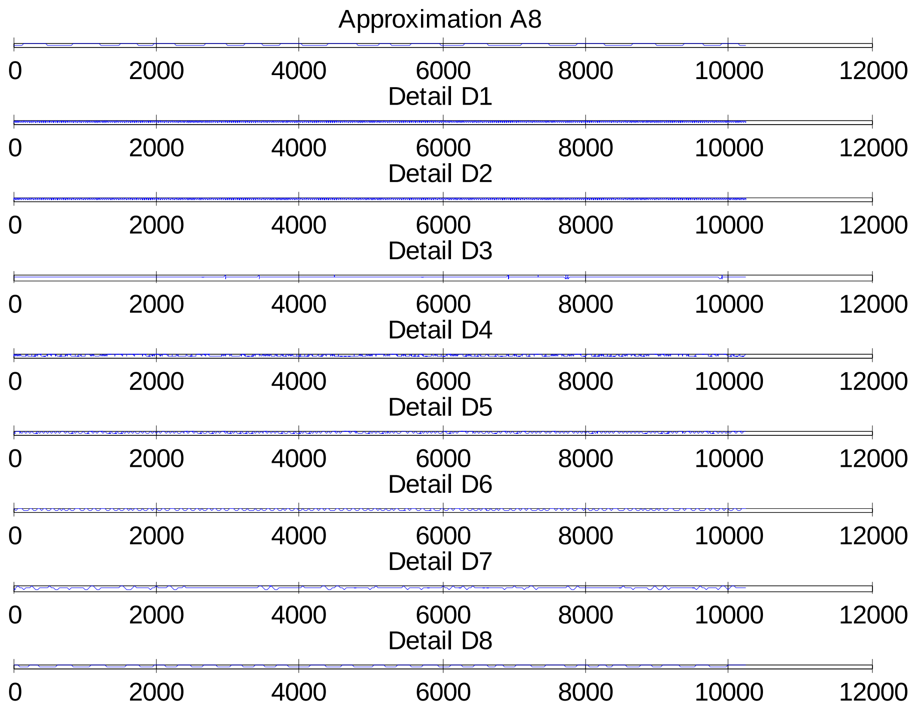

Figure (4.11) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

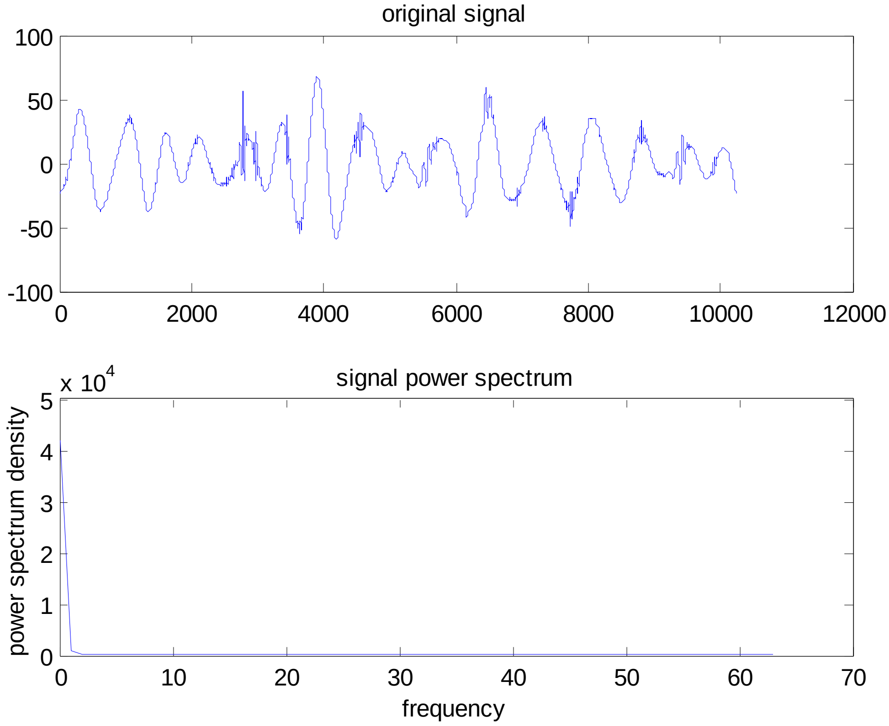

Figure (4.12) (original signal of EEG, power spectrum of EEG signal)

Data 4:

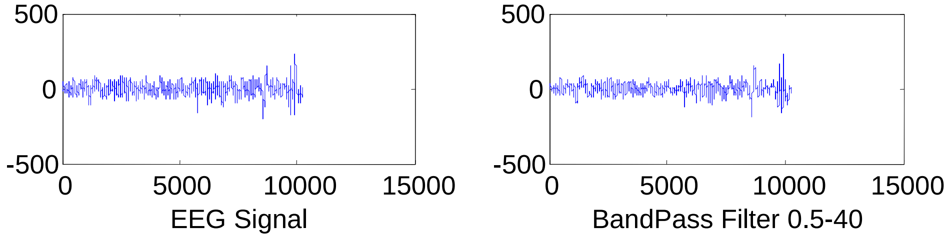

Figure (4.13) EEG signal,EEG signal after, (band pass filter)

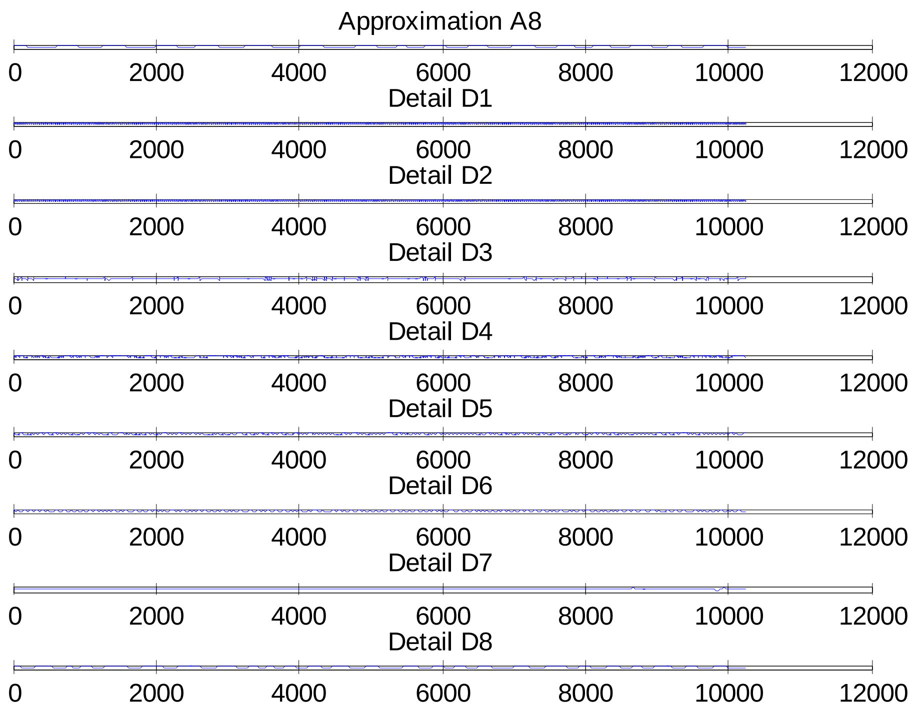

Figure (4.14) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

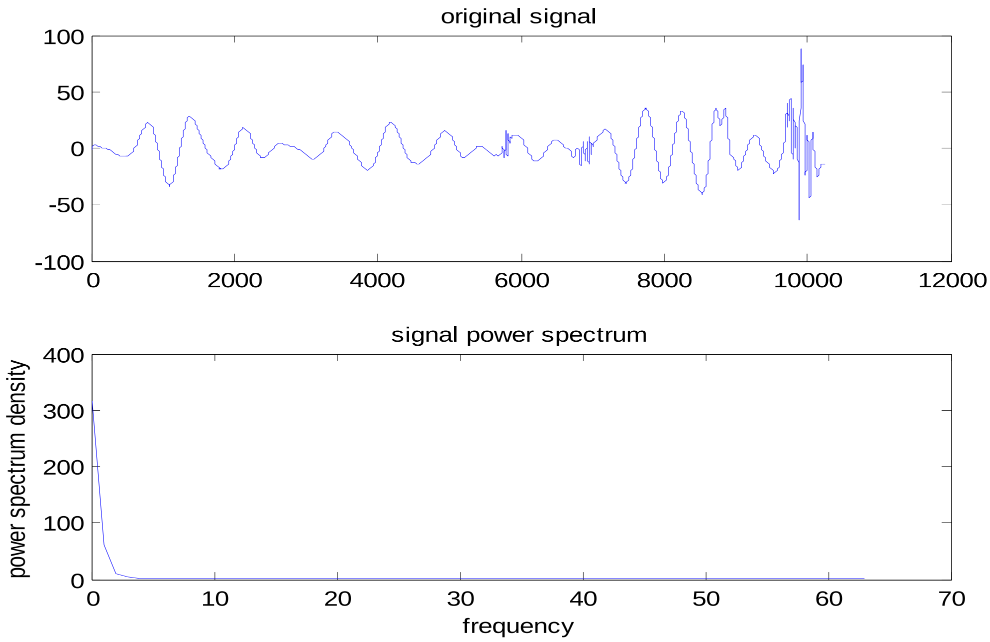

Figure (4.15) (original signal of EEG, power spectrum of EEG signal)

Data 5:

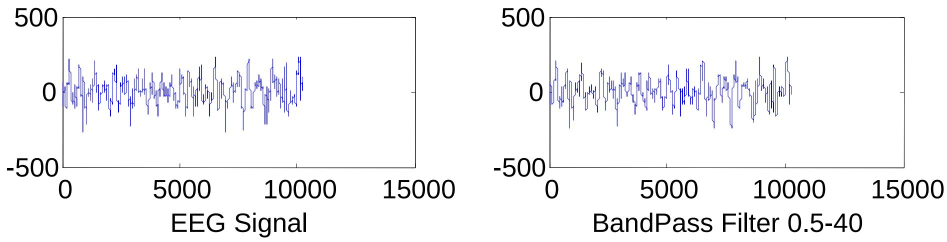

Figure (4.16) EEG signal,EEG signal after, (band pass filter)

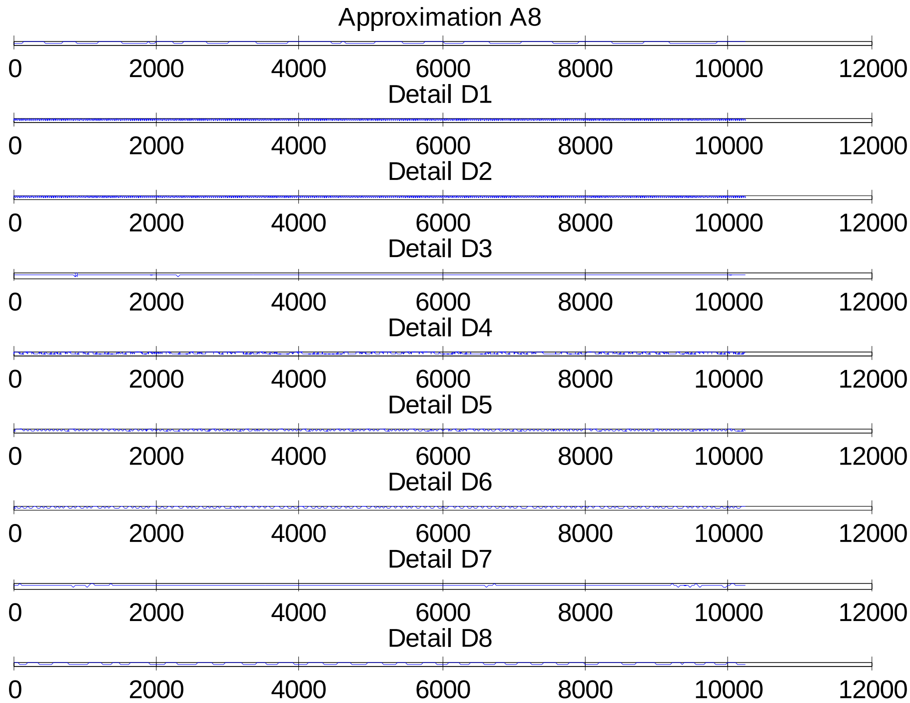

Figure (4.17) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

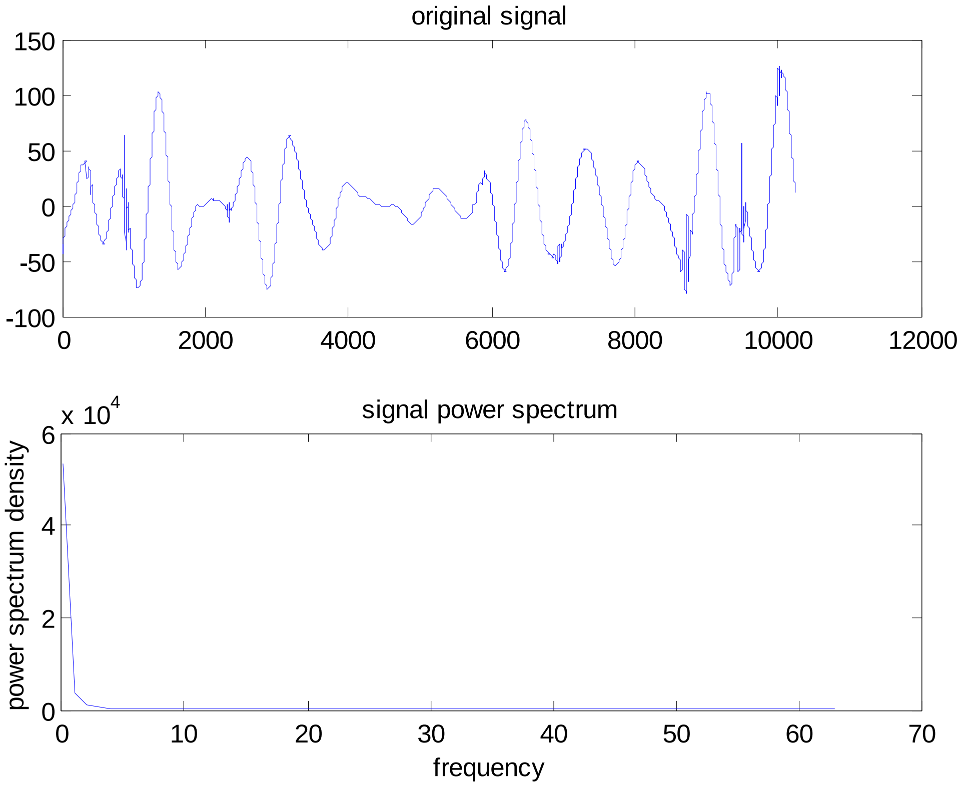

Figure (4.18) (original signal of EEG, power spectrum of EEG signal)

Data6:

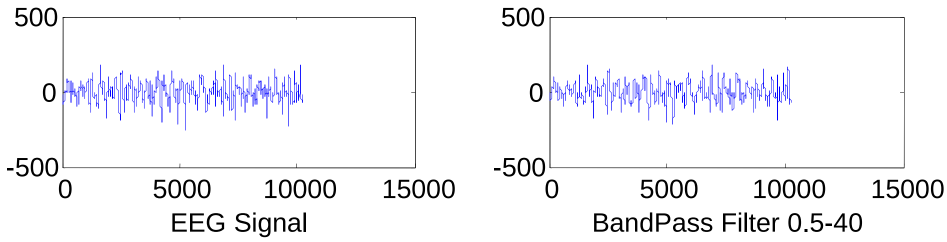

Figure (4.19) EEG signal,EEG signal after, (band pass filter)

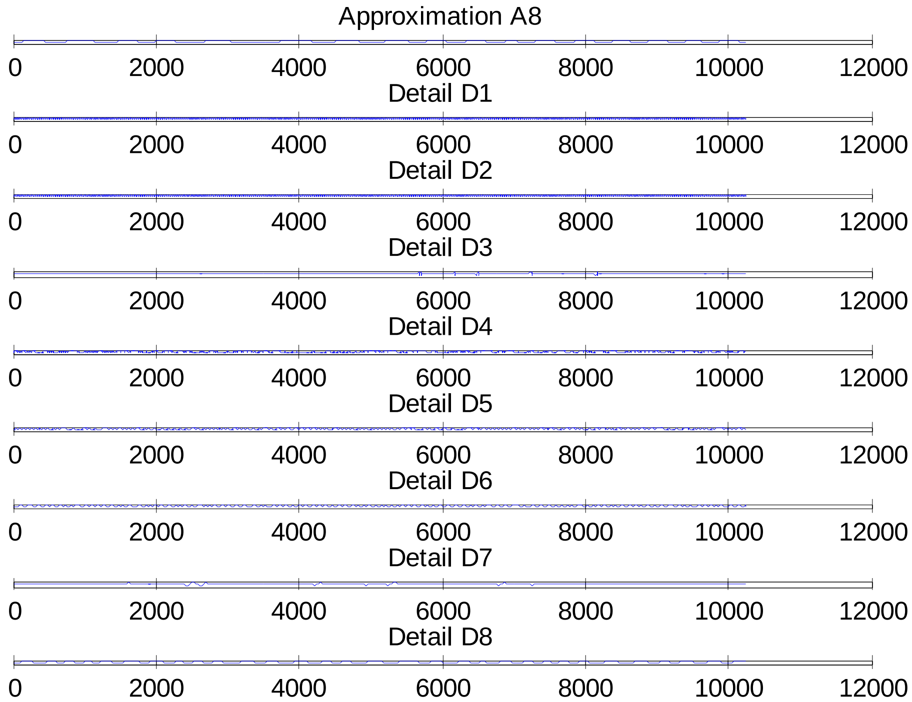

Figure (4.20) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

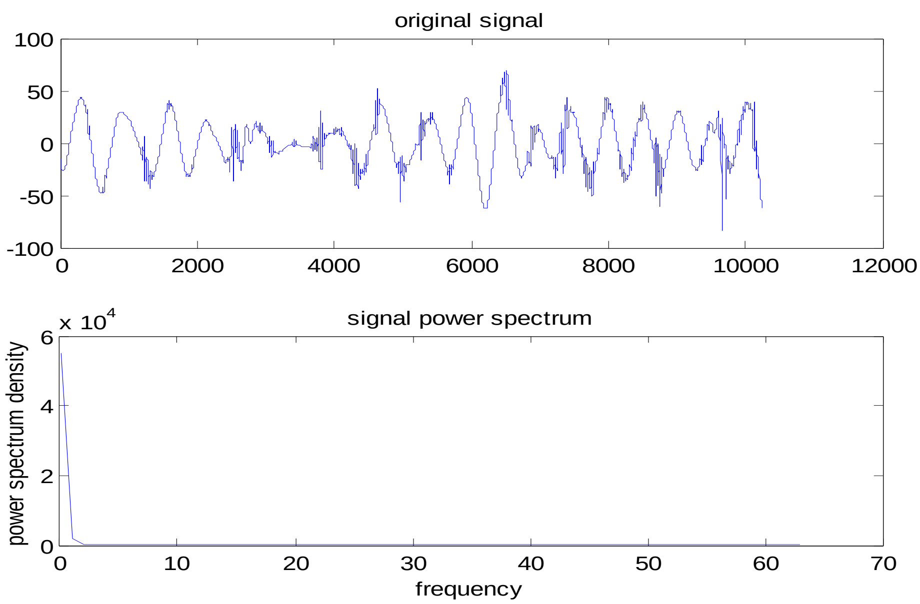

Figure (4.21) (original signal of EEG, power spectrum of EEG signal)

Data 7:

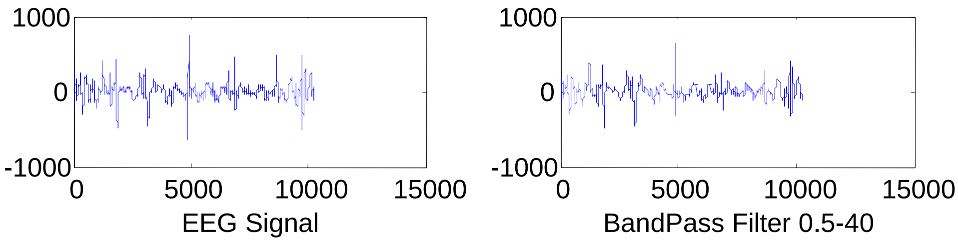

Figure (4.22) EEG signal,EEG signal after, (band pass filter)

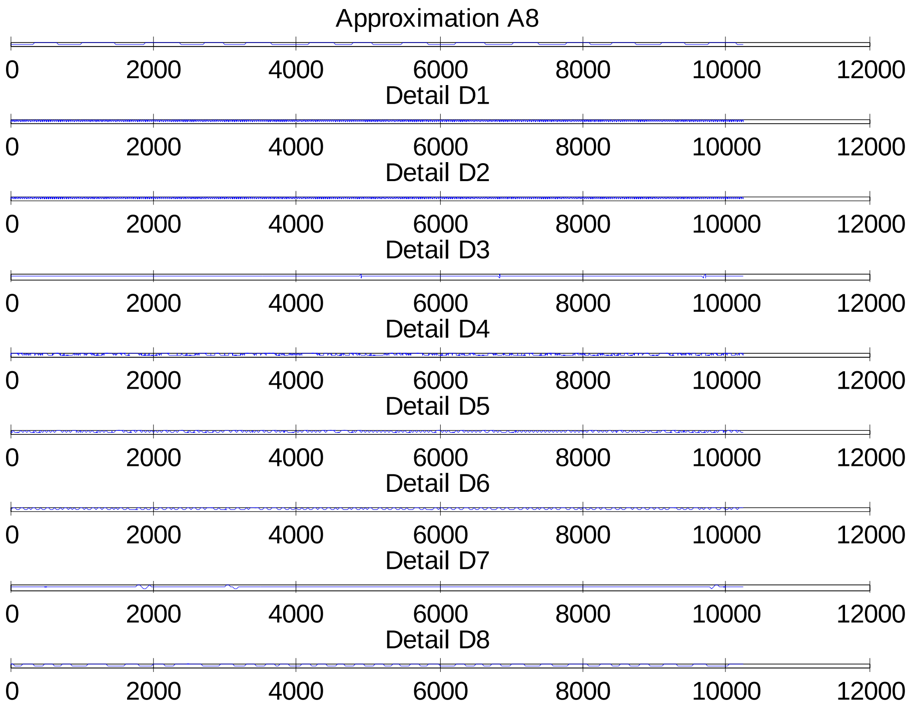

Figure (4.23) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

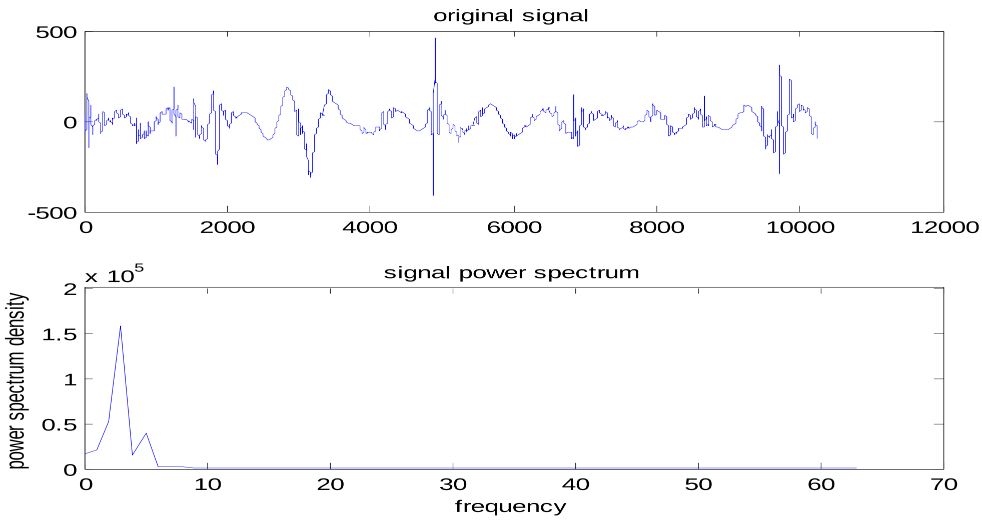

Figure (4.24) (original signal of EEG, power spectrum of EEG signal)

Data 8:

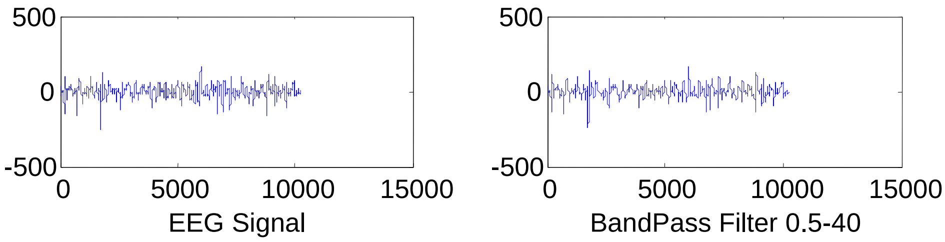

Figure (4.25) EEG signal,EEG signal after, (band pass filter)

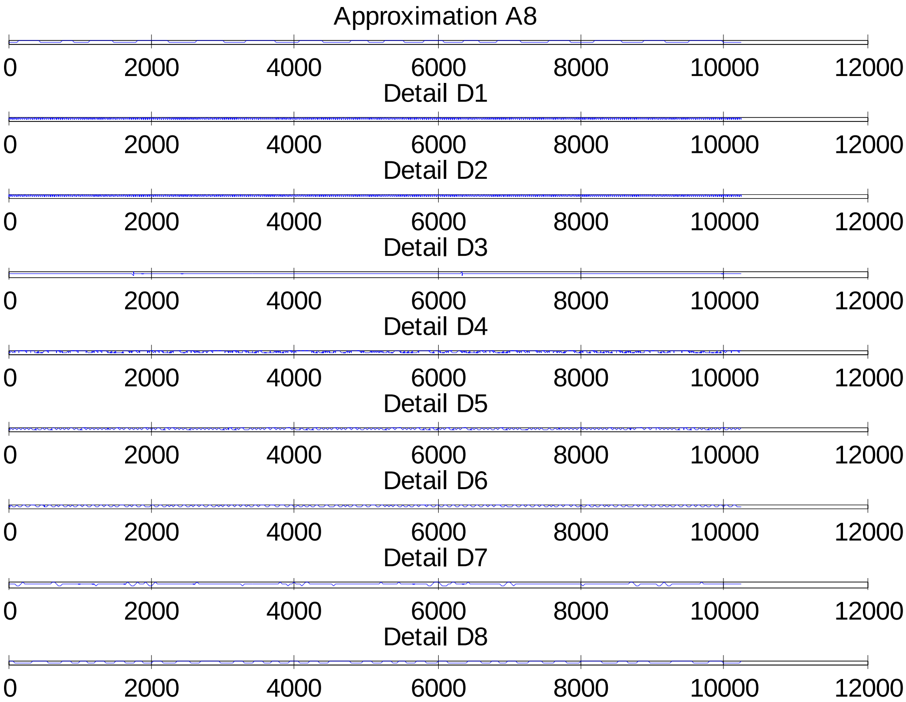

Figure (4.26) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

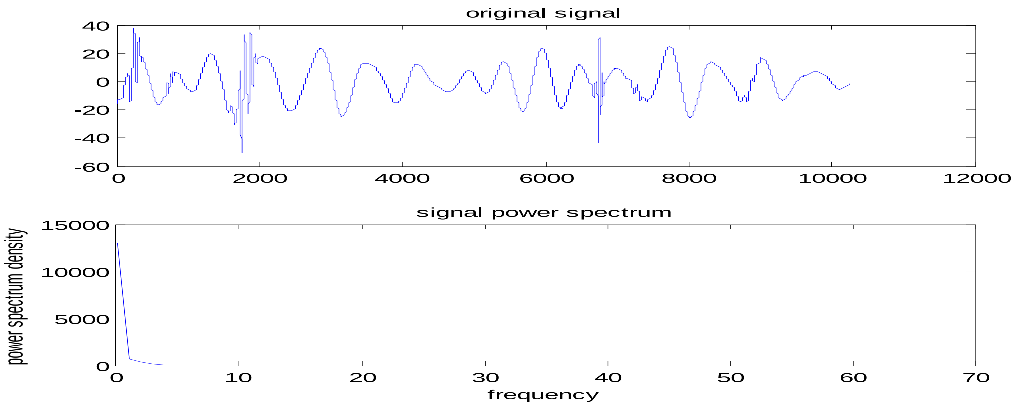

Figure (4.27) (original signal of EEG, power spectrum of EEG signal)

Data 9:

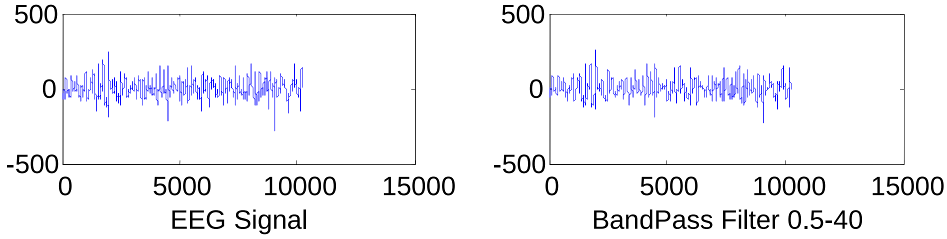

Figure (4.28) EEG signal,EEG signal after, (band pass filter)

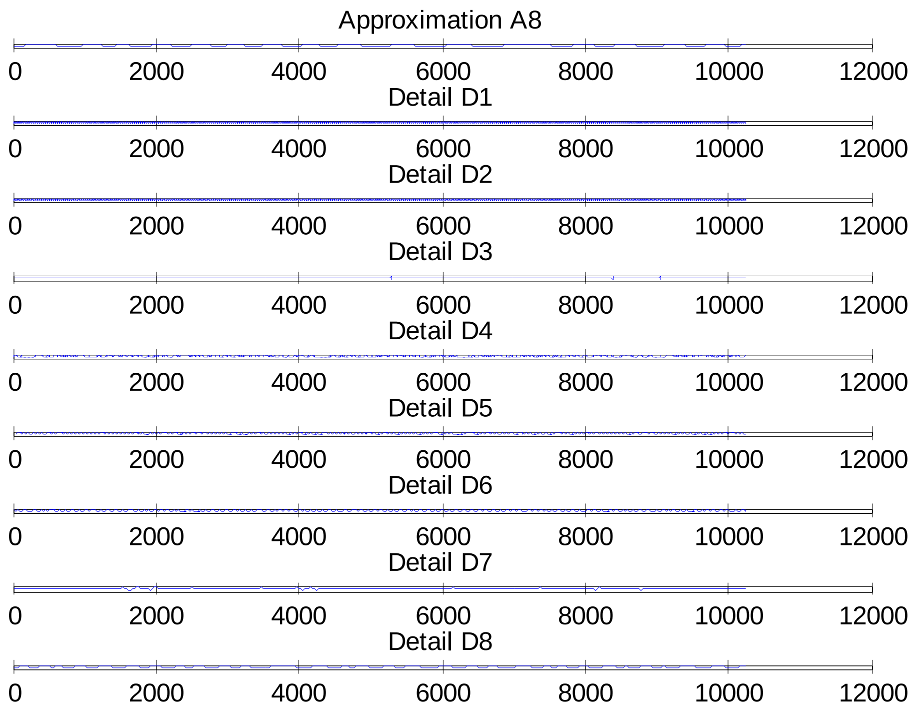

Figure (4.29) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

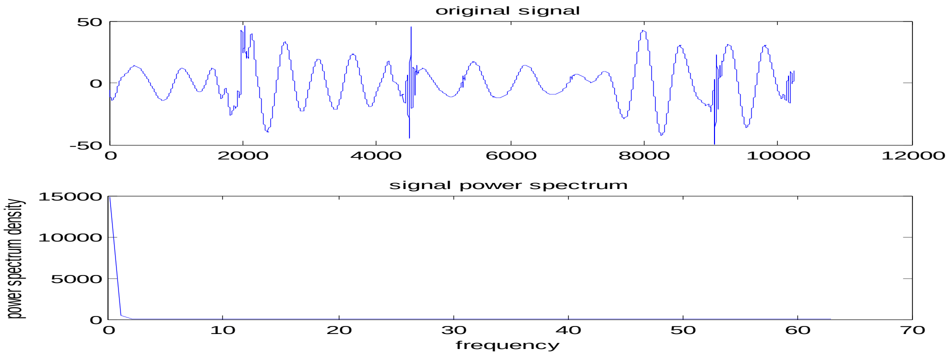

Figure (4.30) (original signal of EEG, power spectrum of EEG signal)

Data10:

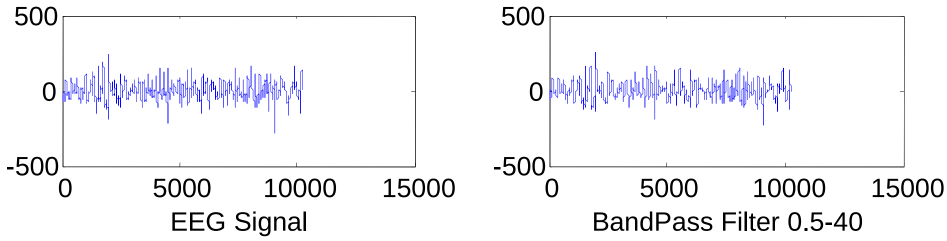

Figure (4.31) EEG signal,EEG signal after, (band pass filter)

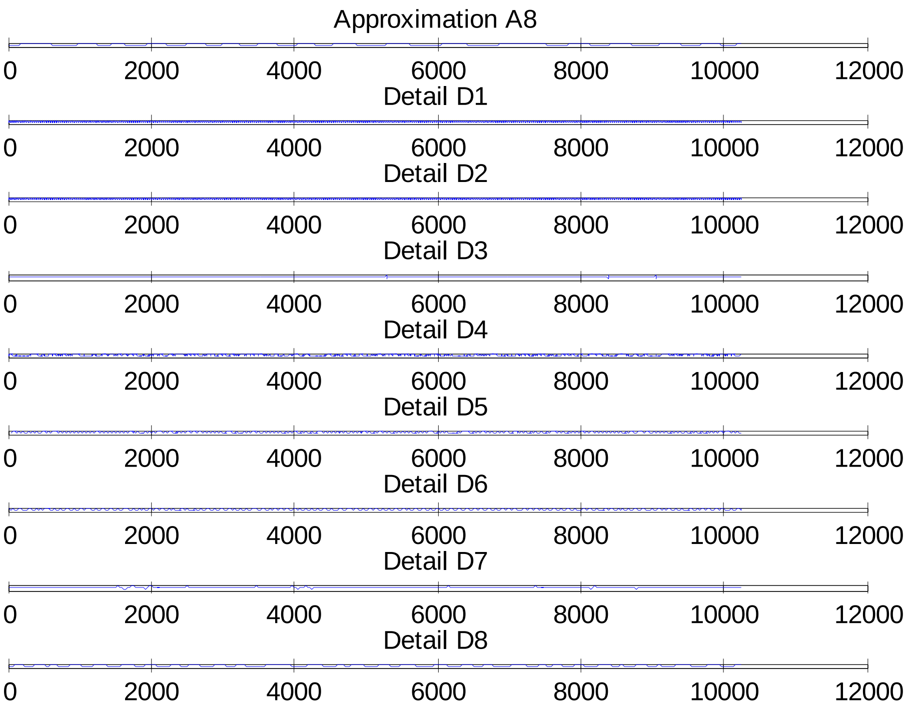

Figure (4.32) wavelet function (A8, D1, D2, D3, D4, D5, D6,D7)

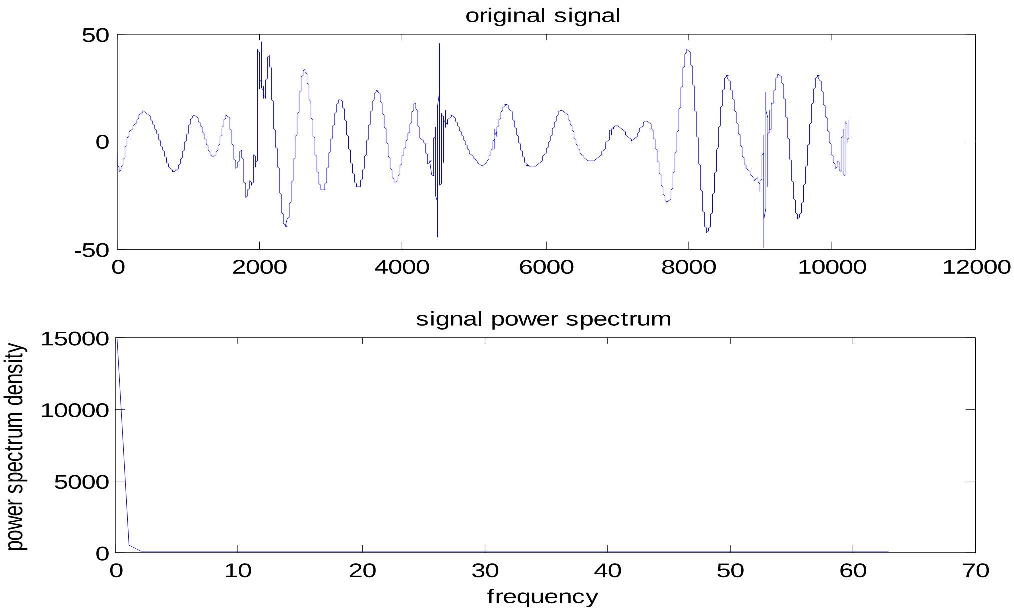

Figure (4.33) EEG signal,EEG signal after, (band pass filter)

4.2.2 Features extraction stage:

The EEG signal features extraction was done using 10 samples, they were used to detect the analysis and compare the features using statistical method by the:

[Mean, Median, Root Mean Square, Standard Deviation table (4.1, 4.2) show the value of each calculated parameters , every 10 samples represent case study [epilepsy] .and also the statistical feature of the 10 data set(normal)

Matlab program found the value of every 10 data which mention a above and also for the 10 normal signals and compare between all of them after using wavelet transformation.

Table (4.3,4.4) show the values of euc for normal and abnormal signals

4.3 Analysis of statistical features:

Table (4.1): extracted features for epilepsy by using wavelet

Data set	Mean	Median	RMS	Std
Data 1	0.1860	0.6131	0.0588	12.1315
Data 2	0.1047	-0.0336	0.0331	11.3041
Data 3	-0.1040	-0.4582	0.0329	22.7213
Data 4	-0.0657	-0.6399	0.0208	15.5692
Data 5	1.4785	0.0606	0.4676	39.0352
Data 6	0.2318	-0.4189	0.0733	23.1581
Data 7	0.5738	1.9812	0.1814	69.6282
Data 8	0.0401	0.4082	0.0127	12.1347
Data 9	0.1294	0.2192	0.0409	16.1405
Data 10	-0.0448	-0.1186	0.0142	24.3168
Data 11	0.0412	-1.2301	0.0412	61.717
Data 12	0.2838	1.1340	0.2838	67.339
Data 13	0.9617	-28.795	0.9617	134.94
Data 14	1.0732	2.8823	1.0733	59.547
Data 15	-0.741	-1.6297	0.7414	83.214

Table (4.2): extracted features for the normal EEG signal

Data set	Mean	Median	RMS	Std
Data 16	0.05051	1.43329	0.05051	32.6699
Data 17	0.1996	1.3946	0.1996	34.846
Data 18	0.3352	0.7022	0.3352	36.2556
Data 19	-0.1506	0.17383	0.1506	30.5392
Data 20	0.4953	-0.6211	0.4953	33.8207
Data 21	0.2117	-1.7391	0.2117	33.623
Data 22	0.2135	-0.4852	0.2135	31.615
Data 23	0.0458	0.3607	0.0458	23.153
Data 24	0.1337	0.9381	0.1337	26.845
Data 25	0.4989	-1.199	0.4989	38.062

In this part of the research a dataset with 25 patients was used to evaluate the performance of the method of the multiple sub signals from EEG signal using wavelet,Using statistical representation the signals, including mean, median, standard deviation, root mean square

A mathematical calculation then was done to evaluate each method used and detect the percentage of each method on its statistical results.

As known that the EEG signal contains sub signals (alpha, beta, theta, gamma, and delta), each has unique frequency, and noise may occur during the acquisition of the signal to the image processing.

Matlab was used to apply the methods, because of the powerful toolbox which designed to accomplish a powerful environment to develop the algorithms.

Matlab 2010 was selected because of its completeness updates on the bugs found in the oldest versions.

4.4 Performance Analysis:

For checking our work we import 25 data set for epilepsy and compare it with normal EEG signal firstly calculated the power spectrum of normal signal(data16) and make it as reference then calculated all the power spectrum for normal and abnormal signal and found the square of different between the reference data and normal ,make summation to all the square different and take square root to the summation, finally take the rounded of the value after that used if condition to identifies which signal is normal and abnormal .Then took the value of power spectrum to calculate the accuracy, sensitivity, specificity, positive predictive value(PPV) and negative predictive value(**NPV**) are calculated Using four categories output which are true positive (TP), false positive (FP), true negative (TN) and false negative (FN).
Selection of the right features is among the most important components in the design of proper classifiers since even the best classifier will perform very poorly if the features are not selected well

Table (4.3): Performance analysis for epilepsy (power spectrum):

Abnormal signal different	Euc
data16 to data1	1.6463
data16 to data2	219.989
data16 to data3	3.9335
data16 to data4	2.2074
data16 to data5	5.0978
data16 to data6	5.2458
data16 to data7	2.44669
data16 to data8	1.0608
data16 to data9	1.2333
data16to data10	7.6512
data16to data11	4.2343
data16 to data12	3.5903
data16 to data13	2.3251
data16 to data14	5.1021
data16 to data15	2.0845

Table (4.4): Performance analysis for normal signal (power spectrum):

normal signal different	Euc
data16 to data16	0
data16 to data17	1.1178
data16 to data18	1.1213
data16 to data20	2.8915
data16 to data21	743.7973
data16 to data21	2.0106
data16 to data22	1.3506
data16 to data23	1.0563
data16 to data23	3.6554
data16 to data24	1.5785

Table (4.5):Performance (power spectrum)

Categories	Case study
TP	13
FN	2
FP	2
TN	8

Accuracy	84%
Sensitivity	86.66%
Specificity	80%
PPV	86.66%
NPV	80%

As a result it was found that the wavelet has the most accurate values while examining the power spectrum of the normal and abnormal EEG signal.

CHAPTER FIVE

Conclusion and Recommendations

5.1 Conclusion

EEG signal provides valuable information of the brain function and neurobiological disorders as it provides a visual display of the recorded waveform and allows computer aided signal processing techniques to characterize them. With an EEG signal free of artifacts, a reasonably accurate detection this problem increases the number of false detection that commonly plagues all classification systems. Moreover the usage of manual prediction cases is a difficult to get accurate classification. This problem increases the number of miss diagnose that commonly plagues all classification systems. We matlab command and if condition for classify the signals and easily differentiate the normality and abnormality(Epilepsy).

Thus the objective of this study is to extract sub-signals from EEG signal using wavelet theories in order to obtain useful results with accepted value .

5.2 Recommendations and Future Works

- The research cover most statically features, and limited database such the one created on the Matlab to compare the samples, Use different type of features, Moreover such huge database can increase time for searching so a search algorithm should be used.
- We can made classification algorithm of EEG data which, based on a large number of features extracted after wavelet transform and statistical pattern recognition by using support vector machine, I tried to use support vector machine in this research but the time was too short.
- Activating real time analysis
- We can add more cases and we can compare between them especially in classification
- Also we can specified about the age of the patient to make research more clear

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Appendices

```
load('data.mat');
 s=data1;% taken values from c3 electrode
data1=data1;
figure;p=plot(s);
title('EEG Signal')
fs = 500;
% Sampling frequency
N=length(s);
figure(1);
rawdata1=data1;
subplot(3,2,1);
plot(data1,'DisplayName','data','YDataSource','data');
xlabel('EEG Signal');
%*********Apply BandPass**************
subplot(3,2,2);
d=fdesign.bandpass('n,fc1,fc2');
d=fdesign.bandpass('n,fc1,fc2',4,0.5,40,1000);
Hd=design(d,'butter');
y1= filter(Hd,data1);
plot(y1);
xlabel('BandPass Filter 0.5-40');
waveletFunction = 'db8';
        [C,L] = wavedec(y1,8,waveletFunction);
        cD1 = detcoef(C,L,1);
        cD2 = detcoef(C,L,2);
        cD3 = detcoef(C,L,3);
        cD4 = detcoef(C,L,4);
        cD5 = detcoef(C,L,5);
        cD6 = detcoef(C,L,6);
        cD7 = detcoef(C,L,7);
        cD8 = detcoef(C,L,8);
        cA8 = appcoef(C,L,waveletFunction,8);
        D1 = wrcoef('d',C,L,waveletFunction,1);
        D2 = wrcoef('d',C,L,waveletFunction,2);
        D3 = wrcoef('d',C,L,waveletFunction,3);
        D4 = wrcoef('d',C,L,waveletFunction,4);
        D5 = wrcoef('d',C,L,waveletFunction,5); %GAMMA
        D6 = wrcoef('d',C,L,waveletFunction,6); %BETA
        D7 = wrcoef('d',C,L,waveletFunction,7); %ALPHA
        D8 = wrcoef('d',C,L,waveletFunction,8); %THETA
        A8 = wrcoef('a',C,L,waveletFunction,8); %DELTA
```

```
            figure(2), Subplot (9, 1, 1);
plot(A8)
title('Approximation A8');
subplot (9,1 , 2);
plot(D1)
title ('Detail D1');
subplot (9, 1, 3);
plot(D2)
title ('Detail D2');
subplot (9, 1, 4);
plot(D3)
title ('Detail D3');
subplot (9, 1, 5);
plot(D4)
title ('Detail D4');
subplot (9, 1, 6);
plot(D5)
title ('Detail D5');
subplot (9, 1, 7);
plot(D6)
title ('Detail D6')
subplot (9, 1, 8);
plot(D7)
title ('Detail D7')
subplot (9, 1, 9);
plot(D8)
title ('Detail D8')
w=D1+D2+D3+D4+D5+D6+D7+A8;
figure,plot(w)
% thresholding and reconstruction
sdenoise=wden(w,'heursure','s','mln',8,'db8');
EEG =sdenoise;
figure,plot(sdenoise);
M1 = mean(EEG);
disp('M1=')
disp(M1)

%***************
M2 = median(EEG);
disp('M2=');
disp(M2);

%**************
```

```
rms_x1 = sqrt(M1^2/10);
disp('RMS1');
disp(rms_x1);

%*************
s1 = std(EEG);
disp('s1=')
disp(s1)
%*************
figure(3);
data=EEG;
data= data';
value1=data(1,:);
fs=128;
T=1/fs;
L=1000;
t=[0:L-1]*T;
subplot(2,1,1);
plot(value1);
title('original signal');
fs=fft(value1,128);
pp=fs.*conj(fs)/128;
ff=(0:63)/128/T;
subplot(2,1,2);
 plot(ff,pp(1:64));
ylabel('power spectrum density');
xlabel('frequency');
title('signal power spectrum');
%y=Fextraction(data1);

%**************
 eucsum=0;
for j=1:128
dis (1,j)= (ppw (1,j)- pp (1,j)).^2;
eucsum = eucsum + dis (1,j);
end
euc=sqrt (eucsum)
euc=round(euc);
if (euc<=2&M1<=0.3&M2<=0.35&RMS1<=0.35&s1<=40);
    text(0.5,0.45,'normal')
 else
     text(0.5,0.45,'abnormal')
end
```