

**REPUBLIC OF TURKEY
FIRAT UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCE**



**EPILEPSY SEIZURE DETECTION IN EEG SIGNALS
USING WAVELET TRANSFORMS AND SUPPORT
VECTOR MACHINES**

Awin Mahmood SALEEM

(142129115)

Master Thesis

Department: Computer Engineering

Supervisor: Asst. Prof. Dr. Ahmet CINAR

January-2017

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ABSTRACT

In the medical science sector, the major focus for the researchers is the medical diagnosis of the abnormalities in brain. The most common brain disorder "epilepsy" that around 1% of total populace experiences this deformity. The Electroencephalogram "EEG" is an apparatus for measuring cerebrum activities which reflect the brain condition. EEG signal is collecting of brain electrical actions and has many information about brain states, also applied in several epilepsy detection methods.

Epileptic seizures are distinguished by abnormal electrical activity happen in the brain. EEG records the seizures pretending changes in signal morphology. All these signal characteristics, however, differ between patients as well as between different seizures in the same patient. Epilepsy is succeed with anti-epileptic medications but in some ultimate cases surgery may be needed. Non-invasive surface electrode EEG measurement gives an estimate of the starting seizure but more invasive intracranial electrocardiogram (ECoG) are wanted at times for accurate localization of the epileptogenic zone.

Methodology BCI Brain Computer Interfacing that expands a path for correspondence with the outside environment utilizing the brain thoughts. The achievement of this methodology relies on upon the select of techniques to handle the brain signal in every phase, BCI techniques framework is comprises of basic four phase. These are for the most part Signal Acquisition, Computer Interaction, Signal Classification and Signal Pre - Processing. The securing of brain signals is achieved by utilizing different non- invasive techniques like Electro Encephalograph (EEG). Magneto Encephalography (MEG), Near Infra-Red Spectroscopy NIRS and functional Magnetic Resonance Imaging fMRI.

After signal acquisition phase, it was done pre-process the signals; can also be called as Signal Enhancement. For the most part, the gained brain signals are polluted by noise and artifacts. Heart beat ECG, eye blinks and eye movements EOG are artifacts. And also these, muscular movements and power line mediations are also blended with brain signals. After

gaining the signals without noise in the signal increase stage, essential features in the brain signals were extracted. The signals are classified into several classes after feature extraction. Classifying electroencephalography, signals is an important step for proceeding EEG to identify the abnormal electrical activity in the brain. In this thesis, we present two BCI systems based on Maximal overlap discrete wavelet analysis which use to filter noise and feature extraction of signals and Support Vector Machine the most generality common Machine Learning techniques it use for classifying the Electroencephalography (EEG) signals and it based on the neuronal activity for the brain. The other system based on Maximal overlap discrete wavelet analysis, principle component analysis, and SVM which are able to identify epilepsy seizures from EEG signals. This work is part of research looking for the normal person and abnormal "epileptic" patients using (EEG), the importance of PCA as reduction of dimensionality of data explained.

Keyword: Epilepsy, Brain Computer Interface, MODWT, PCA, SVM.

ÖZET

DESTEK VEKTÖR MAKİNELERİ VE DALGACIK DÖNÜŞÜMÜ KULLANARAK ELEKTROENSEFALOGRAMDA EPİLEPSİ NOBETİ TANIMA

Tıp bilim sektöründe araştırmacıların odak noktası, beyindeki anormalliklerin tıbbi tanısıdır. Toplam nüfusun yaklaşık % 1inin yaşadığı "epilepsi" en yaygın beyin bozukluğudur. Elektroensefalogram "EEG", beyin durumunu yansıtan beyin faaliyetlerini ölçmek için kullanılan bir cihazdır. EEG sinyali, beyin elektriksel eylemlerinin toplanması ve beyin durumları hakkında birçok bilgiye sahip olup, aynı zamanda birçok epilepsi saptama yönteminde de uygulanmaktadır.

Epileptik nöbetler beynin anormal elektriksel aktivitesi ile ayırt edilir. EEG, sinyal morfolojisinde değişiklikler yapan nöbetleri kaydeder. Bununla birlikte, tüm bu sinyal özellikleri, hastalar arasında aynı hastada farklı nöbetler arasında farklılık gösterir. Epilepsi antiepileptik ilaçlarla başarılı olmakla birlikte bazı nihai durumlarda ameliyat gerekebilir. Yayılmayan yüzey elektrot EEG ölçümü başlangıç nöbetinin tahminini verir ancak epileptojenik bölgenin doğru lokalizasyonu için daha yaygın intrakranyal elektrokardiyogram (ECoG) istenir.

Metodoloji Beyin düşüncelerini kullanarak dış çevreyle yazışmalara giden yolu genişleten BCI Beyin Bilgisayar Arayüzü. Bu metodolojinin başarısı, her aşamadaki beyin sinyalini işlemek için kullanılan tekniklerin seçimine dayanır; BCI teknikleri çerçevesi temel dört aşamadan oluşur. Bunlar çoğunlukla Sinyal Edinimi, Bilgisayarla Etkileşim, Sinyal Sınıflandırması ve Sinyal Ön işleme işlemidir. Beyin sinyallerinin güvenceye alınması, Electro Encephalograph (EEG) gibi farklı yaygın olmayan teknikler kullanılarak gerçekleştirilir. Magneto Ensefalografi (MEG), Yakın Kızıl Ötesi Spektroskopi NIRS ve fonksiyonel Manyetik Rezonans Görüntüleme fMRI.

Sinyal alım aşamasından sonra sinyalleri önceden işleme tabi tutmuştur; Sinyal Geliştirme olarak da adlandırılabilir. Çoğunlukla, kazanılan beyin sinyalleri gürültü ve yapay dokular tarafından kirlenir. Kalp atışı (EKG), göz kırpmaları ve göz hareketleri (EOG) yapay dokulardır. Ayrıca bu kas hareketleri ve elektrik hattı arabulucuları da beyin sinyalleriyle harmanlanır. Sinyal artış aşamasında sinirsiz sinyaller elde ettikten sonra beyin sinyallerindeki temel özellikler çıkartıldı. Sinyaller, özellik çıkarımı yapıldıktan sonra birkaç sınıfa ayrılır. Elektroensefalografiyi sınıflandıran sinyaller, beyindeki anormal elektriksel aktiviteyi tanımlamak için devam eden EEG'de önemli bir adımdır. Bu tezde, beyindeki nöronal aktivite üzerinde, gürültüyü filtrelemek için kullanılan Maksimum çakışma ayrık dalgacık analizi ve sinyallerin öznelik çıkarma ve Destek Vektör Makinesi'nin Elektroensefalografi (EEG) sinyallerinin sınıflandırılması için kullandığı en yaygın genel Makine Öğrenme tekniklerine dayanan iki BCI sistemi sunmaktayız. Diğer sistem ise EEG sinyallerinden epilepsi nöbetlerini belirleyebilen Maximal overlap ayrık dalgacık analizi, birincil bileşen analizi ve Destek Vektör Makinesi üzerine kuruludur. Bu çalışma, normal kişiyi ve anormal "epileptik" hastaları EEG kullanarak araştıran bir parçadır; verilerin boyutsallığının azaltılması olarak PCA'nın önemi açıklanmaktadır.

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List of Abbreviations

AnEn: Approximate Entropy

ANN: Artificial Neural Network

BCI: Brain Computer-Interface

DWT: Discrete Wavelet Transform

ECG: Electrocardiogram

ECoG: Electrocorticography

EEG: Electroencephalogram

EOG: Electrooculography

FFANN: Feed-Forward Artificial Neural Networks

fMRI: Functional magnetic resonance imaging

BOLD: Blood Oxygenation Level Dependent

ICA: Independent Component Analysis

MEG: Magnetoencephalography

MLP: Multilayer Perceptron

MODWT: Maximal Overlap Discrete Wavelet Transform

NIRS: Functional Near Infrared Spectroscopy Signal

PCA: Principal Component Analysis

SVM: Support Vector Machines

STFT: Short-Time Fourier Transform

FT: Fourier Transform

WFT: windowed Fourier Transform

BOCD: Blood Oxygenation level Dependent

ANOVA: Analysis Of Variance

EDOF: Effective Degree Of Freedom

RBF: Radial Basis function

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1. INTRODUCTION

Express a direct communication between the brain and a computer system, this channel gives the possibility of transferring information from the brain in the form of electrical signals [9]. Where it is read electrical activity of the brain using electrodes placed on the surface of the skull (external) or the surface of the brain direct read (internal reading) . This type of connection (computer- brain) allows the user to send commands to a computer by thinking. It also can send information to the brain (brain-computer) by stimulating the brain sends electrical signals are weak. You can find generally two types of Brain Computer-Interfacing systems. They truly are; Invasive Brain Computer-Interfacing and Non-Invasive Brain Computer-Interfacing. It consists of four stages. These are generally; Recording signals, Signal Pre-treatment (Pre-Processing), classification of brain signals and Application interface (Computer Interaction) [13].

The acquisition of brain signals is been consummated by using different non-invasive methods such as Electro Encephalography (EEG), functional Magnetic Resonance Imaging (fMRI), Near Infra-Red Spectroscopy (NIRS) and, Magneto Encephalography (MEG). Brain activity can be measured invasively using electrocorticography (ECoG).

1. EEG:

In 1875 Richard Caton has recorded EEG for animal brain. The first registered one on human brain was by Hans Berger in 1929 [10]. EEG it is been widely used for the diagnosis of epilepsy, which causes abnormal patterns in EEG readings. [2] This mechanism is also used for the diagnosis of sleep disorders, coma, brain disorders, and brain death. EEG was first used as a way to diagnose tumours, stroke and other focal brain disorders. The most used method for signal acquisition is EEG because it has high temporal resolution, safety and ease of use. EEG is non-stationary in nature and it has low spatial resolution. In general (10-20) standard electrodes placement may be used in EEG signal acquisition. There are times, where the brain waves of normal are not enough, especially when planning the necessity of a recording of a

patient during a bout. In this case, the patient can enter the hospital for several days or weeks, where EEG continuously recorded (in conjunction with the recording of the voice and image of the patient). EEG signals are susceptible to artefacts due eye blinks, muscular action, heartbeat, the power line interventions [15] and eye movements.

Epilepsy patient monitoring for the following purposes:

- To distinguish epileptic seizures from other types of spacers, such as non-epileptic seizures psychological origin, fainting, movement disorders underneath the crusty, types of migraines.
- To determine the characteristics of seizures for therapeutic purposes.
- To determine the region of seizures in the brain in order to prepare for possible surgery.

2. fMRI

The (fMRI) technology is a well-known technique, generally is used in a medical sections and clinical laboratories. The level of haemoglobin is useful it is the main factor for fMRI and (it is famed also Blood Oxygenation Level Dependent (BOLD). it is more expensive because of important things that is (spatial resolution and temporal) and sure there will be delay in data time acquisition operation [3].

3. NIRS

The NIRS technology hinders the transformation rates because of low temporal resolution. NIRS is integrated with the EEG also it forms Hybrid BCI, to improve the transmission averages. The accuracies of classification will be also estimated in NIRS by using BOLD. It is cheap and inexpensive but displays completely low performance than EEG based- BCI [21].

4. MEG

In MEG technology, the magnetic signals are captured that are been produced by electrical activities. This methodology needs expensive and heavy sized equipment because it provides vaster frequency domains and perfect spatiotemporal resolution. Table (1.1) shows

discrimination between various signal acquisition methods utilized in Non-invasive BCI systems [4]. In Figure (1.1), non-invasive acquisitions are shown.



Figure 1.1 non-invasive acquisitions

Table 1.1 comparing of Signal Acquisition Methods according to Non-invasive BCI systems [18]

S. No	Method	Signals captured	Advantages	Disadvantages
1	EEG	Electrical Signals on brain Scalp	• High Temporal resolution • Safe and easy technique	• Susceptible to EOG signals, ECG signals, muscular activities and power line interference • Low spatial resolution • Non stationary signal
2	fMRI	Metabolic signals using BOLD response	• High temporal and spatial resolution	• Set up cost is more • Delay in data acquisition process
3	NIRS	Metabolic signals using BOLD response	• High spatial resolution • Inexpensive • Portable	• Hinder transformation rates • Less performance • Low temporal resolution

4	MEG	Magnetic Signals generated by electrical activities	• Wider frequency range • Excellent spatio-temporal resolution	• Needs bulky setup • Expensive experimental setup
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In our work, Brain activity may be measured non-invasively using electroencephalography (EEGs). An electroencephalogram is a medical imaging technique that measures the brain activity in the form of waveforms of different frequencies and amplitudes measured across time. EEG is an instrument for understanding the complex dynamical behaviour for the brain. It was used in medicine for diagnostic and analysis conditions because of electrical signal generated by the cooperative action of brain cells.

EEG system is used for non-invasive measurement of the electrical activity on the scalp in various areas of the brain that is extremely significant to observe neurological disorders and defect of brain like epileptic seizure.

One of the major researches on the field of medical science may be the diagnosis of the abnormalities in brain. An abnormal condition that affects the body of an organism causes a disease. Any deviation from normal structure of an organ is displayed by a characteristic set of symptoms and sign. [12].

Epilepsy is a serious neurological disorder in human after stroke disorder that affects one in every 100 persons of the world's populations. Thus diagnosis of epileptic activity may be helpful. Epileptic activities are clear in EEG signal. For this reason electroencephalogram is used in diagnosis epileptic defect and seizure beginning.

An epileptic brain can be divided into interictal, pre-ictal, ictal and post-ictal categories. Interictal state occurs between two consecutive epileptic seizures and can be characterized as normal or abnormal brain activity as shown in Figure (1.2) during the abnormal interictal state slow activity can be observed. Pre-ictal state occurs right before the beginning of an epileptic seizure. Ictal state is defined as the epileptic seizure during which the

functioning of the brain is impaired. During the post-ictal state the brain is recovering from an epileptic seizure [16]. The dynamics of pre-ictal state are most complex and during this stage there is a reduction in the connectivity of neurons in the epileptogenic zone [1].

The important thing in the diagnosis of epilepsy is a detection of epileptic form discharges that happens in the EEG between seizures [2, 23].

Unfortunately, the appearance of an epileptic seizure seems unpredictable and its Trajectory work is not realized.

In this proposed work, two schemes are presented to detect and find out epileptic seizures from EEG data obtained from normal persons (healthy) and epileptic patients (unhealthy). The first scheme is based on maximal overlap discrete wavelet transform (MODWT) analysis and support vector machine of EEG signals. The two stages for performing seizure detection were done. In the first stage, EEG signals are decomposed by MODWT to calculate approximation and detail coefficients. In the second stage, the support vector machine used to identify an ordinary person and patients with epileptic. The second scheme is based on maximal overlap discrete wavelet transform (MODWT) analysis, the feature extraction of principle component analysis; used to reduce dimensional data, and support vector machine of EEG signals. Then the importance of PCA has identified.

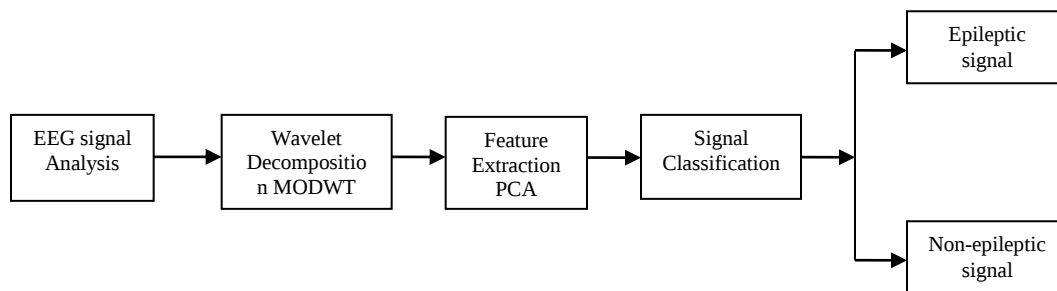


Figure 1.2 EEG Signal Classifications

1.1. Related works

Since 1970s, there are various methods addressing the diagnosis of epileptic activities in brain. For this purpose, up to now, many methods have been used. At the beginning of seizure detection, two methods have been applied; Fourier transforms and parametric [24].

As that EEG signal is non-stationary, maybe it is more suitable to employ and use the time frequency domain methods such as the wavelet transformation (WT) [2, 29]. The decomposition of wavelet depends on the number of samples which is 2^N . In [27] DWT + PCA and SVM are used for emotion recognition on EEG signal and Guerra et al. have used DWT +MODWT and FFANN to detect seizure [11]. Subasi et al classify the EEG signal by using DWT+PCA, ICA, CDA+ SVM and DWT+AnEn+ANN In [25, 28] respectively, In [7] DWT+ Neuro Fuzzy interface system used to classify the EEG signal Also DWT+MLP + ANN used for classifying EEG signal in [14]. In this paper we have used MODWT+ SVM and MODWT+ PCA+ SVM for classification of EEG signal for epileptic seizure detection.

1.2. Organization of thesis

Whatever remains of this thesis is sorted out as take after:

Section 2: Literature Review brings a short definition of brain computer interface (BCI), information about BCI System Components, definition and information about Electroencephalography, definition and explains Epilepsy, explains some reasons that Cause Epilepsy.

Section 3: Materials and Methods : describes data and methods that are used in experimental data, explain two models that are used , explains types of analysis signals as well as its five types (Beta, Alpha, Theta, Delta and Gamma, using MODWT method for pre-processing the signals and classify signal by using SVM .

Section 4: Experimental Results explains the result and summarizes the procedure of the proposed system.

Section 5: Conclusions summarizes and discusses the contribution of this research work.

This section contributes to the detection of epilepsy and comparisons between MPS and MS models by three different methods (Gaussian, Linear and Polynomials) for the real data.



2. LITERATURE REVIEW

2.1. Brain computer interface (BCI)

The BCI technology is a highly increasing domain of research with application systems. It occupies an important area in medical field extending from prevention to rehabilitation for neuronal injury patients. Inspecting mind signals and its activities that have a huge effects.

People with disabilities support by the BCI devices, which are unable to make the motor response to communicate with the computer using the signal from the brain. Brain activity clarifies by this device in a digital form that shows as a command to a client. Highlight extraction systems are utilized to concentrate highlights representing to a special property acquired from cerebral signal pattern. Beforehand EEG analysis was constrained to a visual review only. Visual assessment of the signal is exceptionally subjective and scarcely takes into consideration Standardization or signal allows statistical analysis. In this way, a few unique techniques were planned to evaluate the brain signal data. Numerous linear and non-linear techniques to highlight extraction exist.

2.1.1. The BCI System Components

There are four elements to the practice essential functioning in BCI platform. All four elements must work together to manifest the intention of the user (Wolpaw et al., 2002):

- The signal acquisition signal registered or information system of the brain is the BCI input.
- Signal processing, converting raw data in June useful device control.
- Output of the unit, command functions or overt control administered by the BCI system.

- Protocol operation, including the way the system is modified and turned off and on.

2.2. Electroencephalography

Electroencephalograms are recordings of the electrical signal potentials developed by human brain. Analysis of methodology EEG activity has been achieved basically in clinical settings to determine pathologies and epilepsies activity. An interpretation of the EEG can be used to visual inspection by a neurophysiologist. EEG innovation utilized numerous electrodes on human skull, such signals gives information indirectly about physiological functions, that are related to the brain, these signals are very numerous. The EEG integrated technical devices with embedded intelligence it allows BCI device to analysis EEG methodology design. BCI device is composed of signal collection and processing pattern identification and control systems. Electroencephalogram methodology classification has its own number of features, it comes through some proven facts that are,

- Electroencephalogram signals are non-stationary, thus, features must certainly be computed in a time-varying manner, and
- Large Number of Electroencephalogram channels.

Normally there are four waves can be observed:

1. When the individual is relaxed, his eyes closed it records Alpha waves and the speed between 8-13 Hz / sec
2. When you open an eye Beta and speed of waves is more than 13 Hz / sec show.
3. In the case of drowsiness issued Theta waves speed between 4-7 Hz / sec.
4. When deep sleep and coma appear waves Delta and speed of 1-3 Hz / sec.

2.3. Epilepsy and EEG

Epilepsy is defined as a disorder and illness in the brain's performance in particular and the nervous system in general. In the natural state of the brain electrical energy produced by brain cells move through the nervous system caused by moving the muscles, but in the case of illness, the patient's brain fails to control their electric energy the cells produce sudden and violent impulse of those electric energy and (seizure) may occur.

The difference between an epileptic seizure and other seizure activity is when a person has a seizure activity; this does not necessarily mean that the person has epilepsy. Seizure can infect anyone under certain conditions such as high temperature or dehydration or exposure to severe head injury or lack of oxygen. But when you repeat these seizures for reasons that are not clear in this case we can say that the person has epilepsy.

The causes of epilepsy, any problem disturb normal brain activity can lead to epilepsy style.

It could be the reason the disease, or brain damage, or abnormal growth of the brain. Cannot determine exactly why cases of epilepsy.

Epilepsy has several reasons, including the same brain chemistry, genetic reasons, other disorders, environmental causes or because of injuries, pregnancy and childbirth. Occurring in both sides of the human brain are known as generalized seizure, few types of generalized seizures.

- Absence seizure
- Tonic seizure
- Clonic seizures
- Atonic seizures

In a study to determine the prevalence of epilepsy in the West, it was concluded that 0.5% of the community are infected by the disease. The 2-5% of people has seizure activities at least once in their lives. It also found that the incidence (phenomena) in the industrialized countries is lower than the developing countries.

2.4. Cause of Epilepsy

Each year is mostly reported around 180000 cases epilepsy out of which thirty percent are children. Various epilepsy causes are seen in various age.

There are many factors that may affect the nerve cells in the brain or in the way neurons connect to each other at about 65% of all cases do not know the cause of epilepsy occurs, the following are some reasons:

- It may follow the head and brain injury after accident.
- The lack of some elements, such as lack of blood glucose, lack of calcium, magnesium, lack of oxygen, especially during childbirth.
- Accompanied by some diseases such as metabolic diseases, congenital diseases.
- Possible due to meningitis, inflammation of the brain.
- Because of some toxic elements.
- Disease and brain abnormalities are often accompanied by cramps stroke such as brain tumors and malformations of the brain.
- Trauma at birth or very high heat.
- Carrying Infants violently and repeatedly and subjecting them to violent vibrations.
- Blood flow to the brain stops because of a stroke or tumors or heart problems.

Categorized for Epilepsy as following:

- Symptomatic epilepsy: Some specific epilepsy symptomatic causes like alcohol, birth abnormalities and drugs.
- Idiopathic epilepsy: No specific epilepsy idiopathic causes whereas damage of human brain may lead to cryptogenic epilepsy.
- Cryptogenic epilepsy: Can also happen due to strange level of blood, sugar or sodium. Both of (Seizures - epilepsy) may be avoided by evading the annotated following: lack of proper sleep, drug abuse, anxiety / stress and usage of alcohol.

All the symptoms and signs adversely influences the patient's health epilepsy are anxiety, loss in memory, depression and mental injury of this disease.



3. MATERIALS AND METHODS

3.1. Experimental data

The EEG database used in the experiments presented here was provided by a hospital from Malatya, Turkey. This collection contains EEG data coming from three different events, namely, healthy epileptic subjects during free seizure intervals (known as interictal states) and during ictal seizure states.

The collection contains five datasets identified as: (A, B, C, D and E). First two sets include surface EEG recordings that are gathered from 5 subjects healthy utilizing an institutionalized electrode position plan. The subjects were eyes shut and open with their casual, individually. The (3 - 4) of datasets comprise of intracranial EEG sparing amid free seizure interims interictal periods from inside the epileptogenic zone and inverse the epileptogenic zone of the human brain, individually. Each set holds 1000 segments of EEG signals of 23.6 seconds. The sampling frequency of these signals was 173.6 Hz and was recorded with 10-20 channels.

3.2. Proposed Method

First we have decomposed the EEG signal by MODWT into several sub-bands using five level decompositions and then we have two schemes to identify the normal and abnormality. One is implementing machine learning using SVM algorithm on the training matrix and the other is reducing feature PCA algorithm and then implementing SVM algorithm as shown in Figure (3.1) finally, we have explained the difference of these schemes.

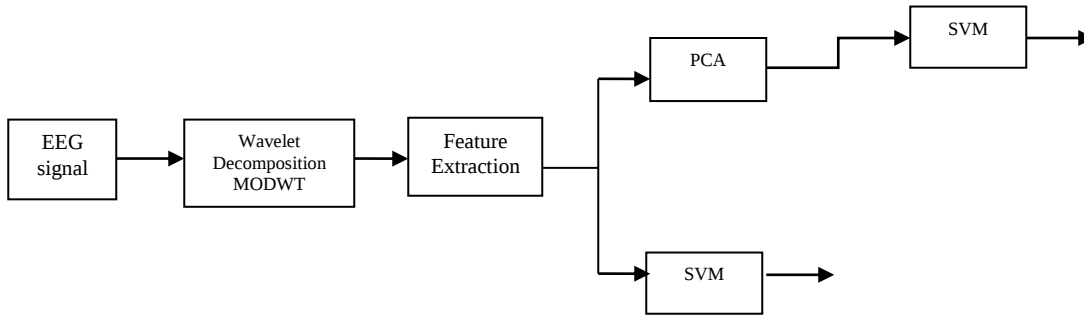


Figure 3.1 Functional diagram

The decomposition of EEG signal which gives us delta waves are between 0-4Hz, shown during infancy, deep sleep and serious organic human brain disease [19]. Frequencies Theta waves between 4-8 Hz, shown mainly in parietal and temporal regions in children and during emotional worry in a few grown-ups [19, 30]. Alpha waves have frequencies between (8-12 Hz).Figure (3.2) below show Sub-band decomposition of MODWT.

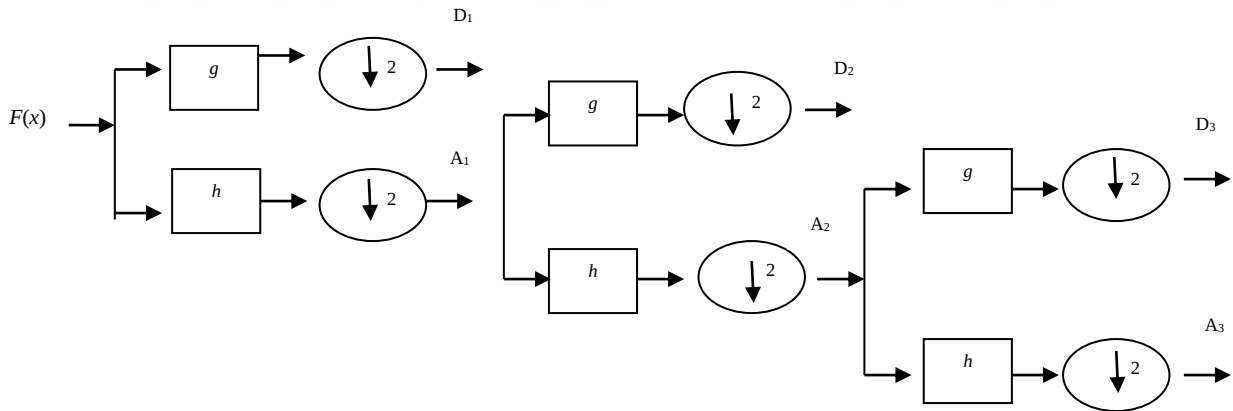


Figure 3.2 Sub-band decomposition of MODWT implementation;
h[n] is the high-pass filter, g[n] the low-pass filter

All subjects almost normal in EEG, when they are awake but in quiet, resting and relaxed condition [19]. Beta waves normally occur in frequencies from 12 to 30 Hz. Active thinking

is normally associated with A beta wave, problem solving or active attention, that is, during intense mental activity [19]. Gamma waves Frequencies are above (30 Hz), related to information processing and the onset of voluntary movements [19]. According to Ravish [19] and Sunhaya [26], the delta and alpha sub-bands provide useful information to localize a seizure. Therefore, only these sub-bands of the EEG signal were used in this work.

3.3 Analyses

The analysis of continuous EEG signals or brain waves is complicated, because of the huge amount of data received from all electrodes. As a science in itself, it has to be completed with its own set of perplexing nomenclature. Different waves, like so many radio stations, are classified by the frequency of their emanations and, in some situations by the waveforms. Although these waves are been emitted alone, the state of consciousness of the individuals may make one frequency range more pronounced than others. Five types are particularly important:

A. Beta waves (12 to 38 HZ)

Beta brainwaves control our state of consciousness when attention is destined to cognitive tasks and the external world. Beta is a 'speed' activity, it is present when we are in a state of alert, attentive, engagement in problem solving, judging, decision making, and been engaged in a focused mental activity. Beta brainwaves are divided into three bands; Lo-Beta (Beta1, 12-15Hz) can be thought of as a 'fast idle, or musing. Beta (Beta2, 15-22Hz) is a high engagement or actively to figure something out. Hi-Beta (Beta3, 22-38Hz) is highly complicated state of thinking, entering new experiences, been anxious, or excited. Continual high frequency processing is not a very effective way to run the brain, as it demands a great amount of energy. Figure (3.3) shows Beta wave.

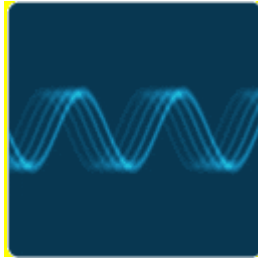


Figure 3.3 Beta wave

B. Alpha wave (8 to 12 HZ)

Alpha brainwaves are present in quiet flow of thoughts, and in some meditative states. Alpha is 'the power of actuality', being here, in the present. Alpha is the resting state for the brain. Alpha waves support above all mental coordination, state of calmness, alertness, mind/body integration and comprehension. Figure (3.4) shows Alpha wave.

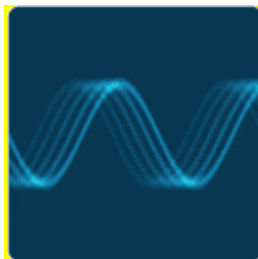


Figure 3.4 Alpha wave

C. Theta wave (3 to 8 HZ)

Theta brainwaves arrive most often in state of a sleep but are also present in deep meditation. It acts as our gateway to learn and memorizes in theta, our senses are

withdrawn from the outside world and focuses on signals offspring from inside. It is that twilight condition which we experience when we are awake or fell to sleep. In theta we are in a dream; vivid imagery, intuition and information beyond our normal state of consciousness. It's where we hold our 'stuff', our fears, troubled history, and nightmares. Figure (3.5) shows Theta wave.

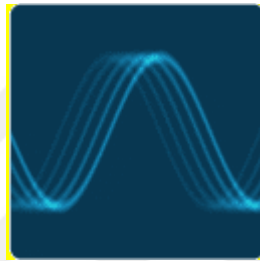


Figure 3.5 Theta wave

D. Delta waves (0.5 to 3 HZ)

Delta brainwaves are slow, loud brainwaves (low frequency deeply penetrate, like a drum beat). They unfold in deepest meditation and dreamless sleep. Delta waves suspend external awareness; they are the source of empathy. And Healing, regeneration are stimulated in this state, that is why deep restorative sleep is so essential to the heal. Figure (3.6) shows Delta wave.

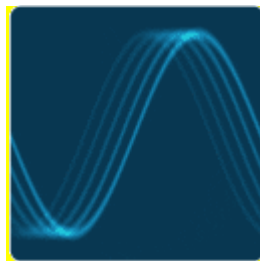


Figure 3.6 Delta wave

E. Gamma waves (38 to 42 HZ)

Gamma brainwaves are the fastest of brain waves (high frequency, like a flute), related to simultaneous process of information from various brain areas. It delivers information fastly, as the most subtle of the brainwave frequencies; the mind has to be calm to access it. Gamma was dismissed as 'spare brain noise' until researchers discovered it was highly operational when in states of universal love, altruism, and the 'higher virtues'. Gamma is above the frequency of neuronal firing, how it is produced remains a vague. It is estimated that Gamma rhythms modulate perception and consciousness, and that more of Gamma leads to expand consciousness and spiritual emergence. Figure (3.7) shows Gamma wave

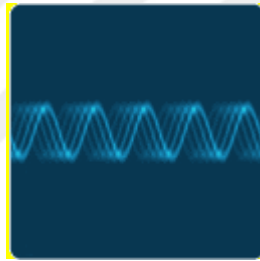


Figure 3.7 Gamma wave

3.4 Time – Scale Domain: Maximal Overlap Discrete Wavelet Transform

Signal change is simply one more shape to speak to the signal. It doesn't change the data content existing in the signal.

A valuable apparatus for investigating the recurrence parts of the signal is Fourier change. Furthermore, on the off chance that it takes the Fourier change over the entire time pivot, it was not state at what moment a particular recurrence will rise. To discover spectrogram, Brief time Fourier change uses a sliding window which gives the information of both time and recurrence. Regardless, yet it was another issue: The length of window compels the assurance

in recurrence. Wavelet change has every one of the reserves of being an unraveling for the issue above. Wavelet changes are relied on upon little wavelets with particular period. The interpreted rendition wavelets with specific period. Though the scaled-adaptation wavelets find where we concern. Though the scaled-variant wavelets let us to examine the signal in various scale.

Fourier Transmission representations as a rule don't include neighborhood data about the first signals. Despite the fact that WFTs can offer limitation data, they can't give adaptable division to the time-frequency plane that may track slow changing wonders while giving more data to higher Frequencies. The wavelet representation was acquainted with enhance the downside for the previous two strategies utilizing a multi resolution conspire.

The use of a wavelet change licenses us to get a time frequency representation for the signal, which gives better knowledge in the frequency division for the signal with time. Furthermore, the scale values for which the change is computed must be powers of two in DWT, the component vectors to be utilized as a part of the procedure are the coefficients of the DWT processed for every trial. Amid the classification phase every one of them is assigned to a particular mark or mental state.

Wavelets classifications have two types of classifications wavelets:

- Orthogonal: same length for the low and high pass filters.
- Biorthogonal: the lower pass and higher pass filters have not similar length. in the time the application, both of them can be used. The Wavelet changes take an interest to the required testing by sifting the signal with interpretations and development of a fundamental capacity called "mother wavelet". The mother wavelet may be associated with shape orthonormal bases of wavelets, which is especially valuable for datum proliferation.

The MODWT is a linear filtering operation that changes a series into coefficients related to changes over pile of scales. Discrete wavelet transformation can be used for easy and fast de-noising of a noisy signal. MODWT really is comparable to the DWT for the reason that both of them are

linear filtering process, it delivers an accumulation of time-ward wavelet and scaling coefficients. They have premise vectors identified with an area t , and a unit less scale $\tau_j = 2^{j-1}$ for all deterioration level $j = 1, \dots, j_0$. The two are legitimate for examination of fluctuation (ANOVA) and multi-determination investigation (MRA). The MODWT unique in relation to the DWT in that it truly is a to a great degree repetitive, non-orthogonal change [17]. The MODWT spares down inspected values at every last level of the disintegration that may be generally disposed of as a result of the DWT. The MODWT is very much characterized for all specimen sizes N , though for an aggregate deterioration of J levels the DWT obliges N to end up distinctly a different of $2J$.

The MODWT present a couple of good conditions from the DWT. The Excess for the MODWT energizes game plan of the broke down wavelet and scaling coefficients at each and every level with all the present interesting time arrangement thus enable to compare between the series and its particular decomposition. ANOVAs decided using the MODWT are not influenced by round moving for any data time plan, while values induced using the DWT rely on the beginning stage for the course of action [17]. At last, the repetition for the MODWT wavelet coefficients unassumingly builds the powerful degrees of flexibility (EDOF) for each scale and in this way diminishes the difference of certain wavelet-based measurable appraisals. Because of the reality MODWT is vitality effective; it is really incredible for breaking down the scale reliance of fluctuation in ANOVA considers. By utilizing the MODWT to levels hypothetically includes the utilization of sets of channels. It was disintegrating a boundless succession of Gaussian irregular factors. The sifting operation at the j^{th} level contain of applying a wavelet (high-pass) $\{\tilde{h}_{j,l}\}$ to produce a set of wavelet coefficients

$$\bar{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-l} \quad (1)$$

And a scaling (low-pass) filter $\{\tilde{g}_{j,l}\}$ to yield a set of wavelet coefficients

$$\bar{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} X_{t-l} \quad (2)$$

for all times $t = \dots, -1, 0, 1, \dots$ [17]. The equivalent wavelet $\{\tilde{h}_{j,l}\}$ and scaling $\{\tilde{g}_{j,l}\}$ filters for the j^{th} level are an arrangement of scale-ward limited differencing and averaging administrators, separately, and can be viewed as extended renditions of the base ($j = 1$) channels. The j^{th} level identical channel coefficients have a width:

$$L_j = (2^j - 1)(L - 1) + 1 \quad (3)$$

Where L is the width of the $j = 1$ base channel. For all intents and purposes, the channels for are not explicitly made in light of the fact that the wavelet and scaling coefficients can be successively using a choice count that incorporates just the $j = 1$ channels chipping away at the j^{th} level scaling coefficients to create the $j+1$ level wavelet and scaling coefficients [17].

The j^{th} level wavelet coefficients depict those fragments of the banner with instabilities planning the unitless scale $\tau_j = 2^{j-1}$. If $\{X_t\}$ On the off chance that in the occasion that is either a stationary method or a non-stationary process with stationary in switch differentiations, and L is sensibly picked, then $\bar{W}_{j,t}$ is a Gaussian stationary process with zero mean and known power repulsive thickness [17].

Moreover, MODWT coefficients for various scales are generally uncorrelated and are thus helpful verifiable measures for distributing changeability by scale.

Commonly EEG signs are inspected over a restricted break at discrete conditions. For completing the isolating operation at each level temporarily game plan $\{X_t\}, t = 0, \dots, N-1$, the MODWT regards the arrangement as though it were occasional, whereby the imperceptibly tests $X_{-1}, X_{-2}, \dots, X_{-N}$ are appointed the watched values at $X_{N-1}, X_{N-2}, \dots, X_0$. The MODWT coefficients are in this manner given by

$$\bar{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-l \bmod N} \quad (3)$$

And

$$\bar{V}_{j,t} = \sum_{l=0}^{L_i-1} \tilde{g}_{j,l} X_{t-l \bmod N} \quad (4)$$

For $t=0, \dots, N-1$. This intermittent augmentation of the time arrangement is known as breaking down utilizing 'round limit conditions'.

Round cutoff conditions can be unusual and unsafe for non-irregular signals that show discontinuities among start and end times. The issue can decrease by applying an appropriate enlargement to the game plan and a short time later figuring the MODWT on the widened course of action. A run of the mill supplement, which it was get, is using of 'reflection constrain conditions' to develop and extend the course of action to length $2N$; i.e., the unobserved samples $X_{-1}, X_{-2}, \dots, X_{-N}$ are assigned the observed values at $X_0, X_1, X_2, \dots, X_{N-2}, X_{N-1}$. formally it was defined the extended series $\{X'_t\}$ by setting $X'_t = X_t$ for $t=0, \dots, N-1$ and $X'_t = X_{2N-1-t}$ for $t=N, \dots, 2N-1$. Thus for the reflection boundary conditions (3) and (4) can be rewritten as

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_i-1} \tilde{h}_{j,l} X'_{t-l \bmod 2N} \quad (5)$$

and

$$\tilde{V}_{j,t} = \sum_{l=0}^{L_i-1} \tilde{g}_{j,l} X'_{t-l \bmod 2N} \quad (6)$$

using the extended series $\{X'_t\}$.

In Matlab 2016 Ra, there exists modwt() function to find the wavelet coefficients for scales $2^j, j=1, \dots, N-1$. The final row of the output data (output=modwt(X)) contains the scaling coefficients at scale 2^N . Also we can find modwt(X) using scaling and wavelet filters and there is a parameter to specify the number of levels as (Haar, Daubechies, symlets, coiflet, and Fejer-Korovkin wavelets) if we use modwt(X) then the default specification level is four level which is 'sym4'. See Matlab 2016 modwt function.

3.5 Principal Component Analysis

Principal Component Analysis (PCA) is a well-established technique that concentrates important data from a huge information set [20, 22] and it is a settled strategy for dimensionality diminishment. In PCA, it was attempt to show the p-dimensional information in a lower-dimensional space. This can diminish the degrees of choice; lessen the time complexities and space. The objective is to show information in a space that best communicates the variety in an aggregate squared blunder sense. This strategy is by and large accommodating for dividing signals from numerous sources. On the off chance that it was know what number of free parts exist early, it will be encourages altogether, as with standard grouping strategies. The essential approach in key parts is hypothetically to some develop simple.

It was state that main segment investigation is a factual method that uses an orthogonal change to change a collection of view of possibly compared variables into a game plan of estimations of straightly uncorrelated components called principal fragments. The amount of focal parts is lower than or proportional to the amount of one of kind elements. This change is known in a way that the primary fundamental part has the greatest possible distinction and each succeeding portion along these lines has the most imperative vacillation possible under the constraint that it is orthogonal to the previous sections. The subsequent vectors are an uncorrelated orthogonal start set. PCA is sensitive to the relative scaling of the first elements.

In 1901 by Karl Pearson the PCA was made, as a straightforward of the main center point speculation in mechanics; later self-governingly it was delivered by Harold Hotelling in the 1930s. Dependent upon the field of use, it was similarly named the discrete Kosambi-Karhunen-Loeve (KLT) change in banner taking care of. PCA is numerically portrayed [8] as an orthogonal direct change that progressions the information to another encourage structure with the true objective that the best variance by some projection of the data comes to lie in the

fundamental compose (known as the essential principal part), the second most noticeable contrast on the second mastermind, and so on.

Consider a data network X with area adroit zero experiential mean (The mean of every fragment has been moved to zero), where all the n lines address a substitute rehash of the examination, of the p portions gives a particular kind of highlight.

Numerically, it was characterized the change by an arrangement of p -dimensional vectors of weights or loadings $w_{(k)} = (w_1, \dots, w_p)_{(k)}$ that map each row vector $x_{(i)}$ of X to a new vector of principal component scores $t_{(i)} = (t_1, \dots, t_k)_{(i)}$, given by $t_{k(i)} = x_{(i)} \cdot w_{(k)}$ in a manner that the individual variable of t considered over the information set progressively acquire the most extreme conceivable difference from x , with every stacking vector w obliged to be a unit vector.

The k^{th} segment of an information vector can along these lines be given as a score $t_{k(i)} = x_{(i)} \cdot w_{(k)}$ in the transformed coordinates, or as the corresponding vector in the space of the original variables, $\{x_{(i)} \cdot w_{(k)}\}_{w_{(k)}}$, where $w_{(k)}$ is the k^{th} eigenvector of $X^T X$. The full principal components decomposition of X can therefore be given as:

$$T = XW \quad (7)$$

where W is a p -by- p matrix whose columns are the eigenvectors of $X^T X$.

The sample covariance Q between of the different principal components over the dataset is given by the matrix form $Q = W\Lambda W^T$ where Λ the diagonal matrix of eigenvalues is

$$\lambda_{(k)} = \sum_{i=1}^p t_{k(i)}^2 = \sum_{i=1}^p (x_{(i)} \cdot w_{(k)})^2 \text{ of } X^T X \quad (8)$$

Remark:

The primary segments change may likewise be identified with another network factorization, the particular esteem deterioration (SVD) of X ,

$$X = U\Sigma W^T \quad (9)$$

Here Σ is a n-by-p rectangular corner to corner cross section of positive numbers, called the singular qualities to X ; U is a n-by-n grid, the fragments which are orthogonal unit vectors of length n called the left specific vectors of X ; and W is a p-by-p whose portion are orthogonal unit vectors of length p and called the right single vectors of X .

As far as this factorization, the lattice $X^T X$ can be written

$$X^T X = W\Sigma U^T U\Sigma W^T = W\Sigma^2 W^T \quad (10)$$

Correlation with the eigenvector factorization of $X^T X$ builds up that the correct particular vectors W of X are proportionate to the eigenvectors of $X^T X$, while the singular values $\sigma_{(k)}$ of X are equivalent to the square underlying foundations of the eigenvalues of $\lambda_{(k)}$ of $X^T X$.

In Matlab 2016, there exist the `pca(X)` function return the principal component coefficients W , that the singular decomposition matrix is used to find it as default argument. See `pca` function in Matlab 2016.

3.6. Support Vector Classification for Classifiers EEG Signal

Support Machine is primarily used for ordering ordinary and seizure brain movement from EEG signal. Support vector machines (SVMs) are a gathering of regulated learning strategies utilized for order, relapse and anomaly's location. SVM calculation characterizes the two classes (epileptic and non-epileptic) by finding an ideal hyperplane with the biggest edge that isolates the information purposes of the classes. The bolster vectors are the information guides nearest toward this hyperplane and on the edges of the outskirts isolating the classes. For non-divisible information, a gentler edge is recognized that isolates many if not all focuses [5]. The essential start of SVM is to deliver a classifier (in light of the preparation lattice) which forecast the characterization of the test information set given just the test information traits.

Training an SVM classifier was achieved in three distinct steps; first step was to train the machine classifier, the second step was to classify the data using the classifier and the third step was to tune the classifier for optimal classification. `fitcsvm()` is a MATLAB function that is available from the statistical toolbox for training SVM. The training matrix containing the epileptic and non epileptic data along with the class matrix containing the classification (class = -1 for epileptic and class = +1 for non-epileptic) was used to train the SVM. For all the aforementioned models, the data matrix changed based on the number of columns used for creating the training matrix, bellow shown Figure (3.8) support vectors.

The radial basis function (RBF) kernel which is a Gaussian function was used for training SVM classifiers. This function non-linearly maps the data points onto a higher dimensional space where it becomes close to linearly separable under the change of variables. The resulting SVM trained classifier contains the optimized parameters that helped classify the test data set. `predict()` function from MATLAB along with the classifier was used to classify the test data set, where each row corresponds to a new time point. The test data set contains all 79 time points for the 20 second data segment for each channel included in the test data. SVM classifier then classifies each time point for the channel as epileptic or non-epileptic. In order to identify whether the entire channel can be classified as epileptic or non-epileptic, the preponderance of classification was used. For the channel to be classified as epileptic, 51% of the 79 time points are required to have a classification as epileptic (class = -1) and for the channel to be classified as non-epileptic, 51% of the 79 time points are required to have a classification as non-epileptic or (class = +1). Keeping in mind the end goal to tune the classifier for ideal execution, it was important to distinguish the best parameters as the punishment parameter and the portion parameter.

Scientifically, SVM is for delivering a model (in light of the preparation information) which predicts the objective qualities for the test information given only the test information traits. Given a preparation set of occasion name sets

$(x_i, y_i), i = 1, \dots, l$ where $x_i \in R^n$ and

$y_i \in \{1, -1\}$, the (SVM) require the arrangement of the accompanying enhancement issue:

$$\min_{w, b, \xi} \quad \frac{1}{2} w^T w + C \sum_{i=1}^l \xi_i$$

Subject to

$$y_i (w^T \phi(x_i) + b) \geq 1 - \xi_i \quad (11)$$

$$\xi_i \geq 0.$$

Its dual is

$$\min_{\alpha} \quad \frac{1}{2} \alpha^T D \alpha - e^T \alpha$$

Subject to

$$y^T \alpha = 0 \quad (12)$$

$$0 \leq \alpha_i \leq C, \quad i = 1, \dots, l,$$

where e is the vector of all ones, $C > 0$ is the upper bound, D is an l - by- l positive semi-definite matrix, $D_{ij} = y_i y_j K(x_i, x_j)$, and $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is the bit. Here preparing vectors x_i are mapped into a higher (perhaps interminable) dimensional space by the capacity ϕ . [6 svm]

The decision function is

$$\text{sgn} \left(\sum_{i=1}^l y_i \alpha_i K(x_i, x) + b \right).$$

Some of the popular kernel functions are as follows;

1. Radial Kernel function (RBF) $K(x_i, x_j) = e^{-\frac{(x_i - x_j)^2}{2\sigma^2}}$,
2. Linear Kernel function $K(x_i, x_j) = x_i^T x_j$,
3. Polynomial Kernel function $K(x_i, x_j) = [(x_i^T x_j) + 1]^d$,

4. Gaussian Function $K(x_i, x_j) = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)$.

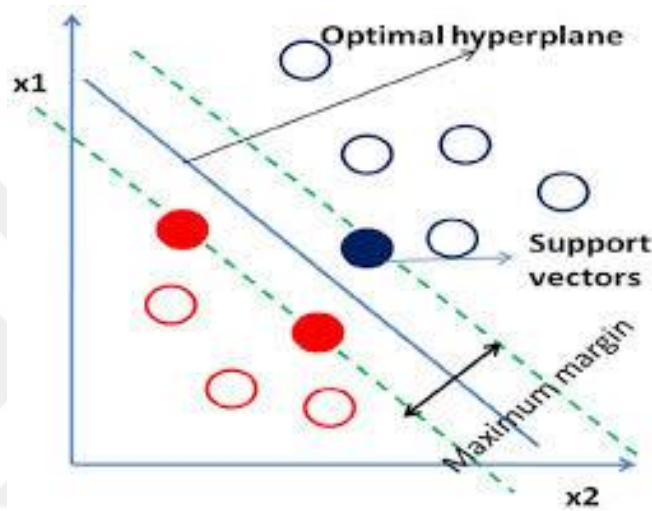


Figure 3.8 A support vectors, red and blue circles represent data points from two different classes. Solid filled circles denote support vectors.

4. EXPERIMENTAL RESULTS

In this thesis, we have a real data set and we can utilize EEG signals for normal (healthy person) and abnormal (epileptic patients). It consists of data acquisition, signal processing, feature extraction, feature reduction and seizure detection. Epileptic seizure detection in EEG can be like as a sort of pattern recognition notation. A narration EEG signal classification method is proposed, which is particularly based on Maximal Overlap Discrete Wavelet Transform (MODWT), then dimension reduction (PCA) and SVM classification.

We are summarized the procedure of the proposed system as follows:

Step 1: We used Matlab 2016 for programming.

Step 2: Decompose the signal using MODWT decomposition.

Step 3: extracting the features using Principal component analysis (PCA) algorithm for reducing the dimensionality.

Step 4: We are using Support Vector Machine (SVM) to classification process for epileptic seizure detection.

Step 5: We used two models for my own data (MODWT+PCA+SVM) abbreviated by (MPS) and (MODWT+SVM) abbreviated by (MS), and comparative between them for estimate the generalization error of MS and MPS, as it shown in figure

Step 6: We have Decision Boundary that is the zone of an issue space in which the output label of a fuzzy classifier. In Decision Boundary (MODWT+ PCA+ SVM + Prediction) abbreviated by (MPSPR) and (MODWT + SVM + Prediction) abbreviated by (MSPR), and comparative between them for estimate the generalization error of MSPR and MPSPR, as it shown in figure

In this work, three different methods are been used (Gaussian, Linear and Polynomials) for the comparative between each two models MPS and MS, and we get the test results which are shown in Table (4.1) by using (Gaussian, Linear and Polynomials).

Table 4.1 Estimate the generalization error of MPS and MS

Models	Methods for SVM			
		Gaussian	Linear	Polynomial
MPS		0.6	0.6	0.6
MS		0.255701754385981	0.377192892456164	0.260526315789490

This thesis contributes to the detection of epilepsy by providing an automated classification method that allows the data to be stored as epileptic or non-epileptic. Support vector machine that classifies subjects as having or not having an epileptic seizure. In this work, as we have demonstrated in the above table, the comparisons is done between MPS and MS models by three different methods (Gaussian, Linear and Polynomials) for my own data, According to this result EEG signal classification using SVMs shows that MS model can improve the performance of classifier and it has less error than the MPS. And the Gaussian method for MS model is better and less error than (linear and polynomial) methods; furthermore the Decision Boundary for MSPR has less error than the MPSPR, as shown in the Figures below.

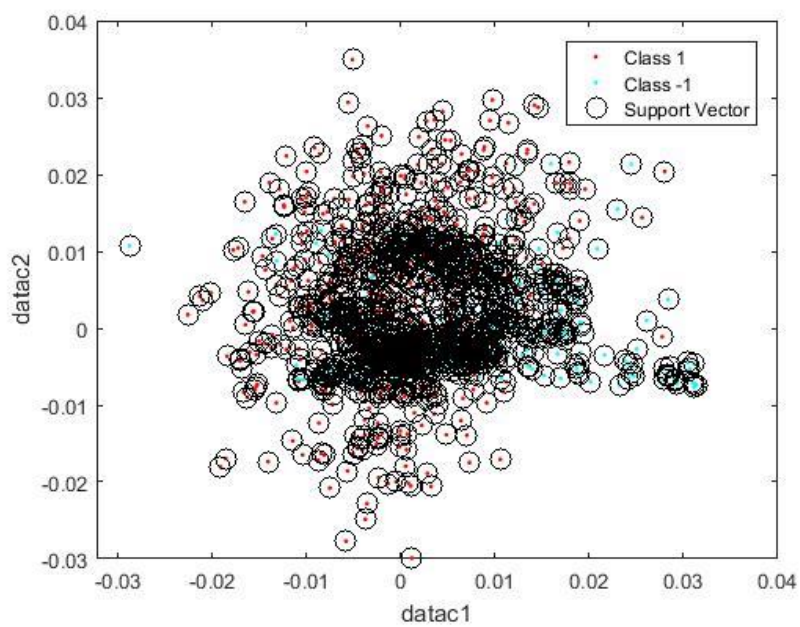


Figure 4.1: MPS for Gaussian method

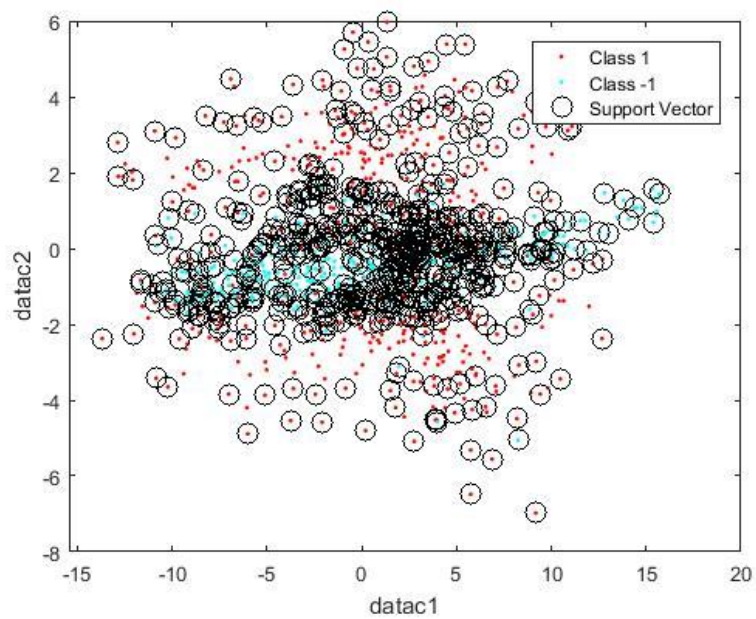


Figure 4.2 MS for Gaussian method

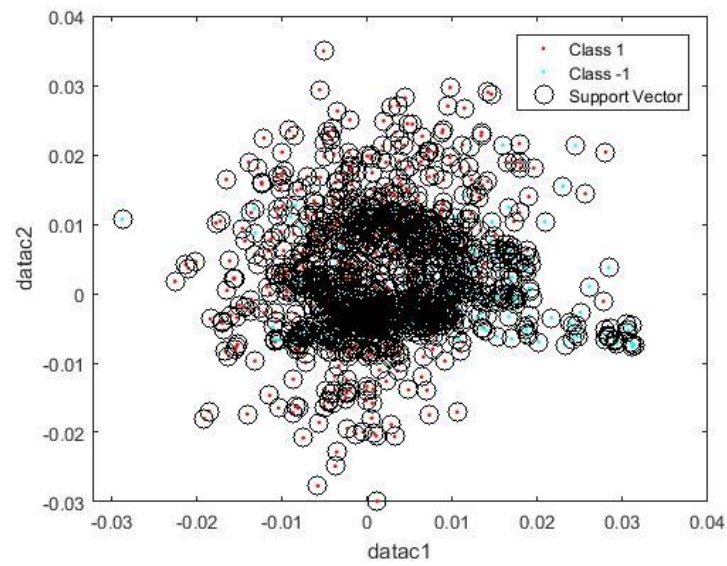


Figure 4.3 MPS for Linear method

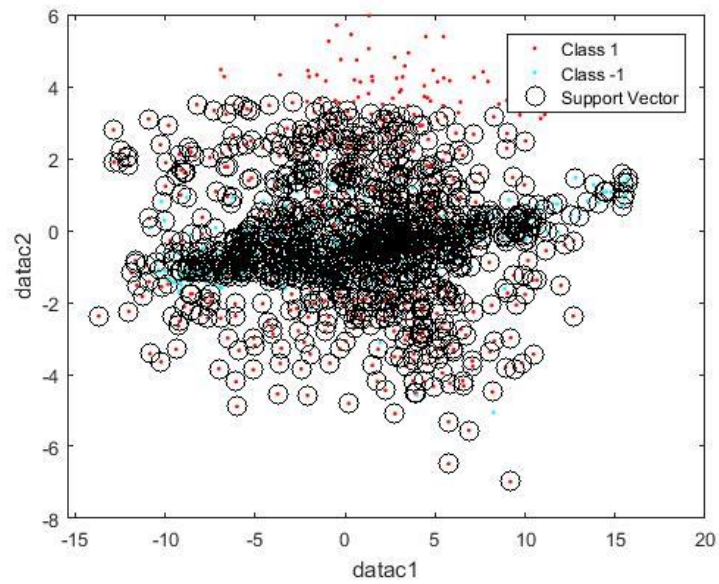


Figure 4.4 MS for Linear method

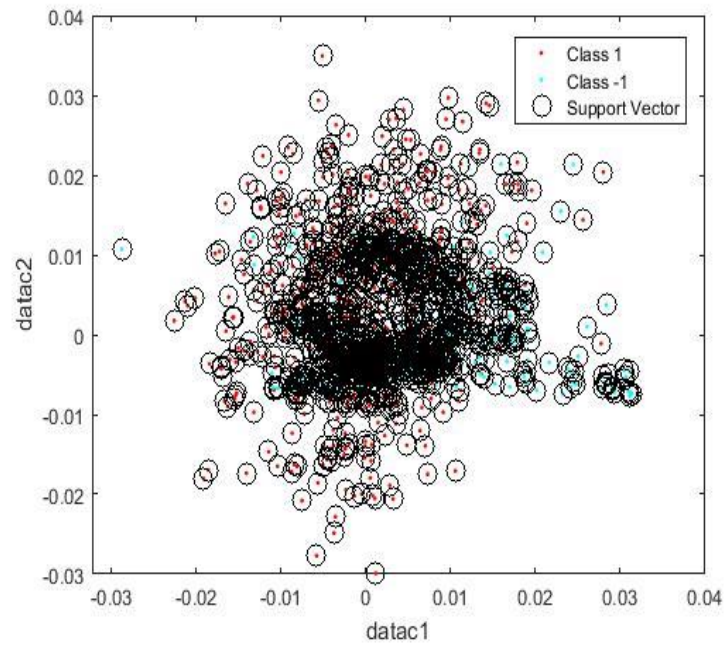


Figure 4.5 MPS for Polynomial method

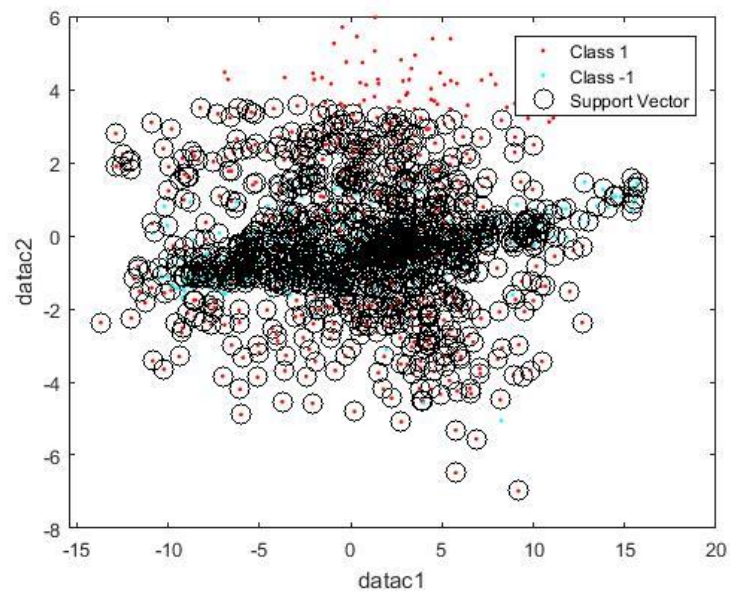


Figure 4.6 MPS for Polynomial method

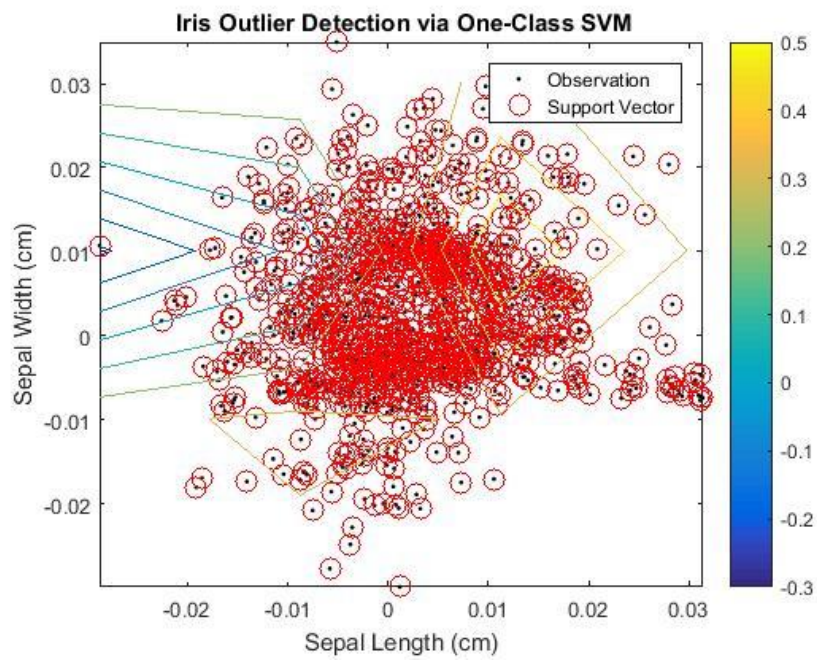


Figure 4.7 MPSPR for Gaussian method

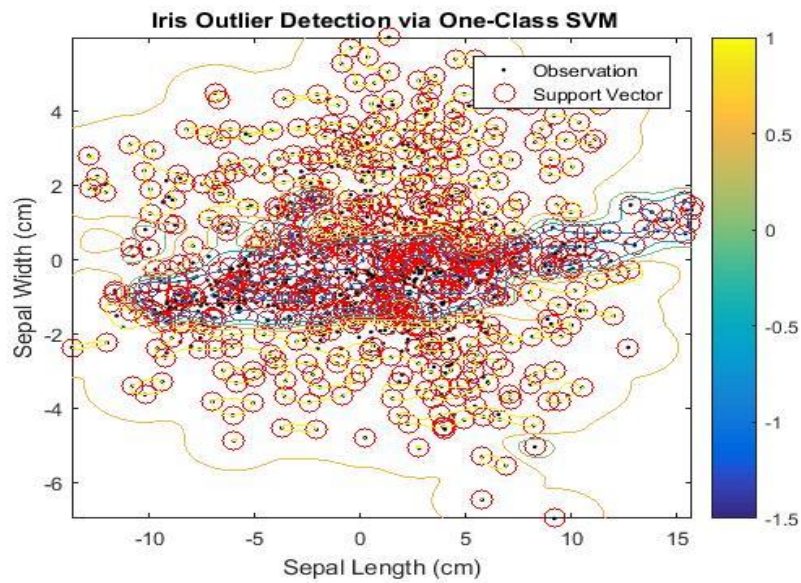


Figure 4.8 MSPR for Gaussian method

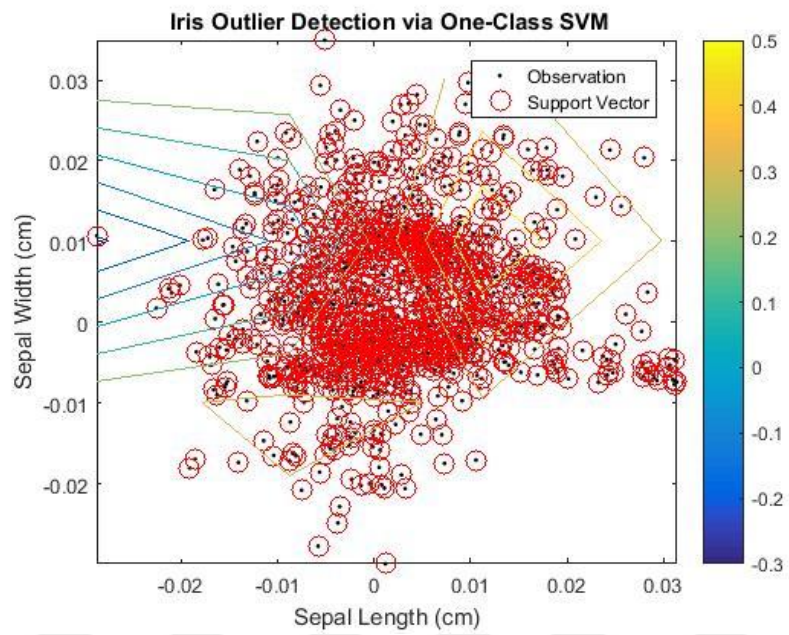


Figure 4.9 MPSPR for Linear method

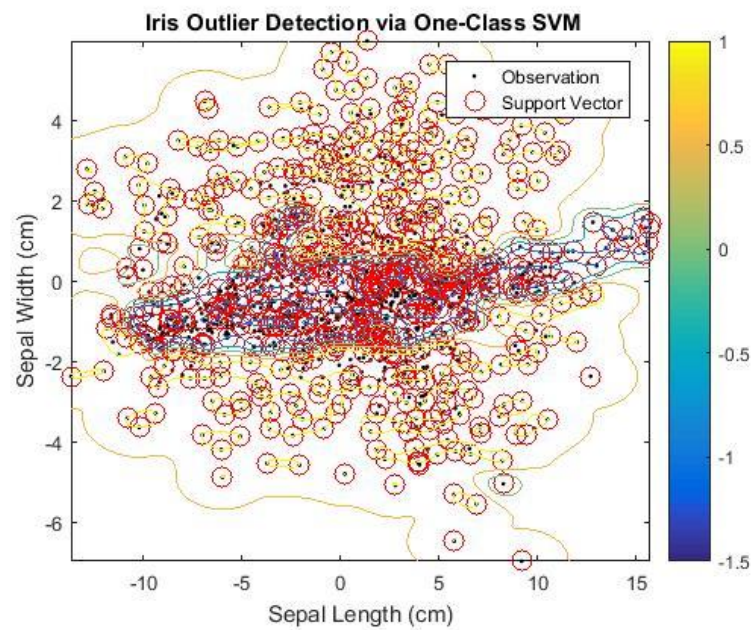


Figure 4.10 MSPR for Linear method

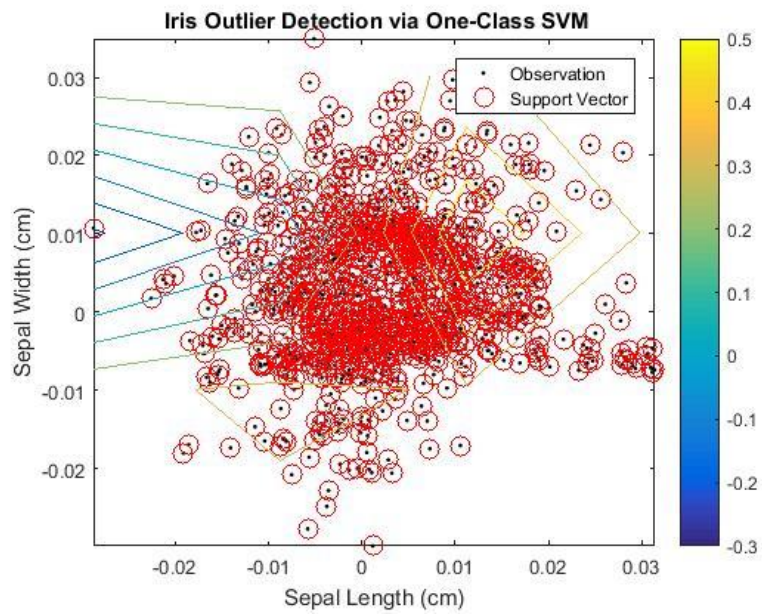


Figure 4.11 MPSPR for Polynomial method

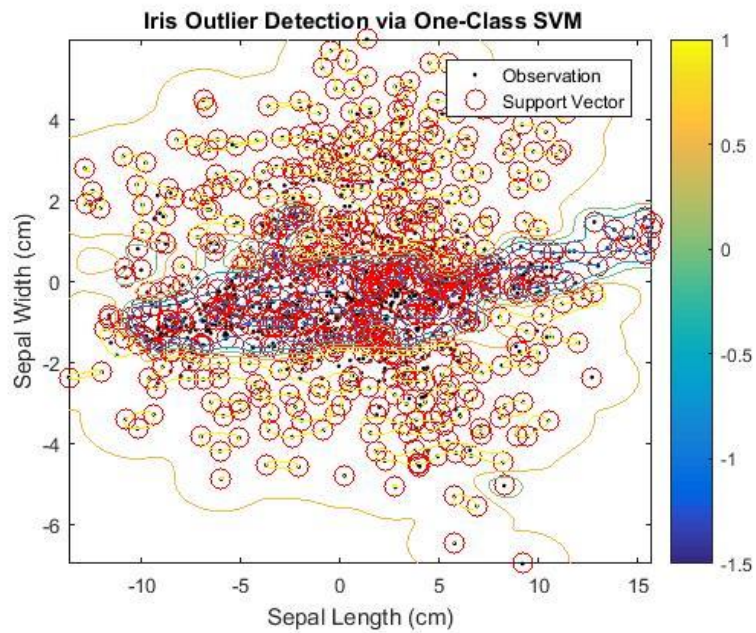


Figure 4.12 MSPR for Polynomial method

5. CONCLUSIONS

In this thesis, detection of epilepsy has been realized by an automated classification method that allows the data to be stored as epileptic or non-epileptic. SVMs classify subjects as having or not having an epileptic seizure. In this thesis, we have done the comparisons between MPS and MS models by three different methods (Gaussian, Linear and Polynomials) for my own data, According to this result EEG signal classification using SVMs shows that MS model can improve the performance of classifier and it has less error than the MPS, the Gaussian method for MS model is better and less error than (linear and polynomial) methods; furthermore the Decision Boundary for MSPR has less error than the MPSPR.

REFERENCES

- [1] Acharya, U. R., Vinitha Sree, S., Swapna, G., Martis, R. J. & Suri, J. S. “Automated EEG analysis of epilepsy” A review. *Knowl.-Based Syst.* Vol.45, (2013) pp 147–165
- [2] Adeli, H., Zhou, Z., & Dadmehr, N, “Analysis of EEG records in an epileptic patient using wavelet transform”, *Journal of Neuroscience Methods*, Vol. 123, (2003) pp 69–87.
- [3] Anders Eklunda, Mats Andersson, Hans Knutsson, *fMRI Analysis on the GPU Possibilities and Challenges*, *Computer Methods and Programs in Biomedicine*, 2012.
- [4] Aruna Tyagi and Vijay Nehra, *Brain–computer interface: a thought translation device turning fantasy into reality*, *Int. J. Biomedical Engg. and Tech.*, Vol. 11, No. 2, 2013.
- [5] Balasubramanian P., “Automated Classification of EEG Signals Using Component Analysis and Support Vector Machines”, *Masters Theses*, Grand Valley State University, 2014.
- [6] Chih-Chung Chang and Chih-Jen Lin, "LIBSVM: a Library for Support Vector Machines", Department of Computer Science, National Taiwan University, Taipei 106, Taiwan, (2006)
- [7] Hekim M., “The classification of EEG signals using discretization-based entropy and the adaptive neuro-fuzzy inference system”, *Turk J Elec Eng & Comp Sci.* Vol. 24 (2016) pp 285 – 297.
- [8] Jolliffe L.T. 'Principal Component Analysis' second edition, Springer, (2002)
- [9] Jonathan R. Wolpaw, Niels Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, Theresa M. Vaughan, “Brain–computer interfaces for communication and control”, *Clinical Neurophysiology* 2002.
- [10] Jonathan R. Wolpaw, Niels Birbaumer, William J. Heetderks, Dennis J. McFarland, P. Hunter Peckham, Gerwin Schalk, Emanuel Donchin, Louis A. Quatrano, Charles J. Robinson, and Theresa M. Vaughan, *Brain–Computer Interface Technology: A Review of the First International Meeting*, *IEEE Trans. on Rehabilitation Engg.*, Vol. 8, No. 2, 2000

- [11] E. Juarez-Guerra, V. Alarcon-Aquino and P. G´omez-Gil, “Epilepsy Seizure Detection in EEG Signals Using Wavelet Transforms and Neural Networks”, Book chapter of ‘New Trends in Networking, Computing, E-learning, Systems Sciences, and Engineering’ Springer International Publishing, Series Volume 312, (2015) pp 261-269.
- [12] M. Kalaivani , V. Kalaivani and V. Anusuya Devi,”Analysis of EEG signal for detection of Brain Abnormalities”, International Conference on Simulations in Computing Nexus, ICSCN- 2014.
- [13] T. Kameswara Rao, M. Rajya Lakshmi, Dr. T. V. Prasad, “An Exploration of Brain Computer Interface and Its Recent Trends”, Int. J. of Advanced Research in Artificial Intelligence, Vol. 1, Issue 8, 2012.
- [14] Kevric. J, Subasi A.,“Classification of EEG signals for epileptic seizure prediction using ANN”, In: 3rd International Symposium on Sustainable Development, May 31 - June 01 2012, Sarajevo.
- [15] Leigh R. Hochberg and John P. Donoghue, “Sensors for Brain-Computer Interfaces”, IEEE Engineering in Medicine and Biology Magazine. Sep/Oct 2006.
- [16] Miller, J. W. & Goodkin, H. P. “Epilepsy”, John Wiley & Sons, Ltd. (2014). at <<http://dx.doi.org/10.1002/9781118456989>>
- [17] Percival, D. B. and A. T.Walden,”Wavelet Methods for Time Series Analysis. Cambridge”, Cambridge University Press(2000).
- [18] M. Rajya Lakshmi, T. V. Prasad, and V. Chandra Prakash, “Survey on EEG Signal Processing Methods”, Inter. J. of Advs.Research in Computer Science and software Engineering, Vol 4 issue 1(2014), pp 84-91.
- [19] Ravish D. K., Devi S.S. ”Automated Seizure Detection and Spectral Analysis Of EEG Seizure Time Series”, European Journal of Scientific Research, Vol. 68, Issue 1, (2012).
- [20] Shiens, J. “A Tutorial on Principal Component Analysis” Center for Neural Science, New York University, 22nd April 2009, version 3.01.

- [21] Siamac Fazli , Jan Mehnert, Jens Steinbrink, Gabriel Curio, Arno Villringer, Klaus-Robert Müller, Benjamin Blankertz, Enhanced performance by a hybrid NIRS–EEG brain computer interface, *Neuro Image* 59 , 2012 519–529.
- [22] I. Smith, “A Tutorial on Principal Component Analysis”, 22 February, 2002.
- [23] Subasi, A. “Automatic recognition of alertness level from EEG by using neural network and wavelet coefficients” *Expert Systems with Applications*, Vol. 28,(2005) pp 701–711.
- [24] Subasi, A. and Erçelebi, E, “Classification of EEG signals using neural network and logistic regression”, *Computer Methods and Programs in Biomedicine*, Vol. 78, (2005) pp 87-99.
- [25] Subasi A. and M. Ismail Gursoy, “EEG signal classification using PCA, ICA, LDA and support vector machines”, *Expert Systems with Applications*, Vol. 37, Issue 12 (2010) 8659–8666.
- [26] Sunhaya, S. Manimegalai, P.: Detection of Epilepsy Disorder in EEG Signal. *International Journal of Emerging and Development*, Vol.2, Issue 2 (2012)] Sunhaya, S. Manimegalai, P.: Detection of Epilepsy Disorder in EEG Signal. *International Journal of Emerging and Development*, Vol.2, Issue 2 (2012).
- [27] C. E. Valderrama and G. ULLOA, "Combining spectral and fractal features for emotion recognition on Electroencephalographic signals", *WSEAS TRANSACTIONS on SIGNAL PROCESSING*, Vol. 10, (2014) p.p 481-496.
- [28] Yatindra Kumar · M. L. Dewal · R. S. Anand, “epileptic seizure detection in eeg using DWT- based ApEn and Artificial neural network” ,*Signal, Image and Video Processing*, Vol. 8, Issue 7, (2014) pp 1323–1334.
- [29] Zarjam, P., Mesbah, M., Boashash, B. “Detection of newborns EEG seizure using optimal features based on discrete wavelet transform”, *Proc. IEEE Int. Conf. Acoust. Speech Signal Process.* Vol. 2, (2003) pp 265 – 268.

[30] Awin Mahmood SALEEM, Ahmet CINAR, "Epilepsy seizure detection in EEG signal using wavelet transforms and support vector machines" .International Engineering Science and Education Conference (INESEC) in DICLE University, Diyarbakir, Turkey.



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