Detection of Epilepsy Disorder by EEG Using Discrete Wavelet Transforms

A Thesis submitted in partial fulfillment of the requirement for the award of degree of

Master of Engineering
in
Electronic Instrumentation and Control

Submitted by:

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Patiala, 147004

DECLARATION

I hereby declare that the report entitled ***"Detection of Epilepsy Disorder by EEG Using Discrete Wavelet Transforms,"*** *is an authentic record of my own work carried out as a requirement for the award of degree of M.E. (Electronic Instrumentation & Control) at Thapar University, Patiala, under the guidance of* ***Dr. Mandeep Singh,*** *Associate Professor, Department of Electrical and Instrumentation Engineering, Thapar University during January to July 2012.*

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It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

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The real spirit of achieving a goal is through the way of excellence and austere discipline. I would have never succeeded in completing my task without the cooperation, encouragement and help provided to me by various personalities.

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ABSTRACT

EEG (Electroencephalogram) is a technique for identifying neurological disorders. There are various neurological disorders like Epilepsy, brain cancer, etc. Epilepsy is one of the common neurological disorders pertaining in approximately 1% of the people in the world. Objective detection efficiently is still a challenging task for many neurological disorders. This is highly related to the diversity of cases that occurs daily. Especially in the case of epilepsy, which is a complex disorder not well-explained at the biochemical and physiological levels, there is the need for investigations for novel features, which can be extracted and used for distinguishing epileptic EEG signals from normal EEG signals. This thesis discusses the design of system that detects the epileptic activity with efficacy. Decomposition of the EEG signal to various subbands by multi-level wavelet decomposition is followed to extract features from these sub-bands. The range of these features in non-epileptic and epileptic group of 50 subjects each from data set is analysed for data available at the Department of Epileptology, University of Bonn, and the parameters with distinct non-overlapping zone are identified [20]. These features are then classified using a scoring system that detects the EEG data for epilepsy. This system is finally validated for another two groups of non- epileptic and epileptic subjects, 50 each from the same data set. The validation process on a different group showed high detection rate.

ORGANIZATION OF THESIS

The thesis begins by introducing EEG (Electroencephalogram), various characteristics of EEG, how a normal EEG different from Epileptic EEG, artifacts that are introduced while recording an EEG signal , Epilepsy, seizures, types of seizures, role of EEG in epilepsy, treatment in Chapter 1. This is followed by a discussion of previous work that has already been carried out in the detection of epileptic activity in Chapter 2. Chapter 3 demonstrates problem statement of the present work done. Chapter 4 explains the methodology on which the whole work stands and Chapter 5 delves into the results obtained into tabular form and discussions over the result. Finally, Chapter 6 concludes the thesis and outlines directions for future work. The thesis ends with references and publications from the present research.

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SYMBOLS

α	EEG subband 8–12 Hz
β	EEG subband 12–30 Hz
γ	EEG subband above 30 Hz
δ	EEG subband 0–4 Hz
θ	EEG subband 4–8 Hz
Hz	Frequency in Hertz
Na^+, Ca^+, K^+	sodium, calcium, potassium ions

ABBREVIATIONS

BCI	Brain-computer-interface
CNS	Central Nervous System
ECG	Electrocardiogram
ECoG	Electrocorticogram
EEG	Electroencephalogram
FFT	Fast Fourier transforms
GABA	gamma-amino butyric acid
PDS	paroxysmal depolarization shift
NMDA	N-methyl-D-aspartate receptor
PET	Positron Emission Tomography
VNS	Vagus Nerve Stimulation
STFT	Short Term Fourier Transform.

CHAPTER 1: INTRODUCTION

1.1 Electroencephalogram

Human Brain is the most complex organ among all the systems in the human body, also the most remarkable one. It exhibits rich spatiotemporal dynamics. In medical terms, human brain is also called an encephalon and the medical technique that reads scalp electrical activity of the encephalon is called ELECROENCEPHALOGRAPH (EEG). Human brain can be divided into three parts: cerebrum, cerebellum and the brain stem. The cerebrum is the largest part and is responsible for initiation of movement, coordination of movement, sensing temperature, touch, vision, hearing, judgment, reasoning, problem solving, emotions and learning. Cerebrum is divided into four lobes as shown in figure 1.1. They are frontal lobe, occipital lobe, parietal lobe & temporal lobe. The smaller part of the brain is called cerebellum. The main purpose of cerebellum is to coordinate voluntary muscle movements and to maintain posture, balance and equilibrium. The brainstem is the middle part of the brain. This part is responsible for movement of the eyes and mouth: it relays sensory messages like temperature, voice pain etc. It is also responsible for controlling hunger, respiration, consciousness, cardiac functions, body temperature etc [1].

EEG is a very powerful tool in neurology. The voltage range for EEG signal is 3-100 μV which is 100 times weaker than ECG signal.

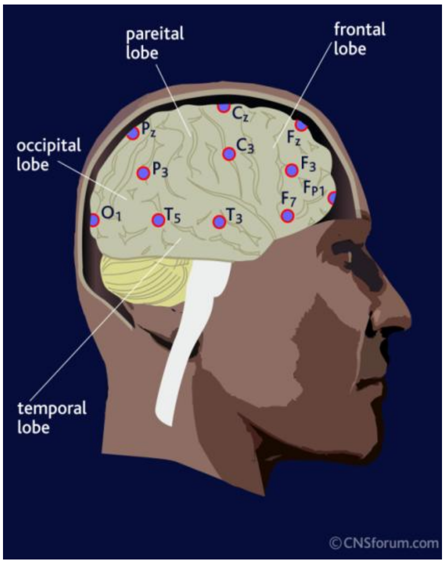

Figure 1.1: Cerebrum divided into four lobes

The electroencephalogram (EEG) is a non-invasive, multi-electrode recording of time-varying electric potentials that generated due to activation of millions of neurons [2]. The electrodes are distributed symmetrically around the scalp as shown in Figure 1.2 to provide a temporal and spatial summary of brain surface activity; each electrode responds to the aggregate potential generated by many neurons in the area beneath it. An invasive EEG recording made with electrodes directly in contact with the brain surface is called Electrocorticogram (ECoG). ECoGs are not so much affected by artifacts and signal attenuation as it is in the case with EEGs. They provide higher spatial resolution since electrodes responds to the activity of a far smaller number of cortical neurons.

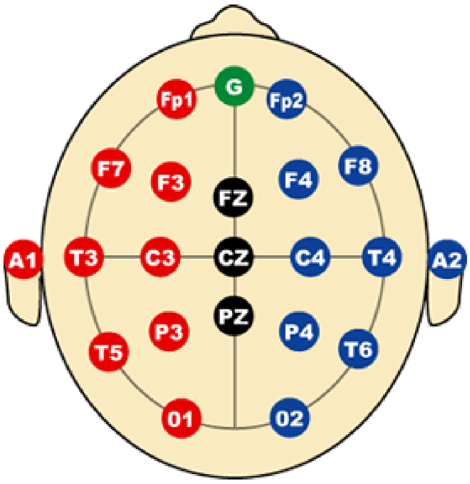

Figure 1.2: The 10–20 international system of electrode placement.

The earliest electroencephalographic recordings were completed and visually characterized in terms of amplitude and frequency content by the Austrian psychiatrist. Ever since then, the electroencephalogram has been studied and relied on as a clinical tool for the diagnosis of various neurological disorders such as epilepsy [3].

One of the main applications of EEG is in diagnosing epilepsy. A person suffering from epileptic attack has a distinctly different electroencephalographic waveform as compared to excessive neural activity in the brain. Also there are many other applications that include diagnosing coma and other disorders of the brain on account of certain injury or illness. EEG is also used to monitor the level of anesthesia given during surgery. This is a critical application, where too little anesthesia may cause trauma to be patient under surgery, while too deep anesthesia may result in respiration or circulation arrest. An anesthetic depth increase from light surgical levels to deep anesthesia, the EEG displays disrupted rhythmic waveforms, high amplitude burst suppression activity where the normal bursts of electrical impulses is suppressed, and finally, a very low amplitude isoelectric or 'flat-line' activity. EEG signals are also being used to design brain computer interfaces and have futuristic applications such as control of machines by thought process. This may help locked-in persons, who cannot move any organ of their body, i.e. they cannot even blink their eyes, to communicate effectively. EEG signals are also highly used to verify brain death.

1.2 Recording EEG

Bipolar recordings and referential recordings are used for visually reviewing EEG. In a referential recording the potential at each electrode is recorded relative to the potential at either one of the reference electrodes A1 and A2. Bipolar arrangement of electrodes for recording EEG is shown in figure 1.3.

Typically, the electrodes from the left-side of the head are cross-referenced to A2, while those from the right-side of the head are cross-referenced to A1. This scheme ensures that electrodes from each side of the head measure activity relative to a reference that is not greatly affected by cerebral activity within their areas of coverage.

In a bipolar recording the difference between pairs of adjacent electrodes, which are otherwise known as a derivation, is the quantity that is recorded.

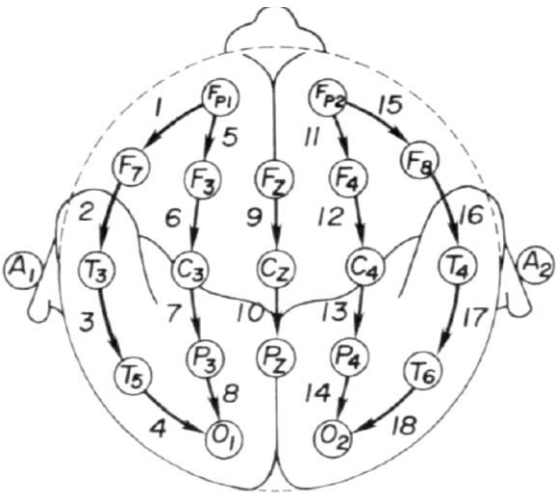

Figure 1.3: Derivations of a Bipolar Recording

Referential recordings have an advantage over bipolar recordings that the change or abnormality is always clearly observed since the absolute potentials of electrodes, rather than their differences, are quantities recorded. On the other hand the disadvantage of referential recordings is that they are very susceptible to common-mode noise as well as contamination of the reference electrode by artifact activity. Once the reference electrode is contaminated it becomes difficult to interpret the activity on electrodes measured against it. The consequence of this operation is a slight attenuation of changes or abnormalities observed in the EEG. An extreme case occurs when a derivations records a zero signal due to cerebral activity that equally affects its electrodes.

1.3 Characterizing EEG

EEG activity can be characterized in terms of several quantitative and qualitative variables that must always be considered in the context of a patient's age and state of consciousness. These variables are fundamental frequency, amplitude, morphology, localization, and reactivity.

- **Fundamental Frequency**

The fundamental frequency of an EEG waveform refers to the rate at which the waveform is repeated over a period of a second. The waveform can have an arbitrary shape and any number of subcomponents. The rate at which the unit as a whole repeats in the span of a second matters. An EEG waveform with a constant, stable fundamental frequency is called *rhythmic*, otherwise it is called *arrhythmic*. Figures 1.4 and 1.5 illustrate the examples of rhythmic and arrhythmic waveforms.

Figure 1.4: Rhythmic EEG Waveform

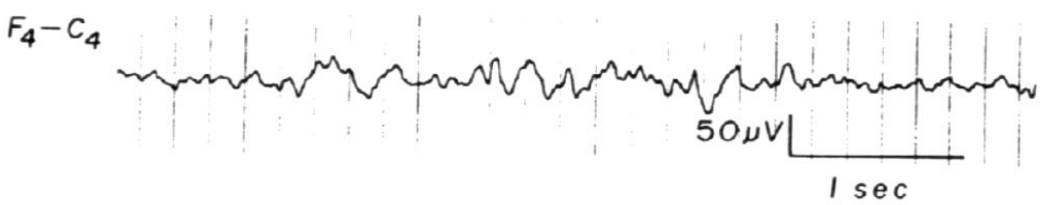

Figure 1.5: Arrhythmic EEG Waveform

- **Amplitude**

Amplitude of a waveform in an EEG trace refers to its peak voltage, which is typically of the order of microvolts. For example, the waveforms in the EEG trace of Figure 1.4 have amplitudes smaller than 75*V*, and those in the trace of Figure 1.7 have amplitude of approximately 100*V*. An EEG waveform demonstrating a sudden or gradual reduction in amplitude, such as that illustrated in Figure 1.9, is said to exhibit suppression or depression.

- **Morphology**

The morphology of an EEG waveform describes its observed shape, which is a function of the amplitude and fundamental frequency of its constituent components. An EEG waveform that is composed of only a single component is called Monomorphic, and one that is composed of several different components is called polymorphic. Examples of these two different morphologies are shown in top and bottom panels of Figure 1.6.

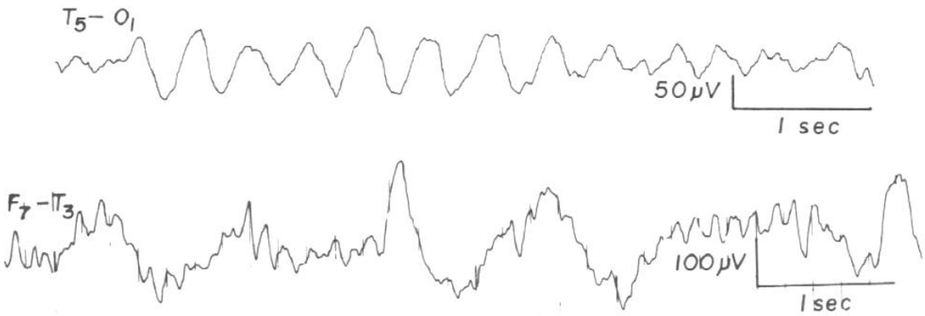

Figure 1.6: Monomorphic (Top) and Polymorphic EEG Waveforms (Bottom)

EEG waveforms consisting of two or more waveforms each with possibly different morphologies are called *complexes*. An example of a commonly observed abnormal complex is the *spike-and-slow-wave complex* shown in Figure 1.7. As its name implies, a spike-and-slow-wave complex is composed of a broad, slow wave and a *transient* spike.

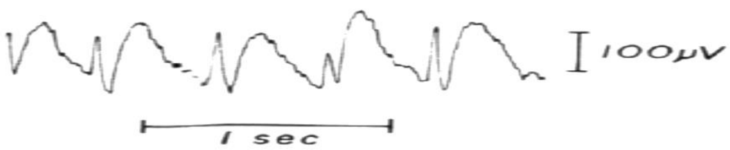

Figure 1.7: Spike-And-Slow-Wave Complex

- **Localization**

The localization of EEG activity refers to the distribution of the activity over the head. EEG activity observed only in a limited region of the head is called *focal*, while activity observed in all regions is called *generalized*. Furthermore, EEG activity exhibiting equal fundamental frequency, amplitude, and morphology on the left and right sides of the head is *symmetric*, otherwise it is *asymmetric*. The clinical designations for different regions of the head are shown in Figure 1.8.

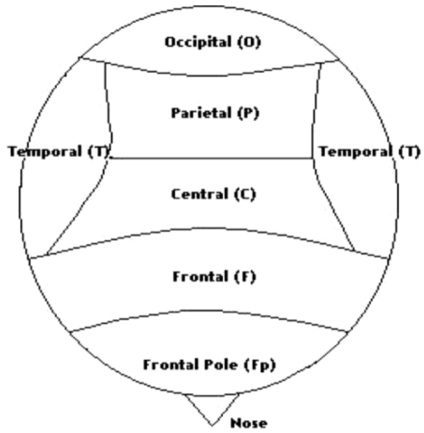

Figure 1.8: Regions of the Head

- **Reactivity**

The reactivity of EEG waveforms refers to the degree of change in anyone of the preceding variables as a result of a stimulus. For instance, Figure 1.9 shows the suppression of 10 Hz occipital activity upon opening of the eyes.

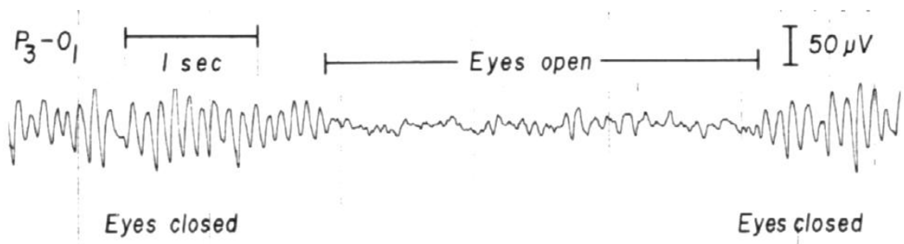

Figure 1.9: Reactivity of EEG Waveforms

1.4 Normal EEG

Normal EEG is electric potential that qualitatively and quantitatively appears mostly in the EEG of subjects not affected by any disease. The following is a description of well-documented normal EEG activity in adults and children. Typical recordings of EEG are shown in Figure 1.10. Normal EEG is the ultimate requirement of every being with certainty of some disorder of brain. It is divided into five subbands named as Delta, Theta, Alpha, Beta, Gamma. Each subband has a peculiar frequency range. Delta (0-4 Hz), Theta (4- 8 Hz), Alpha(8- 12 Hz), Beta(12-30 Hz), Gamma(> 30 Hz).

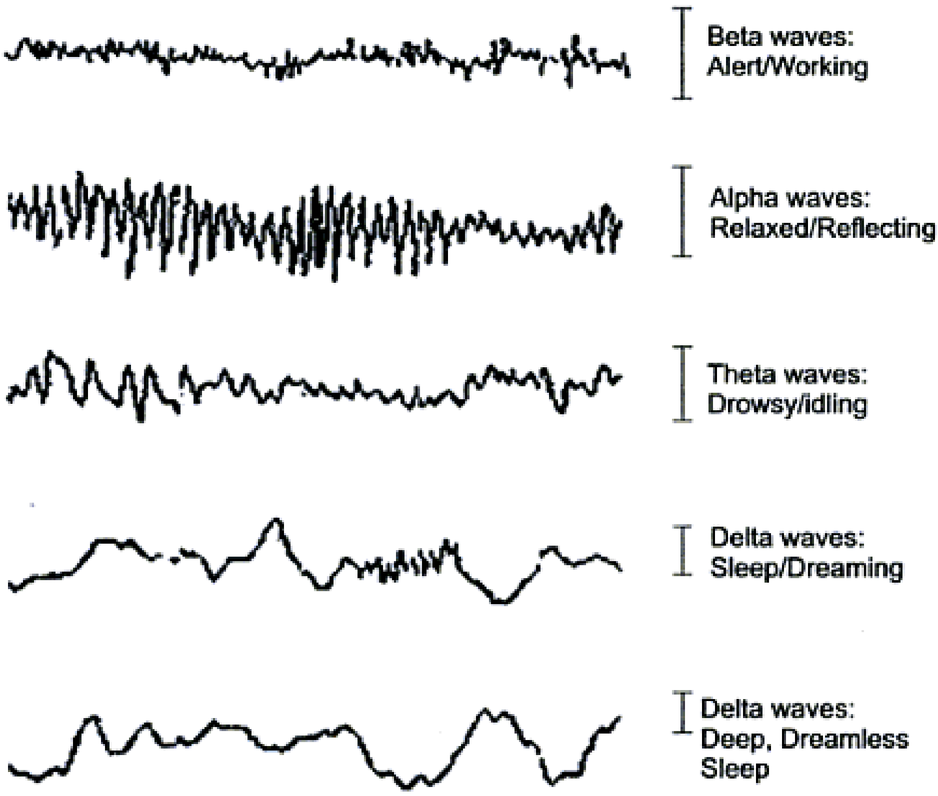

Figure 1.10: EEG signal and its characteristics

As can be observed there are fairly long stretches of data (symbolizing stationary/quasi-stationary activity) some of which appear like noises (random signal) while others have a regular periodic look. These are interrupted by single conspicuous waves with definite shapes called transients. In the language of the clinician these stretches are referred to as “background activity” while occasional short duration signals are called “transients”. Transients are invariably associated with abnormalities and are therefore known as “paroxysms”. These regular stretches are not necessarily abnormal occurring, for example, in all sleep stages in healthy adults. The different kinds of transients are regular stretches of data and are shown in figure 1.11 [12].

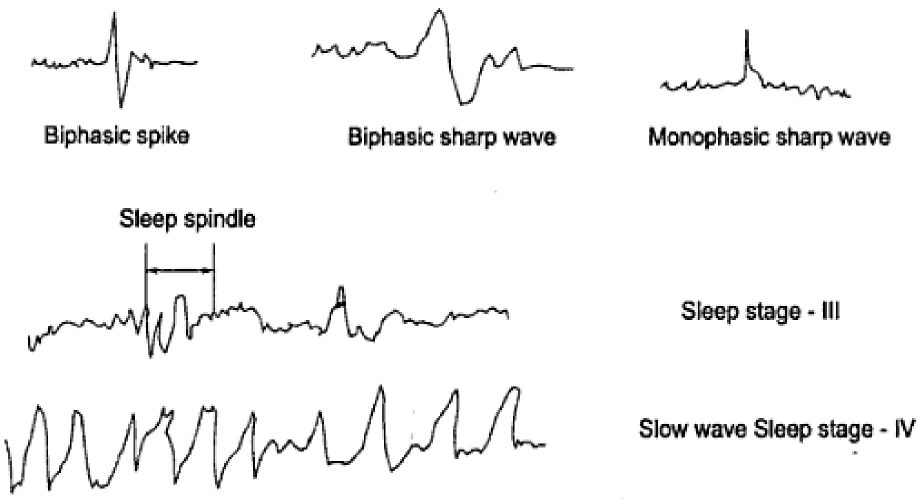

Figure: 1.11 Different kinds of transients of an EEG

EEG typically has amplitudes ranging from 10 to 100μV and will be in the frequency range 0.5 to 50Hz. The periodic activity manifests itself in the form of rhythms known as alpha (α), theta (θ), beta (β), delta (δ), and gamma (γ).

- **Alpha Rhythm**

The alpha rhythm is EEG activity with frequency between 8-12 Hz that is prominent in the occipital regions of normal, relaxed adults whose eyes are closed. Alpha activity is generally attenuated by opening of the eyes, increasing vigilance, or heightened awareness. The mixture of the alpha rhythm with other rhythms results in *alpha variants*, which have different morphology but otherwise exhibit the same reactivity and localization.

The frequency of alpha rhythms in children gradually increases towards the rate observed in adults over the course of their development. Also the alpha rhythm may be as slow as 3 Hz at the age of two months and as fast as 7 Hz at the age of one year. Furthermore, the amplitude of alpha rhythms in children steadily increases until the age of one year and then declines towards the 10*V* level observed in adults.

- **Beta Rhythm**

The beta rhythm is EEG activity with frequency range 12-30 Hz that is most prominently observed in the frontal and central regions in adults, but may also be generalized sometimes. Alertness and vigilance promotes the onset of beta activity, while voluntary movement results in its suppression. The beta rhythm also certainly shows a gradual, age-related increase in frequency for children.

- **Theta Rhythm**

The theta rhythm is EEG activity with frequency between 4-8 Hz. This activity is abnormal in awake adults, but commonly observed in sleep and children below the age of 13 years. Theta activity is asymmetric since it is predominantly observed in the central, temporal, and parietal regions of the left side of the head. Figure 1.12 shows the theta rhythm artificially placed in context of other normal EEG rhythms.

- **Delta Rhythm**

The delta rhythm exhibits a frequency below 4 Hz and amplitudes that exceed those of all other rhythms. It is most prominently found in frontal regions in adults and posterior regions in children in the third and fourth stages of sleep. Figure 1.12 shows the delta rhythm artificially placed in context of other normal EEG rhythms.

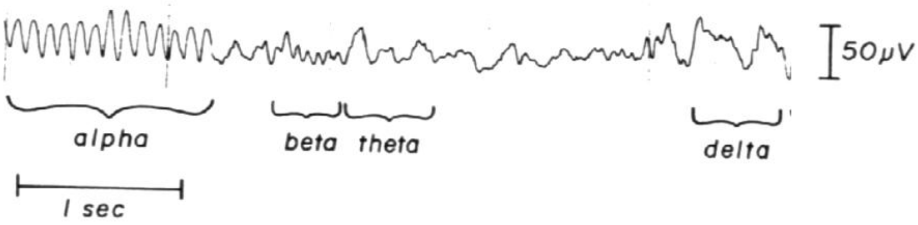

Figure 1.12: Normal EEG Rhythms

- **Mu Rhythm**

The mu rhythm is the EEG activity with frequency between 7-11 Hz that is most prominently observed in the central region. Mu activity is suppressed by movement, imagined movement, or tactile stimulation; in contrast, it is enhanced by immobility and heightened attention. While the frequency range of mu and alpha rhythms overlap, mu rhythms are differentiated by their localization, arch-like morphology, and reactivity. The suppression of mu activity following fist-clenching is shown in Figure 1.13.

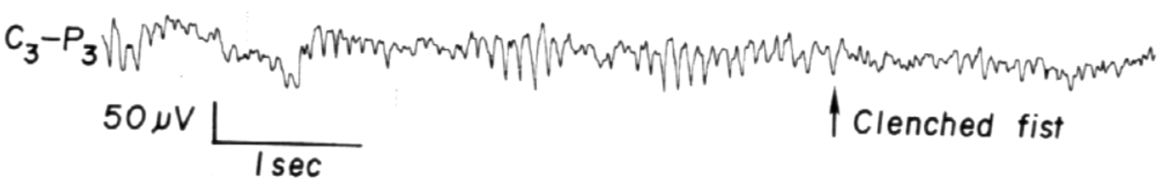

Figure 1.13: Mu Rhythm

- **Lambda Waves**

Lambda waves are transient sharp waves lasting for duration of approximately 0.25 seconds that occur in the occipital region whenever an adult scans a visual field with horizontal eye movement. Lambda waves are not seen when the eyes are closed, or opened in dark settings. Lambda waves exhibit the same localization and reactivity in children as in adults. Figure 1.14 illustrates several examples of occipital lambda waves

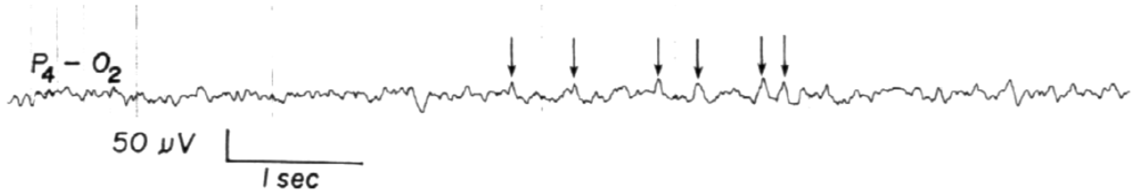

Figure 1.14: Lambda Waves

1.5 Abnormal EEG

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.Abnormal EEG activity is an activity that is prevalent in the EEG of groups of people with neurological or other disease complaints. Abnormal EEG may be an unusual waveform as well as the absence or deviation of normal EEG from well-documented limits on frequency, amplitude, morphology, localization, and reactivity. For instance, an EEG recording exhibiting an absence or change in the nominal frequency and amplitude of sleep-spindles is considered abnormal. The following sections discuss several abnormal EEG waveforms that are commonly observed in the EEG of patient groups. For patients affected by epilepsy, these abnormalities are routinely observed during interictal periods, meaning between seizure episodes; however, they do not necessarily result in the clinical behavior observed during a seizure or match its electrographic signature.

- **Spike and Sharp Waves**

Spike waves are transients with pointed peaks exhibiting durations between 20-70 milliseconds. Sharp waves are similar to spike waves, but exhibit longer durations typically between 70-200 milliseconds as shown in Figure 1.15.

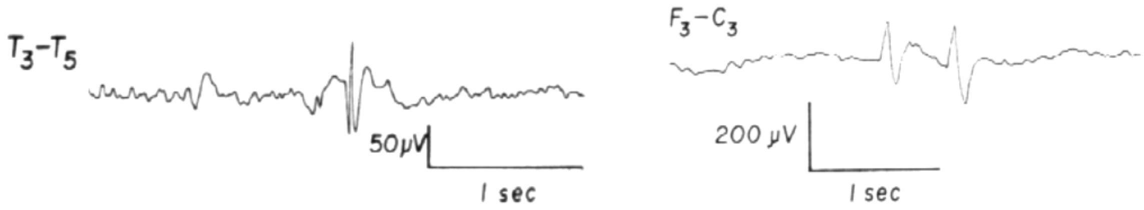

Figure 1.15: Spike Waves (Top) and Sharp Waves (Bottom)

- **Spike-and-slow-wave complex**

It is a spike followed by a longer duration wave as shown in Figure 1.7. Multiple spikes may precede the slower wave and the entire complex may be repeated at a rate of 2.5-6 Hz with intervening periods of quiescence of various durations.

- **Sharp-and-slow-wave complex**

It is identical to the spike-and- slow-wave complex except that a sharp wave precedes the slower, broader wave and the complex is repeated at rates between 1-2 Hz.

- **Periodic discharges**

Periodic discharges refer to time-limited bursts that are repeated at a certain rate. These bursts may exhibit a variety of durations, frequencies, amplitudes, morphologies, and localizations. An example of a periodic discharge is *burst-suppression* activity, which is a discharge of theta or delta frequency waveforms with long intervening periods of very low-amplitude waves. Figure 1.16 shows and instance of burst suppression activity.

Figure 1.16: Burst-Suppression Activity

- **Rhythmic Hypersynchrony**

Rhythmic hypersynchrony refers to rhythmic activity emerging from a quiescent back-ground and exhibiting unusual frequency, amplitude, morphology and localization of any degree. The rhythmic activity may either be continuous or intermittent. Figure 1.17 shows an example of abnormal, high-amplitude, intermittent 2-3 Hz rhythmic activity on a frontal derivation.

Figure 1.17: High-Amplitude Intermittent 2-3 Hz Activity

- **Electrocerebral Inactivity**

Electrocerebral inactivity refers to a variable length period not caused by instrumental or physiological artifacts that exhibits extreme attenuation of the EEG relative to a patient-specific baseline as shown in Figure 1.18. To appreciate the reduced amplitude of this trace, note that a 10*V* scale, rather than a 50*V* scale, is being used for display. Furthermore, the transients in Figure 1.18 are not of cerebral origin, they are the result of electrocardiographic artifact.

Figure 1.18: Electrocerebral Inactivity

1.6 Artifacts

1.6.1 Physiological Artifacts

- **Muscle Potentials**

Artifacts caused by muscle potentials are very common in EEG recordings. They appear as high-frequency bursts in the frontal and temporal electrodes of a bipolar recording, and in all electrodes of a referential recording that uses the ear, chin, or mandible as a reference. Although muscle artifacts can never be completely eliminated, they can be attenuated with the use of a high frequency filter that limits the EEG bandwidth to 35 Hz activity. The risk associated with this strategy is that highly filtered muscle activity may be mistaken for normal beta activity. Figure 1.19 illustrates the high frequency activity associated with muscle artifacts.

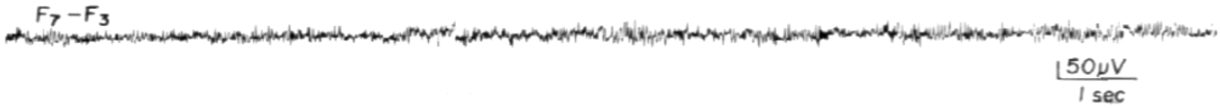

Figure 1.19: Muscle Artifact

- **Electrocardiographic Potentials**

Electrocardiographic artifacts are the ones that are produced by the electrical activity of the heart. They resemble attenuated periodic sharp waves in both referential and bipolar recordings. Electrocardiographic artifacts cannot be easily removed through filtering, but can be distinguished from EEG activity by noting that their period perfectly matches the period of an accompanying ECG signal. Figure 1.20 shows the sharp waves associated with electrocardiographic potentials.

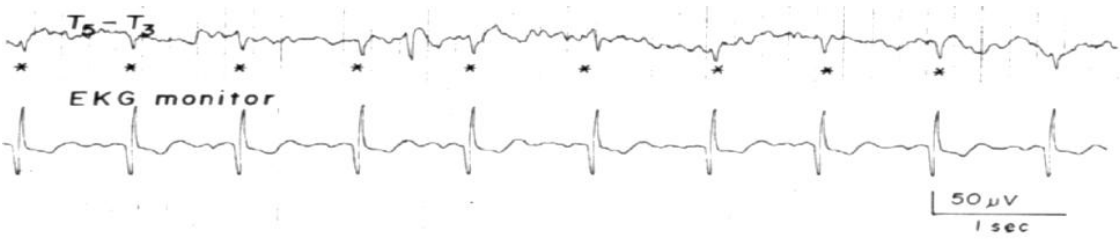

Figure 1.20: Electrocardiographic Artifact

- **Eye Movement Potentials**

Eye movement, eye blinking, and eyelid fluttering gives rise to artifacts resembling transient or rhythmic EEG slow waves. These artifacts appear most prominently in the frontal channels of both bipolar and referential recordings, and can possibly be distinguished from EEG activity of frontal cerebral origin by the addition of electrodes around each eye. However, the extra electrodes are not often used in clinical practice and were not available to our detector. The mixture of eye movement and electrocardiographic artifacts results in rhythmic frontal activity with sharp and slow components. Figure 1.21

illustrates the low frequency activity associated with eye blinking and the higher frequency activity associated with eye fluttering.

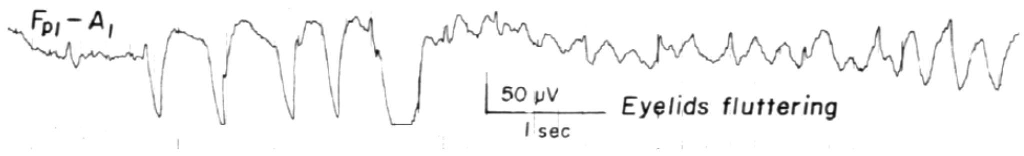

Figure 1.21: Eye Movement Artifact

- **Glossokinetic Potentials**

Artifacts generated by glossokinetic potentials refer to artifacts generated by movement of the tongue. These artifacts appear as single rhythmic slow waves in the temporal regions and can be recognized by the addition of electrodes near the mouth. Chewing and sucking movements mix artifacts generated by muscle potentials and glossokinetic potentials, and can be identified by the addition of electrodes near the jaw. Finally, hiccups and sobbing can generate glossokinetic potentials that may appear in EEG as abnormal spike-and-wave discharges. Figure 1.22 shows the mixture of slow, fast, and spike activity resulting from glossokinetic and muscle potentials caused by chewing.

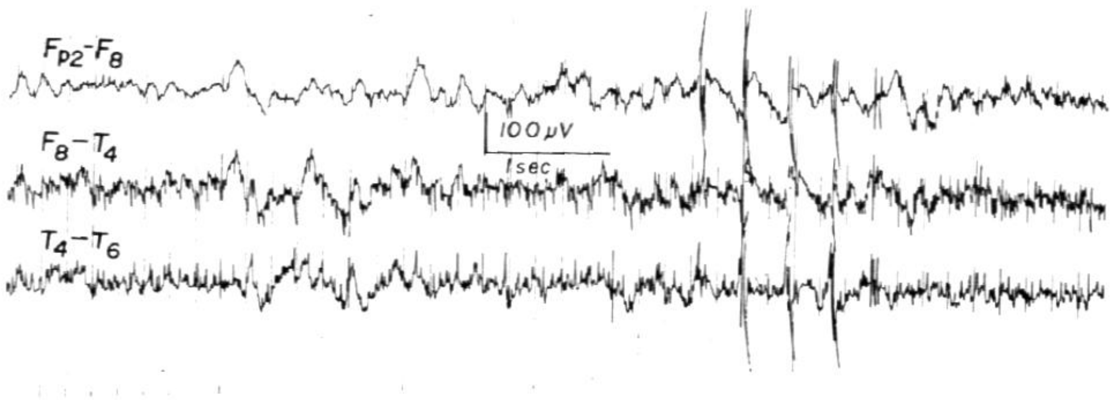

Figure 1.22: Chewing Artifact

- **Skin Potentials**

Changes in skin potential produce low frequency baseline changes in the EEG. The potential of skin may change as a result of the electrical potential generated by active sweat glands, or because of sweat-related changes in electrolyte concentration between the skin and the EEG electrodes. Figure 1.23 shows a less than 1 Hz baseline variation in the referential recording of an $F7$ electrode displayed on a 2 second, $50V$ scale.

Figure 1.23: Low Frequency Baseline Change Caused by Sweat

1.6.2 Nonphysiological Artifacts

Electrodes that are poorly coupled mechanically or electrically to the skin can produce artifacts resembling EEG sharp waves, spike waves, or slow waves. Movement of the wires connecting electrodes to the EEG instrument simulates slow, rhythmic EEG activity with a frequency matching the movement of the wires. Electromagnetic interference that is coupled electrostatically or inductively to recording electrodes can mask the underlying EEG activity. An example of this type of interference is 60 Hz and high frequency radiation from surrounding electronic and radio equipment. Furthermore, the movement of personnel around the wires of EEG electrodes generates electrostatically coupled artifacts that appear as high amplitude rhythmic.

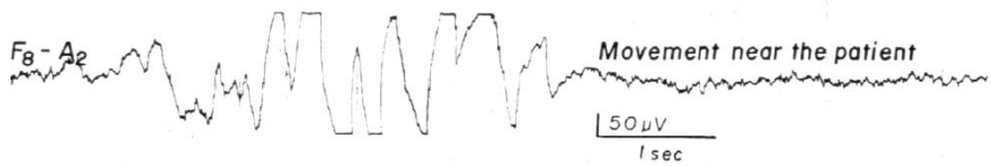

Figure 1.24: Artifact Caused by Movement Around Subject

The electroencephalogram is a non-invasive, multi-electrode recording of time varying potentials generated by the millions of cortical neurons. The electrodes are distributed symmetrically around the scalp to provide a temporal and spatial summary of brain surface activity. EEG activity is characterized by its fundamental frequency, amplitude, morphology, localization, and reactivity. The alpha, beta, theta, delta, mu, and lambda rhythms are types of EEG activity observed in the normal EEG of adults and children; they are differentiated by their unique frequency, morphology, localization, or reactivity. Abnormal EEG is an unusual waveform as well as the absence or deviation of normal EEG activity from well-documented limits.

During interictal periods, or between seizure episodes, the EEG of patients affected by epilepsy will exhibit abnormalities like spike and sharp waves; periodic discharges, rhythmic hypersynchrony; or Electrocerebral inactivity. In ictal periods, or during seizures, the EEG is composed of a continuous discharge of one of these abnormalities, but extended over a longer duration and typically accompanied by a clinical correlate. The electrographic signature of a seizure for a given patient is stereotypical and distinguishable from their non-seizure activity. On the other hand, the seizures of two different patients can exhibit very distinct morphology and localization; moreover, the characteristics of the first patient's non-seizure activity can resemble those of the second patient's seizure activity. EEG is plagued by artifacts and signal attenuation due to the skull. Artifacts of physiological origin may result from muscle potentials, electrocardiographic potentials, eye movement potentials, glossokinetic potentials, and skin potentials. Artifacts of nonphysiological origin result primarily from malfunctioning electrodes and electromagnetic interference. Learning the characteristics of these artifacts is crucial for both an electroencephalographer and seizure detection system, since can be easily confused with both abnormal and seizure activity.

1.7 Epilepsy

Epilepsy is a neurological condition in which is due to chronic abnormal bursts of electrical discharge in the brain. It is a disease known from ancient times, and it was believed to be “given by the Gods”. In fact, the term “epilepsy” was first mentioned more than 3,000 years ago, in ancient Babylon as “*miqtu*”. The word ‘epilepsy’ is derived from the Greek word *epilambanein*, which means ‘to seize or attack’ [4]. It was thought to be an attack by demons or gods. For centuries epilepsy was considered a damning curse from the gods or a strange type of insanity. Today epilepsy is known to be a neurological disorder of the central nervous system that predisposes individuals to experiencing recurrent seizures.

"A disease of the nervous system, characterized (in its severer forms) by violent paroxysms, in which the patient falls to the ground in a state of unconsciousness, with general spasm of the muscles and foaming at the mouth."

The above description of the Oxford English Dictionary is also the common public imagination of an epileptic seizure. Epilepsy is the second most common neurological disorder (after stroke), affecting more than 50 million patients around the world [5, 6]. This is a serious disorder of central nervous system which results in recurrent, unprovoked epileptic seizures due to chronic abnormal bursts of electrical discharge in the brain. The epileptic seizure activity is classified mainly on basis of its generation and area of brain in which it is localized. In a partial seizure epileptic activity begins and remains localized in one part of the brain on the other hand a generalized seizure involves the epileptic activity in entire brain The underlying genetic and molecular mechanisms that give rise to epilepsy remains unknown, but the disorder is most common among people in whom the brain has been compromised by some sort of disturbance. Specifically, in children and young adults, genetic disorders, congenital abnormalities, and birth trauma affecting the brain are most often blamed for the onset of epileptic symptoms; in middle-aged adults and the elderly, strokes, tumors, and cerebrovascular disease are more frequent explanations. People affected by epilepsy do not suffer from an increasingly worsening disorder and are capable of leading normal career and family lives. At the same time, they cannot engage in activities during which a seizure episode could lead to death; for example, driving an automobile. Furthermore, the side-effects of anti-epileptic drugs, episodes of loss of consciousness and motor control; and the public's misconception of the disorder force patients to deal with challenging clinical and psychosocial issues.

Epilepsy is best known for causing convulsions. But seizures can trigger a wide range of symptoms, from starting to fall to fumbling with clothes. Doctors divide seizures into several types depending on how the brain is affected. Each type has a distinct set of symptoms.

1.7.1 Classification of Epilepsy

Epilepsies are classified in five ways:

1. By their first cause (or etiology).
2. By the observable manifestations of the seizures, known as semiology.
3. By the location in the brain where the seizures originate.
4. As a part of discrete, identifiable medical syndromes.
5. By the event that triggers the seizures, such as reading or music.

1.7.2 The Neurophysiology

Although the biochemical mechanisms are not yet clearly explained, certain typical electrical phenomena are observed in epilepsy. Intercellular measurements at epileptic foci show an extraordinary long lasting, high amplitude membrane depolarization accompanied with spike trains. This phenomenon is defined as paroxysmal depolarization shift (PDS). This was first described in neurons lying under experimentally induced foci. The long-lasting depolarization corresponds to epileptic discharges observed at surface electrodes. There may be various mechanisms or combinations of them promoting this phenomenon:

a. decreased inhibition (insufficient gamma-amino butyric acid –GABA),

b. increased excitation (derangement in N-methyl-D-aspartate (NMDA) receptor and glutamate),

c. alterations in Na+, Ca+, K+ ion concentrations, or

d. alterations in membrane ion channels.

Mechanisms of kindling (i.e., long-term sub-threshold stimulation giving rise to persistent primary and secondary foci) and long-term potentiating (i.e., modification of synaptic activity upon synchronously recurrent firing), which are addressed for memory and learning processes in normal brain functioning, are also considered for their involvement in epileptogenesis [7].

1.8 EEG in Epilepsy

The EEG examinations in epilepsy are employed, basically in order to observe the so called epileptic graphoelements which *may* occur in interictal (i.e., the intervals between seizures) periods. The epileptic graphoelements are characterized by short lasting EEG abnormalities such as high amplitude spikes or sharp-waves, spike wave complexes, slow spike wave complexes, and polyspikes [8]. The time characteristics as well as the topography of such graphoelements are considered in epilepsy for diagnosis. The ictal charges (i.e., recorded during a seizure) which vary more, but usually consist of abnormally rhythmic EEG patterns are also important for epilepsy diagnosis. In some rare cases, there might also be alterations (e.g., slowing), which are often unspecific, in EEG background activity. Such alterations in background EEG activity can also be due to medication [8].

The standard EEG measurement in clinical practice lasts commonly between 20-30 minutes. This duration is often insufficient for detecting epileptic graphoelements or a seizure. Additionally, the existence of epileptiform discharges does not always mean existence of a seizure in clinical terms. Therefore, long-term EEG monitoring over 24 hours, either ambulatory or combined with video monitoring if the patients are impatient, is emphasized as an important tool in diagnosis and differential diagnosis of epilepsy.

- *Activation Methods*

Several activation methods, such as hyperventilation, photostimulation, and sleep deprivation are also commonly used in clinical routine in order to provoke epileptic discharges and other diagnostically relevant alterations in EEG [9]. Although all these methods are important tools, the resulting EEG data are in general visually analyzed and evaluated. Therefore, the evaluation depends strongly on the clinical expertise, hence it is subjective.

1.9 Seizures

A seizure is an involuntary alteration in behavior, movement, sensation, or consciousness resulting from abnormal neuronal activity in the brain. In the case of epilepsy, a malfunctioning region of the brain or the dysfunction of a biochemical mechanism causes the abnormal neuronal activity. This is in contrast to non-epileptic seizures, which are a response to a disturbance external to the central nervous system such as alcohol withdrawal, drug abuse, acute illness, or sleep deprivation. There are several different types of seizures as shown in Figure 1.25, and the ability to differentiate between them is crucial since each requires a different treatment regimen.

The two major seizure types are *partial seizures* and *generalized seizures*. In a partial seizure epileptic activity begins and remains localized in one part of the brain, while in a generalized seizure epileptic activity involves the entire brain from the onset. The sections that follow describe further the clinical and electrographic characteristics of the different seizure types.

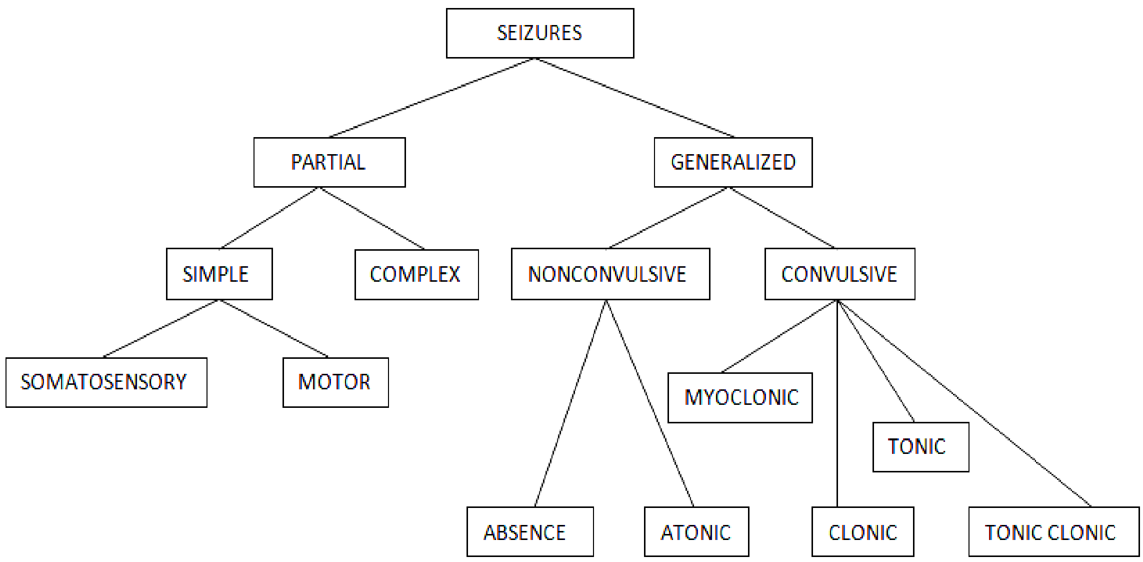

Figure 1.25: Classification of Seizures

1.9.1 Partial Seizures

In a partial seizure epileptic activity begins and remains localized in one part of the brain. Partial seizures that do not affect consciousness are classified as *simple partial seizures*, while those that do are classified as *complex partial seizures*. In the context of epilepsy, impairment or loss of consciousness does not refer to a coma, but rather an individual's lack of understanding and memory of events occurring during seizure episodes.

- **Simple Partial Seizures**

Simple partial seizures do not alter consciousness, but temporarily impair an individual's sensory or motor systems. A simple partial seizure that originates in the somatosensory area of the brain is called a *simple partial sensory seizure*, while one that originates from the motor cortex is called a *simple partial motor seizure*. Individuals typically experience simple partial seizures for less than a minute, and are able to recall events that occurred during the episode.

During simple partial sensory seizures an individual may experience somatosensory, autonomic, or psychic symptoms. Somatosensory symptoms include hallucinations affecting vision, audition, or olfaction; autonomic symptoms include sweating and papillary dilation; and psychic symptoms include sudden sensations of fear, anger, dreamy states, and déjà vu. These clinical manifestations can be very subtle, and are sometimes difficult to distinguish from psychological phenomena. Simple partial motor seizures have clearer clinical manifestations that include rapid muscular jerks and postural movements.

- **Complex Partial Seizures**

Complex partial seizures result in the impairment of consciousness. They are often preceded by auras that include an unusual smell or sensory illusion and are typically accompanied by an automatism such as snapping fingers, picking at clothes, walking aimlessly, mumbling, or lip smacking. After the conclusion of a complex partial seizure, which lasts between 1-3 minutes, individuals will experience a period of confusion lasting several minutes.

1.9.2 Generalized Seizures

In a generalized seizure epileptic activity involves the entire brain from the onset. Generalized seizures whose clinical manifestations include spastic muscle activity are classified as *generalized convulsive seizures*, while those that don't are classified as *generalized nonconvulsive seizures*.

- **Generalized Convulsive Seizures**

The nature of involuntary muscular activity and the individual's state of consciousness during generalized convulsive seizures allows for the further subdivision of this class of seizures into the *myoclonic*, *clonic*, *tonic*, and *tonic-clonic* types. A myoclonic seizure result in unilateral or bilateral rapid alteration of muscular contraction and relaxation, but does not typically alter an individual's state of consciousness. Myoclonic activity is also associated with other neurological disorders, which complicates the classification of this type of seizure. Clonic seizures exhibit muscular activity similar to that of myoclonic seizures, but with slower cycles of contraction and relaxation. Furthermore, clonic seizures result in the loss of consciousness.

Tonic seizures consist of sudden contraction of truncal and facial muscles accompanied by flexion of upper extremities and extension of lower extremities. These seizures are most common in childhood and may result in serious injuries due to dangerous falls. Tonic-Clonic seizures combine the clinical manifestation of both the tonic and clonic seizures. These seizures begin without warning with a generalized contraction of muscle groups interrupted by short periods of relaxation. Gradually, these periods become more frequent ultimately leading to rapid muscular contraction and relaxation. Tonic-clonic seizures last between one and two minutes, but individuals may not regain consciousness until ten to fifteen minutes later and may exhibit symptoms of fatigue for hours or days. Partial seizures, both simple and complex, that progress to become generalized tonic-clonic seizures are classified as *secondarily generalized seizures*. Sensory or motor auras distinguish between generalized and secondarily generalized seizures since they are associated only with partial seizures.

- **Generalized Nonconvulsive Seizures**

Absence seizures are generalized nonconclusive seizures that result in the loss of consciousness, eye blinking, staring, and other minor facial movements. These seizures last between a few seconds and a minute and can occur very frequently over the course of a day. Absence seizures are most common in childhood. Atonic seizures are generalized nonconclusive seizures that do not lead to a loss of consciousness. However, the sudden loss of tone in postural muscles that accompanies atonic seizures leads to dangerous falls that result in serious fractures and injuries to the head.

1.9.3 Status Epilepticus

Any of the above mentioned types of epileptic seizures may lead to status epilepticus, which is an emergency condition characterized by an epileptic seizure that is so frequently repeated that it is virtually continuous. The condition of status epilepticus can exhibit either convulsive or nonconclusive activity. In nonconclusive status epilepticus an individual appears to be in a coma, while in convulsive status epilepticus an individual experiences repeated generalized tonic-clonic seizures without recovering consciousness.

1.10 Treatment of EPILEPSY

Epilepsy affects individuals with variable degrees of severity. Between 70-80% of epilepsy patients suffer from seizures whose severity and frequency can be limited with the use of antiepileptic drugs, each of which essentially limits the capacity of neurons to fire at excessive rates. The correct classification of these patient's seizures is crucial since different seizure types require specific drug regiments. In fact, the use of the wrong antiepileptic drug may exacerbate certain types of seizures. The remaining 20-30% of epilepsy patients suffers from seizures that are refractory to medication. These patients seek alternative treatment options that include surgery, vagus nerve stimulation, and ketogenic diets.

- **Surgery**

Surgery becomes a viable option for epilepsy patients once a team of epileptologists can accurately identify the region of the brain from which seizures originate. This is accomplished by combining clinical and electrographic evidence from long-term sessions of video and EEG monitoring; anatomical evidence from magnetic resonance imaging; functional evidence from neuropsychological testing; and metabolic evidence from both positron emission tomography (PET) scans and single photon emission tomography scans. The four types of surgery available are removal of a temporal lobe through a temporal lobectomy; removal of cortex through a topectomy; removal of a hemisphere through a hemispherectomy; and separation of the two hemispheres by severing the corpus callosum.

- **Vagus Nerve Stimulation**

Patients that are not surgical candidates may be treated using a vagus nerve stimulator. This implantable, electronic device periodically stimulates the vagus nerve on the left side of the neck. Although the optimal setting for the periodicity and strength of stimulation has not been determined, vagus nerve stimulators can be as effective as antiepileptic drugs in reducing seizure frequency and severity. One of the major applications envisioned for seizure onset detection and prediction algorithms is the modulation of the periodicity and strength of VNS is sometimes called a “pacemaker for the brain”. It uses a small surgically implanted device to send electrical pulses to the brain. The pulses travel via the vagus nerve, a large nerve in the neck. VNS is an option for people who don’t do well with medications. Stimulation produced by these devices according to the state of a patient's EEG.

- **Ketogenic Diet**

The ketogenic diet is a high fat, low protein carbohydrate diet that has proven effective in controlling seizures resulting from intractable epilepsy. The diet forces the body to enter *ketosis*, a state in which the brain uses ketones rather than glucose for energy. In this state seizure frequency and severity have been clinically shown to decrease, but the exact mechanism remains unknown. Thus this neurological disorder of the central nervous system that predisposes individuals to experiencing recurrent seizures can be controlled.

1.10.1 Alternative Therapies

There are other treatment approaches which can be summarized under the term alternative treatment. In this category, therapies such as diet , acupuncture or yoga can be listed [10].

1.11 Epileptic Seizure and Non-Epileptic attacks

Often the starting of a clinical seizure is characterized by a sudden rapid change of frequency in the EEG measurement. It is normally within the alpha wave frequency band with a slow decrease in frequency, also increase in amplitude during the seizure period. It may or may not be spiky in shape. The transition from the pre-ictal to the ictal state, consists of a gradual change from chaotic to ordered waveforms. The amplitude of the spikes does not necessarily represent the severity of the seizure. [11]

The distinction of seizure from common artefacts is not difficult. Seizure artefacts within an EEG measurement have a prominent spiky but rhythmical nature, whereas the majority of other artefacts are transients or noise-like in shape. For the case of the ECG, the frequency of occurrence of the QRS waveforms is approximately 1 Hz. These waveforms have a certain shape which is very different from that of seizure signals.

The morphology of an epileptic seizure signal slightly changes from one type to another. The seizure may appear in different frequency ranges. For example, a petit mal discharge often has a slow spike at around 3 Hz, lasting for approximately 70 ms, and normally has its maximum amplitude while higher frequency spike wave complexes occur for patients over 15 years old. Complexes at 4 Hz and 6 Hz may appear in the frontal region of the brain of epileptic patients. As for the 6 Hz complex, patients with anterior 6 Hz spike waves are more likely to have epileptic seizures and those with posterior discharges tend to have neuroautonomic disturbances [12].

CHAPTER 2: LITERATURE REVIEW

Brain is one of the vital organs of human body but the most complex of all. It generates electrical signals to directly or indirectly control the entire body. Epilepsy can be defined as a disorder of the central nervous system that results in recurrent seizures due to chronic abnormal bursts of electrical discharge in the brain. This chapter reviews the different methods proposed by the researchers for detection of Epileptic activity using EEG.

The early methods of epilepsy detection were based on a Fourier transform for processing EEG automatically. For decades the representation of a signal is basically done using Fourier transform. EEG spectrum contains characteristic waveforms that fall basically within four frequency bands. Such methods have been proved beneficial for various EEG characterizations, but fast Fourier transform (FFT) suffer from large noise sensitivity. Power spectrum estimation as a parametric method such as autoregressive reduces the spectral loss problems and gives better frequency resolution. Since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals. Hence, for such transient signals, analysis and representation in time–frequency domain is highly desirable approach.

Themis P. Exarchos et al. in 2006 came up with Association Rules which is a methodology for the epilepsy detection is based on association rule mining and classification of transient events in electroencephalographic recordings which distinguishes between the electrical activity of a healthy subject and an epileptic one. Transient events are classified into four categories: epileptic spikes, muscle activity, eye blinking activity, and sharp alpha activity. The methodology involves four stages: 1. transient event detection, 2. clustering of transient events and feature extraction, 3. feature discretization and feature subset selection, 4. association rule mining and classification of transient events [13].

In 2009 Ocak showed that most of EEG based analysis models requires the time, the frequency or the time-frequency analysis followed by a linear or non-linear classifier. Generally it is seen that the methods using the features in the time-frequency domain usually provide higher successes than the others in the classification studies on EEG signals [14]. However, it is dependent on both the classifier and the features to be applied into that classifier that the classification results in a success.

Alexandros T. Tzallas et al. in 2009 presented time-frequency analysis of EEG signals by Short Term Fourier Transform. Most of the classifiers used in the analysis of EEG signals utilize the statistical features obtained by the time-frequency analysis of EEG signals. Short Term Fourier Transform (STFT) and various Time-Frequency Distributions are used for the *t-f* analysis. For STFT, the signal $x(u)$ at an instant of time t, the Fourier transform is calculated for each instant of time t

$$STFT(t,f) = \int_{+\infty}^{-\infty} x(\tau)h(\tau - t)e^{-if\tau}\, d\tau \qquad \text{........ (1)}$$

where $h(t)$ is a short time window. Short time Fourier Transform undergoes trade-off between its window length and its frequency resolution. Using *t-f* analysis, the Power Spectral Density is calculated of the signal, which represents the distribution of the energy of the signal over the *t-f* plane [15].

Mousavi et al. method of epilepsy detection is based on autoregressive estimation of EEG signals. The optimum order for Autoregressive model is determined by Bayesian Information Criterion and then autoregressive parameters of EEG signals and their sub-bands are extracted by discrete wavelet transform. These parameters are used as a feature to classify the EEG signals into normal and epileptic by multilayer perceptron classifier [16].

Mirzaei et al. work in 2010 was based on Wavelet-Spectral Entropy Based Detection. Entropy was the parameter considered. The spectral entropies basically use the amplitude of the power spectrum of the signal as the probabilities in entropy calculations. This is a method for epilepsy detection by analysing EEG and EEG subbands based on determining discrete wavelet-spectral entropy. The EEG signal is decomposed by discrete wavelet transform into its sub-bands by high pass and low pass filtering to different levels as shown in Figure 2.1 and is then characterized by spectral entropy determining approach.

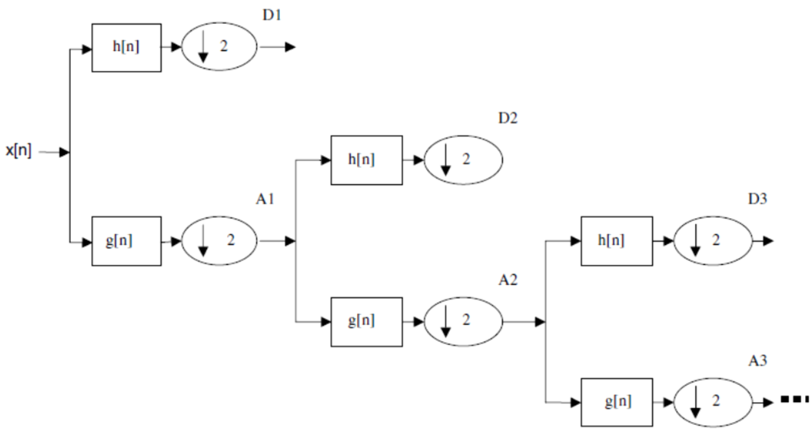

Figure 2.1: Discrete Wavelet decomposition of signal

ENTROPY (e_i) = - $\sum_{j=1}^{n}$ $Dij^2 \log (Dij^2)$ ....

(2)

This method was applied to three different groups of EEG signals: 1) healthy, 2) epileptic during a seizure-free interval, 3) epileptic during a seizure. Spectral entropy is used which differentiated between these three states and their sub-bands. Then statistical approach is applied to determine the measure of distinguishing between different subjects. This method can discriminate between epileptic and non-epileptic subject of alpha sub-band (8-12 Hz). Also there is an approach using wavelet transform where first the pre-processed signal is decomposed into a wavelet packet tree. Then features are extracted from standard frequency pattern i.e. from obtained subbands. These features are then fed to neural network classifier for detection of seizure activity or normal result [17]. The whole technique is explained through this Figure 2.2 shown below.

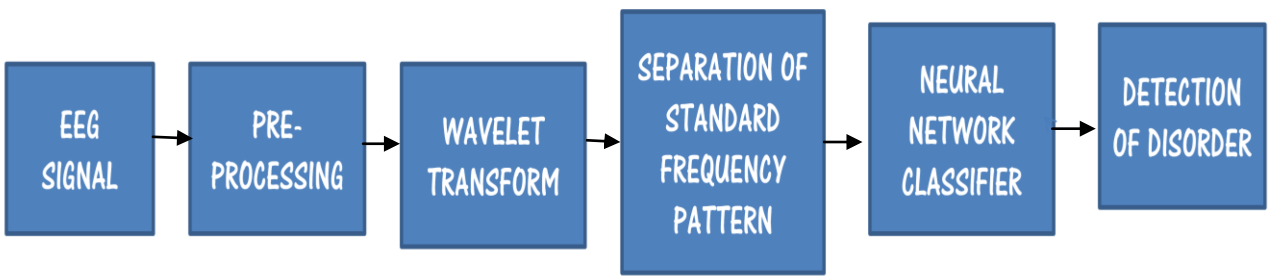

Figure 2.2: Detection using wavelet transforms method.

The Equal Frequency Discretization based probability density approach can be used for detecting epilepsy from EEG signals. These signals are decomposed by using the Discrete

Wavelet Transform (DWT) into its various subbands, the coefficients in each subband are then discretized to several intervals by Equal frequency discretization method, and the probability density of each subband of each EEG segment is computed according to the number of coefficients in discrete intervals. Then, two probability density functions can be defined by means of the curve fitting over the probability densities of the sets of both healthy and epileptic patients. EEG signals are then classified by calculating the mean square error (MSE) of these probability density functions. The result of the classification of epileptic subjects is evaluated by Orhan et al in 2011 [18].

CHAPTER 3: PROBLEM DEFINITION

In 1980 a powerful method called the discrete wavelet transforms (DWT) was introduced. Since early days work done for frequency subband separation of EEG signal for epilepsy detection is based only on decomposition of the signal to certain levels. This is followed by feature extraction from these subbands. The major tasks that need to be undertaken are briefed below:

- The decomposition of EEG signal does not generally include that peculiar frequency range as defined in Delta, Theta, Alpha, Beta, Gamma subbands. To get this frequency band is still a challenge for the researchers. A passing reference about the technique is made by Shantha Selva Kumari et al. [19], however, the methodology for obtaining the signal in this band is not given explicitly. Only decomposition method is described, which alone is not capable of the getting the required frequency band.
- After decomposition of EEG signal into subbands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30Hz) using discrete wavelet transform, extracting features out of all statistical parameters that can be used as a feature vector for distinguishing between an epileptic and non-epileptic EEG is itself a challenge. For identifying the epileptic and non-epileptic EEG, it is required to examine subject for selected features extracted from the subbands of EEG. It is probable that some of the features may have non-overlapping range. Those features are needed to be identified for detection of epilepsy. The wavelet-based features of the EEG signal can be then used as a feature vector for any classifier to detect epilepsy.
- Considering EEG signal to detect epileptic cases using appropriate features extracted from various subbands, the non-overlapping ranges for the epileptic and non-epileptic are needed to be found such that an efficient system can be developed. This system, however should take into account several inaccuracies that may creep in the practical system on account of machine error, human error and other factors. There is a need to develop a system which is tolerant to these inaccuracies and is flexible enough to give high detection rate in practical situations.

CHAPTER 4: METHODOLOGY

4.1 Discrete Wavelet Transform

There are no general methods of EEG analysis. Traditionally time and frequency domains have been considered for analyses of EEG signals. In both time and Frequency methods, an EEG signal is considered as a realization of a random process. Random processes are characterized by probability distributions and their moments (e.g. means, variances, power spectral densities, skewness). Such a description of EEG signals as realization of a RP assumes a mathematical but not a biophysical model. This does not imply that bio-physiological process underlying the EEG signals is itself random. However, it may have a high degree of complexity and only a description of in statistical terms may be justified. The discrete wavelet transform (DWT) is quite an effective tool for Time-Frequency analysis of signals. Wavelet transform can be defined as a spectral estimation technique in which any general function can be expressed as a sum of an infinite series of wavelets. The decomposition of the signal results in a set of coefficients called wavelet coefficients. Signal is decomposed into progressively finer details by means of multi-resolution analysis using complementary low-pass and high-pass filters. Wavelet transform has the advantages of time-frequency localization, multi-rate filtering, and scale-space analysis. Wavelet transform uses a variable window size over the length of the signal, which allows the wavelet to be stretched or compressed depending on the frequency of the signal. The significantly important property of DWT is its appropriate application on non-stationary signals like EEG signals. DWT analyzes frequency bands with different resolution by means of multi-level decomposition into a coarse frequency band. This results in excellent feature extraction from subbands of the non-stationary EEG signals. In this study, the discrete wavelet transform, based on dyadic (powers of 2) scales and positions, is used to make the algorithm computationally very efficient without compromising accuracy.

4.2 Data Collection

The EEG data used in the work is available at the Department of Epileptology, University of Bonn [20]. The complete data set consists of five sets (A–E), each containing 100 single channel EEG signals. These segments of EEG signals were cut out from continuous multi-channel EEG recordings and that too after taken care for artifacts like muscle activity or eye movements. Each signal segment is of 23.6 s duration containing 4096 samples. Sets A and B have EEG segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardised 10-20 electrode placement system.

SET A is of healthy volunteers relaxed in an awake-state with eyes open and SET B with eyes closed. Sets C, D, and E originated from our EEG archive of presurgical diagnosis. For the present study EEGs from five patients were selected, all of whom had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Segments in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. Sets C and D contained only activity measured during seizure free intervals, Set E only contained seizure activity. The signal recordings were done by the 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit resolution. Bandpass filter settings were 0.53–40 Hz (12dB/oct). In this work, two dataset (A and E) of the complete dataset are used.

4.3 Analysis Using Dwt

DWT successfully analyses the multi-resolution signal at different frequency bands, by decomposing the signal into approximation and detail information. The method for frequency band separation for epilepsy detection is implemented in MATLAB 2011a. The flowchart of the proposed methodology for detection of epileptic data from normal data is shown in figure 4.1

Epilepsy Detection using EEG requires feature extraction from the acquired signal in specific frequency range of delta, theta, alpha, beta, and gamma. Though some researchers have mentioned the use of DWT decomposition to obtain these bands, the method given is inadequate to achieve these. First this study explicitly describes the method of up-sampling and recombining of several decomposed subbands to achieve the required frequencies.

Data is first pre-processed by removing dc component from the signal thereby achieving different levels of decomposition for Daubechies order-2 wavelet with a sampling frequency of 173.6 Hz on each signal of 4096 samples. Figure 4.2 shows the decomposition of the EEG signal x(n) at Nyquist frequency which is the maximum useful frequency i.e. half of sampling frequency 86.8 Hz. Signal is subjected to six level decomposition where each stage of this scheme consists of two digital filters.

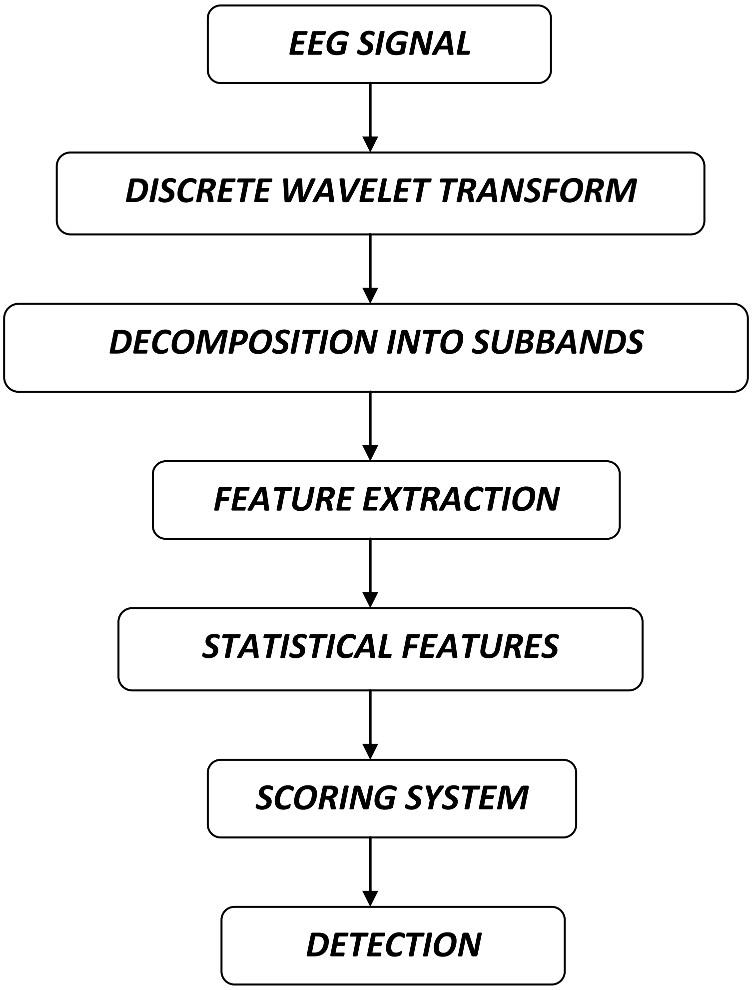

Figure 4.1 flowchart of the methodology for epileptic activity detection

After a first level decomposition, two sequences representing the high (details) and low (approximations) resolution components of the signal are obtained. The low-resolution components are further decomposed into low and high resolution components after a second level decomposition and so on. The multi-resolution analysis, using six levels of decomposition, yields five separate EEG sub-bands. This multiresolution analysis is explained in detail below. The wavelet transform main objective in the proposed method is the division of the original EEG signals into different frequency bands.
The first filter, h[n] is the high pass filter or it is the discrete mother wavelet and the second, g[n] is low-pass filter. After the first level of decomposition, the EEG signal (0-86.81Hz), is decomposed into its lower resolution components, CA1 (0-43.4) Hz and higher resolution components, CD1 (43.4-86.81 Hz).

Likewise six level of decomposition is done The approximation and detail coefficients are shown in diagram by CA_i and CD_i where i is 1,2,3.... at each level of decomposition. The data after decomposition to various levels has approximation and detail coefficients at each level of different frequency resolution. These frequencies are to be then recombined in order to achieve subbands delta, theta, alpha, beta, gamma at their perspective frequencies. The delta band is of frequency range 0-4 Hz so lower resolution components i.e. approximation coefficients CA7 (0-2.7 Hz) and CA8 (2.7- 4.05 Hz) are to be recombined.

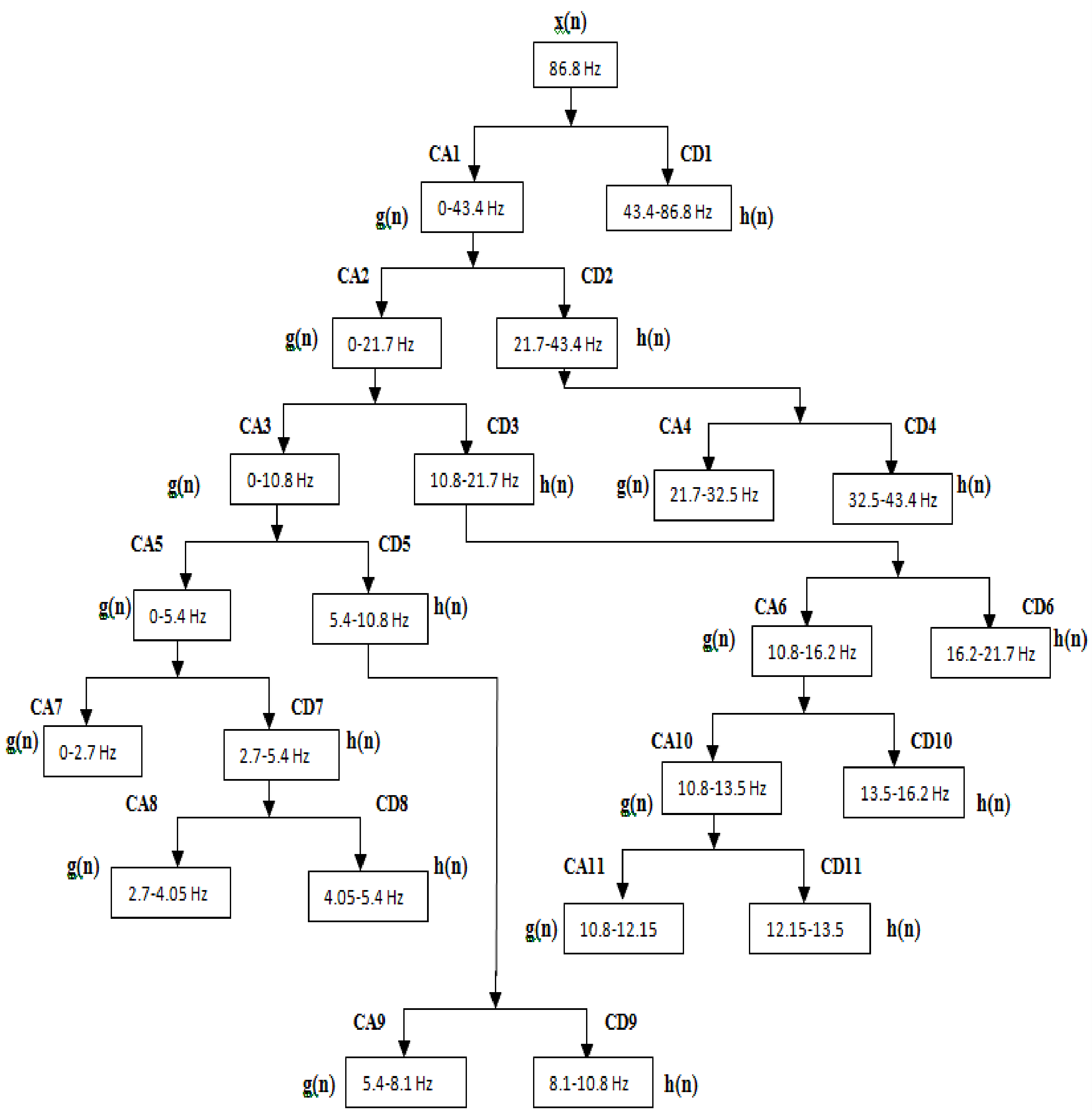

Figure 4.2: Decomposition of Signal into its approximation and detail coefficients.

But the problem arises when the number of samples of CA7 and CA8 mismatch. CA7 has 128 samples while CA8 has 64 samples. For this up-sampling of CA8 is done to 128 samples and then the DELTA band is reconstructed successfully by recombination of CA7 and up-sampled CA8 through Inverse Discrete Wavelet Transform using Daubechies order-2. Similarly THETA Subband is of frequency range 4-8 Hz so CA9 and up-sampled CD8 are recombined.

After recombining all coefficients falling in their respective subbands, delta, theta, alpha band with 256 samples and beta with 1024 and gamma with 4096 samples are achieved as shown in Table 1.

Table 4.1: Subbands with their frequency range, recombining coefficients and no of samples

SUBBAND	**FREQUENCY**	**COEFFICIENTS**	**SAMPLES**
DELTA	**0-4 Hz**	**CA7, CA8(up-sampled)**	**256**
THETA	**4-8 Hz**	**CD8(up-sampled), CA9**	**256**
ALPHA	**8-12 Hz**	**CD9, CA11(up-sampled)**	**256**
BETA	**12-30 Hz**	**CD11(up-sampled), CD10, CD6, CA4**	**1024**
GAMMA	**> 30 Hz**	**CD4(doubly up-sampled), CD1**	**4096**

EEG segment is decomposed to 6 levels discrete wavelet transform and then inverse discrete wavelet transform is used to recombine the various frequency band to form delta (0-4)Hz , Theta (4-8)Hz , Alpha (8-12)Hz , Beta (12-30)Hz, and Gamma (>30)Hz. The delta, theta, alpha band have 256 samples and beta have 1024 and gamma have 4096 samples. The required frequency and the actual frequency achieved after decomposition and recombination is given in Table 2. Thus the recombined subband frequency closely matches with the required frequency in Delta, Theta, Alpha, Beta and Gamma subbands as shown. The subbands can actually and accurately be used further to detect features that can distinguish epileptic EEG signals from non-epileptic EEG signals.

Table 4.2: Required frequency and achieved frequency of each subband

REQUIRED FREQUENCY	FREQUENCY ACHIEVED
0-4 Hz	0-4.05 Hz
4-8 Hz	4.05-8.1 Hz
8-12 Hz	8.1-12.15 Hz
12-30 Hz	12.15-32.5 Hz
> 30 Hz	>32.5 Hz

The subband decomposition of the EEG signal as explained is applied on the sets of epileptic data (SET A) and non-epileptic data (SET E) of 50 subjects each. Each segment in SET A and SET E is composed of 4096 samples at sampling frequency of 173.6 Hz. The discrete wavelet transform is used as a primary computational tool for extracting features of the epileptic EEG signals at different resolutions. Decomposition of Epileptic and Non-Epileptic data into Delta, Theta, Alpha, Beta, Gamma subbands are shown in figure 4.3 & Figure 4.4 resp. It is apparent from figures that the amplitude of gross epileptic signal is considerably higher than non-epileptic one. Also the amplitudes of subbands are significantly high in case of epileptic data, especially in gamma subband.

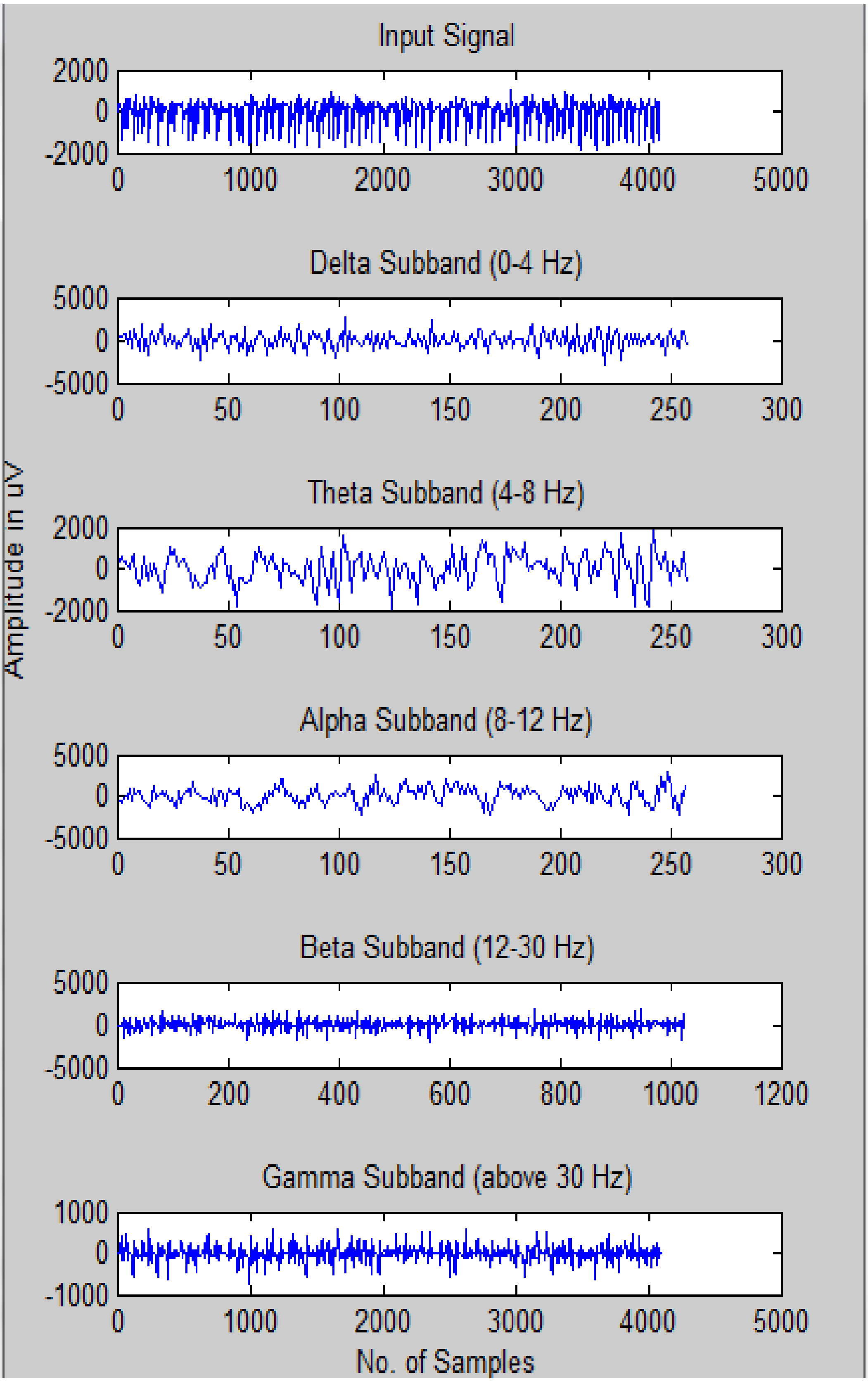

Figure 4.3: Epileptic EEG signal with delta, theta, alpha, beta and gamma subband decomposition

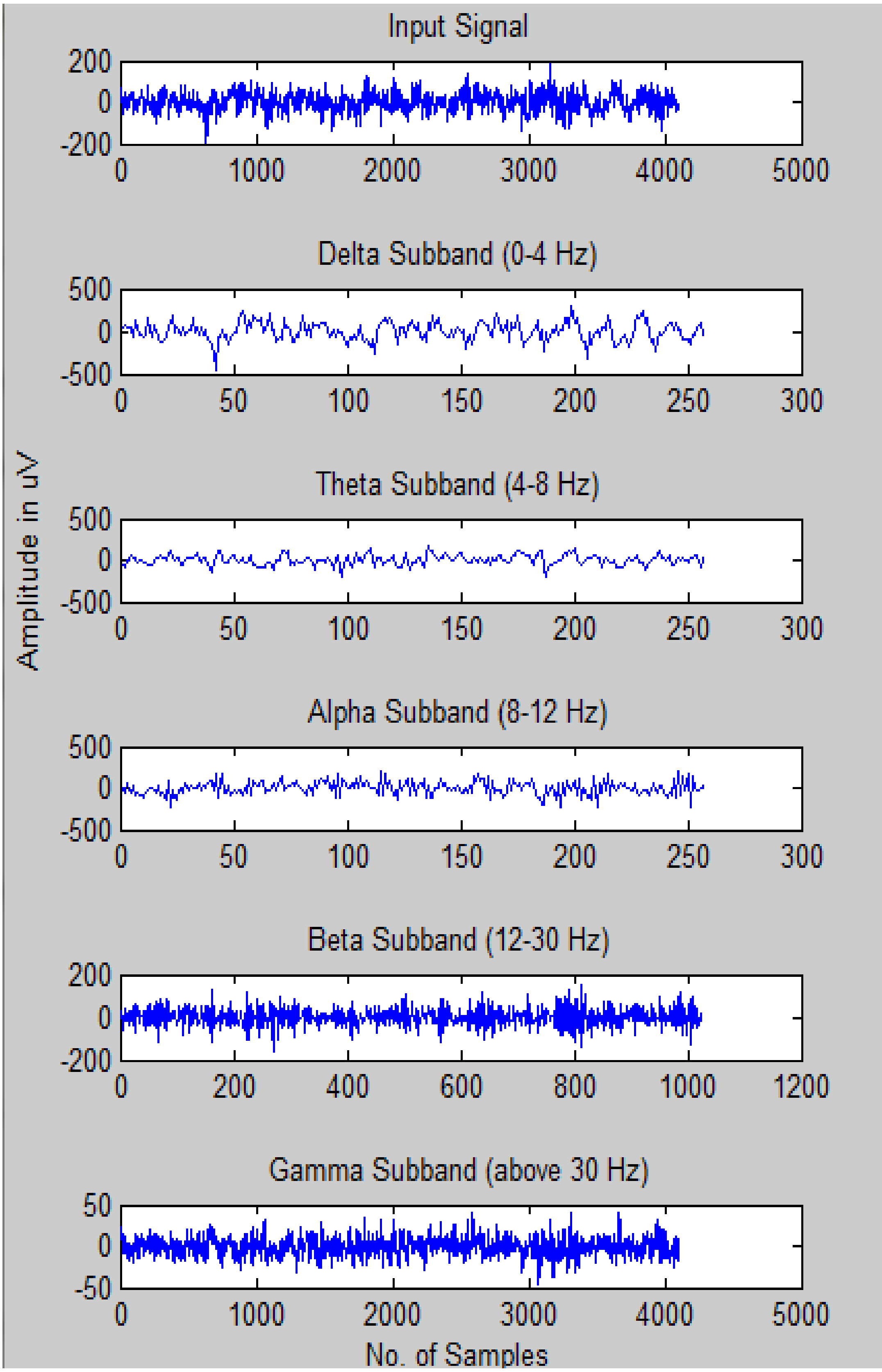

Figure 4.4: Non-epileptic EEG signal with delta, theta, alpha, beta and gamma subband decomposition

4.4 Features to be Extracted

Some of the parameters derived for epilepsy detection are defined here under:

1. Variance: Variance is defined as a measure of the dispersion of a set of data points around their mean value. Assume some random variable X that have the sample values of each EEG subband signal. Let the sample value of X is $X_i=\{X_1, X_2,......X_n\}$ .Where i represent a sample set from the subbands delta, theta, alpha, beta, and gamma. The variance can thus be expressed as

$$y^2 = \frac{\sum(X - \mu)^2}{n} \quad .... \quad (1)$$

where μ is the mean value of the set X and n is the number of samples in the EEG dataset. The Variance of each decomposed subband can be estimated and form a feature Vector. Generally the Variance of Seizure signal is higher than normal signals.

2. Energy: The energy of the signal is defined as the sum of squared modulus of the sample values of any signal. The wavelet based energy of each decomposed subbands such as delta, theta, alpha beta and gamma can be calculated using the formula

$$E = \sum_{n=0}^{N-1} |X|^2 \quad .... \quad (2)$$

where X is the samples values in each subbands and N is the total number of samples.

3. Power Spectral Density (PSD): The PSD is the amount of power per unit frequency as a function of frequency. The integral of the PSD over a given frequency band computes the average power in the signal over that frequency band. Different algorithms are used for the estimation of PSD. Although the FFT method has been widely used to analyze EEG signals yet it is not well suited to the non-stationery characteristics of the EEG signal. To overcome this limitation, the Periodogram method is commonly used for computing PSD. However, the methods require averaging of several periodograms to decrease the variance of the FFT method; this averaging may in fact obscure the detection of dynamic changes in the frequency domain which are of clinical interest as in case of epileptic seizures. PSD is computed by squared modulus of the Fourier transform of the time series of the signal.

$$\max(\omega) = \frac{1}{n}|X(\omega)|^2 \quad .... \quad (3)$$

The Maximum and minimum values are estimated from the PSD of each EEG subbands can be considered as feature for classification.

4. Entropy: Entropy is a numerical measure of the randomness of a signal. Entropy can act as a feature and used to analyze psychological time series data such as EEG data. The Entropy can thus be calculated as:

$$(e) = - \sum_{1}^{n} X^2 \log (X^2) \qquad .... \qquad (4)$$

Entropy is the statistical descriptor of the variability within the EEG signal and is a strong feature for epilepsy detection.

The above mentioned statistical features are extracted from each subband i.e. Delta, Theta, Alpha, Beta, Gamma of each set to represent the time-frequency distribution of the EEG signals and are nomenclatured in Table 4.3

1. Variance of the coefficients in each subband.
2. Energy of the wavelet coefficients in each subband.
3. Power Spectral Density (max) of each subband.
4. Power Spectral Density (min) of each subband.
5. Entropy of wavelet coefficients in each subband.

Table 4.3: Nomenclature of Features of Subbands

Subbands→ features↓	**DELTA**	**THETA**	**ALPHA**	**BETA**	**GAMMA**
Variance	**y1**	**y2**	**y3**	**y4**	**y5**
Energy	**E1**	**E2**	**E3**	**E4**	**E5**
PSD max	**Max1**	**Max2**	**Max3**	**Max4**	**Max5**
PSD min	**Min1**	**Min2**	**Min3**	**Min4**	**Min5**
Entropy	**e1**	**e2**	**e3**	**e4**	**e5**

Using these 25 parameters 50 non-epileptic and 50 epileptic cases taken from database described before are analyzed. There may exist some parameters that do not overlap, means the upper limit in non-epileptic group is lower than the lower limit of epileptic group.

Then a scoring system is developed which efficiently determines any input EEG signal for its nature to be epileptic or normal.

This scoring system has to have a built in tolerance to the inaccuracies that may creep in the practical system on account of machine error, human error and other factors. The system developed is tolerant to these inaccuracies and is flexible enough to give high detection rate in practical situations.

4.5 Matlab Functions

Matlab functions used in the study are summarized in the Table 4.4.

Table 4.4: Matlab functions

FUNCTION		USE	SYNTAX
1.	DWT	DISCRETE WAVELET TRANSFORM	[CA1,CD1]=DWT(s,'db2')
2.	IDWT	INVERSE DISCRETE WAVELET TRANSFORM	A=IDWT(CA1,BD1,'db2')
3.	WENTROPY	ENTROPY	e1 = wentropy(DELTA,'shannon')
4.	VAR	VARIANCE	y1= var(DELTA)
5.	WENERGY	ENERGY	[Ea1,Ed1] = wenergy(C1,L1)
6.	PERIODOGRAM	POWER SPECTRAL DENSITY	[Pxx1,w1] = periodogram(DELTA)

CHAPTER 5: RESULTS AND DISCUSSION

EEG signal of each patient acquired by placing 10-20 electrode system, is decomposed into five EEG subbands: delta (0–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (>30Hz) using discrete wavelet transform. Each EEG signal is sampled at 173.6Hz. From each segment 4096 samples are used for evaluation. The subbands yield more accurate information about the neuronal activities of brain therefore; decomposition into subbands is a necessity. EEG segment is decomposed to 6 levels using discrete wavelet transform and then inverse discrete wavelet transform is used to recombine the various frequency bands to form delta (0-4)Hz , Theta (4-8)Hz , Alpha (8-12)Hz , Beta (12-30)Hz, and Gamma (>30)Hz. The delta, theta, alpha band have 256 samples and beta have 1024 and gamma have 4096 samples. The recombined subband frequency closely matches with the required frequency after decomposition in Delta, Theta, Alpha, Beta and Gamma subbands. For identifying the epileptic and non-epileptic EEG, the subject is examined for selected features extracted from the subbands of EEG.

Variance of the coefficients in each subband (y1, y2, y3, y4, y5), Energy of the wavelet coefficients in each subband (E1, E2, E3, E4, E5), Power Spectral Density (max) and Power Spectral Density (min) of each subband (max1, max2, max3, max4, max5, min1, min2, min3, min4, min5) , Entropy of wavelet coefficients in each subband (e1, e2, e3, e4, e5) are determined from each subband. Of these 25 parameters analysed for 50 non-epileptic and 50 epileptic cases taken from database, it is found that in 10 parameters the upper limit in non-epileptic group is lower than the lower limit of epileptic group. To increase the detection rate, two features namely minima of Power spectral density (min2) and minima of Power spectral density (min3) is dropped. The remaining eight namely, y1, y2, y3, y4, max2, max3, e2, e3 are used in the scoring system. This is illustrated in Table 5.1. These features can be significantly used for detection of epilepsy.

Although there is a significant gap between the lower limit of epileptic and upper limit of non-epileptic group. Yet some tolerance needs to be built in to improve the efficiency of detection. A scoring system is designed to achieve this effect which classifies the epileptic EEG data. Features that resulted in non-overlapping range as shown in table are calculated on 50 subjects from each subband of SET A and SET E respectively. For the purpose of validation Using MATLAB 2011a these non-overlapping features are extracted from other 50 subjects from both sets A and E.

Table 5.1: Non-overlapping parameter ranges of EEG signal

		Y1	Y2	Y3	Y4	Max2	Max3	e2	e3
Epileptic	Upper limit	1733910	1040070	1396296	574335	4945068	7628536	-1263466	-1043503
	Lower limit	74800	22722	7319	2965	59120	40246	-11673332	-8134397
Non-epileptic	Upper limit	32743	8524	5432	2627	23969	32464	-30319327	-12441917
	Lower limit	2676	1467	1043	442	2391	1780	-2419993620	-2885722822

A scoring system is generated by assigning certain score for each feature of a subband and calculating the final score. A tolerance range is decided in order to detect whether that final score falls in the range of epileptic or non-epileptic data.

A score '-1' is assigned to each of the feature falling in the range of normal EEG and '+1' is assigned to each feature falling in the range of epileptic EEG. If a feature falls in neither of the two ranges it is assigned score '0'. For each of 50 subjects of SET A and SET E, these scores of each feature are calculated to get a final score. Considering Tolerance band for normal data is '-5' to '-8' and of epileptic data is '+5' to '+8'. In case the score happens to be between '-5' to '+5', that case will be declared as INDETERMINATE. Assigning scores to each of 8 features and calculating final score we get the number of subjects falling in the category of Epileptic and Non-Epileptic range is shown in Table 5.2. There are no False positives and no False negatives detected. Further none of the cases fell under category INDETERMINATE, so the efficiency is 100% for this particular dataset.
In this work, eight features are extracted from the sub-bands obtained after the decomposition. Based on that a System tolerant to various inaccuracies pertaining in practical situations is developed with high detection efficiency of 100%. Thus the need of accurately detecting the epileptic activity from EEG of a patient is fulfilled.

Table 5.2: Number of subjects with final scores falling in Epileptic and Non-epileptic range

	Epileptic				**Non-Epileptic**				**TOTAL**
Score	**+5**	**+6**	**+7**	**+8**	**-5**	**-6**	**-7**	**-8**	**100**
No. of subjects	**3**	**0**	**10**	**37**	**1**	**0**	**3**	**46**	

Table 5.3 and Table 5.4 illustrates the features extracted for validation of a scoring system from SET A and SET E.

Table 5.3 Features extracted from SET A containing Non-Epileptic Data

y1	*y2*	*y3*	*y4*	*max2*	*max3*	*e2*	*e3*
9953	3705	3616	1359	9661	10356	-4741674	-4143823
6387	3493	3013	1540	5723.8	5262.2	-4991639	-3020657
6841	2468	1711	774.1	6335.7	5490.7	-2722006	-2018621
27299	5558	2188	2160	11984	6746.7	-6863912	-2361240
11109	5252	5365	2009	16392	16134	-6103263	-6095285
17638	7266	2906	2130	17739	5772.7	-10064288	-3921326
23414	5580	3073	1600	12586	8855.4	-7676067	-4260701
10797	4797	2323	1225	15696	6738.9	-4629031	-2256885
10141	3597	3554	901.7	7287.3	28774	-5276942	-5830495
7517	2649	3083	855.9	4896.4	16945	-3269057	-3581607
2739	1536	1156	503.9	3657.2	2897.9	-1168149	-950367.9
21696	7094	4998	1940	17939	22049	-8519552	-5493556
6648	3891	3474	777.2	8211.6	11941	-4588682	-3962045
12293	5867	3333	1677	12348	6093.6	-6589936	-3954320
5328	3472	3240	1365	5230.8	5550.9	-3954475	-3303065
3694	1626	1226	575	3390.4	2097.8	-2116221	-993969.2
17706	5999	2350	1827	13794	6795.7	-5563247	-2702067
11809	4739	2919	1429	6606.7	8347.9	-6182498	-3598343
18308	7744	2984	2178	32366	6493.5	-10492105	-3008853
16317	6653	2475	1541	16983	5735.6	-11232011	-2132250
24189	6628	2667	2415	20217	7100.2	-9623678	-3363138
12876	6067	3412	1852	10629	7778.3	-7904708	-4483806
3769	1958	1293	560.3	4863.3	3457	-2128385	-992550.2
11356	5965	2869	1313	15175	8654.8	-7497155	-3040897
13976	6338	2887	1266	20089	9108.7	-6676946	-4090167
9184	3741	1492	985.1	6676.8	3076	-4343668	-1238820
17878	6892	5432	2358	13852	15498	-9752775	-5484472
6078	3739	3655	1306	7362.7	12771	-5732512	-3387161
9898	3700	2483	1328	8106.6	6270.1	-4215494	-3348070
2957	1438	911.3	525.1	6110.4	2807.7	-1208398	-1008416
10170	5654	2937	1240	12151	5689.4	-6768188	-3263223
11556	7307	4955	2153	10815	14239	-7180838	-5884071
6093	2323	1734	851.3	4853.6	4415.4	-2542198	-2037634

11003	4579	1916	1166	9499.6	5421.3	-5578953	-2547464
13915	6155	2756	1887	10822	8287.4	-7090550	-3791467
9667	4669	3283	1690	13957	11649	-5366523	-3819866
7922	3621	2997	1556	5973.6	10228	-3390132	-3288613
12274	6010	3424	1436	19000	11836	-6602603	-4902475
8891	3781	2605	1089	8800	5433.8	-3972182	-2863719
11955	6377	4795	2226	10596	11304	-6229654	-5672547
14097	6586	2816	1609	16299	9418.6	-9068986	-2420851
10412	4826	3089	1565	9162.6	12522	-5222596	-3876347
9862	5988	3685	1847	12128	7446.5	-7536185	-4692626
21114	7792	4183	2122	17250	11229	-9648638	-5085261
12367	6286	3357	2050	22870	12835	-6853943	-3514248
10411	5680	3630	2267	10452	8214.8	-7707351	-4227963
10220	5899	3563	1357	10874	13849	-7643525	-3773331
12108	4927	2517	1822	11666	6631.8	-5351640	-2532398
10397	6882	3503	2080	12029	8294.1	-10300354	-4862065
11040	5973	3075	1649	10026	10946	-8335687	-3126781

Table 5.4 Features extracted from SET E containing Epileptic Data.

y1	*y2*	*y3*	*y4*	*max2*	*max3*	*e2*	*e3*
111294.5	69243.33	52262.45	8462.187	359923.1	145869.7	-86342116.9	-63787306.2
191453.1	164707.4	139132.8	90578.33	411918.2	354420.6	-232437192	-259757872
457609.5	141204.1	80769.21	30753.24	351600.9	229321.7	-193857433	-111994695
158250.8	177966.6	276579.2	86968.01	393872.9	1263097	-261912311	-473870882
132236.7	76999.37	77294.77	10099.64	308216.9	453768.9	-102615348	-122968385
150451.3	100535.6	71918.31	19278.06	186791.4	210181.3	-165248927	-128801659
272050.5	180177.4	426855.9	66011.99	443118.6	2262923	-284171355	-710436304
382786.7	601071.6	286475.3	55241.18	2359744	869583.6	-1198967328	-460543403
2084440	1306630	1479675	242618	3345380	4881491	-2518012208	-2155850287
1734525	785727.8	424183.6	182478.2	3538644	999629.1	-1206111618	-700904555

130503.5	145650.3	252431.5	97576.03	433163.8	1207745	-221214322	-543020043
481628.2	252896.9	357857.1	56616.21	695149.8	2080318	-396951578	-592040949
53451.73	34929.53	96231.64	14826.92	91598.94	406617.2	-55444222.1	-177366860
111925.3	69831.95	45632.99	11532.8	194008.6	163218.7	-87999096.8	-91822328.3
969717.9	657085.9	389683.2	48776.09	3332928	1563134	-1047036413	-422006694
388537.3	318953.4	350726.5	51866.13	594756.4	1733539	-546796027	-618354931
996630.5	851600	1052391	207853.2	2670171	6651619	-1403848888	-1851419419
616274.9	1213458	921544.6	438056	4477046	2757771	-2009560462	-1350160434
445790.3	174041.2	68781.49	33201.85	508705	129536.8	-322140545	-120586023
128683.3	51347.26	278598	23157.78	111936	2057257	-81662244.6	-544281621
211973.9	59203.18	35562.74	11222.6	139864.9	114314.3	-73104181.9	-35452457.5
245166.3	117536.1	430780	47344.61	393949.7	2305539	-206058483	-785235948
466527.6	551224.1	392431.9	56788.88	1829879	1132212	-1052969751	-915376544
102343.8	31867.13	15940.84	7112.628	75082.49	37259.67	-44691988	-27381108.5
161937.6	75050.89	264923.5	26263.54	178891.6	2437060	-116806811	-365822206
565373.8	789123.7	457329.7	409021	2547016	1040034	-1272162731	-924600726
74830.54	53052.58	34861.67	9353.116	183489	120537.9	-69000880.2	-32452818.6
75327.15	54506.35	56762.97	15977.75	141911.2	225801.5	-75478463.7	-78274524.6
865040.5	772470.1	1166121	281790.8	2357086	12311276	-1756778069	-1401594711
884068.3	503100.7	1958618	216897.5	1471048	9273708	-887191888	-3508138817
1255034	802354.1	401721.9	138459.6	6317626	1146456	-787525203	-695961017
587666.8	384072.2	980295.6	126717.8	1112914	3009250	-636729903	-1915579794
24860.91	25426.59	37269.22	11721.87	71103.27	152918.8	-27424773.9	-54448616.8
208139.4	52112.4	22121.94	5167.125	340869.4	51469.47	-73602099.6	-42277706.3
563552.3	708817	412630.5	293014.1	1749377	1326177	-1187290173	-830853521
57835.97	85709.8	96435.55	47081.58	193910.1	233590.6	-148308285	-164918104
865591	489928.5	592136.9	62485.59	1186256	2495194	-1096940357	-926836298
163019.8	69566.64	203746.1	23294.34	158796.3	1721012	-116621985	-259227142

367000.4	105912.1	24358.93	12305.95	388725.1	50250.44	-197893403	-36343427.5
186392.2	226967.3	150845.1	118111	581536.3	389917.7	-524346700	-233033284
963624.6	408896.3	763953.3	113587.1	804946	2707250	-799815283	-1128892699
314009.7	348799.8	193194.8	53681.99	1347615	532297.5	-539820412	-253233245
1718242	820463	357042.4	192892.5	4119691	1133117	-1573404254	-646613992
302203.9	244392	499804.6	84859.11	527536	2534248	-431909214	-847347127
146505.1	141673.3	247600.3	60267.57	290747	1146252	-270982561	-437034642
50871	35785.5	64697.23	8079.077	79472.27	333853.6	-47805457.7	-124807867
1416844	522615.4	1904072	232117.9	1344329	8467969	-851348931	-3242265548
285613.9	244339.8	488135.4	86282.67	571343.6	2519246	-464289562	-827256102
358345.2	513574.1	462295.9	201042	1258041	1530865	-1133337318	-958437404
346586.6	115488.2	344202.2	56723.17	345929.3	1580807	-179689412	-515652731

CHAPTER 6: CONCLUSION AND FUTURE SCOPE

Epilepsy is a serious neuronal disorder that needs to be detected accurately. Electroencephalogram is a good non-invasive diagnostic tool that can be digitally analyzed to detect the epileptic disorder. Approximately 1% of the world's population suffers from epileptic disorder, a disorder of the normal brain characterized by excessive neuronal activity in the brain. Epileptic seizures are manifestations of epilepsy and are the result of sudden, usually brief, excessive electrical discharges in a group of neurons and that different parts of the brain can be the site of such discharges. The clinical manifestations of seizures therefore vary and depend on where in the brain the disturbance first starts and how far it spreads. They may be localized in certain area of the brain called partial seizures, which can be seen only in a few channels of the EEG recording, or may be involved the whole brain area called generalized seizures, which can be seen in every channel of the EEG recordings.

It can be concluded that a System tolerant to various inaccuracies pertaining in practical situations is developed with high detection efficiency of 100% for this particular dataset. It is achieved by assigning scores to each of 8 features and calculating final score. Final score shows the number of subjects falling in the category of Epileptic and Non-Epileptic range. Since no False positives and no False negatives detected and none of the cases fell under category indeterminate, so the system is highly acceptable to detect EEG signals by their epileptic activity. Thus the need of accurately detecting the epileptic activity from EEG of a patient is fulfilled.

The present work detects Epilepsy in the subjects while they are not having seizures. Further in case of normal subjects EEG is recorded while their eyes are closed. This work may be extended to the epileptic subjects while they are having seizure and to the novel subjects while their eyes are open. Thus from current two class classifier it may be extended to four class classifier.

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