DIAGNOSIS OF EPILEPSY DISORDERS USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Epilepsy is a neurological condition that from time to time produces brief disturbances in the normal electrical functions of the brain. The doctor's main tool in diagnosing epilepsy is a careful medical history with as much information as possible about what the seizures looked like and what happened just before they began. A second major tool is an electroencephalograph (EEG). In a significant number of cases, detection of the epileptic EEG signal is carried out manually by skilled professionals, who are small in number by automatic seizure detection. Therefore there are many automated systems helping the neurologists.

Artificial Neural networks have been provided an effective approach for EEG signals because of its self-adaption and natural way to organize. Artificial intelligence system based on the qualitative diagnostic criteria and decision rules of human expert could be useful as the clinical decision supporting tool for the localization of epileptogenic zones and the training tool for unexperienced clinicians. Also, considering the fact that experiences from the different clinical fields must be cooperated for the diagnosis of epilepsy, integrated artificial intelligence system will be useful for the diagnosis and treatment of epilepsy patients.

This research presents an automated system that can diagnose epilepsy. The system is composed of two phases. The first phase is the features extraction by using discrete wavelet transform (DWT). The second phase is the classification of the EEG signals (existence of epileptic seizure or not), using artificial neural networks.

The proposed system will help and aid the the neurologists to detection of the epileptic activity.

Key words: Epilepsy, electroencephalogram, discrete wavelet transform, artificial neural networks.

ÖZET

Epilepsi zaman zaman beynin normal elektriksel işlevlerinde kısa bozukluklar üreten nörolojik bir durumdur. Epilepsi teşhisinde doktorun ana aracı dikkatli bir tıbbi geçmiş ile krizlerin neye benzediği ve krizler başlamadan hemen önce ne olduğu hakkında mümkün olabildiğince çok bilgidir. İkinci önemli araç bir elektroensefalografi (EEG) 'dir. Vak'a ların önemli miktarında epileptik sinyal tespiti uzmanlar tarafından, çok daha az kısmı otomatik kriz tespit sistemleri tarafından yapılmaktadır. Bu nedenle nörologlara yardımcı birçok otomatik sistem vardır.

Yapay Sinir ağları, kendi kendine adaptasyon ve doğal organizasyon yeteneğinden dolayı, EEG sinyalleri için etkili bir yaklaşım sağlar. Nitelikli tanı kriterlerine ve uzmanların karar verme kurallarına göre kurulan yapay zeka sistemi, epileptojenik bölgelerin lokalizasyonu için klinik karar destek aracı ve tecrübesiz çalışanların eğitim aracı olarak yararlı olabilir. Aslında, farklı klinik alanlardaki deneyimler epilepsi tanısı için birlikte kullanılması, entegre yapay zeka sistemi, epilepsi hastaları tanı ve tedavisi için yararlı olacaktır.

Bu araştırma epilepsi teşhisi yapabilen otomatik bir sistem sunmaktadır. Bu sistem iki aşamadan oluşmaktadır. Birinci aşama ayrık dalgacık dönüşümü ile öznitelik vektörlerinin çıkarılmasıdır. İkinci aşama, EEG signallerinin (epileptik kriz olsa da olmasa da), yapay sinir ağları ile sınıflandırılmasıdır.

Önerilen sistem nörologlara epileptik aktivitenin tesbiti için destek olacak ve yardım edecektir.

Anahtar sözcükler: Epilepsi, Elektroensefalogram, Ayrık dalgacık dönüşümü, Yapay sinir ağları.

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DEDICATION

This work is dedicated to my husband, Saffet,
who has shown unwavering support and encouragement
during the pursuit of my education.

CONTENTS

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
ADD	Attention Deficit Disorder
BP	Backpropagation
BPNN	Back propagation Neural Network
CIR	Correct Identification rates
CWT	Continuous Wavelet Transform
Db	Daubechies
DWT	Discrete Wavelet Transform
ECG	Electrocardiography
EEG	Electroencephalography
ERP	Event-Related potentials
FFT	Fast Fourier Transform
MCN	Modified Combinatorial Nomenclature
MRA	Multiresolution Analysis
MLP	Multilayer Perceptrons
NNs	Neural Networks
MSE	Mean Squared Error
RBF	Radial-Basis Function
REM	Rapid eye movement
SOM	Self-Organizing Map
SSW	Spikes and Sharp Waves
STFT	Short Time Fourier Transform
SWW	Sharp and Slow Waves
TLE	Temporal lobe epilepsy
WT	Wavelet Transform
B	BetaWaves
α	Alpha Waves

θ	Theta Waves
δ	Delta Waves
V	Vertex waves
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital

CHAPTER 1

INTRODUCTION

Epilepsy is the most common serious neurological disorder. According to the World Health Organization, epilepsy affects approximately 4 million people in North America and Europe. Worldwide, 40 million people are believed to have epilepsy. [1] Epilepsy can start at any age, but is most common among young children. The disorder is characterized by seizures, known as "attacks". The symptoms of epilepsy depending on the type of seizure, the individual person, and other factors. Symptoms also include loss of consciousness or unusual emotions, sensations, and behaviors.

The Electroencephalograph (EEG) signals involve a great deal of information about the function of the brain. Electroencephalogram (EEG test) has important role in the diagnosis of epilepsy. Epilepsy is classified as epileptic waves, which include individual spikes, sharps, spike slows complexes, and sharp slows complexes and so on. Visual analysis of EEG is the most common and reliable method of EEG analysis. Highly experienced professionals have to observe plenty of EEG signals very carefully. Detection of the epileptic activity requires a time consuming analysis of the entire length of the EEG data by an expert.This is time-consuming and not economical task.

Therefore there is need to automatic classification of EEG signals. Classification problem is a decision making task where many researchers have been working on. There are a number of techniques proposed to perform classification. Neural network is one of the artificial intelligent techniques that has many successful examples when applying to this problem The aim of this research to develop an automated epileptic diagnosis using EEG and neural network. The proposed system composed of two phases: features extraction and classification.

Chapter two defines the different types of epilepsy. EEG wavegroups and electroencephalography (EEG) technique are also described in this chapter.

Chapter three describes the time domain and frequency domain representations of signals. The following section defines fundamentals of wavelet theory and related multiresolution analysis. The last section discusses importance of wavelet analysis in biomedical applications.

Chapter four introduces fundamental concepts of artificial neural networks, and basic architecture of neural networks. Also biological and artificial neural networks compares in this chapter. Moreover, a table summarizes various learning algorithms and their associated network architectures. Finally, role of neural Networks in medical diagnosis is discussed.

Chapter five presents the proposed system. The proposed system involves two phases. First phase is feature extraction, where feature vectors are obtained by discrete wavelet transform. In phase two, the feed- forward neural network has been trained using back probagation learning algorithm. The Features obtained from the first phase are classified by backpropagation neural network. At the end of this chapter; results and performance of the proposed system are discussed.

The results will verify the performance and the efficiency of the proposed EEG classification system.

CHAPTER 2
ELECTROENCEPHALOGRAPHY (EEG)

2.1 Overview

Epilepsy is a disease in which the affected person tends to have repeated seizures that start in the brain. Despite the fact that epilepsy is the most common of the neurological disorders it remains both feared and misunderstood.

Electroencephalography (EEG) has important clinical tool for the diagnosis, evaluation and treatment of epilepsy. Recent technological advances lead to an expanded role for the EEG in epilepsy.

This chapter describes the major types of brain waves and their characteristics. Following section will discuss the methods for recording the EEG. The last section describe role of EEG in epilepsy syndromes.

2.2 Epilepsy

Epilepsy is a group of brain disorders characterized by recurrent seizures that occurs in 0.5 to 1% of the world's population. There are approximately 2.7 million Americans with epilepsy. Physicians diagnose 200,000 new cases of epilepsy each year. A variety of insults to the brain may result in epilepsy such as a birth defect, birth injury, bleeding in the brain, brain infection, brain tumor, head injury or stroke [2].

There are hundreds of epilepsy syndromes, many of them very rare. These syndromes are often named for their symptoms or for the part of the brain where they originate. Many of these epilepsy syndromes originate in childhood or even in infancy. Others begin in adulthood and even in old age. Some of the most common types of are:

Absence Epilepsy

People with absence epilepsy have repeated absence seizures. Absence epilepsy tends to run in families. The seizures frequently begin in childhood or adolescence. If the seizures begin in childhood, they usually stop at puberty.

Although the seizures don't have a lasting effect on intelligence or other brain functions, children with absence epilepsy frequently have so many seizures that it interferes with school and other normal activities.

Temporal Lobe Epilepsy

Temporal lobe epilepsy (TLE) is the most frequent cause of partial seizure and aura. The temporal lobe is located close to the ear. It is the part of the brain where smell is processed and where the choice is made to express a thought or remain silent. TLE often begins in childhood. Repeated TLE seizures can damage the hippocampus, a part of the brain that is important for memory and learning. Although the damage progresses very slowly, it is important to treat TLE as early as possible.

Frontal Lobe Epilepsy

The frontal lobes of the brain lie behind the forehead. They are the largest of the five lobes and are thought to be the centers that control personality and higher thought processes, including language and speech. Frontal lobe epilepsy causes a cluster of short seizures that start and stop suddenly. The symptoms depend upon the part of the frontal lobe affected.

Occipital Lobe Epilepsy

The occipital lobe lies at the back of the skull. Occipital lobe epilepsy is like frontal and temporal lobe epilepsies, except that the seizures usually begin with visual hallucinations, rapid blinking, and other symptoms related to the eyes.

Parietal Lobe Epilepsy

The parietal lobe lies between the frontal and temporal lobes. Parietal lobe epilepsy is similar to other types in part because parietal lobe seizures tend to spread to other areas of the brain [3].

EEG define epilepsy syndromes and as syndrome determination is the best guide to management ang prognosis, the EEG is clearly the most useful laboratory test for epilepsy. Thus, it is prudent for the user to be aware of EEG's limitations and advantages [4].

The EEG identifies specific interictal or ictal abnormalities that are associated with an increased epileptogenic potential and correlate with a seizure disorder. This is important in determining whether a patient's recurrent spells represent seizures. However, the specificity and sensitivity of the EEG is variable and EEG findings must be correlated with the clinical history. A persistently normal EEG recording does not exclude the diagnosis of epilepsy and false interpretation of nonspecific changes with hyperventilation or drowsiness may lead to an error in diagnosis and treatment. Furthermore, epileptiform alterations may occur without a history of seizures, although this is rare.

For patients with a known seizure disorder, the EEG is helpful in classification of seizure disorder, determination of seizure type and frequency, and seizure localization. Seizure classification may be difficult to determine ictal semiology alone. The appropriate classification affects subsequent diagnostic evaluation and therapy and may have prognostic importance. Therefore, the EEG is esential determining the appropriate treatment for patients with epilepsy. The EEG has fundamental value in evaluating surgical candidacy and determining operative strategy in selected patients with intractable partial epilepsy [5]. Abnormal EEG signals include little electrical "explosions" such as the spikes, spike and wave, and sharp waves that are common in epilepsy. Figure 2.1 (a) and (b) shows examples of the normal and epileptic EEG signals, respectively.

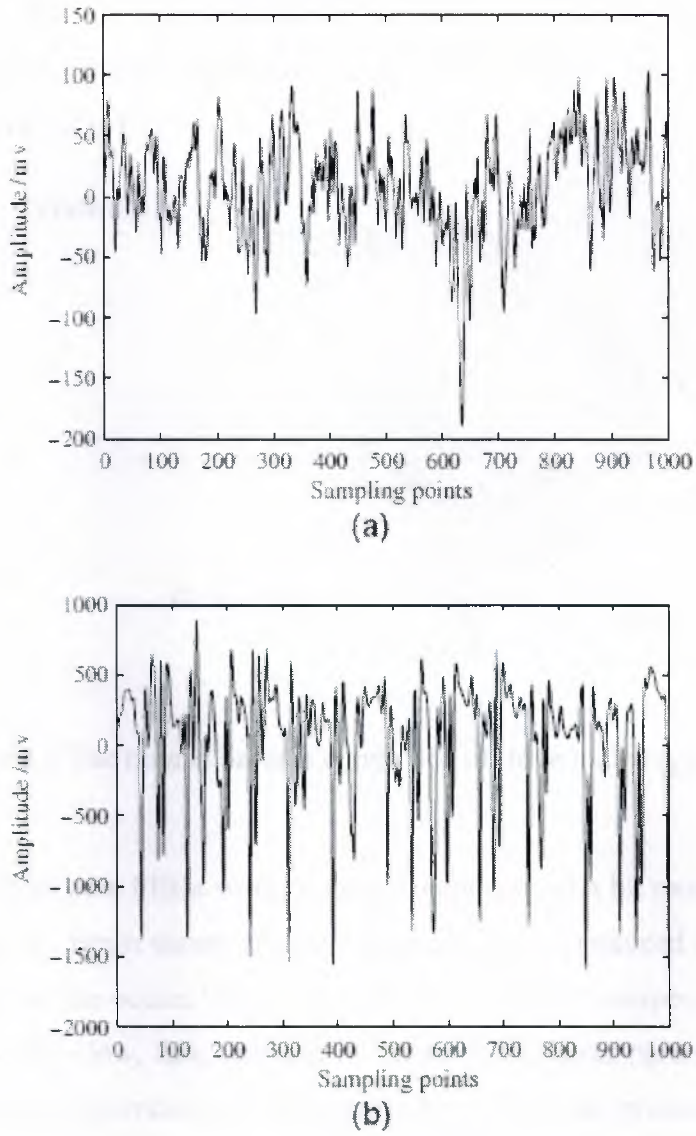

Figure 2.1 EEG signal examples. (a) Normal EEG (b) Epileptic EEG

2.3 Brain Waves

The human brain is a part of the central nervous system and is comprised of more than 100 billion nerve cells. The neurons in the brain are connected to ascending and descending tracts of nerve fibers in the spinal cord. These tracts contain the afferent (sensory) and efferent (motor) nerves that communicate information between the brain and the rest of the body. The brain can be divided into three major sections known as the cerebrum, the cerebellum, and the brain stem. Various types of information in the form of nerve impulses are transmitted and processed in the cerebral cortex. The cerebral cortex, which is the largest part of the brain, is organized in such a way that functionally similar neurons are found in localized regions, and these regions are illustrated in figure 2.2 [6].

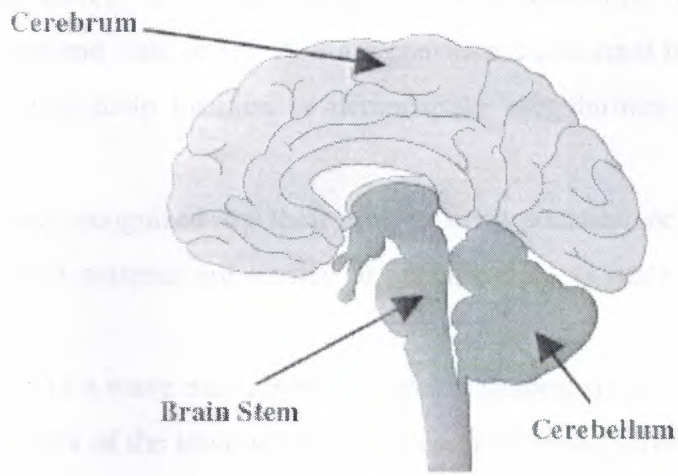

Figure 2.2 The human brain is comprised of three main regions [6].

To really understand how EEGs work, it helps to understand a bit more about the brain waves they measure. Brain waves are the electrical signals produced by neurons in the brain. Like waves in the ocean, brain waves come in different shapes and sizes. Waves can be large, small, slow, fast, uniform or variable. Different parts of brain produce different brain waves depending on what each part of the brain produce is doing at any moment [7].

EEG waveforms are generally classified according to their frequency, amplitude and shape, as well as the sites on the scalp at which they are recorded.

Information about waveform frequency and shape is combined with the age of the patient, state of alertness or sleep, and location on the scalp to determine significance. Normal EEG waveforms, like many kinds of waveforms, are defined and described by their frequency, amplitude, and location.

- Frequency (Hertz, Hz) is a key characteristic used to define normal or abnormal EEG rhythms.

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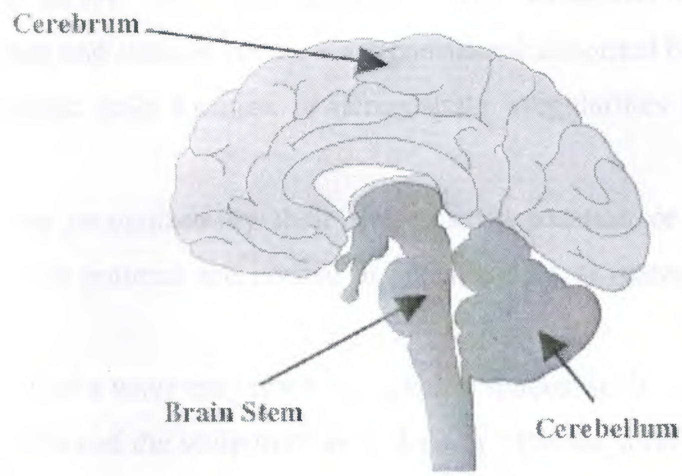

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- Frequency (Hertz, Hz) is a key characteristic used to define normal or abnormal EEG rhythms.

- Most waves of 8 Hz and higher frequencies are normal findings in the EEG of an awake adult. Waves with a frequency of 7 Hz or less often are classified as abnormal in awake adults, although they normally can be seen in children or in adults who are asleep. In certain situations, EEG waveforms of an appropriate frequency for age and state of alertness are considered abnormal because they occur at an inappropriate scalp location or demonstrate irregularities in rhythmicity or amplitude.
- Some waves are recognized by their shape, scalp location or distribution, and symmetry. Certain patterns are normal at specific ages or states of alertness and sleep.
- The morphology of a wave may resemble specific shapes, such as vertex (V) waves seen over the vertex of the scalp in stage 2 sleep or triphasic waves that occur in the setting of various encephalopathies [8].

The EEG periodic rhythms have in turn traditionally been subdivided into 4 categories:

2.3.1 Beta Waves (β): (15 to 40 cycles per second)

Beta waves are of low amplitude and are the fastest of the four brainwaves. Beta waves are characteristics of an active mind. They are present when one is fully engaged, aware, concentrating, thinking logically and in active conversation. A person making a speech or teaching would be in beta. On the negative side, these brainwaves predominate during times of stress and with feelings of paranoia, worry, fear, and anxiety. They are also present with hunger, depression, irritability, and moodiness. Insomnia is believed to be the result of producing excessive beta brainwaves.

2.3.2 Alpha Waves (α): (7-14 cycles per second)

Where beta waves represented arousal, alpha waves represent less arousal. Alpha brainwaves are slower and higher in amplitude. The alpha rhythm is most evident when one is awake, with eyes closed and relaxed. Alpha waves are characterized by relaxed wakefulness where creative thought and the behavioral efficiency of routine behaviors are optimal. A person who takes time to reflect or meditate is usually in an alpha state.

The alpha rhythm decreases or disappears when one is mentally concentrating, physically moving or becoming apprehensive. Some researchers have hypothesized the alpha rhythm to be a possible physiological correlate of the hypnotic state. They have found evidence of hypnotic susceptibility being positively correlated with higher levels of waking alpha production.

2.3.3 Theta Waves (θ): (4-7 cycles per second)

Theta waves have greater amplitude and slower frequency than alpha waves and are associated with the early stages of sleep and dreaming. Theta brainwaves are present for about 60% of sleep and are also present during the barely conscious state just before sleeping and just after waking. The brain also produces theta waves during the Rapid Eye Movement (REM) part of the sleep cycle. If one is quiet and slows their mind down during Alpha, they will naturally go into theta.

Theta waves have been associated with improved creativity, deeper relaxation, daydreaming, and dreaming while asleep. People with more theta wave activity think more creatively than those with less activity. Musicians, painters and designers have more theta waves than average. It has also been found that people with lower levels of anxiety, stress, and neurosis have stable theta brainwave activity.
On the more negative side, theta waves may be the dominate brain wave activity when one is having difficulty concentrating. People with attention-deficit problems (ADD) cannot shift out of the Theta State when events that need focus, such as taking a test, arise.

2.3.4 Delta Waves (δ): (1.5 to 4 cycles per second)

Delta waves have the greatest amplitude and slowest frequency of the brainwaves. They typically range from 1.5 to 4 cycles per second. Brain waves are rarely lower than 1.5 6Hz; zero would suggest no activity in the brain or in other words, brain death. Delta waves are the deepest level of dreamless sleep (2 to 3 Hz), in which, our bodies shut down to focus on healing and growing. Practiced mediators can achieve this state of consciousness while awake.

Delta brainwaves are conducive to healing (the immune system is strengthened), rejuvenation, divine knowledge and personal growth. Peak performers decrease delta waves when high focus and peak performance are required. However, most individuals diagnosed with Attention Deficit Disorder (ADD) naturally increase rather than decrease delta activity when trying to focus [9]. Figure 2.3 shows four types of brain waves.

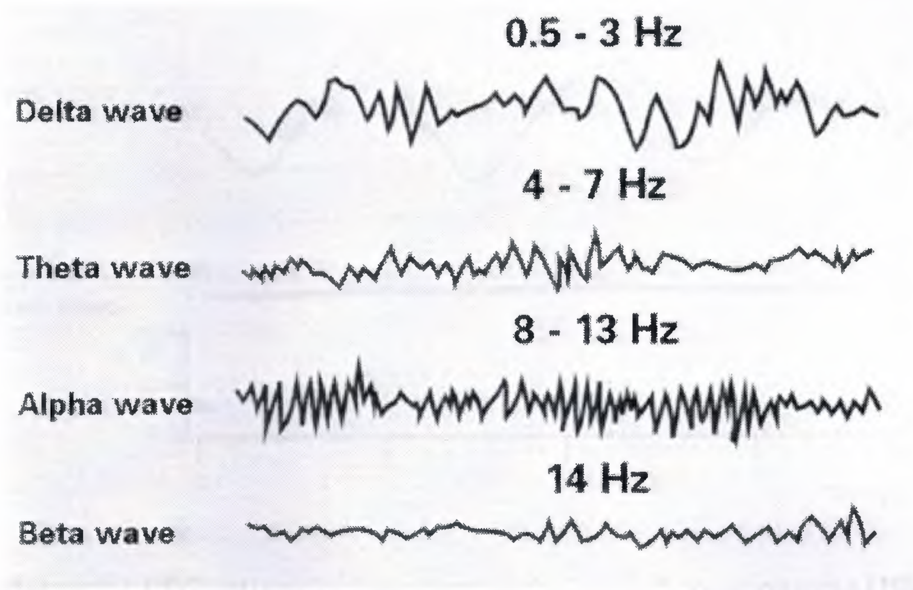

Figure 2.3 Classification of brain waves [8].

2.4 The Basic Principles of EEG Diagnosis

The EEG signal is closely related to the level of consciousness of the person. As the activity increases, the EEG shifts to higher dominating frequency and lower amplitude. When the eyes are closed, the alpha waves begin to dominate the EEG. When the person falls asleep, the dominant EEG frequency decreases. In a certain phase of sleep, rapid eye movement called (REM) sleep, the person dreams and has active movements of the eyes, which can be seen as a characteristic EEG signal. In deep sleep, the EEG has large and slow deflections called delta waves. No cerebral activity can be detected from a patient with complete cerebral death. Examples of the above-mentioned waveforms are given in Figure 2.4 [10].

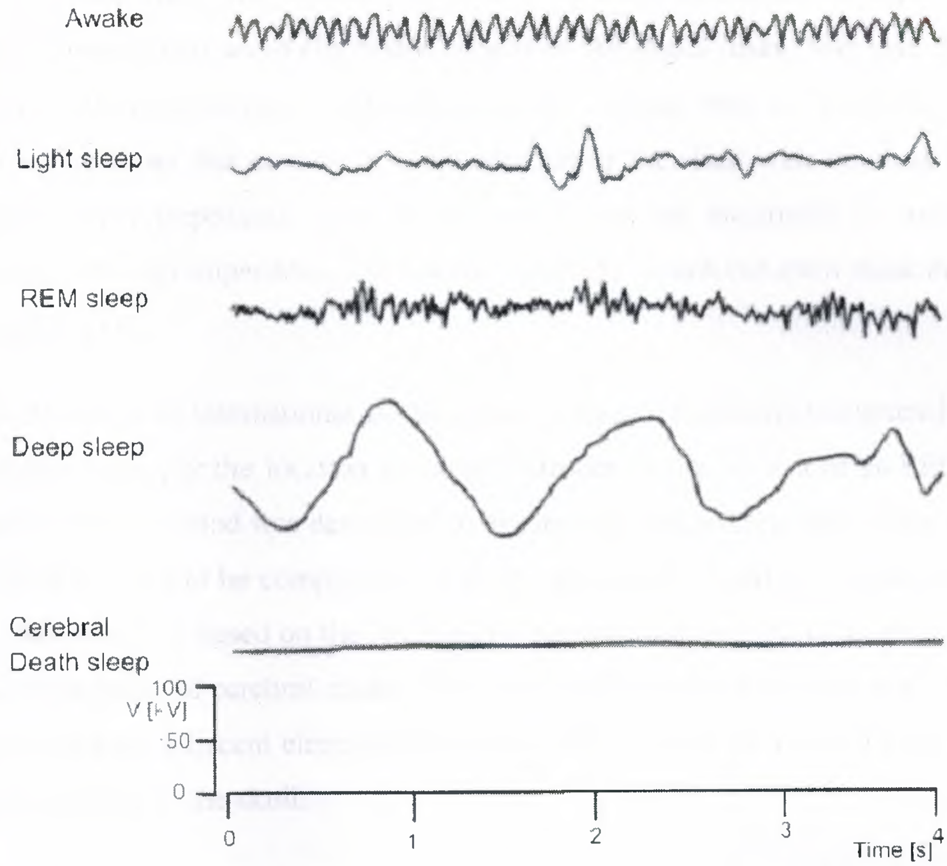

Figure 2.4 EEG activity is dependent on the level of consciousness [10].

2.5 EEG Recording and Measurement

The EEG recording electrodes and their proper function are crucial for acquiring high quality data. Different types of electrodes are often used in the EEG recording systems, such as:

- Disposable (gel-less, and pre-gelled types)
- Reusable disc electrodes (gold, silver, stainless steel, or tin)
- Headbands and electrode caps
- Saline-based electrodes
- Needle electrodes

For multichannel recordings with a large number of electrodes, electrode caps are often used. Commonly used scalp electrodes consist of Ag–AgCl disks, less than 3 mm in diameter, with long flexible leads that can be plugged into an amplifier. Needle electrodes are those that have to be implanted under the skull with minimal invasive operations. High impedance between the cortex and the electrodes as well as the electrodes with high impedances can lead to distortion, which can even mask the actual EEG signals [11].

The 10-20 system or International 10-20 system is an internationally recognized method to describe and apply the location of scalp electrodes in the context of an EEG test or experiment. This method was developed to ensure standardized reproducibility so that a subject's studies could be compared over time and subjects could be compared to each other. This system is based on the relationship between the location of an electrode and the underlying area of cerebral cortex. The "10" and "20" refer to the fact that the actual distances between adjacent electrodes are either 10% or 20% of the total front-back or right-left distance of the skull.

Each site has a letter to identify the lobe and a number to identify the hemisphere location. The letters F, T, C, P and O stand for Frontal, Temporal, Central, Parietal, and Occipital, respectively. Note that there exists no central lobe; the "C" letter is only used for identification purposes only. A "z" (zero) refers to an electrode placed on the midline. Even numbers (2,4,6,8) refer to electrode positions on the right hemisphere, whereas odd numbers (1,3,5,7) refer to those on the left hemisphere.

Two anatomical landmarks are used for the essential positioning of the EEG electrodes: first, the nasion which is the point between the forehead and the nose; second, the inion which is the lowest point of the skull from the back of the head and is normally indicated by a prominent bump.

When recording a more detailed EEG with more electrodes, extra electrodes are added utilizing the spaces in-between the existing 10-20 system. This new electrode-naming-system is more complicated giving rise to the Modified Combinatorial Nomenclature (MCN). This MCN system uses 1, 3, 5, 7, 9 for the left hemisphere which represents 10%, 20%, 30%, 40%, 50% of the inion-to-nasion distance respectively. Figure 2.5 shows the international 10-20 system. The introduction of extra letters allows the naming of extra electrode sites. Note that these new letters do not necessarily refer to an area on the underlying cerebral cortex [12].

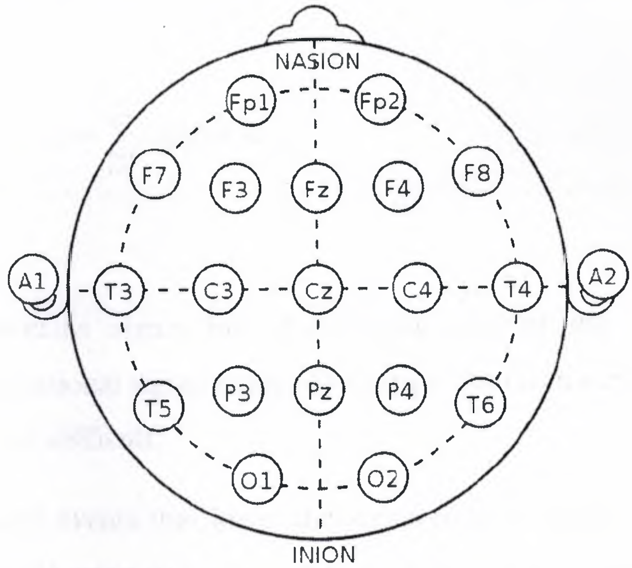

Figure 2.5 21 electrodes of International 10-20 system for EEG [13].

2.5.1 Noise and Artifacts

One of the main problems in the automated EEG analysis is the detection of the different kinds of interference waveforms (artifacts) added to the EEG signal during the recording sessions. The most important reasons for occurrence of the artifacts are the movements of the patient during recording session and the normal electrical activity of the heart, muscles and eyes [14].

Noise and artifacts reduce the signal-to-noise ratio. These problems might have origin in the measurement system or subject's head. It is noteworthy that averaging the trials in it degenerate the signal.

There are two methods for noise reduction. The easier one is to detect and reject the problematic trials. The other way is to try to remove the artifacts even though it distorts the signal.

The EEG signal is composed of multiple oscillations. An EEG signal $x(t)$ can be thought as superposition of several (N) individual signals a_i (t) that have different origin and that are summed up. This model also includes noise $n(t)$. Each of these components has its own origin and some of them are more meaningful for the current problem. This can be expressed as:

$$x(t) = \sum_{i=1}^{N} a_i(t) + n(t) \qquad (2.1)$$

The noise part contains signal that distorts the sum of the interesting physical components. This additional signal randomly changes the clean signal over time making its interpretation more difficult.

Artifacts are transient events that lower the signal-to-noise ratio for a period of time. There are two possible ways to handle artifacts. The first is to detect them with some method and then reject those trials containing artifacts altogether. The second one is to detect and remove the artifact. The latter should be used with caution because removing loses some information and may distort the signal [15].

Artifacts are disturbing peaks that appear sparsely. The causes of these artifacts include motoric muscle movement, heart beats, circulatory system and for example recording equipment. The changing electrical conductivity and other changing features of the environment and of the electrodes also cause unexpected changes. These artifacts include peaks, repeating noise and the 50Hz noise of the electrical Equipment. The rhythmic activity of the brain discussed earlier also contributes to the noise. This is the case especially with alpha-waves, whose frequency range corresponds to the ERP range. One well-known cause of artifacts is the blinking of the eyes.

The overlapping of two or more consequent event-related potentials having prominent amplitude peaks at the same time is also a problem. Similarly, the several components of an ERP may overlap each other or other ERPs. This kind of artifact is hard to remove since the several components need to be separated. This shows that decomposition would facilitate the detection. Normally this usually leads to the rejection of such trials, if they are detected at all [16].

2.6 Summary

This chapter described brain waves and electroencephalogram which measures brain's electrical activity. EEG is used to diagnose a number of conditions, sleep disorders, brain tumours, Parkinson's disease, Alzheimer's disease and autism. The EEG is an important aid in the diagnosis and management of epilepsy. It can provide support for the diagnosis of epilepsy and also assists in classifying the underlying epileptic syndrome.

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CHAPTER3

WAVELET AND MULTIRESOLUTION ANALYSIS

3.1 Overview

Wavelets developed to analyze the frequency components of a signal according to a scale. The purpose of the Wavelet Transform (WT) is to provide a way for analyzing waveforms, bounded in both frequency and duration.

Wavelet transform is used in a wide variety of applications in the areas of medicine, biology, communications, multimedia, and among others.

This chapter describes the time domain and frequency domain representations of signals. Morever, sections will be discussing the fundamentals of wavelet theory and related multiresolution analysis. The last section briefly mentions electroenceplography applications.

3.2 Time Representation and Frequency Representation

The time representation is usually the first (and the most natural) description of a signal, since almost all physical signals are obtained by recording variations with time. The frequency representation, obtained by the well known Fourier transform

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-j2\pi ft}\,dt \tag{3.1}$$

and its inverse

$$x(t) = \int_{-\infty}^{+\infty} X(f)e^{j2\pi ft}\,df \tag{3.2}$$

is also a very powerful way to describe a signal, mainly because the relevance of the concept of frequency is shared by many domains (physics, astronomy, economics, biology, etc.) in which periodic events occur.

If we look more carefully at the spectrum *X(f)*, it can be viewed as the coefficient function obtained by expanding the signal $x(t)$ into the family of infinite waves, $e^{-j2\pi ft}$, which are totally unlocalized in time. Thus, the frequency spectrum tells us which frequencies are contained in a signal, as well as their corresponding amplitudes and phases, but not tell anything about at which times these frequencies occur. This is why the Fourier transform is not suitable if the signal has time varying frequency spectrum, i.e. the signal is non-stationary. This type of signals are of special relevance in the biomedical field since a large amount of the information carried by physiological signals like the EEG and the ECG (Electroencephalography) is found in transient and short duration changes in the ongoing background activity [17].

3.3 Time Frequency Analysis

In many applications such as speech processing, we are interested in the frequency content of a signal locally in time. That is, the signal parameters (frequency content etc.) evolve over time. Such signals are called non-stationary. For a non-stationary signal, $x(t)$, the standard Fourier Transform is not useful for analyzing the signal. Information which is localized in time such as spikes and high frequency bursts cannot be easily detected from the Fourier Transform.

Time-localization can be achieved by first windowing the signal so as to cut off only a well- localized slice of $x(t)$ and then taking its Fourier Transform. This gives rise to the Short Time Fourier Transform, (STFT) or Windowed Fourier Transform. The magnitude of the STFT is called the spectrogram. By restricting to a discrete range of frequencies and times we can obtain an orthogonal basis of functions [18].

3.3.1 The Short Time Fourier Transform

The short-time Fourier transform (STFT) was the first time-frequency method, which was applied by Gabor in 1946 to speech communication. The STFT may be considered as a method that breaks down the non-stationary signal into many small segments, which can be assumed to be locally stationary, and applies the conventional FFT to these segments.

The STFT of a signal $s_t(\tau)$ is achieved by multiplying the signal by a window function $h(\tau)$, centered at τ, to produce a modified signal. Since the modified signal emphasises the signal around time τ, Fourier Transforms will reflect the distribution of frequency around that time.

$$S_t(w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-jwt} s(\tau) h(\tau - t) d\tau \qquad (3.3)$$

The energy density spectrum at time τ may be written as follows:

$$P(t, w) = \left| S_t(w) \right|^2 = \left| \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-jw\tau} s(\tau) h(\tau - t) d\tau \right|^2 \qquad (3.4)$$

For each different time, we get a different spectrum and the ensemble of these spectra provides the time-frequency distribution $P(t, w)$ which is called Spectrogram. The major disadvantage of the STFT is the resolution tradeoff between time and frequency. Resolutions in time and frequency will be determined by the width of window $h(\tau)$ [19].

The window length affects the time resolution and the frequency resolution of the sort time Fourier transform. A shorter window means good time resolution but at the same time poor frequency resolution. On other hand wide window results fine frequency resolution but poor time resolution. The Wavelet transform solves the dilemma of resolution to a certain extent.

3.3.2 The Continuous Wavelet Transform (CWT)

The continuous wavelet transform was developed as an alternative approach to the short time Fourier transform to overcome the resolution problem.

An advantage of wavelet transforms is that the windows *vary.* In order to isolate signal discontinuities, one would like to have some very short basis functions. At the same time, in order to obtain detailed frequency analysis, one would like to have some very long basis functions. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones. This happy medium is exactly what you get with wavelet transforms. Figure 3.1 shows the coverage in the time-frequency plane with one wavelet function, the Daubechies wavelet [20].

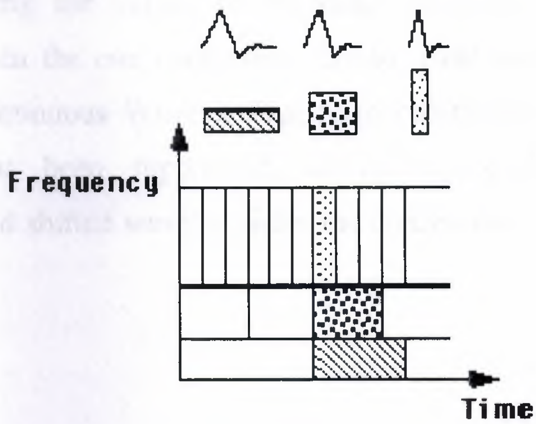

Figure 3.1 Daubechies wavelet basis functions, time-frequency tiles, and coverage of the time-frequency plane [20].

One thing to remember is that wavelet transforms do not have a single set of basis functions like the Fourier transform, which utilizes just the sine and cosine functions. Instead, wavelet transforms have an infinite set of possible basis functions. Thus wavelet analysis provides immediate access to information that can be obscured by other time-frequency methods such as Fourier analysis [20].

In the CWT, the analyzing function is a wavelet, ψ. The CWT compares the signal to shifted and compressed or stretched versions of a wavelet. Stretching or compressing a function is collectively referred to as *dilation* or *scaling* and corresponds to the physical notion of *scale*. By comparing the signal to the wavelet at various scales and positions, you obtain a function of two variables. The two-dimensional representation of a one-dimensional signal is redundant. If the wavelet is complex-valued, the CWT is a complex-valued function of scale and position. If the signal is real-valued, the CWT is a real-valued function of scale and position. For a scale parameter, a>0, and position, b, the CWT is:

$$C(a,b;f(t),\psi(t)) = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{3.5}$$

where * denotes the complex conjugate. Not only do the values of scale and position affect the CWT coefficients, the choice of wavelet also affects the values of the coefficients.

By continuously varying the values of the scale parameter, a, and the position parameter, b, you obtain the *cwt coefficients C(a,b)*. Note that for convenience, the dependence of the Continuous Wavelet Transform coefficients on the function and analyzing wavelet has been suppressed. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal [21].

Scale and Frequency

There is clearly a relationship between scale and frequency. Recall that higher scales correspond to the most "stretched" wavelets. The more stretched the wavelet, the longer the portion of the signal with which it is being compared, and therefore the coarser the signal features measured by the wavelet coefficients.

To summarize, the general correspondence between scale and frequency is:

•Low scale $a \Rightarrow$ Compressed wavelet $\Rightarrow$ Rapidly changing details $\Rightarrow$ High frequency ω.

•High scale $a \Rightarrow$ Stretched wavelet $\Rightarrow$ Slowly changing, coarse features $\Rightarrow$ Low frequency ω.

Shifting

Shifting a wavelet simply means delaying (or advancing) its onset. Mathematically, delaying a function f(t) by k is represented by f($t - k$) as shown in figure 3.2.

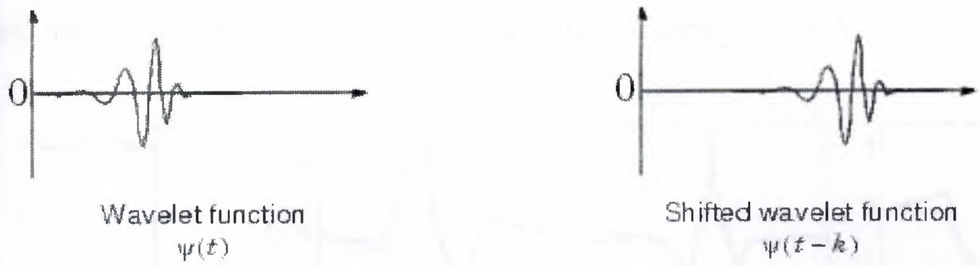

Figure 3.2 Shifting a wavelet function **[21]**.

Coefficients

The wavelet coefficients are the coefficients in the expansion of the wavelet basis functions. The wavelet transform is the procedure for computing the wavelet coefficients. The wavelet coefficients convey information about the weight that a wavelet basis function contributes to the function. Since the wavelet basis functions are localized and have varying scale. The wavelet coefficients therefore provide information about the frequency-like behavior of the function [22].

3.3.3 Wavelet Families

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting and the appropriate mother wavelet should be chosen in order to use the Wavelet transform. Therefore, the details of the particular application should be taken into account effectively. Haar wavelet [23] is one of the oldest and simplest wavelet.

Daubechies wavelets [24] are the most popular wavelets. They represent the foundations of wavelet signal processing and are used in numerous applications. These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and π. This is a very desirable property in some applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. Figure 3.3 illustrates some of the commonly used wavelet functions. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application [25].

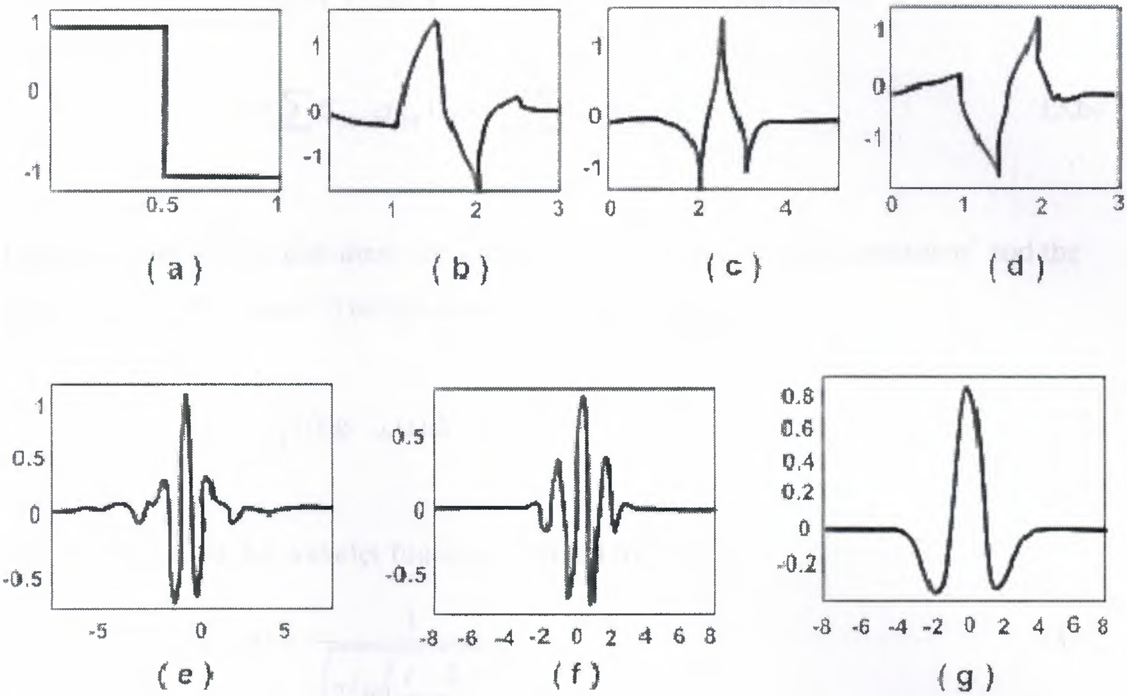

Figure 3.3 Wavelet Families: (a) Haar (b) Daubechies-4 (c) Coiflet (d) Symlet (e) Morlet (f) Meyer (g) Mexican Hat [25].

The large number of known wavelet families and functions provides a rich space in which to search for a wavelet which will very efficiently represent a signal of interest in a large variety of applications. Wavelet families include Biorthogonal, Coiflet, Harr, Symmlet, Daubechies wavelets [26], [27].

There is no absolute way to choose a certain wavelet. The choice of the wavelet function depends on the application. The Haar wavelet algorithm has the advantage of being simple to compute and easy to understand. The Daubechies algorithm is conceptually more complex and has a slightly higher computational overhead. But, the Daubechies algorithm picks up detail that is missed by the Haar wavelet algorithm. Even if a signal is not well represented by one member of the Db family, it may still be efficiently represented by another. Selecting a wavelet function which closely matches the signal to be processed is of utmost importance in wavelet applications [27].

Daubechies Wavelet Transform:

The wavelet expansion of a signal $x(t)$ has the following expression:

$$x(t) = \sum C_{j0k}\varphi_{j0k}(t) + \sum_{j=j0}\sum_{k} d_{ik}\psi_{jk}(t) \tag{3.6}$$

Equation (3.6) shows that there are 2 terms. The first one is '*approximation*' and the second one is the *details*. The the details are represented by

$$d_{jk} = \int x(t)\psi^{*}{}_{jk}(t)dt \tag{3.7}$$

and $\psi_{jk}(t)$ called the wavelet function is given by

$$\psi_{jk}(t) = \frac{1}{\sqrt{2^{j}\psi\left(\frac{t-k2^{j}}{2^{j}}\right)}} \tag{3.8}$$

The approximation coefficients are given by:

$$C_{jk} = \int x(t)\varphi^{*}_{jk}(t)dt \tag{3.9}$$

$\varphi_{jk}(t)$ is called scaling function and is given by:

$$\varphi_{jk}(t) = \frac{1}{\sqrt{2^{j}\varphi\left(\frac{t-k2^{j}}{2^{j}}\right)}} \tag{3.10}$$

Daubechies wavelets [28] are a family of wavelets to have highest number A of vanishing moments, for given support width $N=2A$, and among the $2A-1$ possible solutions the one is chosen whose scaling filter has extremal phase. This family contains the Haar wavelet, *db1*, which is the simplest and certainly the oldest of wavelets. It is discontinuous, resembling a square form.Except for *db1*, the wavelets of this family do not have an explicit expression. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet. Here are the wavelet functions Ψ of the next nine members of the family as shown in the figure 3.4.

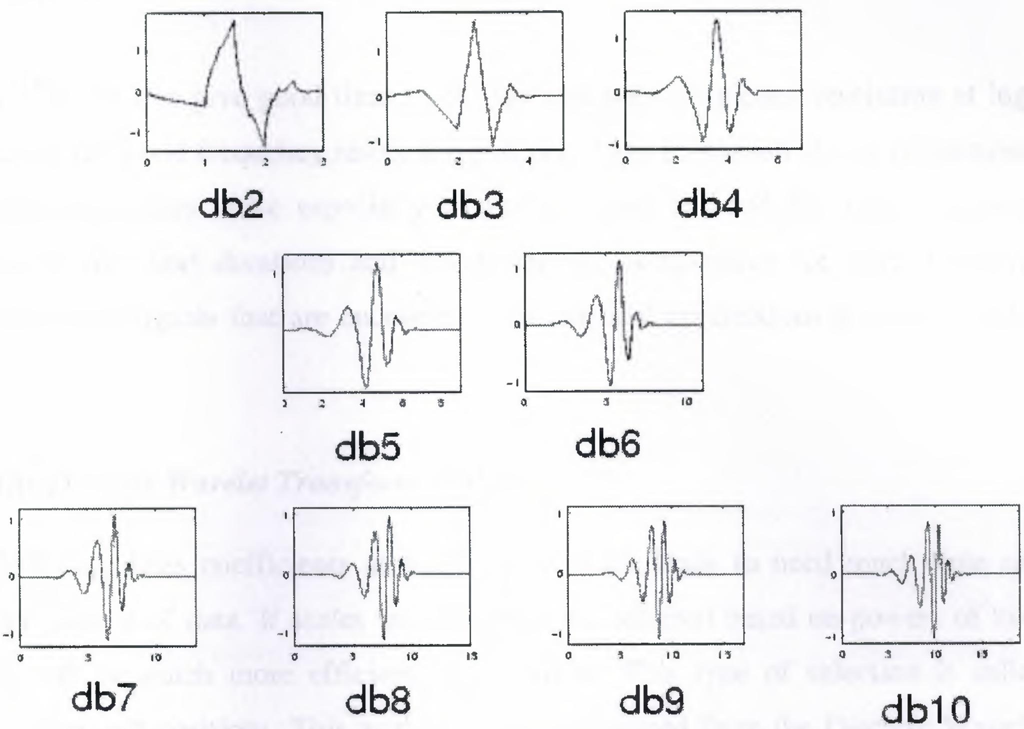

Figure 3.4 The nine members of Daubechies wavelet family [29]

This family has the following properties:

1. The ψ and Π support length is $2N-1$. The number of zero moments of ψ is N;
2. *dbN* wavelets are asymmetric (in particular for low values of *N*) except for the Haar wavelet;
3. The regularity increases with order. When *N* becomes very large, ψ and Π belong to $C\mu N$ where $\mu \approx 0.2$. This value μN is too pessimistic for relatively small orders, as it underestimates the regularity;
4. The analysis is orthogonal. [29]

3.4 Multiresolution Analysis

The time and frequency resolution problems are results of a physical phenomenon (the Heisenberg uncertainty principle) and exist regardless of the transform used, it is possible to analyze any signal by using an alternative approach called the multiresolution analysis (MRA). MRA, as implied by its name, analyzes the signal at different frequencies with different resolutions. Every spectral component is not resolved equally as was the case in the STFT.

MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. This approach makes sense especially when the signal at hand has high frequency components for short durations and low frequency components for long durations. Fortunately, the signals that are encountered in practical applications are often of this type [30].

3.4.1 The Discrete Wavelet Transform (DWT)

The CWT calculates coefficients at every scale which leads to need much time and awful lot amount of data. If scales and positions are selected based on powers of two, analysis will be much more efficient and accurate. This type of selection is called dyadic scales and positions. This analysis can be produced from the Discrete Wavelet Transform (DWT) [31]. The Discrete Wavelet Transform (DWT) is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed efficiently [32].

Discrete wavelets are not continuously scalable and translatable but can only be scaled and translated in discrete steps. This is achieved by modifying the wavelet representation to create

$$\psi_{jk}(t) = \frac{1}{\sqrt{s_0^j}} \psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j} \right) \tag{3.11}$$

Although it is called a discrete wavelet, it normally is a (piecewise) continuous function. In 3.11, j and k are integers and $s_0 > 1$ is a fixed dilation step. The translation factor τ_0 depends on the dilation step. The effect of discretizing the wavelet is that the time-scale space is now sampled at discrete intervals. We usually choose $s_0 = 2$ so that the sampling of the frequency axis corresponds to dyadic sampling. This is a very natural choice for computers, the human ear and music for instance. For the translation factor we usually choose $\tau_0 = 1$ so that we also have dyadic sampling of the time axis. Figure 3.5 shows localization of the discrete wavelets.

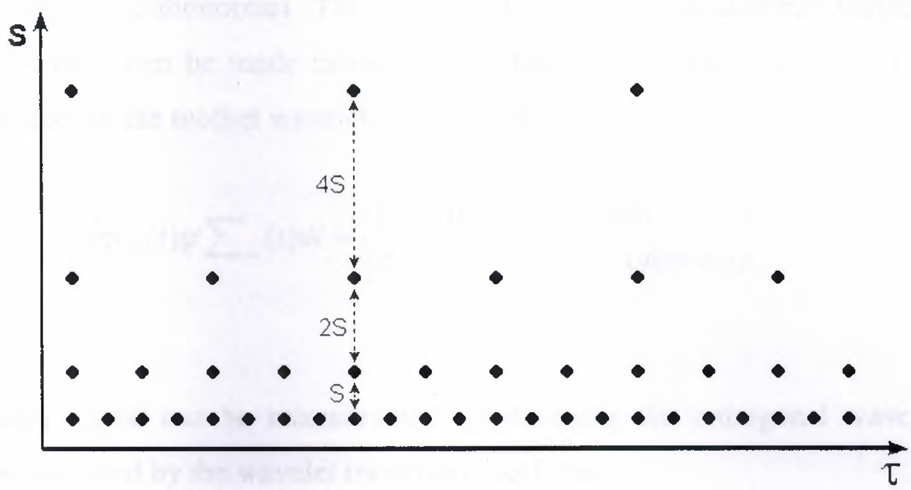

Figure 3.5 Localization of the discrete wavelets in the time-scale space on a dyadic grid [33].

When discrete wavelets are used to transform a continuous signal the result will be a series of wavelet coefficients, and it is referred to as the wavelet series decomposition. An important issue in such a decomposition scheme is of course the question of reconstruction. It is all very well to sample the time-scale joint representation on a dyadic grid, but if it will not be possible to reconstruct the signal it will not be of great use. As it turns out, it is indeed possible to reconstruct a signal from its wavelet series decomposition. It is proven that the necessary and sufficient condition for stable reconstruction is that the energy of the wavelet coefficients must lie between two positive bounds, i.e.

$$A\|f\|^2 \leq \sum_{jk} \left|\langle f, \psi_{jk} \rangle\right|^2 \leq B\|f\|^2 \tag{3.12}$$

Where $\| f \|^2$ is the energy of $f(t)$, $A > 0$, $B < \infty$ and A, B are independent of $f(t)$. When 3.12 is satisfied, the family of basic functions $\psi_{j,k}(t)$ with $j, k \in \mathbf{Z}$ is referred to as a *frame* with frame bounds A and B. When $A = B$ the frame is *tight* and the discrete wavelets behave exactly like an orthonormal basis. When $A \neq B$ exact reconstruction is still possible at the expense of a dual frame. In a dual frame discrete wavelet transform the decomposition wavelet is different from the reconstruction wavelet.

We will now immediately forget the frames and continue with the removal of all redundancy from the wavelet transform. The last step we have to take is making the discrete wavelets orthonormal. This can be done only with discrete wavelets. The discrete wavelets can be made orthogonal to their own dilations and translations by special choices of the mother wavelet, which means:

$$\int \psi_{jk}(t)\psi \sum\nolimits_{mn}^{*}(t)dt = \begin{cases} 1 & if \quad j = m \quad and \quad k = n \\ 0 & \qquad\qquad otherwise \end{cases} \tag{3.13}$$

An arbitrary signal can be reconstructed by summing the orthogonal wavelet basis functions, weighted by the wavelet transform coefficients :

$$f(t) = \sum_{jk} \gamma(j,k)\psi_{jk}(t) \tag{3.14}$$

3.14 shows the inverse wavelet transform for discrete wavelets, which we had not yet seen.

Orthogonality is not essential in the representation of signals. The wavelets need not be orthogonal and in some applications the redundancy can help to reduce the sensitivity to noise or improve the shift invariance of the transform. This is a disadvantage of discrete wavelets: the resulting wavelet transform is no longer shift invariant, which means that the wavelet transforms of a signal and of a time-shifted version of the same signal are not simply shifted versions of each other [33].

3.4.2 The Filter Bank Approach for the DWT

In the discrete wavelet transform, a signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two [34].

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal as shown in figure 3.6. This is called the Mallat algorithm or Mallat-tree decomposition. In this figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by *G0* while the high pass filter is denoted by *H0.* At each level, the high pass filter produces detail information d[n], while the low pass filter associated with scaling function produces coarse approximations a[n] [35].

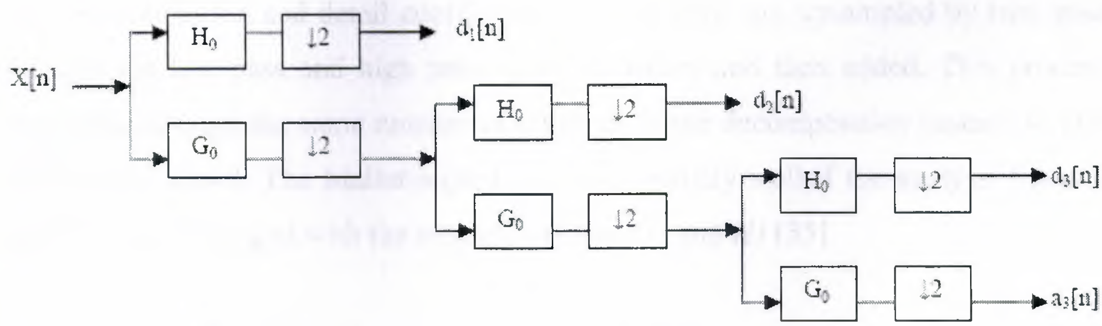

Figure 3.6 Three-level wavelet decomposition tree [35].

At each decomposition level, the half band filters produce signals spanning only half the frequencyband. This doubles the frequency resolution as the uncertainty in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a[n] and d[n], starting from the last level of decomposition. Figure 3.7 shows the reconstruction of the original signal from the wavelet coefficients.

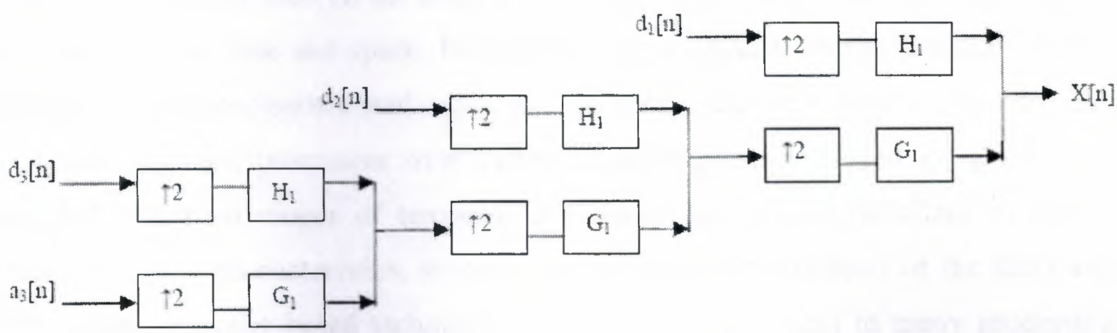

Figure 3.7 Three-level wavelet reconstruction tree [35].

The approximation and detail coefficients at every level are upsampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, *G0* and *H0*, are exchanged with the synthesis filters, *G1* and *H1* [35].

3.5 Wavelets in Biomedical Applications

In the past few years the wavelet transform has been found to be of great relevance in Biomedical engineering. The main difficulty in dealing with biomedical signals is their extreme variability and that, very often, one does not know a priori what is a pertinent information and/or at which scale it is located. Another important aspect of biomedical signals is that the information of interest is often a combination of features that are well localized temporally or spatially (e.g., spikes and transients in the EEG) and others that are more diffuse (e.g., EEG rhythms). This requires the use of analysis methods versatile enough to handle events that can be in at opposite extremes in terms of their time-frequency localization. Thus, the spectrum of applications of the wavelet transform and its multi-resolution analysis has been extremely large [36].

3.5.1 Electroencephalography Applications

Electroencephalographic waveforms such as EEG and event related potentials (ERP) recordings from multiple electrodes vary their frequency content over their time courses and across recording sites on the scalp. Accordingly, EEG and ERP data sets are non-stationary in both time and space. Furthermore, three specific components and events that interest neuroscientists and clinicians in these data sets tend to be transient (localized in time), prominent over certain scalp regions (localized in space), and restricted to certain ranges of temporal and spatial frequencies (localized in scale). Because of these characteristics, wavelets are suited for the analysis of the EEG and ERP signals. Wavelet based techniques can nowadays be found in many processing areas of neuroelectric waveforms, such as:

Noise filtering: After performing the wavelet transforms to an EEG or ERP waveform, precise noise filtering is possible simply by zeroing out or attenuating any wavelet coefficients associated primarily with noise and then reconstructing the neuroelectric signal using the inverse wavelet transform.

Preprocessing neuroelectric data for input to neural networks: Wavelet decompositions of neuroelectric waveforms may have important processing applications in intelligent detection systems for use in clinical and human performance settings.

Neuroelectric waveform compression: Wavelet compression techniques have been shown to improve neuroelectric data compression ratios with little loss of signal information when compared with classical compression techniques. Furthermore, there are very efficient algorithms available for the calculation of the wavelet transform that make it very attractive from the computation requirements point of view.

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Spike and transient detection: As we already know, the wavelet representation has the property that its time or space resolution improves as the scale of a neuroelectric event decreases. This variable resolution property makes wavelets ideally suited to detect the time of occurrence and the location of small-scale transient events such as focal epileptogenic spikes.

Component and event detection: Wavelets methods, such as wavelets packets, offer precise control over the frequency selectivity of the decomposition, resulting in precise component identification, even when the components substantially overlap in time and frequency. Furthermore, wavelets shapes can be designed to match the shapes of components embedded in ERPs. Such wavelets are excellent templates to detect and separate those components and events from the background EEG.

Time-scale analysis of EEG waveforms: Time-scale and space-scale representations permit the user to search for functionally significant events at specific scales, or to observe time and spatial relationships across scales [37].

3.6 Summary

This chapter described Wavelet Theory and multi-resolution analysis. The Fourier transform is only suitable for stationary signals, i.e., signals whose frequency content does not change with time. Most real-world signals, speech, communication, biological signals are non-stationary. Non-stationary signals justify the need for joint time-frequency analysis and representation. For analysis of non-stationary signals the Short-Time Fourier Transform was introduced. The main problem of the Short-Time Fourier Transform is that it uses a fixed window width. The Wavelet Transform uses short windows at high frequencies and long windows at low frequencies thus it provides a better time-frequency representation of the signal than any other existing transforms.

CHAPTER 4

ARTIFICIAL NEURAL NETWORKS

4.1 Overview

Neural networks are computer algorithms that have the ability to learn patterns by experience. There are many different types of neural networks, each of which has different strengths particular to their applications.

This chapter describes the artificial neural network fundamentals. The following section compares between a biological neuron and an artificial neuron. Furthermore, neural network architectures and algorithms are described in detail. The last section will be discussing the role of neural network in medical diagnosis.

4.2 Neural Networks

Work on artificial neural networks, commonly referred to as "neural networks", has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear and parallel computer (information-processing system). It has the capability to organize its structural constituents, known as neurons, so as to perform certain computations (e.g. pattern recognition, perception, and motor control) many times faster than the fastest digital computer in existence today. Consider for example, human vision, which is an information-processing task. It is the function of the visual system to provide a representation of the environment around us and, more important, to supply the information we need to interact with the environment. To be specific, the brain routinely accomplish perceptual recognition task (e.g. recognizing a familiar face embedded in an un-familiar scene) in approximately 100-200 ms, where as tasks of much lesser complexity may take days on a conventional computer.

How, then, does a human brain do it? At birth, a brain has great structure and the ability to built-up its own rules through what we usually refer to as "experience". Indeed, experience is built up over time, with the most dramatic development (i.e. hard wiring) of the human brain taking place during the first two years from birth: but the development continues well beyond that stage.

A "developing" neuron is synonymous with a plastic brain: Plasticity permits the developing nervous system to adapt to its surrounding environment. Just as plasticity appears to be essential to the functioning of neurons as information-processing units in the human brain, so it is with neural networks made up of artificial neurons. In its most general form, a neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest; the network is usually implemented by electronic components or is simulated in software on a digital computer. The interest is confined to an important class of neural networks that perform useful computations through a process of learning. To achieve good performance, neural networks employ a massive interconnection of simple computing definition of a neural network viewed as an adaptive machine.

A neural network is a massively equivalent distributed process or made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

- Knowledge is acquired by the network from its environment through a learning process.
- Inter neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge [38].

4.2.1 Biological Neurons

A biological neuron is the structural and functional unit of the nerve system of the human brain. Numbered on the order of 10^{10}, a typical neuron encompasses the nerve cell body, a branching input called dendrites, and a branching output called the axon that splits into thousands of synapses. Figure 4.1 show a synapse connects the axon of one neuron to the dendrites of another. All neurons highly interconnected with one another. As a specialized cell, each neuron fires and propagates spikes of electrochemical signals to other connected neurons via the axon. The strength of the received signal depends on the efficiency of the synapses. A neuron also collects signals from other neurons and converts it into electrical effects that either inhibit or excite activity in the connected neurons, depending on whether the total signal received exceeds the firing threshold [39].

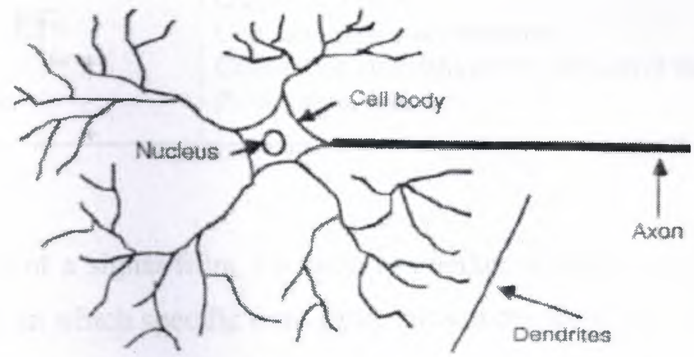


Figure 4.1 Structure of a biological neuron[39].

4.2.2 Artificial Neurons

A biological neuron has a high complexity in its structure and function; thus, it can be modeled at various levels of detail. If one tried to simulate an artificial neuron model similar to the biological one, it would be impossible to work with. Hence an artificial neuron has to be created in an abstract form which still provides the main features of the biological neuron. In the abstract form for this approach, it is simulated in discrete time steps and a neural spiking frequency (or called a firing rate) is reduced to only the average firing rate. Moreover, the amount of time that a signal travels along the axon is neglected.

Before describing the artificial neural model in more detail, one can compare the correspondence between the respective properties of biological neurons in the nervous system and abstract neural networks to see how the biological neuron is transformed into abstract one.

Table 4.1 Comparison of biological and artificial neurons [40].

Nervous system	Artificial neural network
Neuron	Processing element, node, artificial neuron, abstract neuron
Dendrites	Incoming connections
Cell body (Soma)	Activation level, activation function, transfer function, output function
Spike	Output of a node
Axon	Connection to other neurons
Synapses	Connection strengths or multiplicative weights
Spike propagation	Propagation rule

The transmission of a signal from 1 neuron to another through synapses is a complex chemical process in which specific transmitter substances are released from the sending side of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If this potential reaches a threshold, the neuron fires. It is this characteristic that the artificial neuron model proposed by McCulloch and Pitts (1943), attempt to reproduce. The neuron model shown in figure 4.2 is the one that is widely used in artificial neural networks with some minor modifications on it [41].

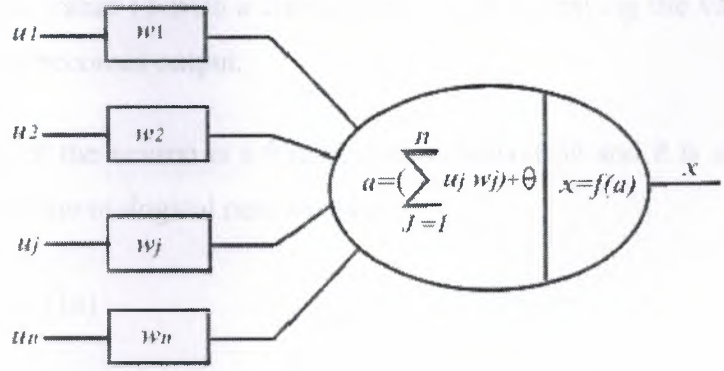


Figure 4.2 Neuron of McCulloch and Pitts (1943) model [41].

Once the input layer neurons are clamped to their values, the evolving starts: layer by layer, the neurons determine their output. This ANN configuration is often called feed-forward because of this feature.

The dependence of output values on input values is quite complex and includes all synaptic weights and thresholds.

The artificial neuron given in figure 4.2 has N inputs, denoted as u_1, u_2, .. u_n. Each line connecting these inputs to the neuron is assigned a weight, which are denoted as w_1, w_2,.., w_n, respectively. Weights in the artificial model correspond to the synaptic connections in biological neurons. If the threshold in artificial neuron is to be represented by θ, then the activation is given by the formula: [41]

$$a = \left(\sum_{j=1}^{N} w_j u_j \right) + \theta \tag{4.1}$$

The input and the weights are real values. A negative value for a weight indicates an inhibitory connection, while a positive value indicates an excitatory one. Although in biological neurons, θ has a negative value; it may be assigned a positive value in artificial neuron models. If θ is positive, it is usually referred as bias. For mathematical convenience, + sign is used just before θ in the activation formula. Sometimes, the threshold is combined for simplicity into the summation part by assuming an imaginary input u_0 having the value +1 with a connection weight w_0 having the value. Hence, the activation formula becomes output.

The output value of the neuron is a function of its activation and it is analogous to the firing frequency of the biological neurons [41]:

$$x = f(a) \tag{4.2}$$

Four different types transfer function illustrated in figure 4.3

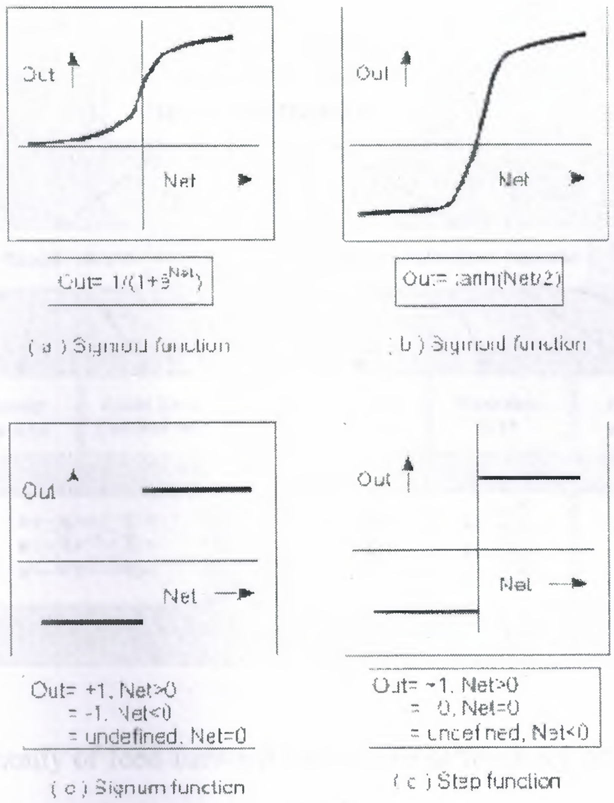


Figure 4.3 Common non-linear functions used for synaptic inhibition. Soft nonlinearity: (a) Sigmoid and (b) tanh; Hard non-linearity: (c) Signum and (d) Step [42].

4.3 Neural Network Architectures

ANNs can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges (with weights) are connections between neuron outputs and neuron inputs.

Based on the connection pattern (architecture), ANNs can be grouped into two categories (see figure 4.4) :

- *feed-forward* networks, in which graphs have no loops, and
- *recurrent* (or *feedback)* networks, in which loops occur because of feedback connections.

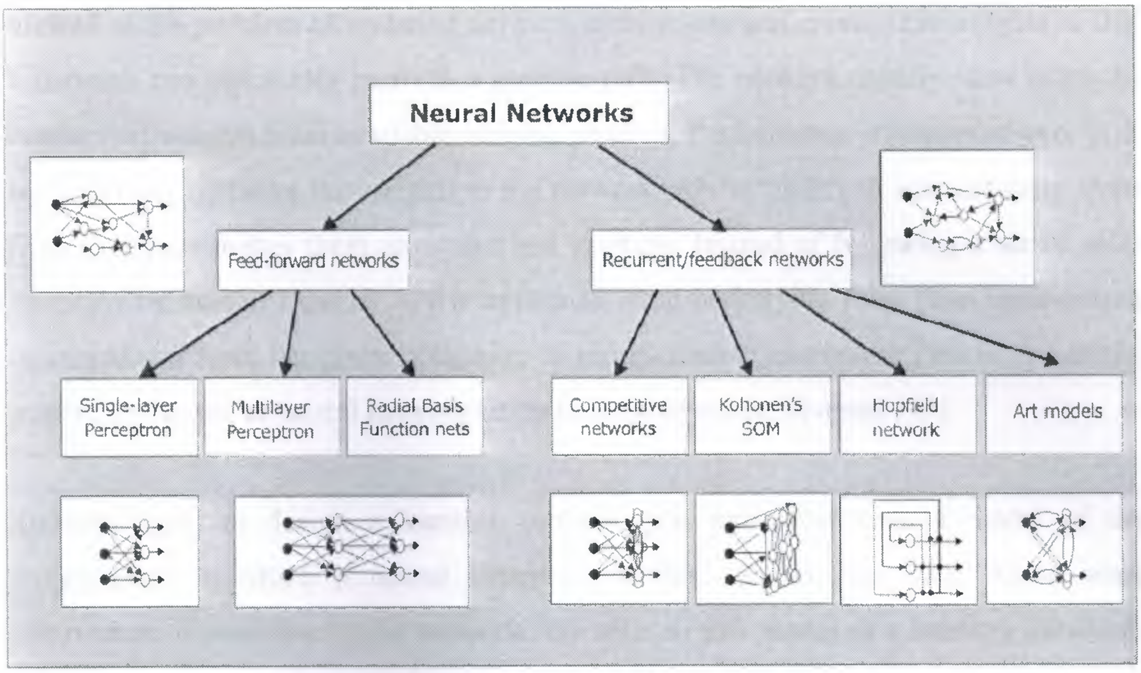


Figure 4.4 A taxonomy of feed-forward and recurrent/feedback network architectures [43].

In the most common family of feed-forward networks, called multilayer perceptron, neurons are organized into layers that have unidirectional connections between them. Figure 4.4 also shows typical networks for each category.
Different connectivity yield different network behaviors. Generally speaking, feed-forward networks are *static,* that is, they produce only one set of output values rather than a sequence of values from a given input. Feed-forward networks are memory-less in the sense that their response to an input is independent of the previous network state. Recurrent, or feedback, networks, on the other hand, are dynamic systems. When a new input pattern is presented, the neuron outputs are computed. Because of the feedback paths, the inputs to each neuron are then modified, which leads the network to enter a new state. Different network architectures require appropriate learning algorithms [43].

4.4 Learning Rules and Algorithms in Neural Networks

The ability to learn is a fundamental trait of intelligence. Although a precise definition of learning is difficult to formulate, a learning process in the ANN context can be viewed as the problem of updating network architecture and connection weights so that a network can efficiently perform a specific task. The network usually must learn the connection weights from available training patterns. Performance is improved over time by iteratively updating the weights in the network. ANNs' ability to automatically *learn from examples* makes them attractive and exciting. Instead of following a set of *rules* specified by human experts, ANNs appear to learn underlying rules (like input-output relationships) from the given collection of representative examples. This is one of the major advantages of neural networks over traditional expert systems [43].

To understand or design a learning process, you must first have a model of the environment in which a neural network operates, that is, you must know what information is available to the network. We refer to this model as a learning paradigm [43][44], you must understand how network weights are updated, that is, which *learning rules* govern the updating process. A *learning algorithm* refers to a procedure in which learning rules are used for adjusting the weights.

There are three main learning paradigms:

- ✓ *Supervised Learning:* In supervised learning, or learning with a "teacher," the network is provided with a correct answer (output) for every input pattern. Weights are determined to allow the network to produce answers as close as possible to the known correct answers. Reinforcement learning is a variant of supervised learning in which the network is provided with only a critique on the correctness of network outputs, not the correct answers themselves.

- ✓ *Unsupervised Learning:* In contrast, unsupervised learning, or learning without a teacher, does not require a correct answer associated with each input pattern in the training data set. It explores the underlying structure in the data, or correlations between patterns in the data, and organizes patterns into categories from these correlations.

- ✓ *Hybrid Learning:* Hybrid learning combines supervised and unsupervised learning. Part of the weights are usually determined through supervised learning, while the others are obtained through unsupervised learning [43].

$$v=\sum_{j=1}^{n} w_j x_j - u \tag{4.3}$$

The outputy of the perceptron is + 1 if v > 0, and 0 otherwise. In a two-class classification problem, the perceptron assigns an input pattern to one class if y = 1, and to the other class if y=0. The linear equation

$$\sum_{j=1}^{n} w_j x_j - u = 0 \tag{4.4}$$

defines the decision boundary (a hyperplane in the n-dimensional input space) that halves the space. Rosenblatt [43][45] developed a learning procedure to determine the weights and threshold in a perceptron, given a set of training patterns. Table 4.2 lists perceptron learning algorithm.

Table 4.2 Perceptron learning algorithm [43].

Perceptron learning algorithm
1. Initialize the weights and threshold to small random numbers **2.** Present a pattern vector $(x_1, x_2, \cdots, x_n)^t$ and evaluate the output of the neurons. **3.** Update the weights according to $w_j(t+1) = w_j(t) + \eta(d-y)x_j$ Where d is the desired output, t is the iteration number, and η(0.0< η<1.0) is the gain (step size).

Note that learning occurs only when the perceptron makes an error. Rosenblatt proved that when training patterns are drawn from two linearly separable classes, the perceptron learning procedure converges after a finite number of iterations. This is the perceptron convergence theorem. Many variations of this learning algorithm have been proposed in the literature. Other activation functions that lead to different learning characteristics can also be used. However, a single-layer perceptron can only separate linearly separable patterns as long as a monotonic activation function is used. The back-propagation learning algorithm is explained in table 4.3 [43].

Table 4.3 Back-propagation algorithm [43].

Back-propagation algorithm
1. Initialize the weights to small random values. 2. Randomly choose an input pattern $x^{(\mu)}$. 3. Propagate the signal forward through the network. 4. Compute δ_i^L in the output layer $(O_i = y_i^L)$ $$\delta_i^L = g'(h_i^L)[d_i^u - y_i^L],$$ Where h_i' represents the net input to the *ith* unit in the *ith* layer, and g' is the derivative of the activation function g'. 5. Compute the deltas for the preceding layers by propagating the errors backwards; $$\delta_i^L = g'(h_i^l)\sum_j w_{ij}^{i+1}\delta_i^{i+1},$$ For l=(L-1),...,1, 6. Update weights using $$\Delta w_{ji}^l = \eta\delta_i^l y_j^{l-1}$$ 7. Go to step2 and repeat for the next pattern until the error in the output layer is below a prespecified threshold or a maximum number of iterations is reached.

4.4.2 Boltzmann Learning

Boltzmann machines are symmetric recurrent networks consisting of binary units (+1 for "on" and -1 for "off'). By symmetric, we mean that the weight on the connection from unit i to unitj is equal to the weight on the connection from unit j to unit i ($w_{ij}=w_{ji}$). A subset of the neurons, called visible, interact with the environment; the rest, called hidden, do not. Each neuron is a stochastic unit that generates an output (or state) according to the Boltzmann distribution of statistical mechanics. Boltzmann machines operate in two modes: clamped, in which visible neurons are clamped onto specific states determined by the environment; and free-running, in which both visible and hidden neurons are allowed to operate freely.

Boltzmann learning is a stochastic learning rule derived from information-theoretic and thermodynamic principles [43][46]. The objective of Boltzmann learning is to adjust the connection weights so that the states of visible units satisfy a particular desired probability distribution. According to the Boltzmann learning rule, the change in the connection weight w_{ij} is given by

$$\Delta w_{ij} = \eta(\bar{\rho}_{ij} - \rho_{ij}), \tag{4.5}$$

where η is the learning rate, and ρ_{ij} and ρ_{ij} are the correlations between the states of units i and j when the network operates in the clamped mode and free-running mode, respectively. The values of ρ_{ij} and ρ_{ij} are usually estimated from Monte Carlo experiments, which are extremely slow.

Boltzmann learning can be viewed as a special case of error-correction learning in which error IS measured not as the direct difference between desired and actual outputs, but as the difference between the correlations among the outputs of two neurons under clamped and free running operating conditions.

4.4.3 Hebbian Rule

The oldest learning rule is *Hebb's* postulate of learning [43][47]. Hebb based it on the following observation from neurobiological experiments: If neurons on both sides of a synapse are activated synchronously and repeatedly, the synapse's strength is selectively increased. Mathematically, the Hebbian rule can be described as

$$w_{ij}(t+1) = w_{ij}(t) + \eta y_i(t) x_i(t), \tag{4.6}$$

where x, and y, are the output values of neurons i and j, respectively, which are connected by the synapse w_{ij} and η is the learning rate. Note that x_i is the input to the synapse. An important property of this rule is that learning is done locally, that is, the change in synapse weight depends only on the activities of the two neurons connected by it. A single neuron trained using the Hebbian rule exhibits an orientation selectivity. Figure 4.6 demonstrates this property.

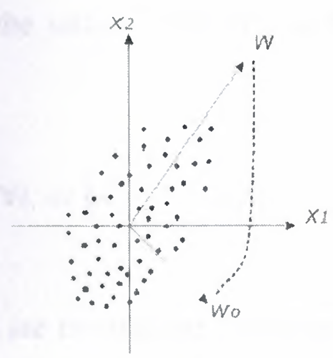


Figure 4.6 Orientation selectivity of a single neuron trained using the Hebbian rule [43].

The points depicted are drawn from a two-dimensional Gaussian distribution and used for training a neuron. The weight vector of the neuron is initialized tow, as shown in the figure. As the learning proceeds, the weight vector moves progressively closer to the direction w of maximal variance in the data. In fact, w is the eigenvector of the covariance matrix of the data corresponding to the largest eigenvalue [43].

4.4.4 Competitive Learning Rules

Unlike Hebbian learning (in which multiple output units can be fired simultaneously), competitive-learning output units compete among themselves for activation. As a result, only one output unit is active at any given time. This phenomenon is known as winner-take-all. Competitive learning has been found to exist in biological neural network [43].

Competitive learning often clusters or categorizes the input data. Similar patterns are grouped by the network and represented by a single unit. This grouping is done automatically based on data correlations.

The simplest competitive learning network consists of a single layer of output units as shown in figure 4.4. Each output unit i in the network connects to all the input units ($x_j's$) via weights, w_{ij} , $j = 1,2,\cdots,n$. Each output unit also connects to all other output units via inhibitory weights but has a self-feedback with an excitatory weight. As a result of competition, only the unit i^* with the largest (or the smallest) net input becomes the winner, that is,

$$w^*_i \cdot x \geq w_i \cdot x, \forall i, or \left\| w_\perp i^T * \cdot - x \right\| \leq \left\| \quad w_i - x \right\|, \forall i. \tag{4.7}$$

When all the weight vectors are normalized, these two inequalities are equivalent. A simple competitive learning rule can be stated as

$$\Delta w_{ij} = \begin{cases} \eta\left(x_j^u - w_{i*j}\right), & i = i^* \\ 0, \quad i \neq i^* \end{cases} \tag{4.8}$$

Note that only the weights of the winner unit get updated. The effect of this learning rule is to move the stored pattern in the winner unit (weights) a little bit closer to the input pattern.

The most well-known example of competitive learning is vector quantization for data compression. It has been widely used in speech and image processing for efficient storage, transmission, and modeling. Its goal is to represent a set or distribution of input vectors with a relatively small number of prototype vectors (weight vectors), or a codebook.

Table 4.4 Summaries various learning algorithms and their associated network architectures.

Paradigm	Learning rule	Architecture	Learning algorithm	Task
Supervised	Error-correction	Single- or multilayer perception	Perceptron learning algotithms Back-propagation Adaline and Madaline	Pattern classification Function approximation Prediciton, control
	Boltzmann	Recurrent	Boltzmann learning algorithm	Pattern classification
	Hebbian	Multilayer feed-Forward	Linear discriminant analysis	Data analysis Pattern classification
	Competitive	Competitive	Learning vector quantization	Within-class Categorization Data compression
		ART network	ARTMap	Pattern classification Within-class Categorization
Unsupervised	Error-correction	Multilayer feed-Forward	Sammon's projection	Data analysis
	Hebbian	Feed-forward or Competitive	Princcipal component Analysis	Data analysis Data compression
		Hopfield Network	Associative memory Learning	Associative memory
	Competitive	Competitive	Vector quantization	Categorization Data compression
		Kohonen's SOM	Kohonen's SOM	Categorization Data analysis
		ART networks	ART1, ART2	Categorization
Hybrid	Error-correction and competitive	RBF network	RBF learning algorithm	Pattern classification Function approximation Prediction, control

Both supervised and unsupervised learning paradigms employ learning rules based on error-correction, Hebbian, and competitive learning. Learning rules based on error-correction can be used for training feed-forward networks, while Hebbian learning rules have been used for all types of network architectures. However, each learning algorithm is designed for training a specific architecture. Therefore, when we discuss a learning algorithm, a particular network architecture association is implied. Each algorithm can perform only a few tasks well [43].

4.5 Multilayer Perceptrons and Back-Propagation Learning

The back-propagation algorithm has emerged as the workhorse for the design of a special class of layered feedforward networks known as *multilayer perceptrons* (MLP). As shown in figure 4.7, a multilayer perceptron has an input layer of source nodes and an output layer of neurons (i.e., computation nodes); these two layers connect the network to the outside world. In addition to these two layers, the multilayer perceptron usually has one or more layers of hidden neurons, which are so called because these neurons are not directly accessible. The hidden neurons extract important features contained in the input data [48].

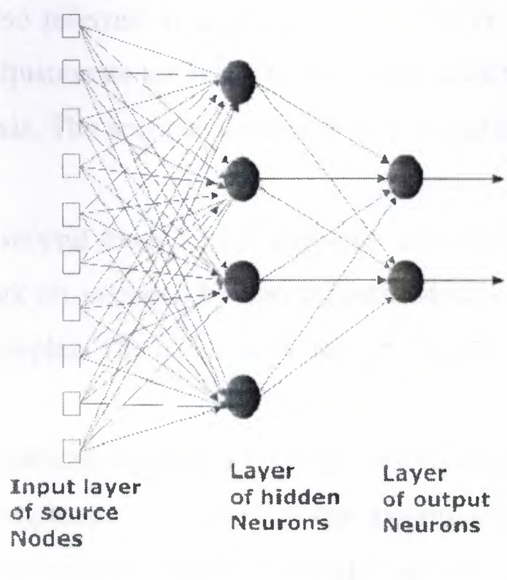


Figure 4.7 Fully connected feed-forward with one hidden and one output layer [48].

The training of an MLP is usually accomplished by using a *backpropagation (BP) algorithm* that involves two phases:

✓ *Forward Phase.* During this phase the free parameters of the network are fixed, and the input signal is propagated through the network of figure 4.7 layer by layer. The forward phase finishes with the computation of an error signal

$$ei = di - yi \tag{4.9}$$

where di is the desired response and yi is the actual output produced by the network in response to the input xi.

✓ *Backward Phase.* During this second phase, the error signal ei is propagated through the network of figure 4.7 in the backward direction, hence the name of the algorithm. It is during this phase that adjustments are applied to the free parameters of the network so as to minimize the error ei in a statistical sense.

Back-propagation learning may be implemented in one of two basic ways, as summarized here:

1. *Sequential mode:* (also referred to as the on-line mode or stochastic mode) In this mode of BP learning, adjustments are made to the free parameters of the network on an example-by example basis. The sequential mode is best suited for pattern classification.

2. *Batch mode*: In this second mode of BP learning, adjustments are made to the free parameters of the network on an epoch by-epoch basis, where each epoch consists of the entire set of training examples. The batch mode is best suited for nonlinear regression.

The back-propagation learning algorithm is simple to implement and computationally efficient in that its complexity is linear in the synaptic weights of the network. However, a major limitation of the algorithm is that it does not always converge and can be excruciatingly slow, particularly when we have to deal with a difficult learning task that requires the use of a large network.

We may try to make back-propagation learning perform better by invoking the following list of heuristics:

- Use neurons with antisymmetric activation functions (e.g., hyperbolic tangent function) in preference to nonsymmetric activation functions (e.g., logistic function).
- Shuffle the training examples after the presentation of each epoch; an epoch involves the presentation of the entire set of training examples to the network.
- Follow an easy-to-learn example with a difficult one.
- Preprocess the input data so as to remove the mean and decorrelate the data.
- Arrange for the neurons in the different layers to learn at essentially the same rate. This may be attained by assigning a learning rate parameter to neurons in the last layers that is smaller than those at the front end.
- Incorporate prior information into the network design whenever it is available.

One other heuristic that deserves to be mentioned relates to the size of the training set,N, for a pattern classification task. Given a multilayer perceptron with a total number of synaptic weights including bias levels, denoted by W, a rule of thumb for selecting N is

$$N = O\left(\frac{W}{E}\right) \tag{4.10}$$

where O denotes "the order of," and E denotes the fraction of classification errors permitted on test data. For example, with an error of 10% the number of training examples needed should be about 10 times the number of synaptic weights in the network.

Supposing that we have chosen a multilayer perceptron to be trained with the back-propagation algorithm, how do we determine when it is "best" to stop the training session? How do we select the size of individual hidden layers of the MLP? The answers to these technique known as *cross-validation*, which proceeds as follows;

- The set of training examples is split into two parts:

• Estimation subset used for training of the model

• Validation subset used for evaluating the model performance

The network is finally tuned by using the entire set of training examples and then tested on test data not seen before [48].

4.6 Radial-Basis Function Networks

Another popular layered feedforward network is the radial-basis function (RBF) network which has important universal approximation, and whose structure is shown in figure 4.8. RBF networks use memory-based learning for their design. Specifically, learning is viewed as a curve-fitting problem in high-dimensional space:

1. Learning is equivalent to finding a surface in a multidimensional space that provides a best fit to the training data.

2. Generalization (i.e., response of the network to input data not seen before) is equivalent to the use of this multidimensional surface to interpolate the test data. RBF networks differ from multilayer perceptrons in some fundamental respects:

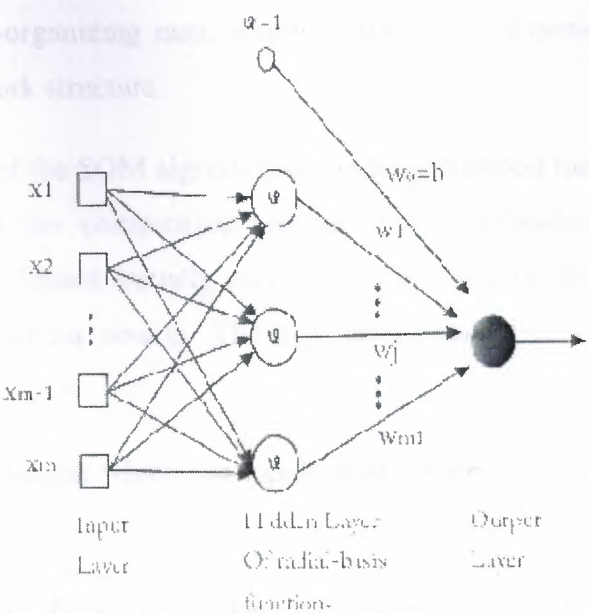


Figure 4.8 Radial-basis function network [48].

• RBF networks are local approximators, whereas multilayer perceptrons are global approximators.

• RBF networks have a single hidden layer, whereas multilayer perceptrons can have any number of hidden layers.

• The output layer of a RBF network is always linear, whereas in a multilayer perceptron it can be linear or nonlinear.

• The activation function of the hidden layer in an RBF network computes the Euclidean distance between the input signal vector and parameter vector of the network, whereas the activation function of a multilayer perceptron computes the inner product between the input signal vector and the pertinent synaptic weight vector [48].

4.7 Self-Organizing Maps

In a self-organizing map (SOM), the neurons are placed at the nodes of a lattice, and they become selectively tuned to various input patterns (vectors) in the course of a competitive learning process. The process is characterized by the formation of a topographic map in which the spatial locations (i.e., coordinates) of the neurons in the lattice correspond to intrinsic features of the input patterns. Figure 4.9 illustrates the basic idea of a self-organizing map, assuming the use of a two-dimensional lattice of neurons as the network structure.

An integral feature of the SOM algorithm is the neighborhood function centered around a neuron that wins the competitive process. The neighborhood function starts by enclosing the entire lattice initially and is then allowed to shrink gradually until it encompasses the winning neuron. The algorithm exhibits two distinct phases in its operation:

1. *Ordering phase*, during which the topological ordering of the weight vectors takes place.

2. *Convergence phase*, during which the computational map is fine tuned.

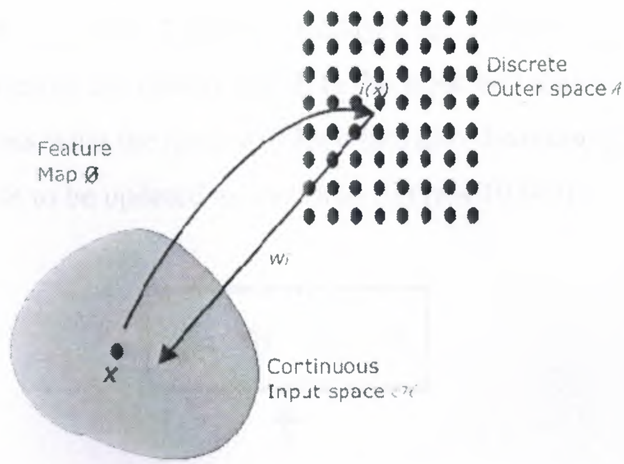


Figure 4.9 Illustration of relationship between feature map f and weight vector w_i of winning neuron i [48].

4.8 Adaptive Resonance Theory Models

ART (Adaptive Resonance Theory) models incorporate new data by checking for similarity between this new data and data already learned; "memory". If there is a close enough match, the new data is learned. Otherwise, this new data is stored as a "new memory". Some models of Adaptive Resonance Theory are:

- ART1 – Discrete input.
- ART2 – Continuous input.
- ARTMAP – Using two input vectors, transforms the unsupervised ART model into a supervised one.
- Various others: Fuzzy ART, Fuzzy ARTMAP (FARTMAP), etc…

The basic ART model, ART1, is comprised of the following components:

1. The short term memory layer: F1 – Short term memory.
2. The recognition layer: F2 – Contains the long term memory of the system.
3. Vigilance Parameter: ρ – A parameter that controls the generality of memory. Larger ρ means more detailed memories, smaller ρ the produces more general memories.

Training an ART1 model basically consists of four steps:

Step 1: Send input from the F1 layer to F2 layer for processing. The first node within the F2 layer is chosen as the closest match to the input and a hypothesis is formed. This hypothesis represents what the node will look like after learning has occurred, assuming it is the correct node to be updated as shown in figure 4.10 [49].

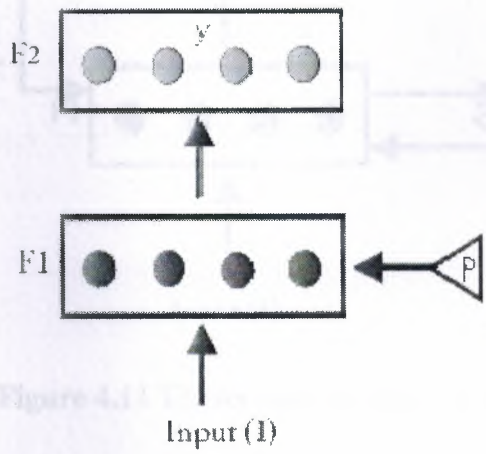


Figure 4.10 Short term memory layer [49].

Step 2: Once the hypothesis has been formed, it is sent back to the F1 layer for matching. Let Tj(I*) represent the level of matching between I and I* for node j

Then:

$$\mathrm{T}_j\left(I^*\right)=\frac{I^\wedge I^*}{I}$$
$$\textit{where } A^\wedge B=\min(A,B) \qquad (4.11)$$

If $T\ (I^*) \geq$ then the hypothesis is accepted and assigned to that node (see figure 4.11) otherwise, the process moves on to Step 3.

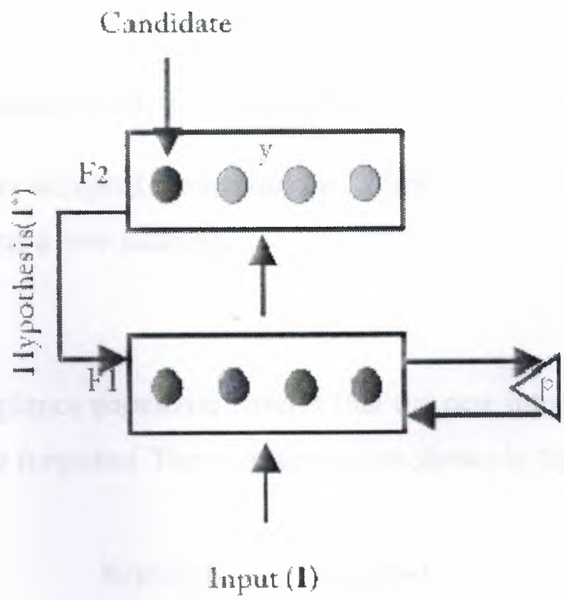


Figure 4.11 The recognition layer [49].

Step 3: If the hypothesis is rejected, a "reset" command is sent back to the F2 layer. In this situation, the j^{th} node within F2 is no longer a candidate so the process repeats for node j+1. This step is shown in figure 4.12.

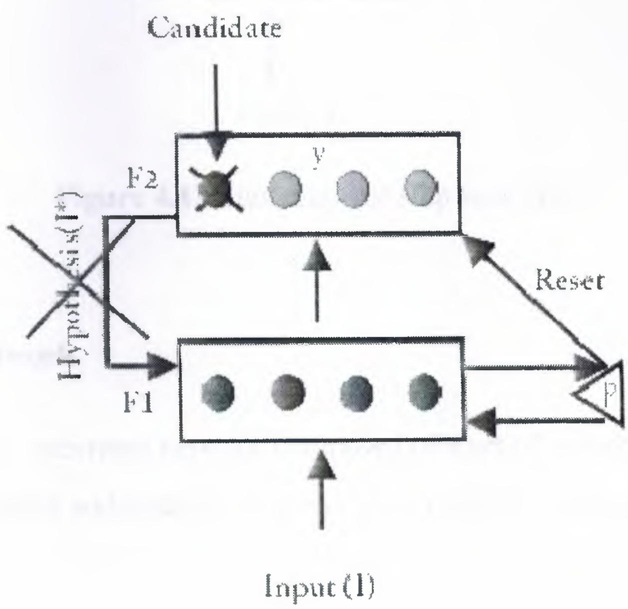


Figure 4.12 Hypothesis rejection [49].

Step 4:

1. If the hypothesis was accepted, the winning node assigns its values to it.

2. If none of the nodes accepted the hypothesis, a new node is created within F2. As a result, the system forms a new memory.

In either case, the vigilance parameter ensures that the new information does not cause older knowledge to be forgotten. These processes are shown in figure 4.13.

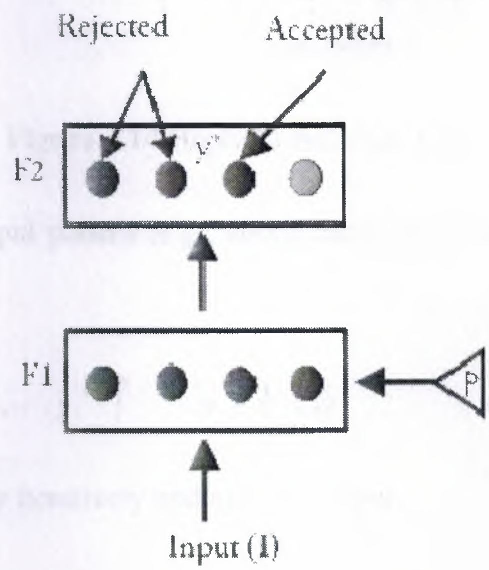


Figure 4.13 illustration of step four [49].

4.9 Hopfield Network

Hopfield network is *recurrent* network composed of a set of n nodes and behaves as an auto associator (content addressable memory) with a set of L patterns $\{y_k, \quad k = 1, \cdots, L\}$ stored in it.

The network is first trained similar to Hebbean learning, and then used as an auto associator. When the incomplete or noisy version of one of the stored patterns is presented as the input, the complete pattern will be generated as the output after some iterative computation.

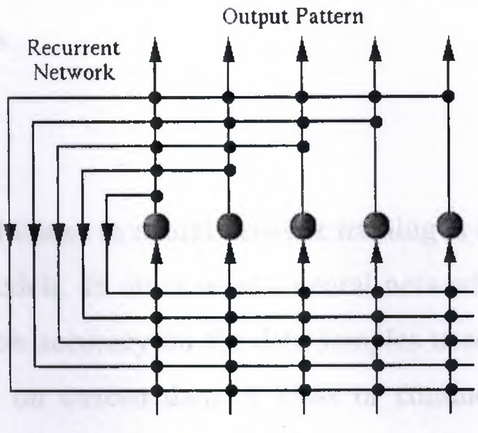


Figure 4.14 Hopfield Network [50].

Presented with a new input pattern (e.g., noisy, incomplete version of some prestored pattern) y_k :

$$y_k = \left[y_1^{(k)}, \cdots, y_n^{(k)}\right]^T \qquad y_i \in \{-1,1\} \tag{4.12}$$

the network responds by iteratively updating its output

$$x = [x_1, \cdots, x_n]^T \qquad x_i \in \{-1,1\} \tag{4.13}$$

until finally convergence is reached when one of the stored patterns which most closely resembles x is produced as the output [50].

4.10 Network Generalization

Generalization ability of Neural Networks (NNs) is considered as the most important performance criterion [51]. So many researchers of this domain have been making intensive efforts to promote neural network generalization ability. Learning method based on combinations of weak classifiers is reported by Chuanyi and Sheng [52]. Weak classifiers such as linear classifiers (perceptrons) which can do a little better than making random guesses, then combined through a majority vote, resulted into good generalization performance and a fast training time. Several methods have been studied such as fuzzification of input vector, regularization, result feedback, early stopping, neural network ensembles.

4.10.1 Regularization

One of the most essential issues in neural network training is to improve generalization of the neural network models. In other words, neural network models should not only have a high approximation accuracy on the data samples used in the training, but also show good performance on unseen data. A class of commonly used techniques for improving generalization of neural networks is known as regularization, which aims to prevent the learning algorithm from over-fitting the training data. Several regularization techniques have been suggested in the literature, such as early stopping, weight decay and curvature-driven smoothing [53].

A popular approach to regularization is to include an additional term in the cost function of learning algorithms, which penalizes overly high model complexity. A hyperparameter, known as the regularization parameter determines to what extent the regularization will influence the learning algorithm. That is to say, this parameter will determine the model complexity of the trained neural network. The larger the parameter is, the higher the penalty will be on the model complexity However, it is usually not trivial to determine a suitable model complexity that is optimal for the problem at hand. Very often, this has been done by minimizing an estimated generalization error [54].
The most common error function in training or evolving neural networks is the mean squared error (MSE):

$$E = \frac{1}{N}\sum_{i=1}^{N}\left(y^{d}(i) - y(i)\right)^{2}, \tag{4.14}$$

where N is the number of training samples, $y^{d}(i)$ is the desired output of the i-th sample, and $y(i)$ is the network output for the i-th sample. In this work, we consider multi-layer perceptron (MLP) neural networks with one output.

It has been found that neural networks can often overfit the training data, which means that the network has a very good approximation accuracy on the training data, but a very poor one on unseen data. To improve generalization of neural networks, regularization techniques are often adopted by including an additional term in the error function:

$$J = E + \lambda\Omega \tag{4.15}$$

where λ is a hyperparameter that controls the strength of the regularization and Ω is known as the regularizer. A most popular regularization method is known as weight decay:

$$\Omega = \frac{1}{2}\sum_k w_k^2, \tag{4.16}$$

where k is an index summing up all weights.

One weakness of the weight decay method is that it is not able to drive small irrelevant weights to zero, which may result in many small weights. The following regularization term has been proposed to address this problem [55]:

$$\Omega\sum_i |w_i| \tag{4.17}$$

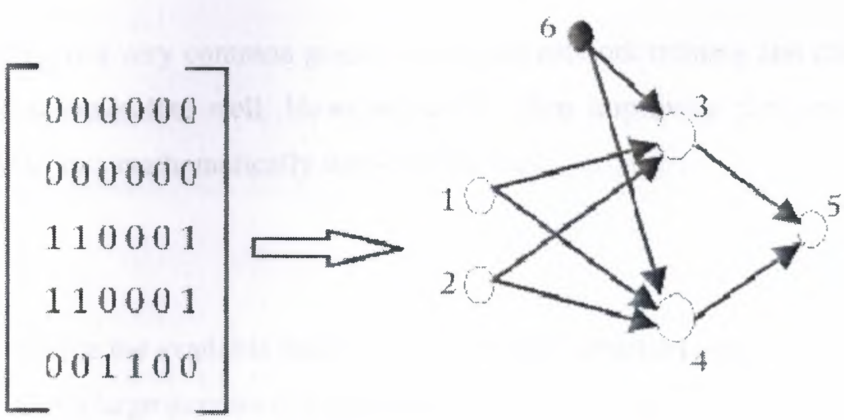


Figure 4.15 Connection matrix and corresponding network structure [56].

This regularization was used for structure learning, because it **is** able to drive irrelevant weights to zero. Both regularization terms in equations 4.15 and 4.16 have also been studied from the Bayesian learning point of view, which are known as the Gaussian regularizer and the Laplace regularizer, respectively [56].

4.10.2 Early stopping

In machine learning, early stopping is a form of regularization used when a machine learning model (such as a neural network) is trained by on-line gradient descent. In early stopping, the training set is split into a new training set and a validation set. Gradient descent is applied to the new training set. After each sweep through the new training set, the network is evaluated on the validation set. When the performance with the validation test stops improving, the algorithm halts. The network with the best performance on the validation set is then used for actual testing, with a separate set of data (the validation set is used in learning to decide when to stop).

This technique is a simple but efficient hack to deal with the problem of overfitting. Overfitting is a phenomenon in which a learning system, such as a neural network gets very good at dealing with one data set at the expense of becoming very bad at dealing with other data sets. Early stopping is effectively limiting the used weights in the network and thus imposes a regularization, effectively lowering the VC dimension.

Early stopping is a very common practice in neural network training and often produces networks that generalize well. However, while often improving the generalization it does not do so in a mathematically well-defined way.

Method

- ✓ Divide the available data into training and validation sets.
- ✓ Use a large number of hidden units.
- ✓ Use very small random initial values.
- ✓ Use a slow learning rate.
- ✓ Compute the validation error rate periodically during training.
- ✓ Stop training when the validation error rate "starts to go up".

It is crucial to realize that the validation error is not a good estimate of the generalization error. One method for getting an unbiased estimate of the generalization error is to run the net on a third set of data, the test set, that is not used at all during the training process. The error on the test set gives estimate on generalization; to have the outputs of the net approximate target values given inputs that are not in the training set.

Early stopping has several advantages:

- It is fast.
- It can be applied successfully to networks in which the number of weights far exceeds the sample size.
- It requires only one major decision by the user: what proportion of validation cases to use.

Issues

- It's not clear on how many cases to assign to the training and validation sets
- The result might highly depends on the algorithm which is used to split the data into training and validation set

Notion of "increasing validation error" is ambiguous; it may go up and down numerous times during training. The safest approach is to train to convergence, then determine which iteration had the lowest validation error. This impairs fast training, one of the advantages of early stopping [57].

4.10.3 Neural Network Ensembles

The generalization ability of a neural network can be significantly improved through ensembling neural networks, i.e. training several neural networks to solve the same problem and combining their results in some way. The simplest ensemble can be formed by training all the ensemble members with the same training set and randomly initializing the weights and biases of each member with different values. Then, the general output of the ensemble can be obtained by simply majority voting, i.e. the decision taken by the overall ensemble corresponds to the decision taken by the majority of the members. There are more elaborated techniques for ensembling classifiers, for example:

Bagging: Bagging employs bootstrap sampling to generate several training sets from the original training set, and then trains an individual network from each generated training set. The individual predictions are often combined via majority voting. The Bagging algorithm is shown in table 4.5, where T bootstrap samples $S_1, \cdots, S_T$ are generated from the original training set and an individual neural network N_t is trained from each S_t, an ensemble N^* is built from $N_1, \cdots, N_T$ whose output is the class label received the most number of votes [58].

Table 4.5 Bagging Algorithm [58]

1. $for\ t = 1\ to\ T\{$
2. $S_t = bootstrap\ sample\ from\ S$
3. $N_t = L(S_t)$
4. $\}$
5. $N^* = \arg\max_{y \in Y} \sum_{t:N_{TT}(x)=y} 1$

Adaboost (Adaptive Boosting): Adaboost sequentially generates a series of individual neural networks, where the training instances that are wrongly classified by the previous individual networks will play more important role in the training of later networks.

The individual predictions are combined via weighted voting where the weights are determined by the algorithm itself. The Adaboost algorithm is shown in table 4.6, where T is the number of trials, $S_1, \ldots, S_T$ are sequentially generated training sets and an individual neural network N_t is trained for each S_t. ϵ_T denotes the weighted error of N_t on S_t. An ensemble N^* is built from $N_1, \ldots, N_T$ whose output is the class label received the most number of votes [58].

Table 4.6 The Adaboost algorithm

1.	*All the instance weights are set to* 1
2.	*for* $t = 1$ *to* $T\{$
3.	*normalize the weights so that the total weight is* m
4.	S_t = *sample from* S *with the normalized instance weight*
5.	$N_t = L(S_t)$
6.	$\in_t = \frac{1}{m}\sum_{x_i \in S_t : N_t(x_i) \neq y_i} weight(x_i)$
7.	$\beta_t = \in_t / (1 - \in_t)$
8.	*for each* $x_i \in S_t\{$
9.	*if* $N_t(x_i) = y_i\{$
10.	$weight(x_i) = weight(x_i) \cdot \beta_t$
11.	$\}$
12.	$\}$
13.	$\}$

Other techniques: There are many other methods to build neural network ensembles. Some of them use complex procedures to select an optimum subset of members of the ensemble in order to calculate the weighted output of the ensemble.

4.11 Medical Diagnosis Using Neural Network

The major problem in medical field is to diagnose disease. Human being always make mistake and because of their limitation, diagnosis would give the major issue of human expertise. One of the most important problems of medical diagnosis, in general, is the subjectivity of the specialist. It can be noted, in particular in pattern recognition activities, that the experience of the professional is closely related to the final diagnosis. This is due to the fact that the result does not depend on a systematized solution but on the interpretation of the patient's signal [59].

Medical Diagnosis using Artificial Neural Networks is currently a very active research area in medicine and it is believed that it will be more widely used in biomedical systems in the next few years. This is primarily because the solution is not restricted to linear form. Neural Networks are ideal in recognizing diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognize the disease is not needed [60].

4.12 Summary

This chapter described basic information about artificial neural network. Biological neuron and artificial neuron compared in this chapter. Furthermore the various types of neural networks explained. Neural networks have been used in many applications to model the unknown relations between various parameters, based on large numbers of examples. They are successfully used in medical decision and medical applications.

CHAPTER 5

MATERIAL AND METHOD

This thesis is about automated epilepsy diagnostic system using the artificial neural network. Diagnosis system consists two phases which are feature extraction and classification. The features of the EEG signals were extracted by the discrete wavelet transform (DWT). Classification of EEG signals were performed by feed-forward neural network that trained with the error back-propagation algorithm.

5.1 *EEG Database and Data Pre-processing:*

EEG Database:

The EEG data sets were downloaded from the avilable database at Bonn University [61].

The complete dataset consists of five classes (A,B,C,D,E) each of which contains 100 single channel EEG segments of 23.6 sec duration.

These segments were selected and cut out from continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements.

Sets A and B consisted of segments taken from surface EEG recordings that were carried out on healthy volunteers using a standardized electrode placement scheme (International 10-20 system). Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B) respectively.

Sets C, D, and E originated from the EEG archive of presurgical diagnosis. 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. While sets C and D contained only activity measured during seizure free intervals, set E only contained seizure activity [62].

Five classes of EEG signals are illustrated figure 5.1.

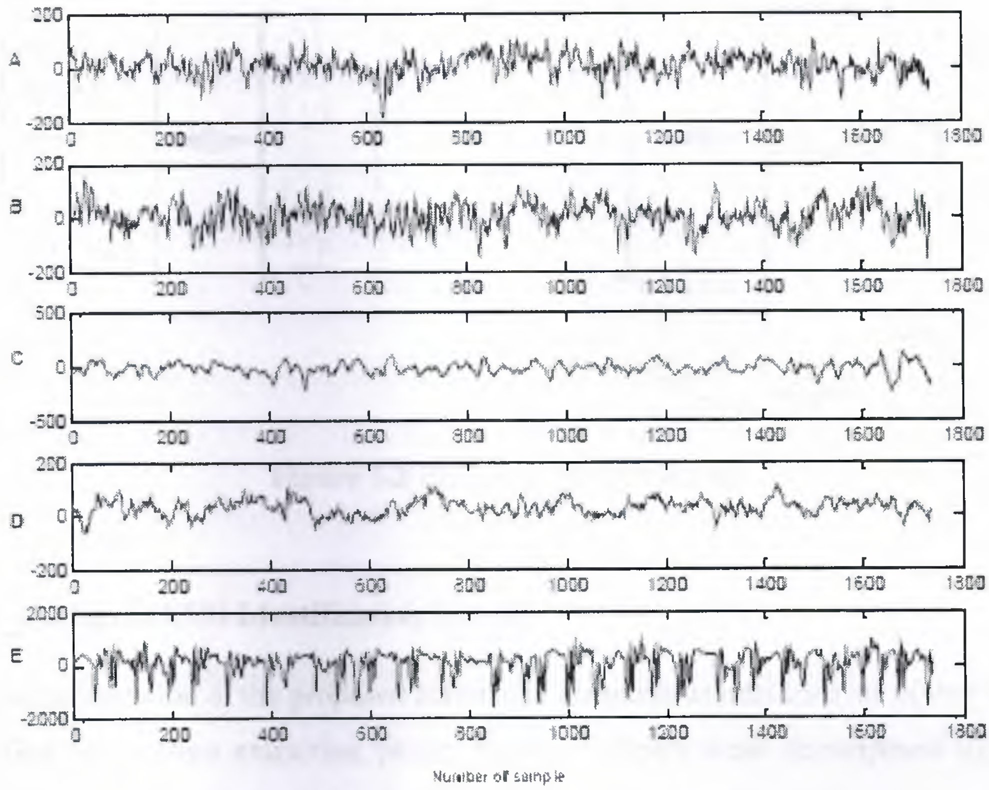


Figure 5.1 Five classes (A, B, C, D, E) of EEG signals.

EEG data pre-processing:

EEG data pre-processing phase consists of the following steps:

1. Each set (A-E) containing 100 TXT-files and each txt file consists of 4097 samples of one EEG time series in ASCII code.
2. All sets were converted to 4096 by 100 matrices. Each column of the matrix represents one person.
3. Finally all columns were converted to 16 by 256 matrices.

The process described above is shown in the figure 5.2.

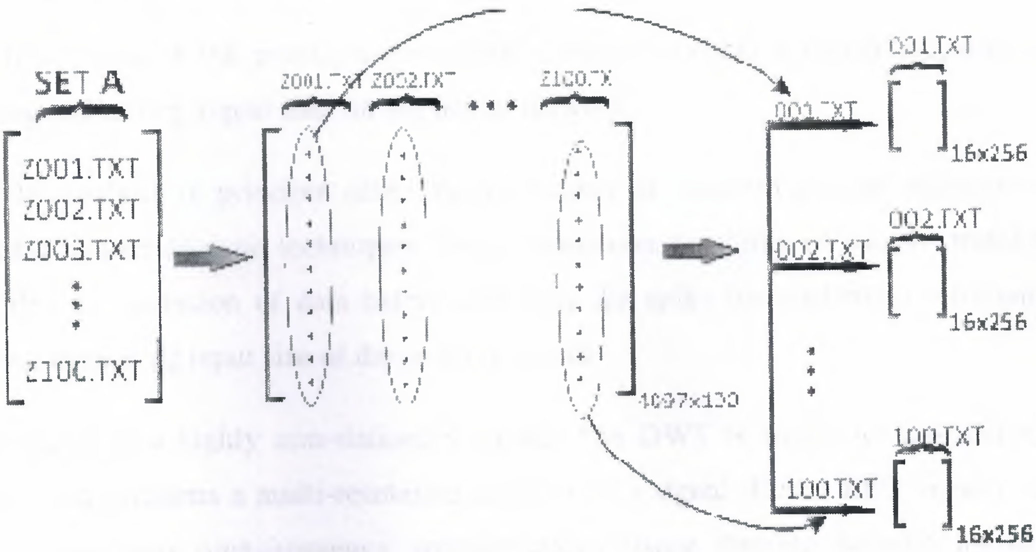


Figure 5.2 EEG data pre-processing

5.2 Intelligent EEG Identification System

The implementation of the proposed automated diagnosis system consists of two phasis. The first one feature extraction phase; which is signals were decomposed by using discrete wavelet transform till 5th level of decomposition tree.

The second phase is training a back propagation neural network to classify the different EEG signals.

Figure 5.3 is the block diagram of automated epilepsy diagnostic system using discrete wavelet transform (DWT) and back propagation neural network (BPNN).

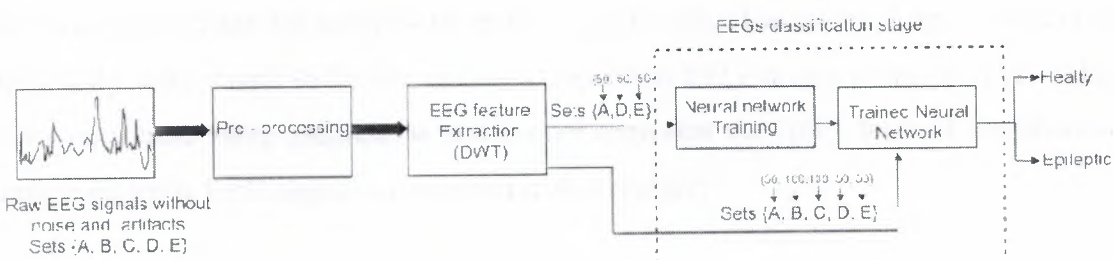


Figure 5.3 The block diagram of automated diagnosis system

5.2.1 Feature Extraction using Discrete Wavelet Transform

The first phase of the proposed automated diagnosis system involves preparing the training and testing signal data for the neural network.

Wavelet analysis in principle offers the researcher or clinician a good alternative to standard Fourier analysis techniques. The compression capability of wavelet transform provided the inclusion of data before and after the spike for contextual information without increasing input size of the neural network.

EEG signal is a highly non-stationary signal. The DWT is suited to non-stationary signals and performs a multi-resolution analysis of a signal. Hence EEG signals were decomposed into time-frequency representations using discrete wavelet transform (DWT)

Selection of appropriate wavelet and the number of decomposition levels are very important for the analysis of signals using DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal.

The Daubechies's family of wavelets is one of the most commonly used orthogonal wavelets satisfying the admissibility conditions, thus allowing reconstruction of the original signal from the wavelet coefficients. Examples of wavelet and scaling functions for Daubechies's family of orthogonal wavelets are shown in figure 5.4 Daubechies's family is designed with the maximum regularity (or smoothness).

Daubechies wavelets of different orders (2, 3, 4, 5, and 6) were investigated for the analysis of epileptic EEG records. This family of wavelets is known for its ortogonality property and efficient filter implementation. Daubechies order 4 wavelet was found tobe the most appropriate for analysis of epileptic EEG data. The lower order wavelets of the family were found to be too coarse to represent EEG spikes properly. The higher order ones have more ascillations and cannot represent the spiky form of the absence seizure epileptic EEG signal investigated in this research.

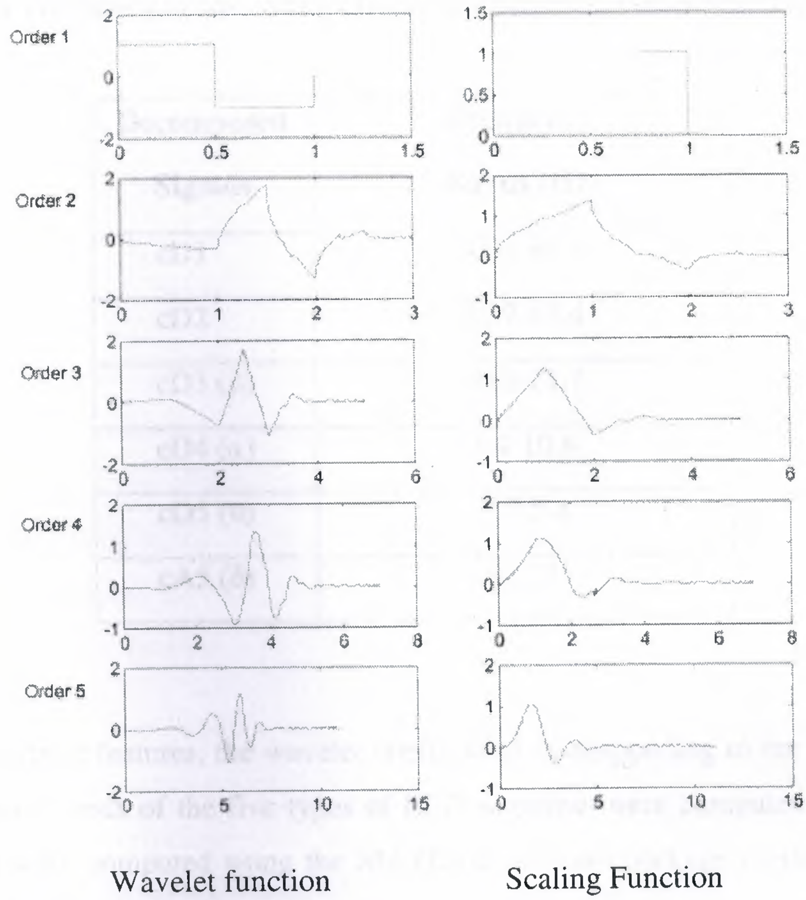


Figure 5.4 Daubechies wavelet and scaling functions of different orders [66].

In this research EEG signals do not have any useful frequency components above 30 Hz, the number of decomposition levels was chosen to be 5. So, signals were decomposed till 5th level of decomposition tree.

Wavelet analysis that decomposes EEG whole signals into its sub-bands: delta (0-4 Hz), theta (4-8 Hz), alpha (8-15 Hz), beta (15-30 Hz), and gamma (30-60 Hz). Table 5.1 presents frequencies corresponding to different levels of decomposition for Daubechies order 4 wavelet with a sampling frequency of 173.6 Hz.

The smoothing feature of the Daubechies wavelet of order 4 (db4) made it more appropriate to detect changes of EEG signals. Hence, the wavelet coefficients were computed using the db4 in this research.

Table 5.1 Frequency bands corresponding to different decomposition levels [67].

Decomposed Signals	Frequency Bands (Hz)
cD1	43.4-86.8
cD2	21.7-43.4
cD3 (β)	10.8-21.7
cD4 (α)	5.4-10.8
cD5 (θ)	2.7-5.4
cA5 (δ)	0-2.7

In order to extract features, the wavelet coefficients corresponding to the cD1-cD5 and cA5 frequency bands of the five types of EEG segments were computed. The wavelet coefficients were computed using the MATLAB software package (version 7.0). This process is shown in figure 5.5.

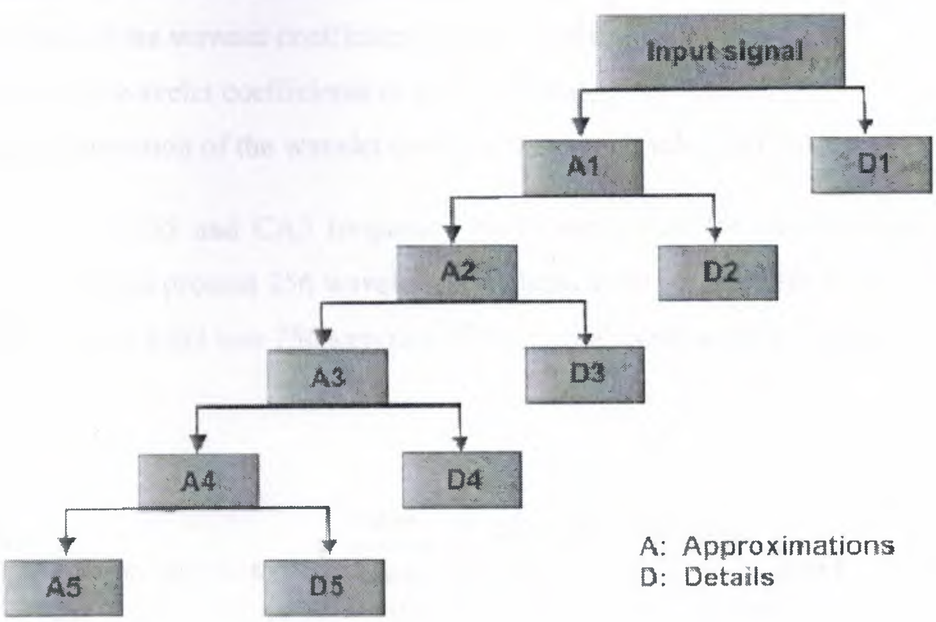


Figure 5.5 Five level wavelet decomposition.

The computed detail and approximation wavelet coefficients of the EEG signals were used as the feature vectors representing the signals. For each EEG segment, the detail wavelet coefficients (d^k , k = 1, 2, 3, 4) at the first, second, third, fourth and fifth levels (131 + 69 + 38 + 22 +14 coefficients) and the approximation wavelet coefficients (*A5*) at the fifth level (14 coefficients) were computed. Thus, 288 wavelet coefficients were obtained for each EEG segment.

There are five broad spectral band of clinical interest: delta (0-2.7 Hz), theta (2.7-5.4 Hz), alpha (5.4-10.8 Hz), beta (10.8-21.7), and gamma (30-above Hz). This work was focused on the analysis of the δ (delta), θ (theta), α (alpha), and β (Beta) rhythms and their relation to epilepsy. CD3, CD4, CD5 and CA5 wavelet coefficients have considerable impact on the epileptic seizure detection in EEG. So that these coefficients were used as feature vectors.

The high dimension of feature vectors increased the computational complexity. In order to further decrease the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients was used. The following statistical features were used to represent the time-frequency distribution of the EEG signals:

(1) Maximum of the wavelet coefficients in each subband.
(2) Minimum of the wavelet coefficients in each subband.
(3) Mean of the wavelet coefficients in each subband.
(4) Standard deviation of the wavelet coefficients in each sub-band [64].

So CD3, CD4, CD5 and CA5 frequency bands were used for classification of EEG signals. End of this process 256 wavelet coefficients were obtained for each segment so, the length of each EEG was 256 samples. Figure 5.6 illustrates of first phase.

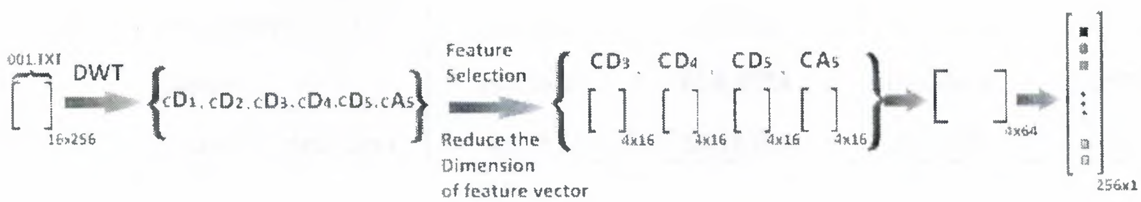
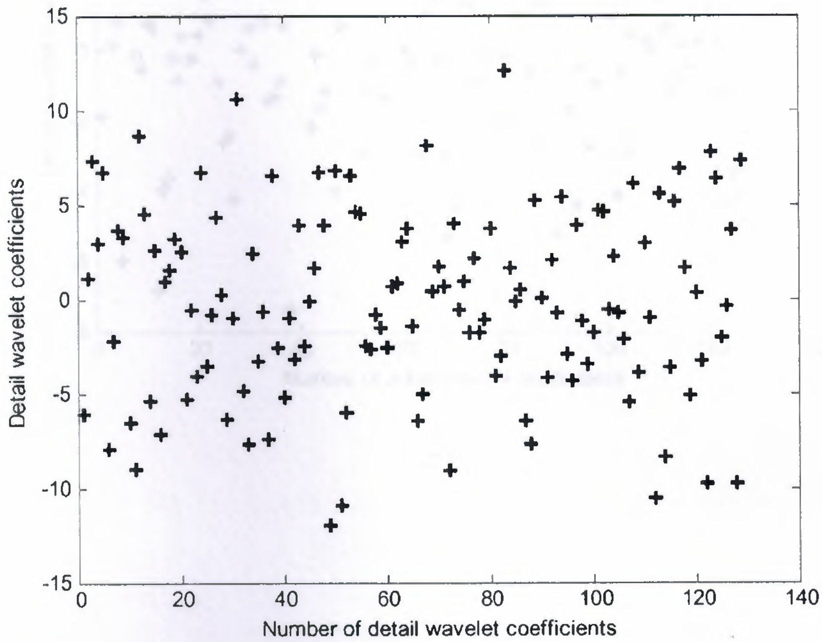


Figure 5.6 Feature extraction and selection process

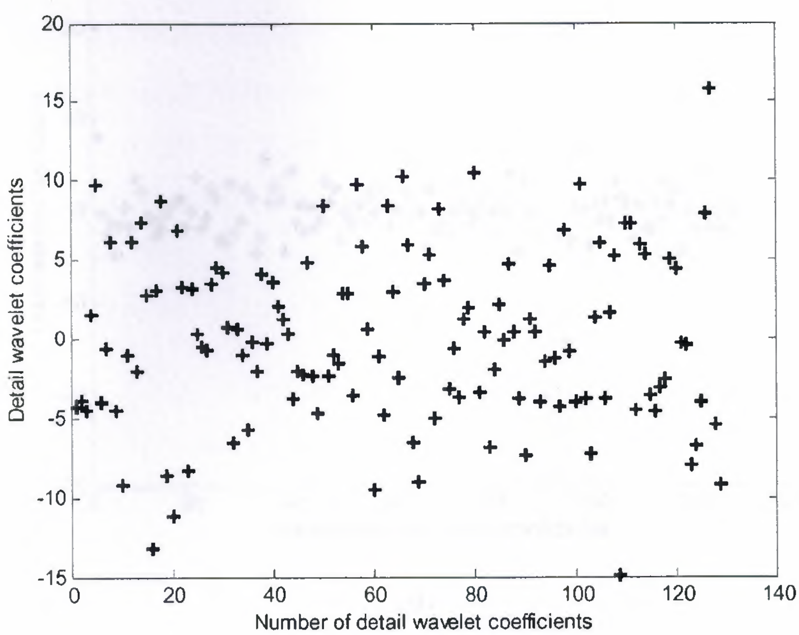
Table 5.2 Examples of obtained features of five classes using DB4

Dataset	Extracted Features	Wavelet Coefficients Sub-bands			
		CD3	CD4	CD5	CA5
SET A	Maximum	125,1068	144,2923	153,1748	74,70831
	Minimum	-131,069	-125,572	-142,762	-434,793
	Mean	56,59357	66,22242	79,78413	155,0132
	Standard deviation	-0,55618	0,718982	0,940695	-193,544
SET B	Maximum	358,0607	435,1563	274,7375	367,6155
	Minimum	-384,271	-346,235	-241,721	-660,626
	Mean	188,4973	202,3104	127,5415	284,5769
	Standard deviation	2,936003	25,0308	1,1522	-136,144
SET C	Maximum	54,54361	101,183	139,605	356,2448
	Minimum	-60,1896	-104,745	-165,499	-399,656
	Mean	25,18715	50,10766	83,28697	231,8734
	Standard deviation	0,100159	-0,38791	-7,6743	-29,7843
SET D	Maximum	43,4577	97,55487	126,1609	-26,4257
	Minimum	-43,2257	-94,1762	-134,328	-375,077
	Mean	19,14589	46,20267	70,36983	102,857
	Standard deviation	0,189221	2,151444	-5,75872	-199,628
SET E	Maximum	697,6851	1196,466	1109,812	1313,062
	Minimum	-599,952	-1116,15	-1161,75	-1291,09
	Mean	297,6884	604,9824	648,0876	757,8099
	Standard deviation	-0,73574	16,28145	-45,1981	46,01672

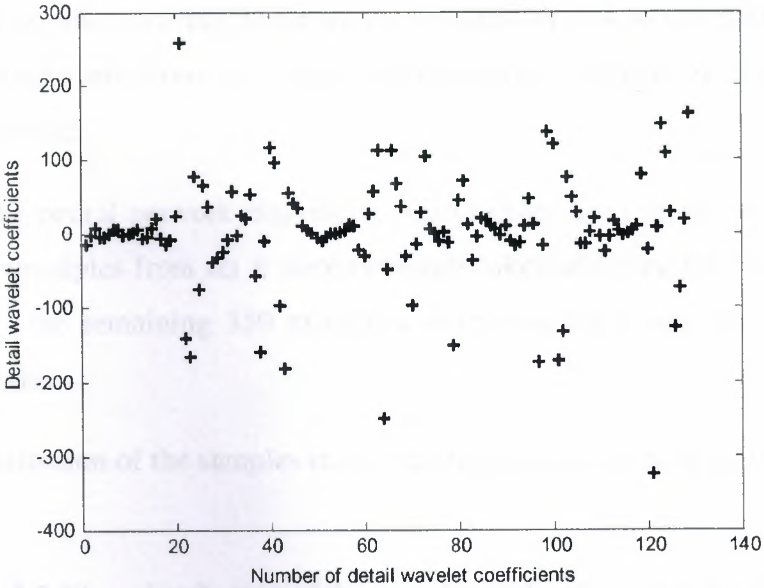
The detail-wavelet coefficients at the first-decomposition level of the five types of EEG signals are presented in figure 5.7 From these figures, it is obvious that the detail-wavelet coefficients of the five types of EEG signals are different from each other and, therefore, they can serve as useful parameters in discriminating the EEG signals.



(a)



(b)



(e)

Figure 5.7 Detail-wavelet coefficients at the first decomposition level of the EEG segments. (a) Set A. (b) Set B. (c) Set C. (d) Set D. (e) Set E.

5.2.2 Neural Network Training Phase

In a back propagation neural network, the learning algorithm has two stages. Initially, a training input pattern is presented to the network input layer. The network propagates the input pattern from layer to layer until the output pattern is produced by the output layer. If this pattern is dissimilar from the preferred output, an error is intended and then propagated backward through the network from the output layer to the input layer. The weights are customized as the error is propagated.

The second phase of the proposed automated diagnosis system is the implementation of a back propagation neural network classifier. This phase consists of training the neural network using the wavelet coefficients (CD3, CD4, CD5, CA5) obtained from the first phase. Extracted features were defined as input layers to the neural network algorithm.

A 3-layer feed forward neural network with 256 input neurons, 40 hidden neurons and 2 output neurons is used to identify the EEG signals and classify them into: healty or epilepsy syndrome.

The objective of the modeling phase in this application was to develop classifiers that are able to identify any input combination as belonging to either one of the two classes: normal or epileptic.

For developing neural network classifiers, 50 examples from set A, 50 examples from set D and 50 examples from set E were randomly taken and used for training the neural networks, and the remaining 350 examples were kept aside and used for testing the developed models.

The class distribution of the samples in the training and testing data set is shown in table 5.3.

Table 5.3 Class distribution of the samples in the training and test data set

Dataset	Training set	Test set
SET A (Normal EEG-healthy)	50	50
SET B (Normal EEG-healthy)	-	100
SET C (Interictal EEG-epileptic)	-	100
SET D (Interictal EEG-epileptic)	50	50
SET E (Ictal EEG-epileptic)	50	50
TOTAL:	**150**	**350**

Figure 5.8 shows the topology of the neural network. The number of neuron was obtained from the number of wavelet coefficients (CD3, CD4, CD5 and CA5). These coefficients were used as an input to ANN. The choice of optimal number of hidden neurons is the most interesting and challenging aspect in designing multilayer feed-forward networks. The choosing of 40 neurons in the hidden layer was a result of various training experiments using lower and higher hidden neuron values.

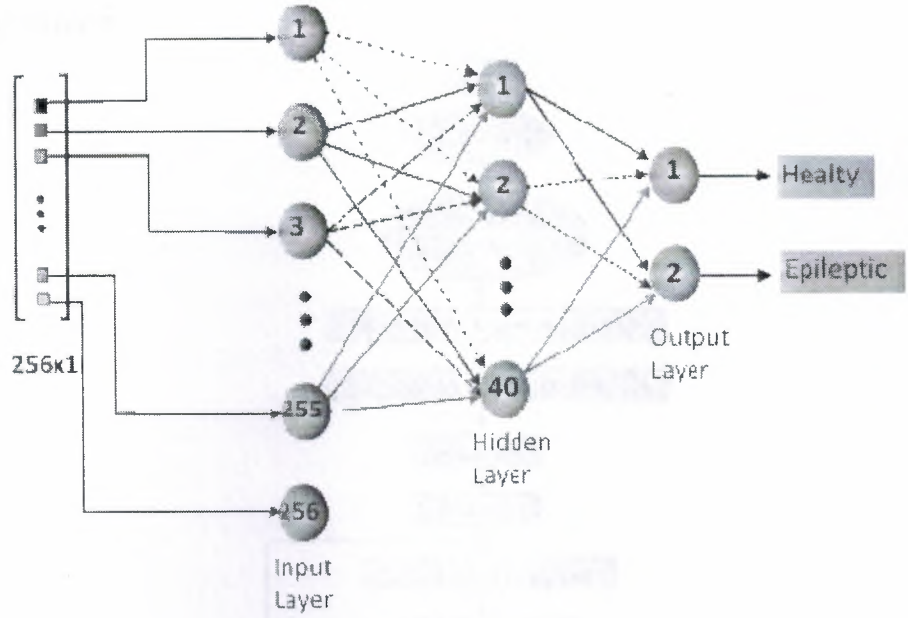


Figure 5.8 EEG signal classification neural network topology

5.2.3 Flowchart

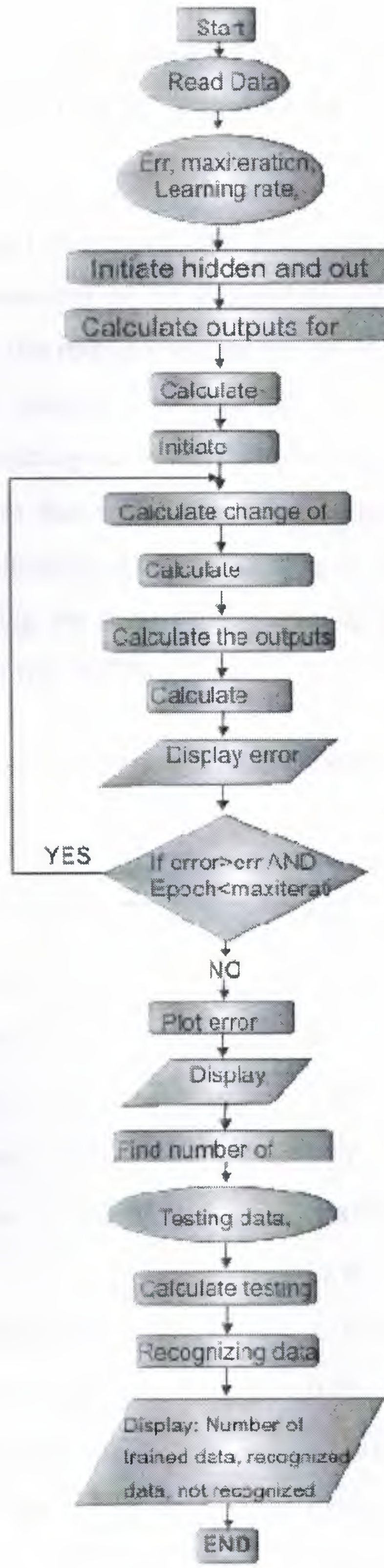


Figure 5.9 Flow chart presents the concept of identification

5.3 Result and Discussion

The results of implementing the proposed EEG signal identification method were obtained using 2.2 GHz Core Duo PC with 4 GB of RAM, Windows Vista OS and Matlab 7.0 software tools.

The neural network learnt and converged after 2856 iterations and within 203 seconds. Table 5.4 lists the final parameters of the successfully trained neural network, and the correct identification rates. The implementation results of the trained intelligent system were as follows: using the training data (150 samples) yielded 100% recognition as would be expected. The intelligent system implementation using the EEG signals testing samples (350 samples that were not previously exposed to the neural network) yielded correct EEG signal identification of 335 images, thus achieving 95.71% correct identification rate. Combining the results using training and testing samples yields an overall correct identification rate of 97%.

Table 5.4 Neural network final parameters and correct identification rates (CIR)

Input Neurons	256
Hidden Neurons	40
Output Neurons	2
Learning rate	0.005
Momentum rate	0.37
Minimum Error	0.0003
Iterations	2856
Training time (seconds)	203.99
Testing time (seconds)	0.48
CIR – Training data	(150/150) 100%
CIR – Testing data	(335/350) 95.71%
CIR – Overall	(485/500) 97.00%

The speed of classifier is very good 0.0013 sec. To classify an EEG segment of 23.6 sec. The value of goal error was 0.0003. The neural network reached to goal error during the training process so that maximum number of iteration wasn't completed. The error rate decreases rapidly at the beginning and much more slowly afterward. Figure 5.10 shows a plot of the training errors against number of the iteration.

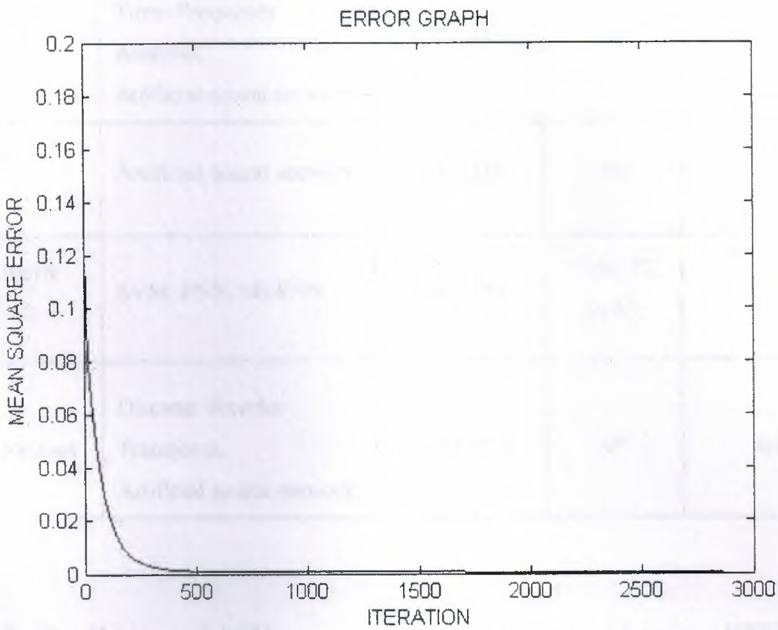


Figure 5.10 error versus number of iteration graph

5.3.1 Comparison to the Previous Identification Systems

Literature presents a number of researches that deal with detection of epileptic seizure detection from EEG signals.

Different methods from the literature and their respective classification accuracies are shown in table 5.5. Only methods that are evaluated using the *same dataset* are included. Based on these results proposed method system achieves an impressive 97% accuracy. The speed of classifier is very good 0.0013 sec. to classify an EEG segment of 23.6 sec.

Table 5.5 Comparison between the developed system and other existing systems using same dataset.

Authors	Method	Dataset	Accuracy	Processing time for an EEG segment
A.T. Tzallas et al.[63].	Time–Frequency Analysis, Artificial neural network	A,B,C,D,E	89	-
Kifah Tout et al.[65].	Artificial neural network	A,B,C,D,E	88	-
Guler and Ubeyli [64].	SVM, PNN, MLPNN	A,B,C,D,E	75.60, 72, 68.80,	-
Developed System	Discrete Wavelet Transform, Artificial neural network	A,B,C,D,E	97	0.0013 sec.

Alexandros T. Tzallas, *et.al* [63] presented a comparison of using STFT and other 12 well known time-frequency distribution to access the non-stationary properties of the EEG signal with respect to epileptic seizure detection. They utilized an approach based on *t-f* analysis and extraction of features reflecting the distribution of the signal's energy over the *t-f* plane. The results for classification accuracy is 89%.

Kifah Tout *et al.* [65] have proposed a scheme for epileptic seizure prediction based on neural networks. They have applied the parameters that most probable could symbolize the long term EEG signal as inputs of the multilayer neural network .They have trained the neural network to detect the ictal and non-ictal patterns, and then, tested the network for prediction. Moreover, they determined the sensitivity and specificity of the prediction. They have also concluded that with 5 parameters used as inputs of the MLP network, the prediction had a high sensitivity and a high specificity (88%).

Guler and Ubeyli [66] in order to find the neural network model with the highest accuracy for classification of the EEG signals implemented three types of classifiers [multilayer perceptron neural network (MLPNN), probabilistic neural network (PNN), multiclass support vector machine (SVM)]. The total-classification accuracies of the SVM, PNN, and MLPNN obtained were 75.60%, 72.00%, and 68.80%, respectively.

CHAPTER 6

CONCLUSIONS

Epilepsy is a disorder of brain function that affects about 1% of the population. It is characterized by an excessive and uncontrolled activity of either a part or the whole central nervous system.

The electroencephalogram (EEG) is the brain signal containing valuable information about the normal or epileptic state of the brain. Hence electroencephalogram (EEG) signal plays an important role in the diagnosis of epilepsy. Traditional epileptic diagnosis is based on the visual scanning of lengthy EEG recordings by neurologists.

As mentioned before electroencephalogram (EEG) is one of the most efficient tools in the diagnosis of epilepsy syndrome. Two categories of abnormal activity can be observed in the EEG signal of an epilepsy patient: ictal (during an epileptic seizure) and inter-ictal (between seizures). A patient's ictal EEG is very important, according to which, misdiagnosis can be avoided effectively. However, it is difficult to be recorded because of the sudden, unforeseen occurrence of seizures. Recently, long-time continuous recording of EEG has been widely used to catch an actual seizure, but it brings another problem to us: analysis by visual inspection of long recording of EEG to find an actual epilepsy seizure is usually a time-consuming, high-cost progress.

Therefore, we proposed in this thesis an automated system for diagnosis of epilepsy that addresses these problems. The proposed system consists of feature extraction phase and classification phase.

In the first phase, discrete wavelet transform is used to process EEG data as input to a feed forward neural network for the detection of epileptic waveforms. EEG signals are decomposed by using DWT into its sub-bands. A five level wavelet decomposition tree was used to obtain 5 sub bands with different frequency. In order to reduce the dimensionality of the feature vectors, statistics over the set of the wavelet coefficients were used. The maximum, minimum, mean and standard deviation for each of the sub band was calculated. These values from the sub bands were combined into a vector, which was used as a set of data for a subject in classification. This method was applied to three different groups of EEG signals: 1) healthy,2) epileptic states during a seizure-free interval (interictal EEG) and 3) epileptic states during a seizure (ictal EEG).

The second phase of the proposed identification system is the implementation of a back propagation neural network classifier. This phase consists of training the neural network using the feature vectors (they were extracted from EEG signals) obtained from the first phase. Once the network learns, this phase will only compose generalizing the trained neural network using one forward pass. The neural network was trained using 150 EEGs, 350 EEGs were tested. The test sets were not used for training.

An overall 97% correct identification has been achieved. Therefore, proposed system has succesfully classified the EEG signals and reduced the computational complexity of the classifier.

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