Büşra KURU

CLASSIFICATION OF EPILEPSY AND PSYCHOGENIC PATIENTS WITH ANALYSIS OF EEG SIGNALS

M.S.
2015

FATİH UNIVERSITY

The Graduate School of Sciences and Engineering

Master of Science in
Computer Engineering

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by

Büşra KURU

June 2015

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A thesis submitted to

the Graduate School of Sciences and Engineering

of

Fatih University

in partial fulfillment of the requirements for the degree of

Master of Science

in

Computer Engineering

June 2015
Istanbul, Turkey

APPROVAL PAGE

This is to certify that I have read this thesis written by Büşra KURU and that in my opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Computer Engineering.

_____
Assist. Prof. Kadir TUFAN
Thesis Supervisor

I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science in Industrial Engineering.

_____
Assist. Prof. Kadir TUFAN
Head of Department

Examining Committee Members

Assist. Prof. Kadir TUFAN _____

Assist. Prof. Aişe Zülal ŞEVKLİ _____

Assoc. Prof. Fethullah KARABİBER _____

It is approved that this thesis has been written in compliance with the formatting rules laid down by the Graduate School of Sciences and Engineering.

_____
Prof. Nurullah ARSLAN
Director

June 2015

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Büşra KURU

M.S. Thesis – Computer Engineering
June 2015

Thesis Supervisor: Assist. Prof. Kadir TUFAN

ABSTRACT

Epilepsy is the most common neurological disorder. The disease affects a large population. However, it is often difficult to clearly establish the diagnosis of epilepsy, especially for epileptic seizures and psychogenic seizures. In fact, psychogenic non-epileptic seizures (PNES) are extremely common and difficult to differentiate from epileptic seizures. Physicians can diagnose both conditions by visual analysis of electroencephalograph (EEG) signals. When the patients are misdiagnosed between epileptic and psychogenic, they indicate serious problems such as late in the drug treatment for epilepsy patients, financial burden or possible side effects of antiepileptic drugs for psychogenic patients. These problems cause loss of labor, time, and money in both groups of patients. In this paper, we propose an automatic classification method for epileptic and psychogenic seizures on the basis of EEG signals. To the best of our knowledge, this is the first study to discriminate epileptic seizures from psychogenic ones.

Discrete wavelet transform (DWT) is used to breakdown each EEG channel into frequency bands. Non-linear largest Lyapunov exponent (LLE) of each band is calculated. A feature vector is created by using this parameter. Support vector machine (SVM) was used to classify the two conditions, and the results obtained for the accuracy, sensitivity, and specify values showed that our method is a promising tool for physicians.

Keywords: support vector machine, electroencephalogram, epileptic seizure, psychogenic seizure, non-linear analysis, wavelet, largest Lyapunov exponent

EEG SİNYALLERİNİN ANALİZİ İLE EPİLEPSİ VE PSİKOJENİK HASTALARIN SINIFLANDIRILMASI

Büşra KURU

Yüksek Lisans Tezi – Bilgisayar Mühendisliği
Haziran 2015

Tez Danışmanı: Yrd. Doç. Dr. Kadir TUFAN

ÖZ

Epilepsi en sık karşılaşılan nörolojik rahatsızlıktır. Bir çok insanda görülmesinin yanısıra, epileptik nöbetler ile psikojenik nöbetlerin tespiti oldukça zordur. Psikojenik (epileptic olmayan) nöbetler (PNES), epileptic nöbetler ile karşılaştırıldığında ayrımının yapılması zor hastalıklardan biridir. Doktorlar, hastadan alınan EEG sinyallerinin görsel analizi ile bu iki hastalığın tespitini yaparlar. Hastalarda epileptic ve psikojenik hastalıkları teşhisinde yanlış veya geç tespit yapıldığında, hasta üzerinde yanlış ilaç tedavisiyle meydana gelen ciddi problemler oluşmaktadır. Bu sorunlar hastalarda emek, zaman ve para kaybına neden olabilir. Bu tez çalışmasında, EEG sinyallerinin analizi yapılarak epileptic ve psikojenik hastalar için otomatik sınıflandırma metodu amaçlanmıştır. Bizim bilgimize göre, epileptik hastaların psikojenik hastalardan ayrımını yapan ilk çalışmadır.

Ayrık dalgacık dönüşümü (ADD), EEG kanallarını frekans bantlarına göre ayırmak için kullanılmıştır. Her bandın doğrusal olmayan Büyük Lyapunov Üssü (BLÜ) hesaplanmıştır. Bu parametreye göre özellik vektörü oluşturulmuştur. Destek vektör makinesi (DVM) yukarıda bahsedilen hastalıkların sınıflandırılmasında kullanılmıştır. Elde edilen doğruluk, duyarlılık ve özel değerler kullanılan metodun doktorlar için umut verici bir metot olduğunu göstermiştir.

Anahtar kelimeler: destek vektör makinesi, electroencephalogram, epileptic nöbet, psikojenik nöbet, büyük Lyapunov üssü, ayrık dalgacık dönüşümü

To my family

ACKNOWLEDGEMENT

I express sincere appreciation to Assist. Prof. Kadir TUFAN for their guidance and insight throughout the research.

Thanks go to the doctor, Assist. Prof. Mehmet ERYILMAZ for him valuable suggestions and comments. The technical assistance of Oğuzhan KARAARSLAN is gratefully acknowledged.

I express my thanks and appreciation to my family for their understanding, motivation and patience. Lastly, but in no sense the least, I am thankful to all colleagues and friends who made my stay at the university a memorable and valuable experience.

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SYMBOL/ABBREVIATION

BSP	Biomedical signal processing
DWT	Discrete Wavelet Transform
EEG	Electroencephalograph
HV	Hyperventilation
LLE	Largest Lyapunov Exponent
PNES	Psychogenic non-epileptic seizure
SVM	Support Vector Machine
Twin	EEG Clinical Software Program

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

In recent times, significant progress has been made in the field of biomedical signal processing (BSP). The aim of BSP is to extract the required information directly from raw signals [1]. In particular, the classification of the data obtained by BSP has helped physicians detect and diagnose diseases, such as epilepsy [1].

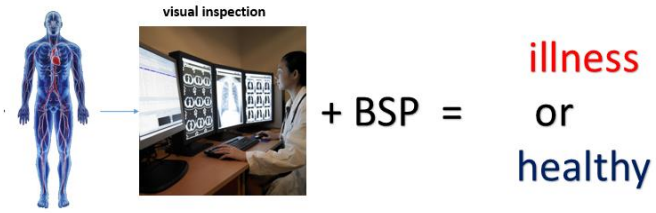


Figure 1.1 Aim of biomedical signal processing.

Epilepsy is one of the neurological disorders which abnormal electrical activity in the human brain. Approximately forty to fifty million patients worldwide are affected by epilepsy [2]. Further, approximately one in every 100 persons will experience a seizure at some time in their life [3]. The brain has millions of nerve cells which control the human body. The nerve cells do this by passing electrical signals to each other. If these signals are disrupted, or too many signals are sent at once, this causes a seizure. Sometimes seizure is called attack. Seizures involve causes disturbances of awareness, behavior, emotion, movement and it can affect patients of all ages [4]. A seizure is a temporary loss of control, often with abnormal movements, unconsciousness, or both.

There are several different types of seizures: epileptic seizure and non-epileptic seizures. In this research, epileptic and psychogenic (non-epileptic) seizures have examined. The human brain are generated sudden abnormal electrical discharges during epileptic seizures. Psychogenic (non-epileptic) seizures are look like epileptic seizure. But, these non-epileptic seizures are about emotional or stress- related. Psychogenic seizures are not caused abnormal electrical discharges in the human brain. These seizures are named as psychogenic non-epileptic seizures (PNES).

For the diagnosis of epileptic or psychogenic seizures, it is important to obtain correct information from the patient's relatives regarding the frequency of the seizures; patients should be examined and observed carefully during the seizure by relatives and the relatives should be communicated to the doctor. Communication between doctors and the patient's relatives are important [5]. These treatments are generally long term, and therefore, conclusive evidence is necessary to establish a firm diagnosis. For this, some tests are needed. An electroencephalography (EEG) test must be performed for the diagnosis of neurological diseases.

The EEG enables the evaluation of the electrical activity of the brain. These signals are essential for the diagnosis of the disorders of the nervous system. Spikes and surges that occur in EEG recordings of epilepsy patients play an important role in the diagnosis of the disease [6]. The EEG signal can be analyzed by analysis of either stationary signals or non-stationary signals to extract reliable diagnostic information [7]. Assuming that EEG signals are stationary, the time-domain features and frequency-domain features have been used for the detection and classification of epileptic seizures from EEG signals [8].

1.2 STATEMENT OF THE PROBLEM

All patients who have seizures do not have epilepsy. The differential diagnosis of PNES firstly involves ruling out epilepsy as the cause of the seizure episodes, along with other organic causes of non-epileptic seizures, such as syncope, migraine, vertigo. The seizures are classified as epileptic when it is spontaneous or is triggered by certain factors [9]. Other than that, other seizures are grouped under name of psychogenic seizures [10]. Psychogenic seizures appear similar to other kinds of epileptic seizures.

However, these seizures are not caused by abnormal cortical discharges, which is the case with epilepsy patients. Psychogenic seizures usually occur due to a functional disorder (dysfunction) in the processing of psychological or social distress [11].

The review of the EEG test is long term process to distinguish between epileptic seizures and psychogenic non-epileptic seizures [12]. Most of the time, EEG tests may not be helped to find different between these two seizures [13]. Because false-positive rate may be high for abnormal symptoms in general population. Sometimes, patients have some abnormal symptoms with psychiatric disorders that similar to epilepsy.

1.3 PURPOSE OF THE STUDY

Clinically, epileptic and psychogenic seizures are differentiated on the basis of EEG records. However, EEG signals are too complex. Further, each EEG recording generates a large amount data for electroencephalographic changes. Visual analysis of EEG signals is not routinely possible by the physician [14]. Additionally, it is a time-consuming task. Moreover, psychogenic seizure can be difficult to distinguish from epileptic ones, and lead to misdiagnosis. Therefore, automated techniques are becoming increasingly important in the diagnosis of epileptic and psychogenic non-epileptic seizures [15]. This research is necessary for better understanding of the mechanisms to distinguish between these seizures.

Several EEG signal-processing techniques have been described in literature for the automatic detection and classification of epileptic seizures. For instance, the features based on the Wavelet chaos analysis and correlation dimension (CD) and largest Lyapunov exponent (LLE) have been used to classify normal and epileptic seizure EEG signals [16]. The linear prediction error energy and fractional linear prediction error–based methods have been proposed for the detection of epileptic seizures by using EEG signals [17, 18]. A novel principal component analysis (PCA)-enhanced cosine radial basis function neural network classifier is presented with the mixed-band wavelet-chaos methodology for accurate and robust classification of electroencephalogram (EEG) into healthy, ictal, and interictal EEG [19]. The features based on the Euclidian distance computed from phase-space representation (PSR) of wavelet coefficient have been used to classify normal and epileptic seizure EEG signals [20]. Discrete Daubechies and

harmonic wavelets are investigated for analysis of epileptic EEG records [21]. There are different nonlinear parameters. The largest Lyapunov exponent (LLE) has been shown to be very useful in the diagnosis of epilepsy in otherwise healthy subjects [22]. To the best of our knowledge, no study has been hitherto been reported on the direct classification of epilepsy and psychogenic patients in the literature.

In the currently study, three steps were implemented for the classification of EEG signals. Firstly, decomposition of EEG signals was performed with wavelet transform (WT). Then, we calculated the LLE of the wavelet bands. The calculated values of LLE were classified using support vector machine (SVM).

At the first step, all EEG records were decomposed into several frequency sub-bands by using discrete wavelet transform (DWT). Then, wavelet coefficients of the sub-bands were produced.

At the second step, the LLE of each sub-bands were calculated. EEG signals are chaotic signals. Therefore, we used a non-linear dynamics tool, the computation of LLE for a reliable classification method on electroencephalographic changes [23]. LLE can provide important details about changes in EEG recording for the analysis of signals that are epileptic and psychogenic [14].

In the third step, feature sets were created by the calculation of the LLE bands, which were decomposed by DWT. These feature sets were classified using SVM. SVM was chosen because it has been successfully applied in the classification method of biomedical signals [24].

The paper is organized as follows: In Chapter 2, we describe background knowledge related to epilepsy and psychogenic diseases. In Chapter 3, we describe the data of the EEG signals used in this study. In Chapter 4, we explain the methods, including the DWT and LLE to extract the features of the examined signals. Further, we describe SVM for the classification. The procedures applied in the study are described and experimental results are provided in Chapter 5. Chapter 6 provides the conclusion.

CHAPTER 2

LITERATURE REVIEW

2.1 INFORMATION RELATED TO EPILEPSY AND PSYCHOGENIC

2.1.1 Human Brain

The brain manages the human body. It's the central part of the nervous system. It receives input from the sensory organs and sends output to the muscles. The brain can be divided into three parts; cerebrum, cerebellum and brainstem [25]. All the parts of the brain work together, but each part has its own special properties. The largest part of the human brain is the cerebrum, which is divided into two hemispheres: right and left hemispheres. Each hemisphere can be divided into four lobes: frontal, parietal, occipital and temporal [26] as shown in Figure 2.1. The lobes are named for the skull bones that cover them.

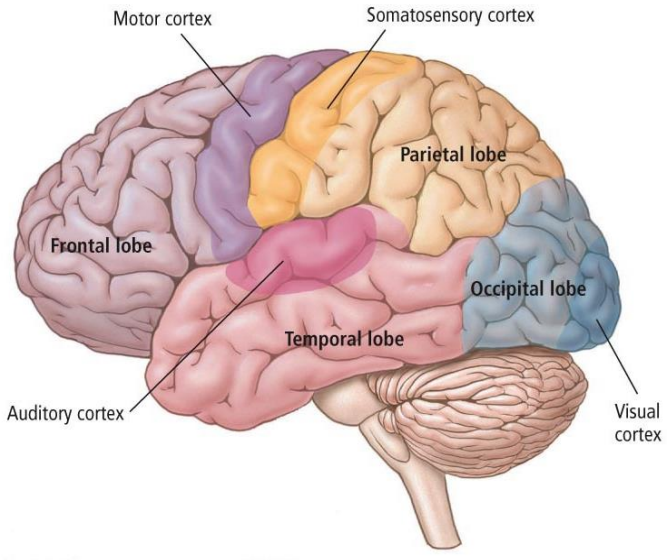


Figure 2.1 Anatomical brain regions [25].

- Frontal Lobe is located at the front of the brain and is associated with reasoning, motor skills, higher level cognition, and expressive language. This area of the brain receives information from various lobes of the brain and utilizes this information to carry out body movements [25].
- Parietal Lobe contains neurons that receive sensory information from the skin and tongue, and processes sensory information from the ears and eyes that are received in other lobes [25].
- Occipital Lobe is important to being able to correctly understand what your eyes are seeing. These lobes have to be very fast to process the rapid information that our eyes are sending [25].
- Temporal Lobe is to processing auditory sounds. There are two temporal lobes located on both sides of the brain that are in close proximity to the ears [25].

2.1.2 Electroencephalography (EEG)

An electroencephalogram (EEG) is a test that measures and records the electrical activity of your brain. The EEG is used in the evaluation of brain disorders. Most commonly it is used to show the type and location of the activity in the brain during a seizure. It diagnose neurological disorders such as epilepsy, brain tumors, head injury and sleep disorder. An EEG is performed by an EEG technician in a specially designed room that may be in the doctor's office or at a hospital.

In 1929, an Austrian physician named Hans Berger discovered that electrodes placed on the scalp could detect various patterns of electrical activity [26]. He suggested that brain currents changed based on the functional status of the brain such as sleep, anesthesia, and epilepsy. These were revolutionary ideas that helped create a new branch of medical science called neurophysiology.

During the EEG measurement, small metal disks called electrodes are placed on your scalp. The disks are placed onto your scalp using a sticky substance. The electrodes are connected by wires to send signals to a computer to record the results. The machine record the signals as wavy lines onto paper or on a computer. Each channel produces a signal during an EEG recording. It is a safe and painless procedure.

There are several types of EEG tests: routine EEG, ambulatory EEG and video EEG. The EEG machine records the brain’s electrical activity as a series of waveforms

called traces. Each trace corresponds to a different region of the brain as shown in the Figure 2.2.

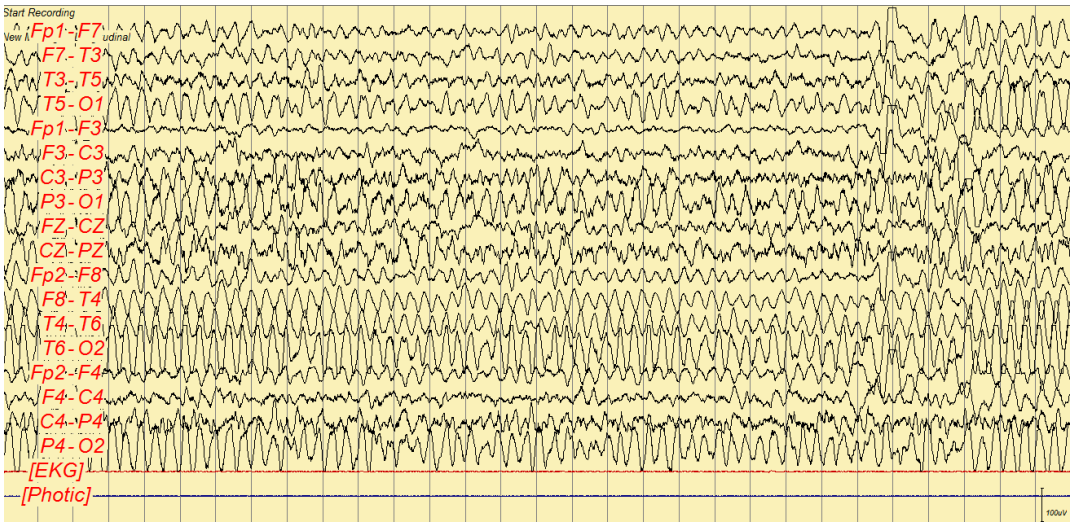


Figure 2.2 Sample EEG recording of a patient.

The EEG shows sudden bursts of electrical activity (spikes) or sudden slowing of brain waves in the brain. These changes may be caused by a brain tumor, infection, injury, stroke, or epilepsy. Spikes on the EEG are markers of hyper-excitable parts of the brain, which mark potential locations where seizures may arise.

The electrode placement is important, because different lobes are responsible for processing different types of activities. The international 10-20 electrode system is the standard method for the scalp electrode localization.

Figure 2.3 shows International 10-20 electrode placement method is used to describe the location of scalp electrodes. Each location uses 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. The abbreviations Fp1, Fp2, F7, F3, FZ, F4, and F8 stand for the frontal lobe; T3, T5, T4, and T6 for the temporal lobe; P3, PZ, P4 stand for the parietal lobe; and O1 and O2 stand for the occipital lobe. Note that there exists no central lobe; the letter "C" is used only for identification purposes, while "Z" (zero) refers to an electrode placed on the midline.

Even numbers refer to electrode positions on the right hemisphere, while odd numbers refer to those on the left hemisphere. These electrodes are connected to each other to form a channel.

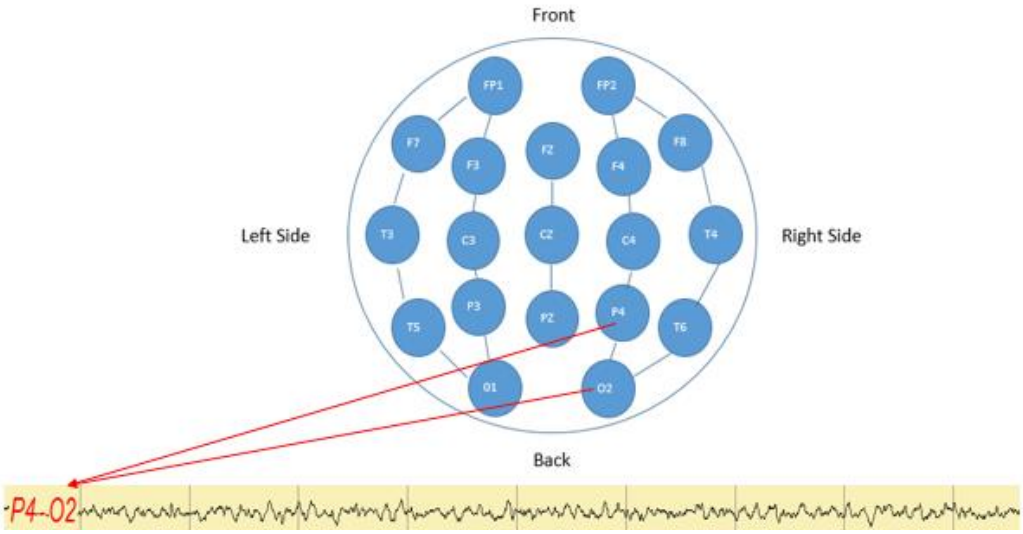
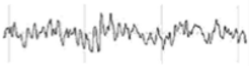
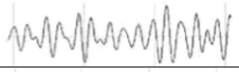


Figure 2.3 International 10-20 electrode placement scheme and an EEG wave of between two electrodes.

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. Frequency (Hertz, Hz) is a key characteristic used to define normal or abnormal EEG rhythms. There are five different EEG rhythms which are categorized in specific bands such as 0.5-4 Hz (delta, δ), 4-8 Hz (theta, θ), 8-13 Hz (alpha, α), 13-30 Hz (beta, β) and larger than 30Hz (gamma, γ) [21]. Table 2.1 illustrates examples of these EEG rhythms.

Table 2.1 Types of brain waves.

Frequency Band Name	Frequency Bandwidth	Example of Frequency
Raw EEG	0-45 hz	
Delta	0.5 – 3.5 hz	
Theta	4 – 7.5 hz	
Alpha	8-12 hz	
Beta	13 – 35 hz	

• Delta (<4 Hz): Delta waves are generated in deepest meditation and dreamless sleep. They suspend external awareness and are the source of empathy. Healing and regeneration are stimulated in this state, and that is why deep restorative sleep is so essential to the healing process.

• Theta (4-7.5 Hz): Theta rhythm occurs as a normal rhythm during drowsiness. In young children, this occurs with a predominance over the front-central regions during drowsiness between the ages of 4 month to 8 years of age. In adults, theta slowing can occur diffusely or over the posterior head regions during drowsiness. Theta waveforms can be present over the temporal regions in older adults.

• Alpha (8-12 Hz): Alpha waves are present only in the waking state when your eyes are closed but you are mentally alert. Alpha waves go away when your eyes are open or you are concentrating.

• Beta (13-35 Hz): Beta activity is mostly marked in front central region with less amplitude than alpha rhythms. Beta rhythms occur in individuals who are alert and attentive to external stimuli or exert specific mental effort, or paradoxically, beta rhythms also occur during deep sleep.

• Gamma (>35 Hz): Gamma is modulated by sensory input and internal processes such as working memory and attention.

2.1.3 Epilepsy and psychogenic disease

Epilepsy is the most common neurological disorder and it is estimated that around 50 million people all over the world suffer from recurrent epileptic seizures [27]. More than 750 thousand people in the Turkey have experienced an unprovoked seizure or

been diagnosed with epilepsy [27]. Moreover, about 10% of the world's total population will some time in their life experience a grand epileptic seizure. Epilepsy is characterized by recurrent seizures [28]. Seizures are defined as uncontrolled electrical activity in the brain, which may produce a physical convulsion, minor physical signs, thought disturbances, or a combination of symptoms.

In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behaviors, or sometimes convulsions, muscle spasms and loss of consciousness. There are many different epilepsy caused by head injury or brain tumor. During a seizure, the nerve cells leave their normal activities, and fire in massive, synchronized bursts [29].

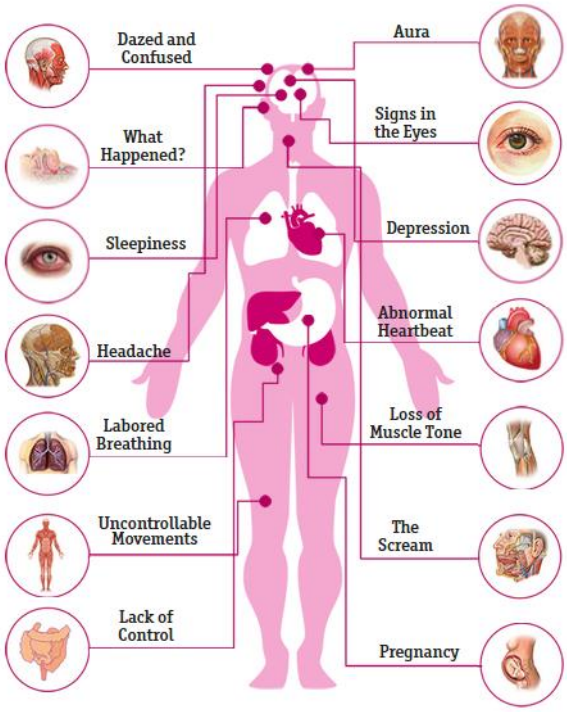


Figure 2.4 Effects of Epilepsy [29].

Psychogenic non-epileptic seizures (PNES) are complicated because, while they look like seizures, PNES's do not result from abnormal electrical discharges in the brain. They are caused by psychological distress. Patients who have difficulties managing

anger or controlling their hostility toward others may manifest these difficulties with PNESs [30].

Several studies document that the misdiagnosis of PNES as epilepsy remains a significant problem [31]. Community-based epidemiological studies have reported rates of misdiagnosis of epilepsy ranging from 20 to 26%, and PNES has been found to be the second most common condition to be mistaken for epilepsy after syncope [32].

The diagnosis of epilepsy is more difficulties without being questioned. The results of misdiagnosis of epilepsy are the usual diagnostic delay and cost associated with PNES. Physicians are taught almost exclusively to consider physical disorders as the cause of physical symptoms. Furthermore, patients with PNES are often prescribed some drugs because of misdiagnosis of epilepsy, and many have been taking drugs for some time. The drugs are not normally prescribed until after development of the attack disorder [33].

EEG recordings contain valuable information for understanding neurological disorders. Epileptic activity can create clear abnormalities on a standard EEG. EEG technologists may use activation procedures such as hyperventilation and photic stimulation to enhance the ability of EEG to detect epileptic or psychogenic seizures. Experienced electroencephalographs can readily identify normal variants, but some neurologists may misidentify or misinterpret these EEG findings.

Clinically, epileptic and psychogenic seizures are differentiated on the basis of EEG records. However, EEG signals are too complex. Further, each EEG recording generates a large amount data for electroencephalographic changes. Visual analysis of EEG signals is not routinely possible by the physician [14]. Additionally, it is a time-consuming task. Moreover, psychogenic seizure can be difficult to distinguish from epileptic ones, and lead to misdiagnosis. Therefore, automated techniques are becoming increasingly important in the diagnosis of epileptic and psychogenic non-epileptic seizures [15].

CHAPTER 3

DATA ACQUISITION

3.1 HARDWARE

EEG recordings are obtained by using the Universal Personality Modules (UPM-PLUS) proposed for EEG application. Personality modules are produced by Grass Technologies (Natus Neurology Incorporated - Grass Products, U.S.A). The module for the EEG recording is shown Figure 3.1 while recording the patient's EEG signals. All records was obtained and saved with Twin EEG Clinical Software Program™. This multi-functional Windows®-based software permits recording and analysis of routine EEG studies as well as long-term epilepsy monitoring.

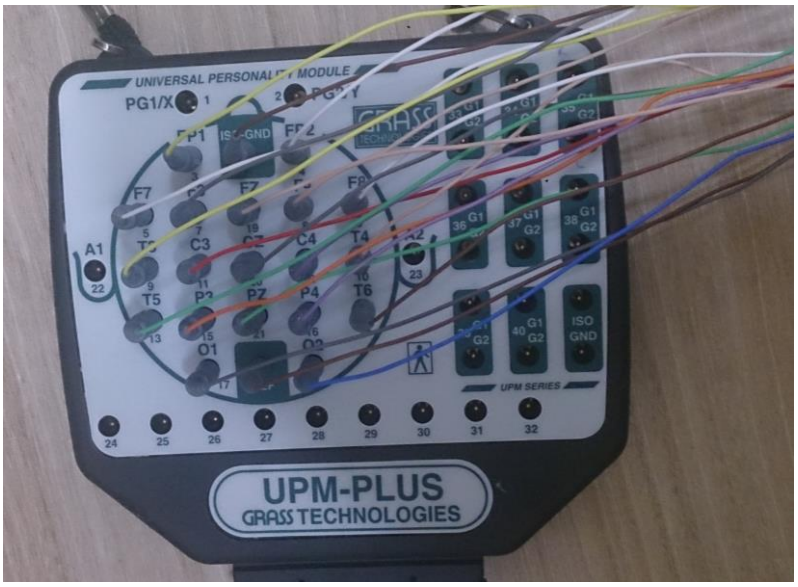


Figure 3.1 The Universal Personality Modules (UPM-PLUS).

3.2 DATA INFORMATION

The experimental EEG data were obtained at the Neurological Department of the Fatih University Hospital in Istanbul. EEG recordings were performed by an expert physicians. The complete dataset consisted of two groups: epileptic and psychogenic. Each subject is examined and recorded by using a 20-channel routine EEG unit for 20 minutes. In all, 99 distinct recordings are obtained at the hospital. The first group consists of 66 psychogenic (non-epileptic seizure) people, while the second group has 33 epilepsy patients. 30 male and 63 female patients were enrolled in this study. The average age of epilepsy patients was 32 years, while that of psychogenic patients was 35 years. The demographic and clinical characteristics of the patients are shown in Table 3.2.

EEG recordings were performed by an expert physicians. The complete dataset consisted of two groups: epileptic and psychogenic. Each subject is examined and recorded by using a 20-channel routine EEG unit for 20 minutes. In all, 99 distinct recordings are obtained at the hospital. The first group consists of 66 psychogenic (non-epileptic seizure) people, while the second group has 33 epilepsy patients. 30 male and 63 female patients were enrolled in this study. The average age of epilepsy patients was 32 years, while that of psychogenic patients was 35 years. The demographic and clinical characteristics of the patients are shown in Table 3.2.

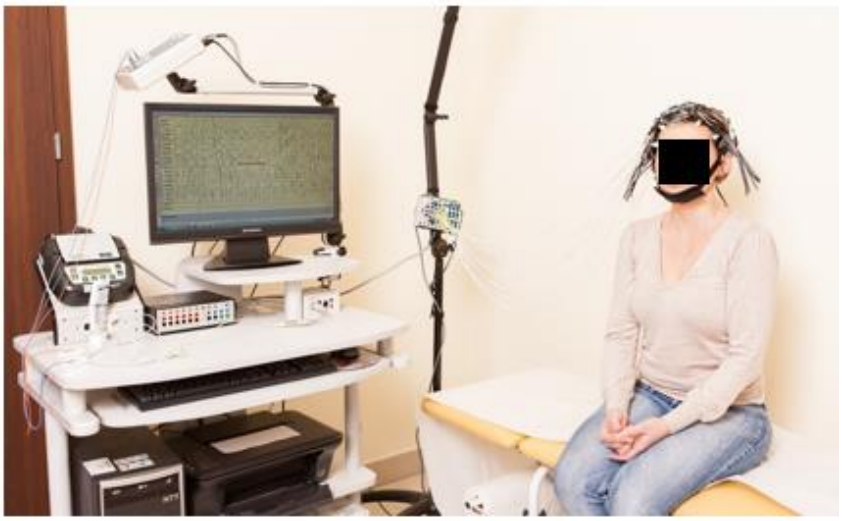


Figure 3.2 A moment of the EEG recording.

Table 3.1 EEG recording demographics.

	# of Subjects	Male	Female	Minimum age	Maximum age	Average age
Epilepsy	33	13	20	7	86	32
Psychogenic	66	17	43	7	80	35

In this study, the Ethics Committee report was sought for obtaining EEG records of patients. These patients consist of routine patients who visited the clinic. The demographic data of the patients were not considered in the study. Figure 3.3 shows the 20-channel raw EEG signal of an epileptic seizure patient. Figure 3.4 shows the 20-channel raw EEG signal of a psychogenic seizure patient.

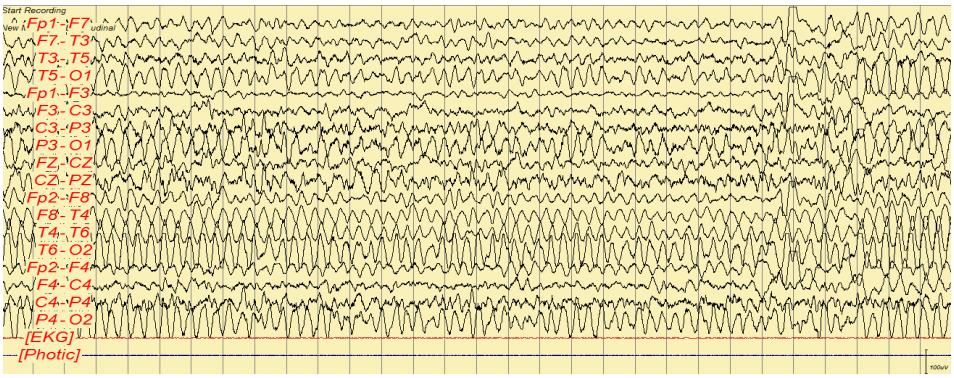


Figure 3.3 EEG recording of an epilepsy patient.

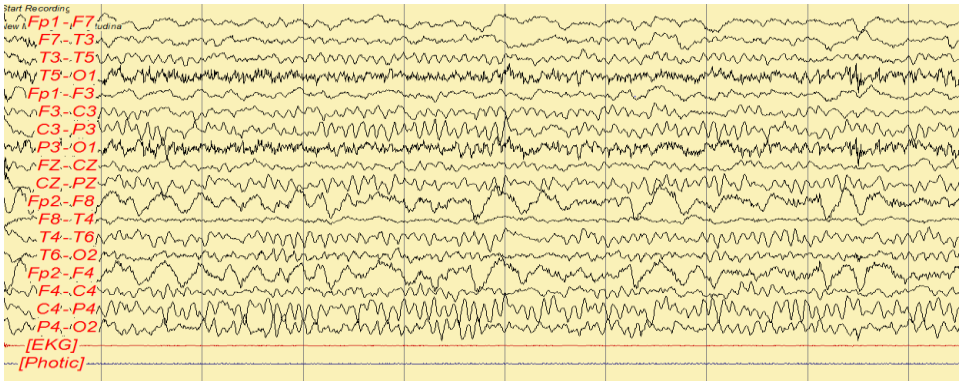


Figure 3.4 EEG recording of a psychogenic patient.

Two different types of EEG records were prepared depending on whether the signal was obtained from the scalp or intracranial. In this study, the scalp EEG recordings were used. For scalp EEG recordings, small metal discs, also known as electrodes, are used. Electrodes were placed on the scalp with good mechanical and electrical contact. Scalp EEG signals are synchronous discharges from cerebral neurons detected by electrodes attached to the scalp [21].

Table 3.2 Specifications of EEG recording.

Name	**Value**
Channel mode	Mono
Sampling rate / Resolution	210 Hz / 16 bits (0.06 μV/bit)
File type	.QQQ (recording type in the program of Twin)

In this study, we used scalp EEG recordings with 20 electrodes placed on areas corresponding to specific regions of the brain. The duration of each EEG recording is 20 minutes. The patient was placed in the supine position during the EEG. Then, the patients were instructed to make the desired movements according to the directives of the EEG technician during the EEG recording. The conventional visual inspection of EEG recordings includes the examination of the following features: frequency or wavelength, voltage or amplitude, waveform regularity, and reactivity to eye opening, hyperventilation, and photic stimulation [21]. These movements are shown in Figure 3.5. In the first step, the patient was instructed to open and close the eyes six or seven times in a span of 5 minutes. In the second step, which was related to hyperventilation (HV), the patient was required to breathe rapidly during 5 minutes. The last step involved photic stimulation, for which the technician repeatedly switched the light on and off during a period of 5 minutes.

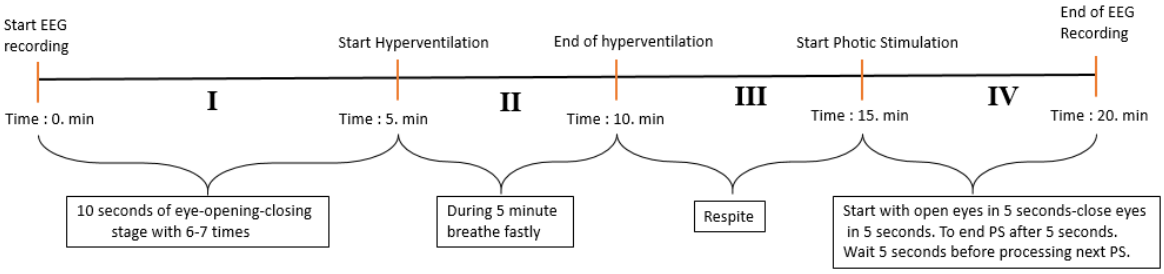


Figure 3.5 Timeline of EEG recording.

Recording EEG signals during HV, i.e. rapid breathing, is a standard procedure because it allows for a physiological slowing of brain rhythms [34]. Generally, HV is used to provoke EEG abnormalities. HV indicates the striking difference in threshold of EEG waves [35]. According to clinical experience, the patient's brain signals show some changes during HV at the time of EEG recording. We believed that the HV phase of EEG can be used to distinguish epileptic seizures from psychogenic seizures. For this reason, we conducted a study on the HV phase, which is the between 5–10 minutes of EEG recording.

Each signal was recorded with 20 channels (electrodes), 16-bit resolution, and 210Hz frequency, as shown in Table 3.2. All EEG signal recordings were performed with international 10–20 electrode placement scheme, as shown in Figure 2.3.

The neurological department of Fatih University Hospital uses the Twin EEG Clinical Software. This program saves all the recording with the ".QQQ" format. For using the records in our research, each EEG recording was converted to a ".dat" file using this program. After the data conversion, the signal analysis and classification processes were implemented using MATLAB software (Matlab 7.6.0, R2008a, The MathWorks Inc., and Natick, MA, USA).

CHAPTER 4

METHODS

Figure 4.1 shows the flowchart for classifying psychogenic and epileptic seizure signals. The flowchart consists of three parts. The first and second parts are related to processing for feature extraction with the Wavelet Transform (WT) and Largest Lyapunov Exponent (LLE) methods. The third part deals with the classification using Support Vector Machine (SVM).

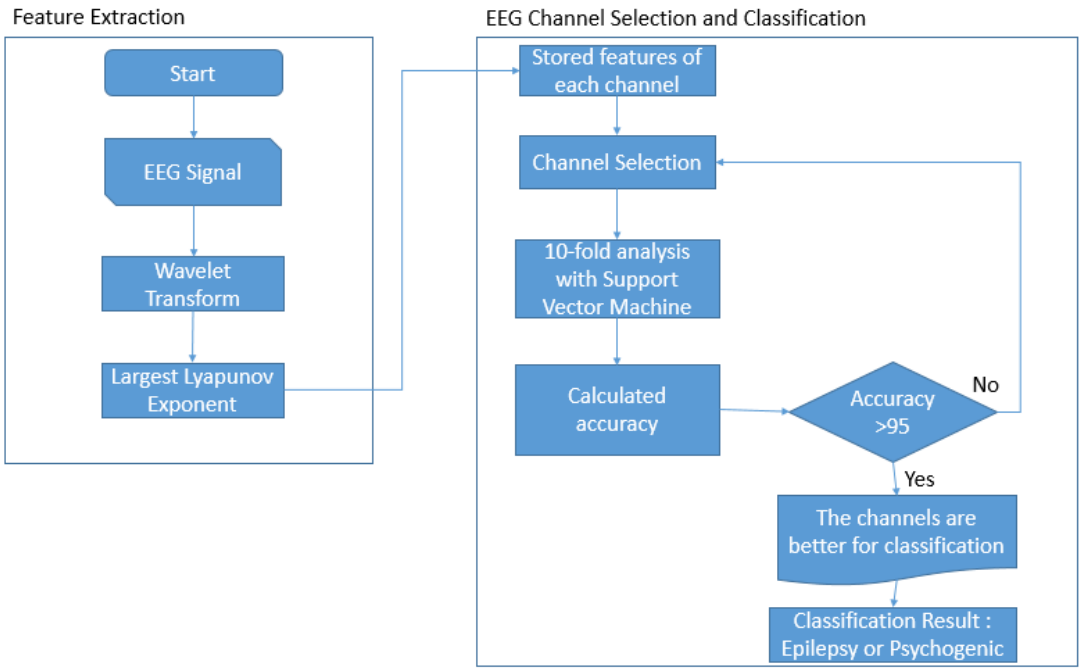


Figure 4.1 Flow chart of channel selection and classification of epileptic and psychogenic EEG data.

4.1 WAVELET TRANSFORM

The attributes of the EEG signal can be found in the time domain; further, the attributes of the frequency domain may also be useful for the classification process. Fourier transform yields a very good frequency resolution of stationary signals [36]. However, time resolution is eliminated. This implies that this method is not suitable for processing any time–frequency information [20]. In other words, it cannot be used for the combined assessment of time and frequency. Further, it was considered that frequency analysis alone would be insufficient; therefore, there is a transition from frequency analysis to scale analysis. This is because with different scales of analysis, it is clear that the measured average fluctuation is less sensitive to noise [37]. Therefore, instead of making decisions on the basis of the overall time series, it may be worthwhile to consider small fluctuations that occur on a regional scale [37]. Therefore, we used WT method for analyzing EEG signals in this study. Wavelets can be stretched or compressed and used to analyze the signal at various levels of resolution [38]. In addition, WT is suitable for spectral analysis of non-stationary signals and is more advantageous than other methods of spectral analysis. The most important advantage of WT is the changing window size, which is large for low frequencies and narrow for the high frequencies [37]. For a signal with rapid variation, a small window can be applied, whereas for a signal with slow variation, a larger window can be used.

WT is analyzed in two different forms, namely continuous and discrete. Continuous Wavelet Transform (CWT) is the sum of the entire duration of the signal, which is obtained by multiplying the shifted and scaled values of the main wavelet in the time domain. Depending on the results of these operations, the wavelet coefficients are obtained according to scale and location. If scaling and offset are selected as the two bases, the results of the analysis are more effective and accurate than those obtained by continuous WT [39]. This type of analysis is called Discrete Wavelet Transform (DWT).

In continuous WT, due to the continuous changes in the scaling and conversion parameters, calculation of the wavelet coefficients for each scale is difficult and time consuming. For this reason, DWT is used more frequently. DWT decomposes non-station signals at different frequency intervals with various resolutions [40]. Figure 4.2 shows the decomposition to three level components of a signal. Decision of the number

of decomposition levels are very important in analysis of signals using the DWT method.

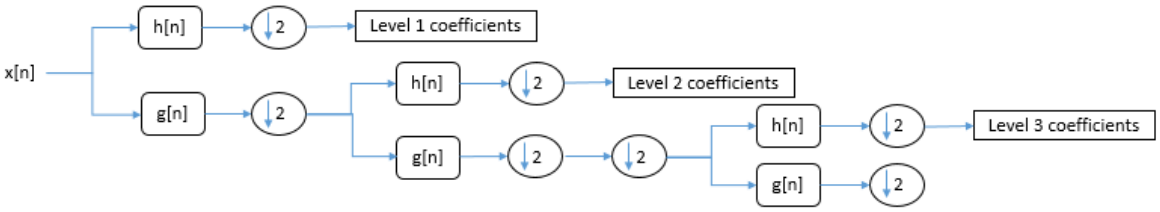


Figure 4.2 Decomposition four-level components of a signal.

Signals are passed from high-pass filter for analyzing high-frequency changes and through signal are passed through the low-pass filter for analyzing low-frequency changes. The components obtained by sub-sampling of signals with the low-pass filter are called approximation coefficients. The components are obtained by sub-sampling of signals with the high-pass filter are called detail coefficients [41]. As shown in Eq. (4.1) and Eq. (4.2), c_A is the approximation coefficient and c_D is the detail coefficient.

$$c_A = \sum_{n=-\infty}^{\infty} x[n]g[2k-n] \tag{4.1}$$

$$c_D = \sum_{n=-\infty}^{\infty} x[n]h[2k-n] \tag{4.2}$$

The level of the decomposition of the component is determined by n in the expression of 2^n [42]. For example, a given signal has 1024 samples. This signal can be decomposed into a maximum of 10 decomposition levels because $2^{10} = 1024$.

Table 4.1 Frequencies corresponding to different levels of wavelet decomposition with a 210 Hz sampling rate.

Decomposed Signal	Frequency Range (Hz)
D1	52.5 – 105
D2	26.25-52.5
D3	13.125-26.25
A3	0-13.125

In this study, we produced wavelet coefficients, including detail and approximation coefficients, at levels 1–3, by using Daubechies 4 (DB4), which is the most frequently used method for EEG signal analysis with DWT. Table 4.1 shows the frequencies corresponding to different levels of wavelet decomposition for the EEG signals with a 210-Hz sampling rate.

4.2 LARGEST LYAPUNOV EXPONENT

In 1889, the Russian mathematician, Sonya Kovalevsky (1850-1891), who was a professor at Stockholm University described the use of invariant exponential to examine the stability of nonlinear differential equations [43]. In 1892, Kovalevsky's study was developed by another Russian mathematician Alexander Mikhailovich Lyapunov (1857-1918).

The reason of showing of the non-periodic dynamics by chaotic systems that is each of phase space curves having different exponential growth rates at the same initial conditions [44]. In phase space, the movements at the two starting points which are close to each other, divergence and convergence from each other with an exponential average factor in the time. This is a fact that exists in chaotic systems. This exponential factor is referred to as Lyapunov exponent. It is shown as (γ). The distance between the two starting point as;

$$d(t) = d_0 e^{\gamma t} \tag{4.3}$$

So, the first Lyapunov exponent is calculated as:

$$\gamma = \frac{1}{t_N - t_0} \sum_{k=1}^{N} \log_2 \frac{d(t_k)}{d(t_{k-1})} \tag{4.4}$$

According to the size of the phase space, divergence and convergence in each dimension is expressed by a γ. Lyapunov exponent spectrum of the system; including the biggest exponent is λ1, as written $\gamma 1 > \gamma 2 > \gamma 3 \ldots$ That must have at least one positive Lyapunov exponent to mention of a chaotic system. Lyapunov exponent calculation usually gives the best results over the long term and clean recorded time series [44].

4.3 SUPPORT VECTOR MACHINE

Support vector machine (SVM) is a machine-learning technique based on the statistical learning theory and it is useful for the pattern recognition problem [24]. The main application of the SVM is to find a hyper-plane that can separate two classes with the most appropriate in the feature space. Although many other linear learning machines also apply this logic, the different viewpoint of SVM from the others may offer a solution that will minimize the likelihood of incorrect classification of the objects to be tested [45].

SVM is used with variations of the original feature space $\vec{x_i}$, into $\varphi(\vec{x_i})$ (a higher dimensional space). Non-linear decision boundaries is calculated in the original feature space, because of perform a linear classification in this high dimensional.

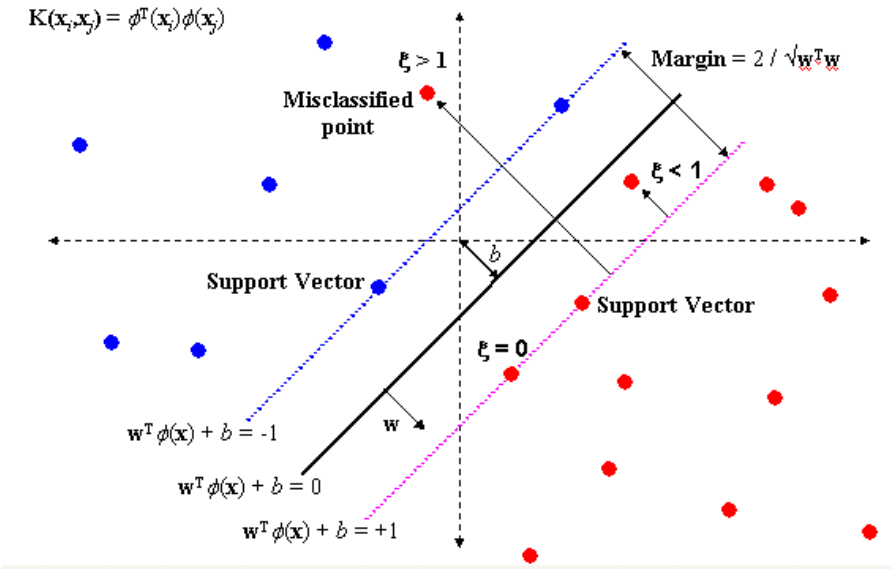


Figure 4.3 Standard support vector machine [46].

SVM constructs a hyper-plane between vectors from two classes. The formula of hyper-plane is $\vec{w} * \varphi(\vec{x_i}) + b = 0$. The distance of the two nearest vectors (v_+, v_-) from each class is maximized. The hyper-plane is calculated by quadratic optimization [47]. SVM finds the solution to the minimization problem as follows:

$$L(\vec{w}) = \frac{||\vec{w}||^2}{2} + C \sum_{i=1}^{n} \varepsilon_i \tag{4.5}$$

For data points, ε_i are non-zero and C is the cost of data points on the wrong side of the decision boundary and C is a user-determined value. v_j is decision boundary which determined by classifier. It is calculated as follows:

$$v_j = \sum_{i=1}^{n} \alpha_i y_i \varphi(\vec{x_i})^T * \varphi(\vec{x_j}) + \frac{\sum_j \left(\sum_{i=1}^{n} \alpha_i y_i \varphi((\vec{x_i}))^T * \varphi(\vec{x_j}) - y_i \right)}{N_{sv}} \tag{4.6}$$

where α_i are Lagrange multipliers which are only non-zero for points on the margins. N_{sv} is the number of α_i that are non-zero. Further, $\varphi(\vec{x_i})^T * \varphi(\vec{x_j})$ is called the "kernel" [48].

Kernel functions provide a way to manipulate data as though it were projected into a higher dimensional space, by operating on it in its original space. There are

several kernel functions, and the generally used kernel functions are given as follows [46]:

- Linear Kernel: The Linear kernel is the simplest kernel function.

$$K(x_i, x_j) = (\overrightarrow{x_i})^T \overrightarrow{x_j} \tag{4.7}$$

- RBF Kernel: The RBF kernel on two samples *x* and *x'*, represented as feature vectors in some input space, is defined as:

$$K(x, x') = \exp\left(-\frac{||x - x'||^2}{2\sigma^2}\right) \tag{4.8}$$

$||x - x'||^2$ may be recognized as the squared Euclidean distance between the two feature vectors. σ is a free parameter.

- Polynomial Kernel: The polynomial kernel looks not only at the given features of input samples to determine their similarity, but also combinations of these.

$$K(x, y) = (x^T y + c)^d \tag{4.9}$$

where x and y are vectors in the input space, i.e. vectors of features computed from training or test samples and $c \geq 0$ is a free parameter trading off the influence of higher-order versus lower-order terms in the polynomial.

CHAPTER 5

APPLICATION AND RESULTS

In this study, a diagnostic classification method utilizing DWT, LLE, and SVM was developed to distinguish the EEG recordings of epileptic and psychogenic subjects. Five-minute EEG recording samples (5-10 minutes of recording) of the subjects obtained during hyperventilation were analyzed. These recordings were digitized into the ".QQQ" format. Later, digitized data were converted to the ".dat" format for further analysis. DWT was used to breakdown the EEG recordings into frequency sub-bands. Then, non-linear features were extracted from each sub-band by using LLE. According to the experience of the physician, the channels were divided into four regions. In the regions with 4 channels (frontal, temporal, occipital regions), the feature vectors had 12 features as shown in Figure 5.1. On the other hand, the parietal region, which has 6 channels, exhibited 18 features in its feature vector. These feature sets are classified using SVM.

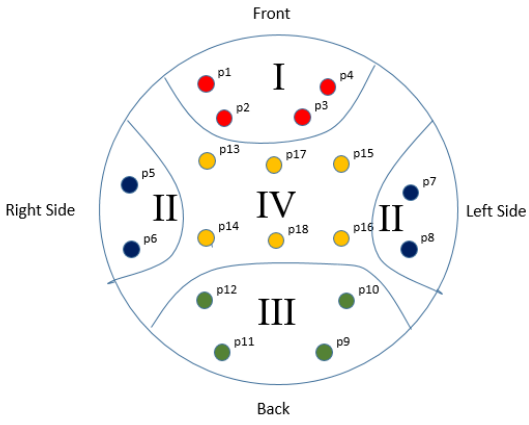


Figure 5.1 Regions of the brain.

For the creation of features, there are two steps. In the first step, DWT was applied to decompose the EEG signal into several sub-signals within different frequency bands. Proper selection of the number of decomposition levels and suitable wavelet function are important for EEG signal analysis. In this study, Daubechies wavelet decomposition with order 4 was chosen because it was the most suitable wavelet algorithm for EEG signal analysis in epileptic seizures [2]. The frequency bands responding to 3 levels of DWT decomposition, with sampling frequency of 210 Hz on the EEG signals, are shown in Table 4.1. The proposed scheme uses the 3rd level decomposition of data and complete features set was created, as explained in Section 4.1. Each sub-band represents the original signal in different frequency bands, which are described in Table 4.1. The LLE of 5-minutes HV phase of each sub-band was calculated as a non-linear feature. LLE was also used for the feature-reduction purpose. The fourth sub-band yielded zero for LLE calculation for all subjects. Therefore, feature vector is constructed by using 3 non-zero LLE values. Since each recording has 20-channels and each channel gives 3 LLE values, each EEG signal has 60 LLE. Thus, the total number of features is 5940.

In this study, the electrodes placed on the patient's head in the EEG were considered to reflect 4 regions of the brain, as per the physician’s experience. We worked on these groups locally by using the obtained features by the calculation of the LLE bands, which are separated by WT.

The first area is called frontal, the second areas are called temporal, the third area is called occipital and the fourth one is called parietal. Three of them have 4 channels and fourth area has 6 channels. Each channel is formed from the difference of electrical potential between the two electrodes. Therefore, the 6 electrodes of the first, second, and third areas recorded the electrical activity between each other, as shown in Figure 12. In the other area, 9 electrodes is formed electrical activity between each other. The electrodes of the channels, as per the regions of the brain, are shown in the Figure 5.2.

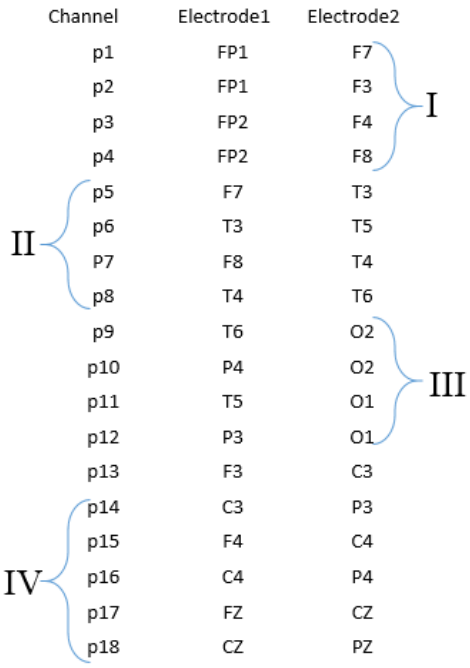


Figure 5.2 The electrodes of each channel in brain regions.

The abbreviations Fp1, Fp2, F7, F3, FZ, F4, and F8 stand for the frontal lobe; T3, T5, T4, and T6 for the temporal lobe; P3, PZ, P4 stand for the parietal lobe; and O1 and O2 stand for the occipital lobe. Note that there exists no central lobe; the letter "C" is used only for identification purposes, while "Z" (zero) refers to an electrode placed on the midline. These electrodes are connected to each other to form a channel.

For SVM classification, firstly, a linear kernel function was chosen because of its simplicity. Linear kernel function is just a dot-product operation [49]. If this choice does not produce satisfactory results, polynomial and radial basis functions (RBF) were going to involve. As explained in detail later, the linear kernel function yields highly satisfactory results. Therefore, other kernel functions were excluded from the study.

5.1 K- FOLD CROSS-VALIDATION TECHNIQUE

K-fold cross-validation technique was used for a reliable measurement on the performance of the SVM. In this process, an original sample set is randomly partitioned into K sample subsets. Among the K subsets, a single subset is regarded as the

validation data for testing the model. The remaining K−1 subsets are used as training data. The cross-validation process is repeated K times (the folds) as shown in Figure 5.3. Each of the K subsets being used exactly once as the testing data.

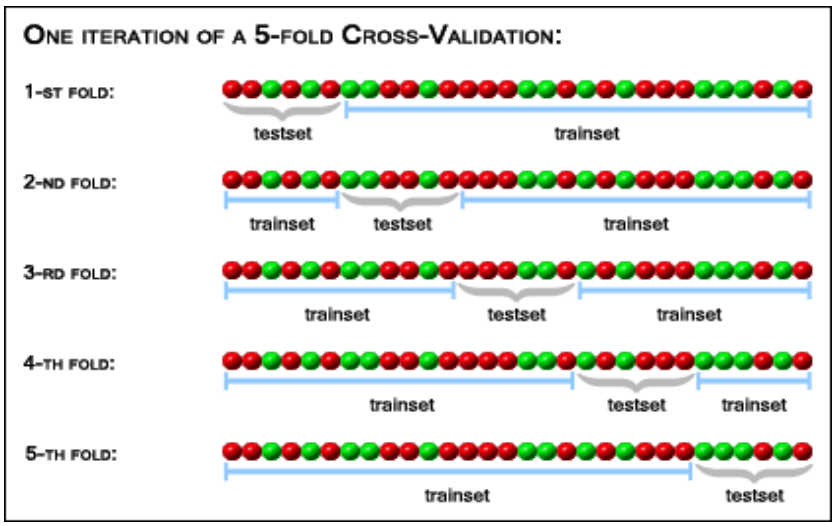


Figure 5.3 An example of 5-fold cross validation technique.

5.2 EFFECTIVENESS RESULTS OF THE CLASSIFICATION

The effectiveness of the classifier can be evaluated using different performance parameters. The terms true positive (TP) and true negative (TN) refer to the total number of correctly identified "epilepsy people correctly diagnosed as epilepsy" and "psychogenic people correctly identified as psychogenic," respectively. False positive (FP) and false negative (FN) are the total number of correctly identified "psychogenic people incorrectly identified as epilepsy" and "epilepsy people incorrectly identified as psychogenic," respectively. The performance parameters can be defined as follows:

- Sensitivity: It is a measure which indicates the proportion of the positive samples from test set, correctly identified as positive samples [50] and can be expressed as follows:

$$Sensitivity = \frac{TP}{TP+FN} * 100(\%) \quad (5.1)$$

- Specificity: It is a measure of the ability of the classifier to accurately identify the proportion of negative samples correctly identified from the negative samples [50] and can be expressed as follows:

$$Specificity = \frac{TN}{TN+FP} * 100(\%) \tag{5.2}$$

- Accuracy: It is defined as the proportion of the samples correctly classified out of the total number of samples [50] and can be defined as follows:

$$Accuracy = \frac{TP+TN}{TN+FP+TP+FN} * 100(\%) \tag{5.3}$$

For each kernel function, some parameters were optimized in the SVM classification. There are parameters that can be utilized for SVM. *C* determines the trade-off between the training errors. *C* is a user-defined constant. In this study, the trial and error method was applied to set the optimal *C* value.

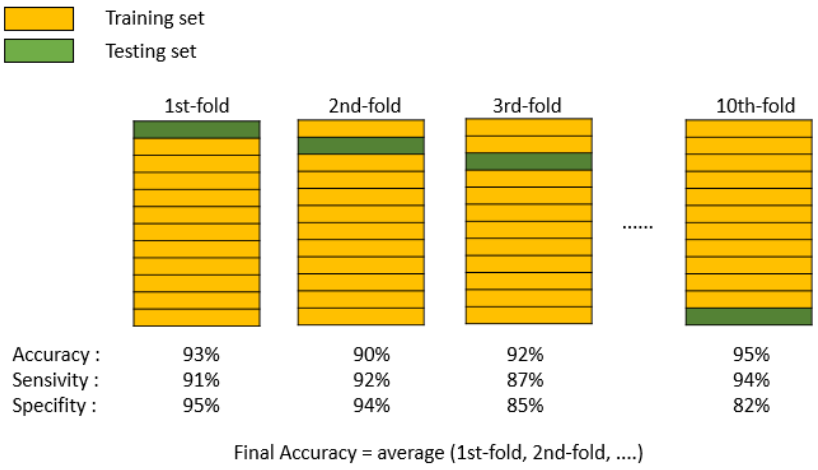


Figure 5.4 An example of 10-fold cross validation.

The K results from the folds were then averaged to produce a single estimation. We choose 10-fold cross-validation because it is widely used in literature [51].

5.2.1 Results of Polynomial Kernel Function

When using the polynomial kernel function as SVM non-linear function for *C=2*, the training and testing accuracy were shown in Table 5.1.

Table 5.1 Classification results all regions of brain with using polynomial kernel function.

Brain Region	Average Training Accuracy (%)	Average Test Accuracy (%)
Frontal	85	79
Occipital	84	74
Temporal	76	72
Parietal	66	65

5.2.2 Results of Radial Basis Kernel Function

When using the radial basis function (RBF) as SVM non-linear function for *C=2*, the training and testing accuracy were shown in Table 5.2.

Table 5.2 Classification results all regions of brain with using RBF kernel function.

Brain Region	Average Training Accuracy (%)	Average Test Accuracy (%)
Frontal	87.7	84
Occipital	85.2	79
Temporal	72	73
Parietal	67	50

5.2.3 Results of Linear Kernel Function

The best classification results were obtained by using linear kernel function. When using the features of the frontal area for *C=0.01*, the sensitivity and specificity were 100% and 100%, respectively. The results of this analysis are shown in Table 5.3. The same procedures are applied the other regions. Their classification results are

provided in Table 5.7. For each region, the C value was optimized, and the best results obtained are provided in the table.

Table 5.3 10-fold classification results of frontal area by using linear kernel function.

Fold number	**Margin**	**# of support vector**	**Training Accuracy (%)**	**Test Accuracy (%)**	**Test Sensitivity (%)**	**Test Specificity (%)**
1	9.59	29	100	100	100	100
2	9.21	30	100	100	100	100
3	9.17	30	100	100	100	100
4	9.51	29	100	100	100	100
5	9.50	29	100	100	100	100
6	9.21	30	100	100	100	100
7	9.18	30	100	100	100	100
8	9.19	30	100	100	100	100
9	9.18	30	100	100	100	100
10	9.21	30	100	100	100	100
	Average		100	100	100	100

As is clear from the table, the frontal area out-performed the others. Followed by the occipital region and temporal region, in that order. The performances of these two regions were over 90%. The performance of the parietal region was quite low as compared to the others. When using the features of the parietal area, the training and testing accuracy were 82.5% and 82.2%, respectively. The sensitivity and specificity results were 85.9% and 75.5% respectively. The results of this analysis are shown in Table 5.4.

Table 5.4 10-fold classification results of parietal area by using linear kernel function.

Fold number	Training Accuracy (%)	Test Accuracy (%)	Test Sensitivity (%)	Test Specificity (%)
1	67	64	71,4	64,5
2	80	88	89,5	79,4
3	70	86	89,6	81,5
4	90	80	83,3	75
5	70	70	76,6	75
6	80	86	92	80
7	100	88	93,5	85,4
8	90	80	89	85,5
9	90	100	100	99,9
10	88	80	83,7	69,2
Average	82,5	82,2	85,9	75,5

The training and testing accuracy of the temporal area were 94.4% and 93.2%, respectively. The results of this analysis are shown in Table 5.5.

Table 5.5 10-fold classification results of temporal area by using linear kernel function.

Fold number	Training Accuracy (%)	Test Accuracy (%)	Test Sensitivity (%)	Test Specificity (%)
1	100	99,9	99,9	99,9
2	99,9	100	100	100
3	100	100	100	100
4	90	90	90,9	89,8
5	90	99,9	99,9	99,9
6	90	90	97,7	98,8
7	100	99,9	99,9	99,9
8	100	90	95,3	96,7
9	90	80	87,5	89,9
10	90	90	95,1	94,5
Average	94,4	93,2	96,6	97

The training and testing accuracy of the occipital area were 96.7% and 95.4%, respectively. The results of this analysis are shown in Table 5.6.

Table 5.6 10-fold classification results of occipital area by using linear kernel function.

Fold number	**Training Accuracy (%)**	**Test Accuracy (%)**	**Test Sensitivity (%)**	**Test Specificity (%)**
1	99,9	99,9	99,9	99,9
2	100	100	100	100
3	100	99,9	99,9	99,9
4	90	90	93,5	92,6
5	99,9	100	100	100
6	90	90	91,5	90,2
7	99,9	99,9	99,9	99,9
8	100	99,9	99,9	99,9
9	100	100	100	100
10	90	80	83,9	85,1
Average	96,7	95,4	96,9	96,8

As per the experience of the physicians, the frontal area is the most effective region to distinguish between epilepsy and psychogenic patients. As seen in Table 5.7, this hypothesis was confirmed with linear kernel function in this study.

Table 5.7 Classification results all regions of brain by using linear kernel function.

Brain Region	**Average Training Accuracy (%)**	**Average Test Accuracy (%)**
Frontal	100	100
Occipital	96,7	95,4
Temporal	94,4	93,2
Parietal	82,5	82.2

The linear kernel function gives the best classification results in this study. However, we noted that the non-linear SVM types are not beneficial for the classification of epileptic and psychogenic seizures.

Literature is poor on the classification of epileptic and psychogenic patients. Therefore, the performance of the proposed method did not compare with another study since we could not identify similar studies in literature. Our proposed method provides a highly accurate classification method for the classification of epilepsy and psychogenic EEG signals.

If region-by-region analysis does not provide satisfactory results, we planned to use all the frontal, temporal, and occipital regions for classification. Since the shows the frontal region gives ultimate classification performance, we do not need to analyze all features in one feature set.

CHAPTER 6

CONCLUSION

In this work, EEG recordings were obtained from patients treated for epileptic and psychogenic seizures at the neurological department of Fatih University Hospital. All recordings were converted to a format readable by the MATLAB program. WT analysis was performed on the obtained data. The LLE was calculated as the non-linear feature, and feature sets were constructed with LLE values for different brain regions, as described by the physician. The SVM method was applied for the classification of EEG signals of epileptic and psychogenic seizures.

In this study, the patients' EEG recordings were obtained, and only these data were used for the classification of seizures. Our findings will enable better diagnosis of the conditions because establishing the diagnosis on the basis of the physician's observations and experiences is difficult and time consuming.

Physicians find it difficult to diagnose some patients by examining their EEG graphs alone. In such cases, the diagnosis is made using the physician's experience, medical history, patient's behavior, and consumed drugs. The proposed method does not involve any parameter other than EEG recordings. Therefore, non-linear analysis yields further information from the signal utilized characteristic features of the EEG signal, which cannot be observed by the physician during clinical examination and history taking alone.

Channels of the frontal area provided better classification accuracy for classifying EEG signal elated to epileptic and psychogenic seizures. Thus, we were able to prove the hypothesis based on the physician's experience that the EEG signals of the frontal region are important to distinguish between epileptic and psychogenic seizures. We

observed that the patterns of the temporal and occipital regions were also distinctive in these two diseases. However, we noted that the parietal region is not beneficial for the classification of epileptic and psychogenic seizures.

We believe that in future, the proposed method can be extended for the classification of other brain conditions such as sleep-stage classification; assessment of patient's emotional state using EEG signals; or the differentiation between epilepsy and other diseases, which is otherwise difficult.

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