**A COMPARATIVE ANALYSIS OF NONLINEAR FEATURES FOR AN HMM-BASED SEIZURE DETECTION SYSTEM**

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**MS Project Report**

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# ABSTRACT

An electroencephalogram (EEG) indirectly measures brain activity by recording electrical activity along the scalp. EEG recordings are used by neurologists to diagnose any disorder that interrupts cortex functions. Commonly diagnosed abnormalities include epileptic events, seizures and strokes. Neurologists manually read and interpret EEGs, which is very time-consuming process due to complex nature of these signals. Diagnosing diseases using an EEG recording requires a detailed knowledge of the patient’s medical history, mental and physical state during the recording process so that abnormal variations in the signal are properly interpreted. Though automated systems have been developed for the past 30 years, the performance of such systems fails to meet clinical standards. The lack of a large amount of clinical data has been a major impediment to the development of such automated systems, preventing the application of a new generation of powerful statistical models.

Hidden Markov models (HMMs) provide a simple and effective framework for modeling time-varying sequences and are used in a wide range of temporal pattern recognition applications. However, HMMs have not yet been applied to EEGs. The objective of this project is to optimize the features used in an HMM-based system. In this work, we show that a combination of traditional speech recognition features and some EEG specific features such as zero-crossing rate produced a 36% reduction in the false alarm rate on a seizure detection task based on the Children's Hospital of Boston (CHB-MIT) database.

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# CHAPTER 1 INTRODUCTION

It is believed that electrical signals generated by the brain represent not only the brain function but also the status of the whole body. Electroencephalogram (EEG) is an important investigation carried out on most patients suspected of having nervous disease. EEG signals are measurements of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex.

EEG helps us to diagnose all neurological disorders that effects on cortex and many other abnormalities or may be used for investigation of the following clinical problems (Teplan, 2002) ;(Bickford, 1987):

(1) Monitoring alertness, coma, and brain death;

(2) Locating areas of damage following head injury, stroke, and tumor;

(3) Investigating mental disorders;

(4) Controlling anesthesia depth (servo anesthesia);

(5) Investigating epilepsy and locating seizure origin;

(6) Testing epilepsy drug effects;

(7) Assisting in experimental cortical excision of epileptic focus;

(8) Investigating sleep disorders and physiology;

EEG machine records electrical potential between two electrodes using surface electrodes and that potential can be recorded using surface electrode. Electrode impedances should be maintained between 100 and 5000 ohms. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology has recommended the conventional electrode setting (also called 10–20) for 21 electrodes (excluding the earlobe electrodes). Electrode placement has been standardized by international 10-20 system that uses anatomical landmarks on the skull including a heart pulse electrode that is known by EKG. The designations; Fp (fronopolar), F(frontal), T(temporal), O(occipital), C(central), P(parietal) are utilized in the 10-20 system. Numbers combined following the letters for location reflect either the left (odd numbers) or right (even numbers) hemisphere of electrode placement. The “z” designation reflects midline placement (i.e. Cz is central midline).

While electrodes conduct electrical potentials from the patient scalp to an electrode box (or jack box), a montage selector allows physicians to use either *bipolar* montage or *referential* montage.

(1) Bipolar montage compares active electrodes sites adjacent to each other and may be arranged in many different spatial formats including longitudinally (also known as “double banana”), transverse fashion, or in a circumferential pattern. Two electrodes that are close to each other have almost same amplitude value and their amplitudes cancel each other and it doesn’t show absolute voltage very well.

(2) Reference montage uses an active electrode to show absolute voltage through amplitude measurement that is related to the area. Physical references can be used as vertex (Cz) linked-ears, linked-mastoids, ipsilateral ear, contralateral ear, C7, and tip of the nose (Sanei et al, 2007).

This chapter will focus first on introduction to normal brain rhythms, the first thing that physicians use to interpret EEG records, and explanation of essential conditions that have to be observed in each subject to be considered as normal case followed by brief explanation of different abnormal morphologies. This includes most common and widespread findings that are slowing in brain rhythms and epileptiform discharges. Finally a brief overview of physiological artifacts that may observe in EEG recordings is provided.

## Normal EEG

Physicians diagnose brain disorders by visual inspection of EEG signals using amplitude and frequency from different states of the subject. The state of wakefulness and age are critical features for accurate interpretation of normal EEG. In healthy adults, the amplitudes and frequencies of such signals change from one state of a human to another. There are four major brain waves distinguished by their different frequency ranges.

*Alpha* is the most prominent rhythm in the whole realm of brain activity with frequencies between 8-13 Hz and it may appear in the posterior half of the head and are usually found over the occipital region of the brain in normal subjects when there is no attention and it is usually reduced or eliminated by opening the eyes or mental concentration or attention. An alpha wave has a higher amplitude over the occipital areas and has an amplitude of normally less than 50µV. Alpha frequency may reduce with advancing age.

*Beta* rhythms are frequencies that are more than 13 Hz. They are common and normally observed within the 18- to 25 Hz with the amplitude of less than 20 µV. Voltages beyond 25µV in amplitude are abnormal. Beta activity is the usual waking rhythm of the brain and is mostly marked in frontocentral region with less amplitude than alpha and normally increases during drowsiness, light sleep, and with mental activation.

*Theta* waves lies within the range 4-7 Hz frequencies of varying amplitude. Theta waves have been associated with access to unconscious material, creative inspiration and deep meditation. Approximately one third of normal awake, young adults show intermittent 6 to 7 Hz theta rhythms of less than 15 µV and it can be seen in the frontal or frontocentral head regions. Presence of high theta activity in awake adults suggests abnormal and pathological conditions. Theta activity is normally enhanced by hyperventilation, drowsiness, and sleep.

*Delta* waves are the waves with frequencies less than 4 Hz and primarily associated with deep sleep stages of adults. Otherwise, they suggest pathologies. The normal elderly may have rare irregular delta complexes in the temporal regions.

****

Figure 1 Typical dominant brain rhythms
from high frequency and low amplitude to low frequency and high amplitude

The value of understanding the normal EEG is for identifying abnormalities. For the successful interpretation of abnormal define normal patterns EEG we must first understand the criteria necessary. The most important factors that a subject must have to be considered as normal are:

***Anterior-posterior gradient***: A normal subject in waking state with close eyes must has beta frequencies in anterior regions with low amplitude, changing the position towards posterior region, frequency decreases and amplitude increases in the way that over occipital region normally we should observe alpha rhythm. This phenomenon vanishes during sleep state.

***Posterior dominant rhythm****:* In the normal EEG, a posterior dominant rhythm is represented bilaterally over the posterior head regions and lies within the alpha frequency. This rhythm remains stable between 8 and 12 Hz even during normal aging into the later years of life and it is distributed maximally in the occipital or parietal-occipital regions. But with advancing age, the frequency decreases.

***Having symmetric activity***: Left and right hemispheres have to be recorded the same activities. Having asymmetric activity represents abnormality. A persistent hemispheric difference more than 1 Hz should be regarded as being abnormal when asymmetry is seen. Additionally, while the right hemisphere is often asymmetrical in respect to voltage, persistent of asymmetry amplitude more than 50% should be regarded as abnormal.

***Normal sleep architecture***: Most noticeable change that occurs during sleeping state is attenuating anterior-posterior gradient. Other wave forms may be seen during sleep states. Stage 1 defined by presence of vertex waves and POSTS. During stage 2 sleep spindles and k complexes can be seen. Although during this stage progressive slowing of background frequencies can be observed. Slow wave sleep describes no REM deep sleep, stage 3 occupying with 1 to 2 Hz delta frequencies and v waves. Eventually non REM and REM sleep alternate in cycle four to six times during a normal night’s sleep. REM sleep characterized by rapid eye movements.

*Vertex sharp transients*: They are usually seen in stages 1, bilateral, symmetrical with maximal amplitude at Cz. They may be seen in central regions and they also exist in frontal regions as well. Vertex waves can be spiky but should normally never be consistently lateralized.

*Positive Occipital Sharp Transients of Sleep* (POSTS): They have frequencies of less than 8 Hz and exist in occipital region.

*Spindle*: Sleep spindles are sinusoidal transients with a frequency between 12 to 14 Hz with wax and wane amplitude seen in central regions with frontal representation by slower frequencies of 10 to 12Hz.

*K complex*: They are high amplitude diphasic waves less than 4 Hz followed by high amplitude slow waves often associated with a sleep spindle in the frontocentral regions.

*V wave*: They lies within the range 4-13 Hz frequency range and can be seen in frontal and central regions.

Sleep elements are normally maximal in frequency in the central location, although they may appear in the frontal regions as well. Spindles are very stable in the bilateral appearance and a persistent slowing of frequency or unilateral appearance should be regarded as an abnormal nonepileptiform feature.

## Abnormal EEG

Nonspecific abnormalities in the EEGs can be divided into three categories: (1) widespread intermittent slow wave abnormalities, often in the delta wave range and associated with brain dysfunction; (2) bilateral persistent EEG, usually associated with impaired conscious cerebral reactions; and (3) focal persistent EEG usually associated with focal cerebral disturbance (Sharbrough, 1999).

Diffuse slowingon the EEG may occur intermittently or continuous and reflects abnormal cerebral function and it may have various morphologies. The slower the frequency, the higher the amplitude and the greater the persistence, the more likely abnormality exists. Diffuse intermittent slowing may reflect either a cortical or subcortical cerebral dysfunction. When theta frequencies are seen in the frontal or frontocentral regions and voltages are greater than 100 µV or when theta is present more than 10% of the time in the adult (not in childhood or elderly), them theta may reflect nonspecific abnormality (but may be seen in young adults). Slowing of posterior dominant rhythm is defined as slowing of the normal posterior background activity to a frequency slower than the normal alpha and is also known as background slowing. Generally whenever blood pressure in brain (cerebral perfusion pressure) decreases, diffuse slowing occurs such as syncope.

Focal abnormalities on the EEG provide electrographic evidence of a localized abnormal cerebral function but not specific for etiology. Temporal intermittent rhythmic delta activity (TIRDA) contains of burst of delta frequencies maximal typically in a strong a temporal derivation and associated with interictal epileptiform discharges. Frontal intermittent rhythmic delta activity (FIRDA) appears in bursts of delta that is often high voltage and well formed. FIRDA may rarely be asymmetrical and is most often associated with encephalopathies of toxic or metabolic origin (Tatum et al, 2008).

Activation Procedures are useful techniques of EEG in clinical practice and represent various types of stimuli or modalities that are able to trigger abnormalities. *Hyperventilation* and *intermittent photic stimulation* are routinely performed to induce slowing and/or epileptiform abnormalities.

Hyperventilation is routinely performed for 3 to 5 minutes in most EEG laboratories. The purpose is to create cerebral vasoconstriction and normally produces a bilateral increase in theta and delta frequencies in the frontal region and often of high amplitude and effects normally within 1 minute. Hyperventilation may produce focal slowing in patients with an underlying structural lesion.

Intermittent photic stimulation normally produces potentials exquisitely time locked to the frequency of the intermittent light stimulus, and is referred to as photic driving or photic response. Photic driving is usually greatest in the occipital location, in frequencies approximating the alpha rhythm, when the eyes are closed.

### Epileptiform Abnormalities

EEG helps us to diagnose epilepsy using signals that are consistent with epilepsy diagnose we can diagnose the disease. Clinically speaking epilepsy is abrupt cessation of brain function. Therefore during seizure, because of abnormal firing neurons that creates abnormal potential particular EEG channels record abnormal signals. Epileptic seizure is an abnormality in EEG recordings and is characterized by brief and episodic neuronal synchronous discharges with dramatically increased amplitude and this may occur in the brain locally (partial seizures) which is seen only in a few channels of the EEG signal, or involving the whole brain (generalized seizures) which is seen in every channel of the EEG signal.

Interictal epileptiform discharges (IED) represent a distinctive group of waveforms that are characteristically seen in persons with epilepsy. Focal IEDs may be either focal, regional, lateralized, or secondarily generalized discharges in their field of involvement. They may help provide information useful in localizing the epileptogenic zone for the purposes of surgical treatment. Frontal, anterior temporal, and midline IEDs have the highest correlation with seizures. The location of focal interictal epileptiform discharges, vary with respect to the potential to generate clinical seizures. Epileptiform discharges appear in different morphologies. Commonly identified IEDs are spikes and sharp waves with or without after going slow waves. Sharp waves are more “blunted” than spikes. Spike –another abnormal epileptiform discharge- has very frequently negative polarity at the surface of the scalp EEG. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology (IFSECN) defined ‘spike’ as a transient, clearly distinguished from the background activity, with pointed peak at a conventional EEG recording speed of 3 centimeters per second and a duration from 20 to 70 ms (i.e. 1/50-1/15s), and a ‘sharp wave’ as a transient with similar characteristics but a duration of 70-200ms (i.e. 1/14-1/5s). Spike-and-slow wave and sharp-and-slow wave are complex discharges, which consist of a spike or sharp wave followed by a slow wave, respectively (IFSECN, 1974). Those discharges of <20 msec are suspect for non-cerebral potentials. Combinations of IEDs often occur in the some patient at different times.

## Artifacts

Since the EEG signals are naturally contaminated by internal and external interferences, various generators of non-physiological and physiological artifacts may deceive the interpreter, the signals have to be preprocessed and restored from artifacts, such as ocular artifact (OA) and eye-blinking, electrocardiograms (ECGs), and any other internal or external disturbing effects. Artifacts such as eye blinks and heart rhythm (ECG) cause the main interfering signals within EEG measurements (Shoker et al. 2005).

Ocular Artifact (OA) artifact seen in the EEG is generated by the electrical potential produce by vertical movement of eye and it creates a DC potential of higher amplitude (mV) than the amplitude produce by brain (µV). The artifact is produced in electrodes around the eye that are Fp1, Fp2, F7, F8, F3, and F4 during vertical eye movements and creates downward deflection. The presence of this artifact helps define the state of patient as being awake. Interfering eye blinks generate a signal within EEGs that is on the order of ten times larger in amplitude than cortical signals and can last between 200–400 ms. The eyeball can be considered as a dipole rotating in a socket. This means that as the eye rotates, the cornearemainsatapotential0.4–1mV positive with respect to the retina. Rotations of the eyeball in saccadic eye movements cause large external field variations that can contaminate EEG readings. Eye-blinking artifacts are very clear in both frontal and occipital EEG recordings. ECG can be seen more over the occipital electrodes (Sanei, 2007). Fine eyelid movements may produce rhythmic 4-8 Hz high amplitude activity in the frontal leads (disappear on fixation). To eliminate eye movement artifacts except closing eyes or fixation, placing extra-ocular electrodes can easily distinguish from frontal slow waves.

Being useful of EKG is not limited to identifying an artifact. Heart rate range represents either normal or abnormal situations for example monitoring heart rate during seizure gives 100 heart rate or greater and also 30 to 40 heart rates represent syncope. The EKG should be monitored during EEG to provide information about the relationship between the heart and brain. The most important usage of EKG is to identifying an artifact that may appear simultaneously seen in several channels and it occurs when an electrode is in a position that is near an artery such as T6.

Myogenic artifact consist of brief potential that may occur individually or continuous. Contraction of the anterior muscles of the scalp produce EMG artifact superimposed upon EEG activity and may cause misinterpretation by resembling spike or control beta activity. EMG activities also created during a seizure or during movements are due to increased muscle tone and are maximal in the temporal or frontopolar derivations. EMG potentials are of extremely short duration (2-20 m sec) compare to cortical spikes. During sleep EMG activity is reduced whereas cortical spikes increase.

There are many other myogenic artifacts such as swallowing (Usually produces a short burst activity), glossokinetic (movement of the tongue during speaking 2-6 Hz usually on Fp1/2), sniffling artifact (small EMG component with a slow wave), chewing (high voltage temporal due to contraction of the muscles associated with mastication), clenching and grinding teeth.

In order to reduce this kind of artifacts patient may use relaxation techniques, close eyelids lightly and relax (frontal), open the mouth (temporal), and put pillow under neck (occipital).

## The Overview

The remainder of this project will be broken down into the following sections. In Chapter 2 details of data acquisition are explained and Chapter 3 explains baseline system followed by explanations of appended discriminative features including temporal features, frequency features, and non-linear features. Chapter 4 provides a detailed analysis of the results found from the experiments and finally chapter 5 presents discussion and conclusion.

# CHAPTER 2DATA COLLECTING

1.

## Dataset

The EEG data used in this project is CHB-MIT database. The dataset consist of 916 hours of artifact free, continuous EEG from 24 patients. This database, collected at the Children's Hospital Boston, consists of EEG recordings from pediatric subjects with single type seizures (temporal lobe seizure).

These EEG data had been acquired and sampled at a 256 Hz sampling rate, and digitized to 16 bit by an analogue-to-digital converter. In the source dataset, a certified epileptologist had previously selected seizures. The data was segmented into one hour long records. There were in total 664 EEG recordings files, among these 129 files consisted of one or more seizures. In all, these records include 198 seizures. EEG signals were recorded using 23 channels in most and 24 or 26 in few cases according to international 10-20 placement system. More details of CHB-MIT database can be found in Shuaib & Guttag 2010.

## EDF Format

The European Data Format (EDF) is a format for exchange and storage of multichannel biological and physical signals. It was created and developed by a few European 'medical' engineers to compare the sleep analysis algorithms and their results and they agreed upon a very simple file format to exchange their sleep recordings. This format became known as the European Data Format. In August 1990, all participating labs had contributed an EDF sleep recording to the project. An extension of EDF, named EDF+, was developed in 2002 and is largely compatible to EDF: all existing EDF viewers also show EDF+ signals. But EDF+ files can also contain interrupted recordings, annotations, stimuli and events. Therefore, EDF+ can store any medical recording such as EMG, Evoked potentials, ECG.

# CHAPTER 3AUTOMATIC CLASSIFICATION

1.

## Baseline System

The baseline system is created by ISIP members, written in C++ environment. The primarily version of the software extracts four types of signal processing features from each frame. Based on these signal processing features, the system builds statistical models for both seizure and non-seizure segments. The statistical model applies Gaussian Mixtures to model the segments over these features.

The features that the system generates are Temporal Energy, Frequency Energy, Filter bank Amplitude, Cepstral coefficients. Temporal Energy is the corresponding energy value in time domain for each frame, Frequency Energy is the energy value in frequency domain transformed by FFT. Filter bank amplitude is the output of each filter as the signals go through them. Cepstral coefficients are the result of taking the FFT of the logarithm of the estimated spectrum of a signal. These values are stored in binary file that feature generation system returns containing a 3-dimensional matrix. First dimension corresponds channels number, second dimension corresponds frame number, and the third is feature.

As it is mentioned before the data was segmented into one hour long records, thus for each subject we have 16 to 49 records. To train a model we perform one leave out cross validation over records of each subject in a way that we considered one record as test record and built the model using other records, Therefore this system is a subject dependent system.

Before feature extraction a specific type of window (i.e. hamming or linear …) applies to the signal as well as a filter bank. All parameters such as window duration, frame duration, and filter bank details. The software gives these details as well as many other parameters as an argument in form of a text file called parameter file. Parameter file contains three main sections. The first section contains file processing parameters. Output directory, the folder that output feature files are stored, is defined by user within this section, channel selection and montage can be determined in first section. The second section determines signal processing parameters including frame duration, window duration, window type, filter bank details including cut off frequency, passing frequency and number of filters, filter bank FFT order, and details of feature computation (i.e. method of temporal energy computation, number of desired Cepstral coefficients) are to be set in this section. Third section defines the features that have to be computed and the order of features that are returned in feature matrix.

Then using these features it builds statistical models for both seizure and nonseizure segments. These models are GMM with 10 mixture components. A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features in a biometric system, such as vocal-tract related spectral features in a speaker recognition system. GMM parameters are estimated from training data using the iterative Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) estimation from a well-trained prior model. A Gaussian mixture model is a weighted sum of M component Gaussian densities as given by the equation,

where is a D-dimensional continuous-valued data vector (i.e. measurement or features), , i = 1, . ..,M, are the mixture weights, and , i = 1, . . . ,M, are the component Gaussian densities. Each component density is a D-variate Gaussian function of the form,

with mean vector and covariance matrix .

Decoding with these models gave us the sensitivity value of %86.86, total number of false alarm (the number of false positives declared during analysis of non-seizure EEGs) of 14058, and the average of false alarms per 24 hours is 425.93 as they are shown in Table 1. The average detection latency (i.e. the average delay between electrographic seizure onsets marked by the electroencephalographer and algorithmic seizure event declaration) is 2.6. Note that these results are obtained from feature set that contains fenergy followed by 8 Cepstral coefficients (first coefficient C0 replaced by energy), applying left to right frame based algorithm with 2 second duration hamming window and one second frame length, FFT of 512 points followed by a filter bank of 8 channels uniformly between 0.5 Hz – 25 Hz.

Table 1 The Baseline System Results

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **#FA** | **#FA/24h** | **median(Fa/24)** | **#seizures** | **#detected seizures** | **average delay** | **Sensitivity** |
| **Baseline System** | **14058** | **425.93** | **119.51** | **198** | **172** | **2.6** | **0.8686** |

## Appended Features

As it is mentioned before the objective of this project is to add and apply six other discriminative features to the system to analyze the performance of the system using each of these features and compare the results. These features are divided to three main categories which are temporal features, frequency domain features, and information theory features.

### Temporal Features

### Zero-Crossing

Zero crossing determines how many times the data cross zero and the value is strongly related to changes in the frequencies. During seizure activity the value of zero crossing changes. Throughout the literature a variety of seizure detection experiments used zero crossing and Van Putten et al. 2005 performed one of the good ones.

### Kurtosis

Kurtosis is a measure of the "peakedness" of the probability distribution and shows data are peaked or flat relative to a normal distribution. The kurtosis for signals with normal distributions is three. The kurtosis for a real signal is defined as

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

 is the *i*th moment of the signal that is

Data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak. The signals with more uniform distributions such as normal brain rhythms have a low kurtosis, whereas seizure signals or event related potentials (ERP signals) often have high kurtosis values (Sanei et al, 2007).

### Average Peak, Average Valley

Average peak amplitude finds the base-10 logarithm of the mean-squared amplitude of each of the *K* peaks, where a peak is defined as a change from positive to negative in the signal derivative sign. Let be the index of the th peak and its value

Average valley amplitude finds the base-10 logarithm of the mean-squared amplitude of each of the *K* valleys, where a peak is defined as a change from negative to positive in the signal derivative sign. Let be the index of the th peak and its value (Wulsin et al. 2011)

### Frequency Domain Features

### Wavelet Transform

The Wavelet Transform is an effective and powerful tool in signal processing especially for non-stationary signals which localizes the signal components in the time-frequency space and exploits the dependency between time and frequency components. In order to process digital signals a discrete approximation of the wavelet coefficients is required. Different method was presented by Ocak to detect epileptic seizure in EEG using wavelet transform decomposition followed by extraction of Approximate Entropy from approximation and detail coefficients (Ocak, 2009).

In DWT, the inner product of the original signal with the basis wavelet function is taken at discrete points and the result is weighted sum of a series of bases functions. The discrete wavelet transform (DWT) can be derived in accordance with the sampling theorem if a frequency band-limited signal is processed. Since generally the wavelet function *ψ(t)* is not band-limited, it is necessary to suppress the values of the frequency components above half the sampling frequency to avoid aliasing effects.

### Daubechies Wavelet

Daubechies wavelets of different orders were investigated for the analysis of epileptic EEG records. This family of wavelets is known for its orthogonality property and efficient filter implementation. Daubechies order 4 wavelet was found to be the most appropriate for analysis of epileptic EEG data (Adeli et al 2003). The lower order wavelets of the family were found to be too coarse to represent EEG spikes properly. The higher order ones have more oscillations and cannot represent the spiky form of the absence seizure epileptic EEG signal. Therefore selection of suitable wavelet and the number of decomposition levels is very important in analysis of signals using DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlates well with the frequencies required for classification of the signal are retained in the wavelet coefficients (Subasi 2007). The signal is decomposed to details (e.g. for five levels of decomposition D1-D5) and one final approximation. Original signal is the sum of the first level of approximation A1 and the first level of details D1. Approximation A1 is obtained by superimposing details D2 on approximation A2 in other word the first level of approximation A1 is the sum of the second level approximation A2 and the second level detail D2; and so on. Table 1 contains corresponding wavelet sub-band frequencies with sampling frequency 256 Hz.

Table 2 Frequencies corresponding to different levels of decomposition for Daubechies 4 filter wavelet with sampling frequency of 256 Hz

|  |  |
| --- | --- |
| Decomposed signal | Frequency range (hz) |
| D1D2D3D4D5A5 | **64 – 128****32 – 64****16 – 32****8 – 16****4 – 8****0 – 4** |

Note that for n level of decomposition the length of the signal has to be equal or greater than .

### Wavelet Energy

Wavelet coefficients provide a representation showing the energy distribution of the EEG signal in the time and frequency. After decomposition of EEG signals using Daubechies’ forth order wavelets, energy feature is extracted from the wavelet sub-band frequencies. Since the EEG signals do not have any useful components above 30Hz, wavelet energy extracts from A5 (delta range), D5 (theta range), D4 (alpha rang), and D3 (beta range) coefficients.

The energy of each band is calculated using the corresponding coefficients as follows:

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

Which is coefficient value for each epoch containing N samples.

### Information Theory Features

Neuronal systems certainly involve non-linear mechanisms at the microscopic level, therefore it seems reasonable to hypothesize that some of the complex and, at times, unpredictable behavior of human EEG, reflects the effects of those underlying non-linear mechanisms (Casdagli et al., 1997). Non-linear time series analysis (NTSA) offers a variety of algorithms and measures, each extracting different dynamical features from the underlying dynamical system. Non-linear dynamical analysis has emerged as a novel method for the study of complex systems in the past few decades. Application of non-linear dynamics methods to the physiological sciences demonstrated that non-linear models are useful for understanding complex physiological phenomena such as abrupt transitions and chaotic behavior. The analysis helps us to understand complexity and highly irregular and non-stationary property. The non- linear dynamical techniques are based on the concept of chaos and it has been applied to many areas including the areas of medicine and biology and also is effectively applied to EEG to study the dynamics of the complex underlying behavior by proposing several features to detect the hidden important dynamical properties of the physiological phenomenon.

### Approximate Entropy

Entropy is an indicator of the degree of the disorder of a system, and reflects how well one can predict the behavior of each respective part of the trajectory from the other. From an information theory perspective, the above concept of entropy is generalized as the amount of information stored in a more general probability distribution. Approximate Entropy is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time series data. ApEn assigns a non-negative number to a time series, with larger values corresponding to more complexity or irregularity in the data while moment statistics will not distinguish between two series which one alternates 0 and 1 perfectly and second one chosen randomly, each with probability of ½. ApEn reflects the likelihood that “similar” patterns of observations will not be followed by additional “similar” observations. A time series containing many repetitive patterns has a relatively small ApEn, a less predictable (i.e., more complex) process has a higher ApEn. Smaller values of ApEn imply a greater likelihood that similar patterns of measurements will be followed by additional similar measurements. If the time series is highly irregular, the occurrence of similar patterns will not be predictive for the following measurements, and ApEn will be relatively large.

ApEn was initially developed to analyzed medical data such as EEG and heart rate. It can be employed to characterized interictal and ictal EEGs. During an epileptic seizure, the loss of complexity in ictal EEG results in the decrease of ApEn (Diambra et al., 1999), thus it can remarkably enhanced the recognition accuracy.

Pincus proposed approximate entropy and successfully applied it to relatively short and noisy data. The algorithm for computing ApEn proposed by Pincus (Pincus et al 1991, Pincus 1991), here a brief summary has been provided:

***1.*** Form the series data . These are N raw data values from measurement in time.

***2.*** Fix *m* and *r*

*m* is an integer represents length of compared run of data (length of window) also known as embedding dimension. And r, vector comparison distance, is positive real number specifying a filter level. Choosing m and r depends greatly on the application.

***3.*** Form a sequence of vectors defined as in, real m-dimensional space.

***4.*** For each i, 1≤ i ≤ N-m+1 in which

|  |
| --- |
|  |

|  |  |  |
| --- | --- | --- |
|  ***5.***  |  | (3) |

The are the m scalar component of x and d represents the distance between the vectors and

|  |  |  |
| --- | --- | --- |
| ***6. ApEn =***  |  | (4) |

A number of authors have looked for the presence of non-linearity in human EEG signals with varying applications applied to EEG signals to detect different states or abnormalities. Kannathal et al. tested the seizure detection performance of various entropy measures including Approximate Entropy and Kolmogorov entropy and they demonstrated that the entropies of epileptic activity are less as compared to that of non-epileptic activity (Kannathal et al. 2005).Diambra et al. classified epileptic activity from EEG background activity using Approximate Entropy. The studies demonstrated that entropy values computed for the epileptic EEG were lower compared to the values computed for the normal EEG (Diambra et al. 1999a) ;(Diambra et al. 1999b). Archarya et al. used non-linear analysis to distinguish various sleep stages (Acharya et al., 2005).

### Hurst Exponent

Hurst exponent is an indicator that has been used to describe the correlation properties and self-similarity of physiological time series data and can be employed to characterize the degree of long-range dependence in EEG time series. Yuan, Q. demonstrated that Hurst exponent of ictal EEG are generally lower than interictal EEGs which shows that the anti-persistent density of the EEG signal becomes stronger and the persistent density turns weaker during an epileptic seizure.

Hurst exponent H can be employed to characterize the degree of long-range dependence in EEG time series. If H= 0.5, the analyzed time series is similar to a random walk. If 0<H< 0.5, the behavior of the time series exhibits anti-persistence, i.e., if the time-series increases, it acquires a higher likelihood of decreasing in the future time, and vice versa. If H is close to 1 reflects the persistent density and closer to zero is H, the anti-persistent density is stronger. If 0.5 <H< 1, there are persistent effects in the behavior of the time series so that the process displays a tendency that if the time-series increases, it is more probable that then it will keep on increasing (Acharya et al, 2005)

R/S algorithm for Hurst exponent is defined as:

|  |  |  |
| --- | --- | --- |
|  |  | (5) |

 denotes the standard deviation of the time series ,

 is the difference between the maximum value and minimum of deviations corresponding to n:

Which is the deviation from the mean for the first k data points is defined as

 , where 1 ≤ k ≤ n, 1 ≤ n ≤ N.

# CHAPTER 4 RESULTS

Chapter 4 focuses on the results found from the experiments using the baseline and various feature sets described in Chapter 3. The evaluation experiments are used to test the effects of different statistical features on seizure detection performance. In this work, first step is to perform six sets of experiments to see the performance of the system using each feature set. The six new feature vectors are constructed by simply appending the features to the existing baseline features as Table 3 shows their details.

Table 3 Description of the different feature sets used for evaluation

|  |  |  |  |
| --- | --- | --- | --- |
| **Feats\_01** | **fenergy** | **8 Cepstral, no C0** | **Zero-Crossing** |
| **Feats\_02** | **fenergy** | **8 Cepstral, no C0** | **Kurtosis** |
| **Feats\_03** | **fenergy** | **8 Cepstral, no C0** | **Hurst** |
| **Feats\_04** | **fenergy** | **8 Cepstral, no C0** | **Peak, Valley** |
| **Feats\_05** | **fenergy** | **8 Cepstral, no C0** | **Wavelet Energy** |
| **Feats\_06** | **fenergy** | **8 Cepstral, no C0** | **ApEn** |

Decoding with the models that are built with these six models gave us up to 1.75 percent improvement in sensitivity and up to 36 percent improvement in false alarm rate and they are obtain from feats\_03 and feats\_01 respectively. For feature sets containing Approximate Entropy, zero-crossing, and Hurst exponent significant improvements were observed for false alarm rates. The improvements in sensitivity were seen for Hurst exponent, Approximate Entropy, and zero-crossing. Table 4 shows detailed results of decoding for each of six features including number of detected seizures and average delay.

Table 4 Detailed results of first feature sets

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **#FA** | **#FA/24h** | **median(fa/24)** | **#seizures** | **#detected seizures** | **average delay** | **Sensitivity** |
| **Baseline System** | **14058** | **425.93** | **119.51** | **198** | **172** | **2.6** | **0.8686** |
| **Zero-Crossing** | **8969** | **271.74** | **58.43** | **198** | **174** | **1.8** | **0.8787** |
| **Kurtosis** | **12714** | **385.21** | **139.53** | **198** | **171** | **2.67** | **0.8636** |
| **Hurst** | **9669** | **292.92** | **105.58** | **198** | **175** | **1.88** | **0.8838** |
| **Peak/Valley** | **14062** | **426.05** | **119.51** | **198** | **172** | **2.6** | **0.8686** |
| **Wavelet Energy** | **14062** | **426.05** | **119.51** | **198** | **172** | **2.6** | **0.8686** |
| **ApEn** | **9736** | **294.98** | **122.71** | **198** | **169** | **1.87** | **0.8535** |

All these six feature sets resulted in a decreased average delay to the baseline system. The evaluation results for six feature sets are presented in Figure 2 and Figure 3.

Figure 2 Sensitivity for different feature sets

Figure 3 False alarm (per 24 hour) for different feature sets

Table 5 represents improvements in sensitivity and false alarm for each feature set.

Table 5 Improvements of sensitivity and false alarm

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **#FA** | **FA Improvement** | **Sensitivity** | **Sensitivity Improvement** |
| **Baseline System** | **14058** |  | **0.8686** |  |
| **Zero-crossing** | **8969** | **0.3620** | **0.8787** | **0.0116** |
| **Kurtosis** | **12714** | **0.0956** | **0.8636** | **-0.0058** |
| **Hurst** | **9669** | **0.3122** | **0.8838** | **0.0175** |
| **Peak/Valley** | **14062** | **-0.0003** | **0.8686** | **0.0000** |
| **W-energy** | **14062** | **-0.0003** | **0.8686** | **0.0000** |
| **ApEn** | **9736** | **0.3074** | **0.8535** | **-0.0174** |

The next step is combining these six feature sets and compare the performance of the system. These feature vectors are constructed by adding two or more of the features to the existing baseline features and also combining all these six features to construct a feature vector. The performance of the system using each of these feature sets is shown in Table 6.

Table 6 Comparison of all feature vectors

# CHAPTER 5DISSCUSSION AND CONCLUSSION

The purpose of this work was to determine whether selected features could improve recognition performance for a seizure detection system. As results shows three feature sets have improved false alarm rates and also two of them have better sensitivity rates. According to the results of the experiments presented in the previous section, the appended features used in this work are able to have a great improvement in false alarm rate but slight improvement in sensitivity. For Approximate Entropy, zero-crossing, and Hurst exponent overall relative improvements of %36.3, %36.2, and %31.2 were observed for false alarm rates respectively. The relative improvements in sensitivity %1.7, and %1.1 were seen for Hurst exponent, and zero-crossing. Therefore these results suggest that these features can be applied in order to have vast improvement in false alarm and to have a more accurate seizure model.

One reason that improvement in sensitivity is small may be that the feature computation method is frame base, since frame-based feature extraction estimates features from small segments of the signal, the length of the seizure segment may be too long to estimate accurately.

The performance improvements suggest that most of appended features have a significant contribution to seizure detection and can be used to construct more accurate seizure models.

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