DETECTION OF SEIZURES IN AN EPILEPTIC EEG SIGNAL
Implementation and comparison of STFT and Wavelet techniques

Poojitha Kale
Pxk51@psu.edu

ABSTRACT

This project focuses on detection of seizures in an Epileptic EEG signal using the STFT, wavelet and sparsity techniques. Detection sensitivity and false-positive detection for each technique is compared. During the course of this project, Short-time Fourier Transform (STFT), Wavelet and Sparsity techniques will be applied to EEG signals to extract features from the segments of data which will help classify the epileptic signal into normal, ictal and interictal changes in brain activity.

1. INTRODUCTION

Epilepsy is the 4th most common neurological disorder affecting nearly 1% of the world's population. It is characterized by a series of unpredictable seizures, which are periods of sudden surge in electrical activity of the brain. EEG electrodes are used to capture, monitoring and analyzing the electrophysiological signals from the brain. It is very tedious, expensive and impractical to have a person constantly observe the EEG recordings of every patient that is monitored. Hence, automatic seizure detection becomes necessary in long-term epilepsy monitoring. Careful analysis of the EEG records can prove to be a valuable insight in improving the understanding of the mechanisms causing epileptic disorders.

EEG signals contain a wealth of information regarding the activity of the brain. Clinicians have studied the epileptic EEG segments and classified them into three types of electroencephalographic changes: ictal – which is characterized by continuous rhythmical activity that has a sudden onset when a patient is exhibiting a seizure; interictal – which is characterized by small spikes and subclinical seizures that generally occur during the time between seizures; and normal EEG segments. The detection of these activities by visual inspection is strenuous and requires training and good experience in order to make a credible prediction. These issues can be solved by developing algorithms to automatically detect the change in activity. Such techniques are faster, easier, more effective and inexpensive to study epileptic activity.

Firstly, spectral analysis of the EEG signals is performed using the short-time Fourier transform (STFT), this involves dividing the signal into small sequential (or overlapping) data frames and fast Fourier transform (FFT) is applied to each frame. To obtain short data frames, the signal is multiplied with a window which modifies the signal so that it is zero outside the data frame. The analyze the entire signal, the window is translated in time and applied to the signal. The outputs of successive STFTs provide a time-frequency representation of the signal.

The next approach would be the discrete wavelet transform (DWT). It is a versatile signal processing tool which can be employed successfully to detect seizures because it captures transient features and localizes them in both time and frequency domains. It is important to select a wavelet that matches the shape or frequency characteristics of seizures. The wavelet coefficients for different scales are obtained using a simple recursive digital filter. The output of the high pass filter gives the set of DWT coefficients that capture the fine information carried in the signal while the output of the low pass filter gives the coarse information of the signal. Therefore, wavelets can be viewed as a set of functions that can be used to represent natural, highly transient phenomenon such as spikes and seizures in the EEG.

This project will be able to classify the epileptic EEG signals using the STFT method and Wavelet method. The accuracy of this classification will be measured in terms of detection accuracy and false-positive detection.

2. TECHNIQUES

2.1 Short-time Fourier Transform (STFT):

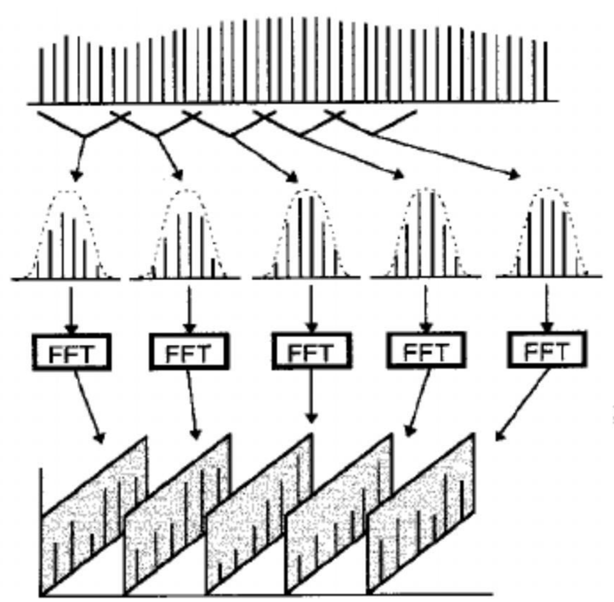
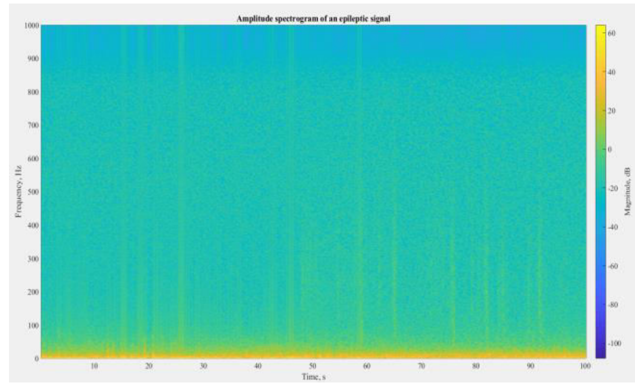
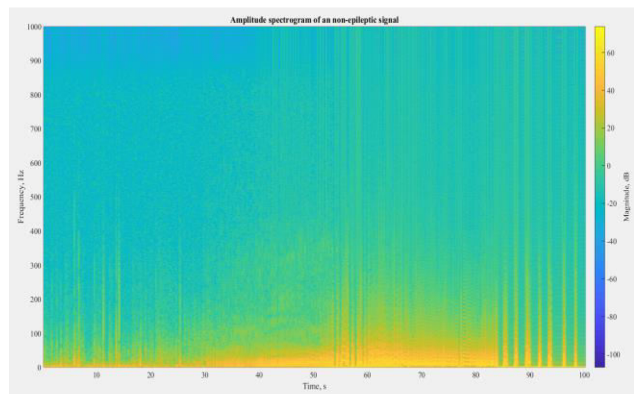


Fig 1. STFT on an EEG signal

Spectral analysis of the EEG signal is performed using the short-term Fourier transform (STFT), in which the signal is divided into small overlapping data frames and fast Fourier transform (FFT) is applied to each one.



(a)



(b)

Fig 2. This figure shows the frequency content of an EEG signal with an epilepsy in (a) and without epilepsy in (b). It can be seen that the average frequency content of the EEG signal with seizure is relatively lower.

A special case to Short-time Fourier transform (STFT), Gabor transform, is applied in epileptic seizure analysis. Gabor Transform and Frequency Band Relative Intensity Ratio (FBRIR) describe the EEG signal patterns during ictal epileptic discharge. A filter bank consisting of a number of Gabor filters, with different parameters such as orientations and central frequencies, are used to detect the seizure and non-seizure epochs in the signal. Rational functions are used to represent a segment of the EEG signal. Here, I use the rational system to the STFT to obtain a representation of the EEG signal in time-frequency domain.

Figure 2 shows that the frequency versus time plot of the EEG signal. We can see high frequency components in the 2(b) which is the STFT of the non-seizure signal. Based on this observation we use Features from the STFT such as:

a) absolute mean value of coefficients
b) absolute median value of coefficients
c) absolute maximum value of coefficients
d) absolute minimum value of coefficients
e) absolute standard deviation value of coefficients

The coefficients for the channels that observed the seizure activity are lower compared to the channels that did not observed the seizure activity.

2.1.1 Rational Functions

A brief introduction about the theory of rational functions. So, let ℂ stand for the set of complex numbers, 𝔻: = {z ∈ ℂ: |z| < 1} for the open unit disc, ℕ: = {1, 2, 3, . . .} for the set of natural numbers, and 𝕋: = {z ∈ ℂ: |z| = 1} for the unit circle (or torus).

Consider the series with different elements $a0, \ldots, an \in \mathbb{D}$ and the sequence $m0, \ldots, mn \in \mathbb{N}$ called poles and multiplicities. Then, the modified rational functions (MRF) are defined as follows:

$$\varphi_{k,i}(z) = \frac{z_{i-1}}{(1 - \overline{a_k}Z)^i} \quad (k = 0, \ldots, n, i = 1, \ldots, m_k)$$

The parameter a_k is referred to as inverse pole (because $1/\overline{a_k}$ is a pole in the standard sense), i is said to be the order of the basic function. Using a terminology similar to the trigonometric case, the value i = 1 corresponds to the fundamental tone and i > 1 the overtones.

The corresponding biorthogonal rational functions and the so-called Malmquist-Takenaka (MT) system are

$$\Psi_{k,i}(z) = \frac{\Omega_{kn}(z)(z - a_k)^{i-1}}{\Omega_{kn}(a_k)} \sum_{s=0}^{m_k - i} \frac{\omega_{kn}^{(s)}(a_k)}{s!} (z - a_k)^s,$$

$$\Phi_k(z) = \frac{\sqrt{1 - |a_k|^2}}{1 - \overline{a_k}Z} \prod_{j=0}^{k-1} \frac{z - a_j}{1 - \overline{a_j}z},$$

$$(z \in \mathbb{C} \backslash \{1/\overline{a_j}\})$$

Where,

$$\Omega_{kn}(z) = \frac{1}{(1 - \overline{a_k}Z)^{m_k}} \prod_{i=0, i\neq k}^{n} \left(\frac{z - a_i}{1 - \overline{a_i}z}\right)^{m_i}$$

$$\omega_{kn}(z) = \frac{\Omega_{kn}(a_k)}{\Omega_{kn}(z)}$$

with $0 \leq k \leq n$ and $1 \leq i \leq m_k$. The systems above are biorthogonal and orthogonal with restpect to the scalar product of the Hardy space $\langle F|G\rangle = \frac{1}{2\pi}\int_{-\pi}^{\pi} F(e^{it})\overline{G}(e^{it})\,dt$ for $F, G \in H^2(\mathbb{D})$. Additionally, we note that the MT and the biorthogonal systems Φ and ψ with the modified rational functions φ are referred as the rational orthogonal basis (ROB).

2.1.2 Generalized Short Time Fourier Transform

Fourier transform is a tool well-known for analyzing the frequency distribution of a signal. Unfortunately, the time information is lost during the transformation. Short time Fourier transform (STFT) attempts to solve this problem.

Let us denote the uniformly sampled $f(t)$ and $g(t)$ functions by $f[n]$ and $g[n]$. Then the discrete STFT over a compactly supported g window function can be written as

$$\mathcal{F}_g f[n,k] = \sum_{m=0}^{M-1} f[n-m]g[m]\epsilon_k[m],$$

where $\epsilon_k[m] = e^{-2\pi m\frac{k}{N}}$, M is the window length of g and N is the number of samples in f. This can be interpreted as a successive evaluation of Fourier transforms over short segments of the whole signal. Additionally, the frequencies can be computed by the squared magnitude of the Fourier coefficients at each section. This is called the spectrogram of the signal f.

Similar representation of the signal by replacing the trigonometric bases ϵ_k with the elements of the ROB. More precisely, let us consider a single pole a_0 with multiplicity $m_0 = M$, and an $f \in H^2(\mathbb{D})$ uniformly sampled function. Then the generalized rational DSTFT can be written as

$$R_\phi \mathcal{F}_g f[n,k] = \sum_{m=0}^{M-1} f[n-m]g[m]\phi_k[m],$$

where $\phi_k[m] = \Phi_k\left(e^{-2\pi\frac{m}{M}}\right)$, but $\psi_k[m] = \Psi_{0,k+1}\left(e^{-2\pi\frac{m}{M}}\right)$ or $\varphi_k[m] = \varphi_{0,k+1}\left(e^{-2\pi\frac{m}{M}}\right)$ can also be used. The related inverse transforms can be written in a similar form

$$f[n-m] \approx \frac{1}{g[m]}\sum_{k=0}^{N-1} R_\phi \mathcal{F}_g f[n,k]\phi_k[m]$$

This can be interpreted as a windowed Fourier transform, but with a different basis. In addition, if $a_0 = 0$ then $\varphi_k[m] = \phi_k[m] = \epsilon_k[m]$ so we get back the ordinary DSTFT.

Since these are orthogonal and biorthogonal projections onto the k dimensional subspaces of $H^2(\mathbb{D})$ the following statements hold:

$$\sum_{m=0}^{M-1}(f[n-m]g[m])^2 = \sum_{m=0}^{M-1} R_\psi \mathcal{F}_g f[n,k]\, \overline{R_\varphi \mathcal{F}_g f[n,k]}$$

$$\sum_{m=0}^{M-1}(f[n-m]g[m])^2 = \sum_{m=0}^{M-1}\left|R_\phi \mathcal{F}_g f[n,k]\right|^2$$

for the related nonuniform discretization. It can be interpreted as the Parseval's formula of this transformation. Hence, it means that the energy of the windowed and the transformation signal are equal, so we have the same property as in the case of the ordinary DSTFT.

2.1.3 Feature extraction

We will apply the generalized rational DSTFT to EEG time-series. To obtain a compact time-frequency resolution, we represent each second of EEG time-series using 16 coefficients of MT rational DSTFT. To extract features from the rational DSTFT representation of the signal, we consider the absolute value of each coefficient. Furthermore, we add five statistical values to our feature vector which are extracted for each 1s long segment as follows: a) absolute mean value of coefficients; b) absolute median value of coefficients; c) absolute maximum value of coefficients; d) absolute minimum value of coefficients; e) absolute standard deviation value of coefficients. Therefore, for each segment containing 1 second of the EEG time-series we obtain a feature vector with 21 feature elements.

An optimal pole is chosen using the particle swarm optimization (PSO) algorithm to minimize the mean square error of the reconstructed signal. Taking advantage of this adaptive behavior of the rational function systems, the error of the projection can be minimized. The purpose of the optimization procedure is to make a compact representation of each segment. Consequently, the coefficients can carry more information and they can be used as a feature. Precisely, the rational systems can be varied from segment to segment in contrast with the uniform representations such as STFT or even the Wavelets where the shapes of the base functions are fixed for all the segments. By this reason, we expect an improvement of the classification algorithms based on the classical STFT.

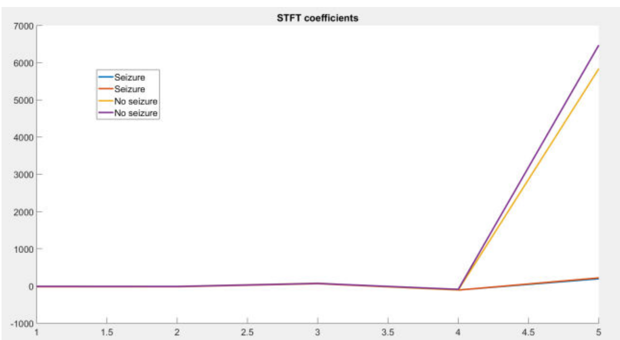


Fig 3. Shows the coefficients of STFT. The coefficients for the channels that observed the seizure activity are lower compared to the channels that did not observed the seizure activity.

2.2 WAVELET TRANSFORM

The wavelet transform has developed into an important tool in signal analysis and feature extraction. It has the ability of providing a representation of the signal in both time and frequency domains. In contrast to the Fourier transform, which provides the description of the overall regularity of signals, the wavelet transform identifies the temporal evolution of various frequencies. This property suits the EEG signal, which is not stationary by nature and has a time varying frequency content and contains paroxysmal events. It becomes important to choose a wavelet that matches the shape and frequency characteristics of seizures.

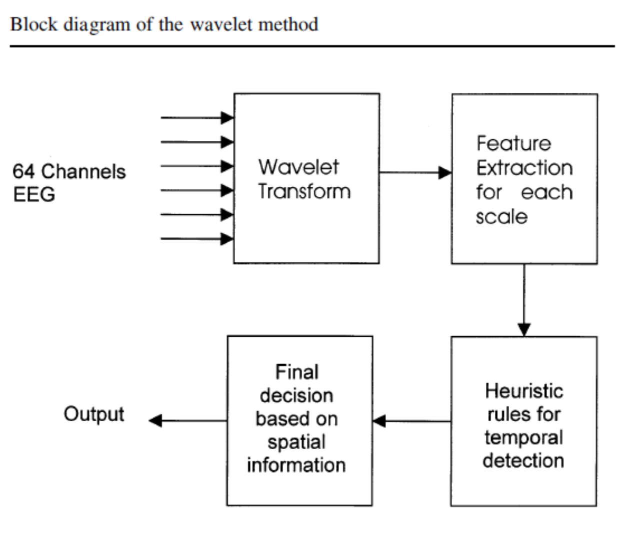


Fig 4. Block diagram of the wavelet method

2.2.1 Features

A. Energy

In the interictal period, the EEG is spread across most scales. In contract, when a seizure occurs the EEG shows rhythmic behavior i.e. a repetition of same waveforms over a period of time, thus exhibiting most of its energy in limited scales of the multi-resolution framework. For the Daubechies wavelet, which forms an orthogonal basis in time-frequency plane, sum of the squares of the coefficients of the wavelet is the energy of the signal. Energy for the DWT for level 'l' is given as:

$$e(l) = \sum_{i=1}^{n} D_i^2 * \frac{\Delta t}{n}$$

Where n is the number of DWT coefficients (D) present in the level 'l' and 'Δt' is the sampling interval.

The relative energy $e_r(l)$ for the level 'l' is evaluated as:

$$e_r(l) = {e(l)}\Big/{\sum_{i=1}^{n} e(i)}$$

Therefore, for the part of the recording where a seizure occurs, the relative energy of the DWT coefficients for a particular level rises to a high value
and can be detected by setting as appropriate threshold (E_{TH}).

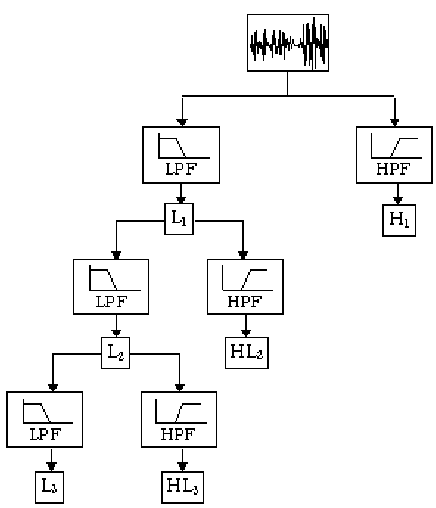


Fig 5. Represents the wavelet decomposition,

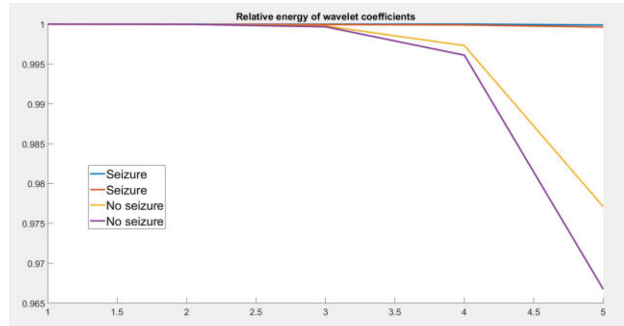


Fig 6. This figure shows the relative energy of the wavelet coefficients at each level of decomposition of the signal. It can be observed from the figure that the energy of the EEG signals that contains the seizure is relatively higher from the signals that do not carry ant seizure.

B. Coefficient of variation

When using EEG amplitude analysis, features often used are the mean (μ), the standard deviation (σ) and the coefficient of variation (${\sigma^2}/{\mu^2}$).

For this project the coefficient of variation (c) is computed on the DWT coefficients for the scaled level 'l'. For this, the waveform decomposition method in which the waveform is broken into segments is utilized. A segment is a section of the waveform between a minimum and the following maximum and vice-versa. Each segment is characterized by its duration, amplitude and direction. The mean and the standard deviation of the amplitudes of the segments is computed and from these we compute the coefficient of variation ($c(l)$) of the amplitudes of the segment. The coefficients od variation are likely to give smaller values for the signals exhibiting rhythmic behavior of regular amplitude, which is seen during many seizures. Thus, a pre-set threshold (C_{TH}) is employed and this coefficient of variation is used as a second feature for seizure analysis.

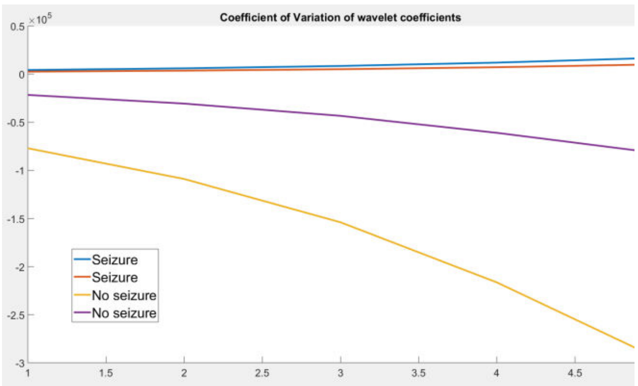


Fig 7. This figure shows the coefficient of variation of the wavelet coefficients at each level of decomposition. From this figure it can be seen that there is little or no variation in the signal during a seizure.

C. Median of relative energy

The value of the median energy level for each EEG signals at all the levels of decomposition is calculated. It is observed that due to the rhythmic behavior of seizures the median of the channels containing the seizure will be low. This is used as the third feature for seizure analysis.

D. Mode of coefficients of variation

The mode of the coefficient of variation of each signal is calculated. This signifies that there is little or no variance in a EEG signal which has seizures. This is used as the fourth feature for seizure analysis.

2.2.2 Detection

One of the major causes of false seizure detection is the occurrence of paroxysmal rhythmic discharges that are part of the 'normal' background. There is a need for the algorithm to learn such paroxysmal non-seizure bursts as it analyzes the EEG. And after some time, it should be able to ignore such non-seizure patterns. To identify and reject such rhythms, a procedure that mimics the human behavior in a sense that the human decision is based on the past content of the EEG is used.

Whenever the features for one epoch pass all the thresholds given above, then a preliminary detection is said to have taken place. Preliminary detections are an indication of the presence of paroxysmal rhythmic activity. For each channel, we run a background array for the mean frequency of the signal for each preliminary detection. When a new preliminary detection is made, we compare its frequency to those in the background array. If preliminary detections with a similar frequency have occurred often in the past, that detection probably originates from rhythmic activity that is occurring frequently in this channel. It is probably not a seizure.

In order for a channel detection to take place in a 5-s epoch of EEG, there must be at least two confirmed Preliminary. For a seizure detection to take place, there must be at least two channel detections separated by less than 15 s in the same channel.

3. PROJECT GOAL:

This project aims to compare the performance of the three techniques described above. The statistical measures to identify the performance are:

- True positive (TP): The no of seizures identified by the automated system and by the EEG experts.
- False positive (FP): The events identified as seizures by the automated system but not by the EEG experts.
- False negative (FN): The events identified as seizures by the experts but missed by the automated system.
- Sensitivity: The ratio of the number of true positives to the total number of seizures detected by the system

$$Sensitivity = \frac{TP}{TP + FN + FP} * 100\%$$

4. Results and Conclusion

The project is implemented in MATLAB. The code was run on two input signals obtained from the same patient. One input has seizures in 6 of the 55 recorded channels, and the other input had no seizures recorded in any of the 55 channels. Wavelet and Short-term Fourier Transform techniques were run on both the input signals.

It was observed that while applying the wavelet transform to the input which had seizures, the computer was able to recognize 5 of the 6 seizures in the patient. But it also recognized 3 seizure that were actually not present in the patient. While in the case of STFT on the input which had seizures, the computer was able to recognize % of the 6 seizures. It also recognized 1 seizure that was not present in the patient. However, for the second input signal no seizures were detected in either of the two methods.

Input 1 (with Seizure)	Wavelet	Total seizures detected: 8 TP: 5 FP: 3 FN:1
	STFT	Total seizures detected: 6 TP: 5 FP: 1 FN:1
Input 2 (without Seizure)	Wavelet	Total seizures detected: 0 TP: 0 FP: 0 FN:0
	STFT	Total seizures detected: 0 TP: 0 FP: 0 FN:0

Table 1: seizures recorded

Method	Sensitivity
STFT	85.7%
Wavelet	80%

Table 2. Shows the sensitivity achieved with each method.

Thus, from the experiment we calculate the sensitivity of each method. The values of sensitivity are shown in the table above. STFT shows a sensitivity of approximately 86% and the wavelet transform shows a sensitivity of 80%. Hence, STFT performs a better job in classifying the seizures in an EEG signal compared to the wavelet transform.

NOTE:
There are a large number of false detections between the correct detections. Care has to be taken that the algorithm does not sacrifice seizure detection performance to achieve the goal of reduced false detections. However, it is important to mention that a perfect seizure detection rate with no false detections is nearly impossible to obtain. This is due presence of great variability in the morphology and the mode of occurrence of seizures.

The data that was used as a part of this experiment was from a research project between the Hershey medical center and the computer science department at University Park.

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