EEG Analyses for Seizure Detection

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Abstract

The EEG allows spontaneous electrical activity in the brain to be measured. The signal recording can be used to detect different information about the patient, such as an epileptic seizure. Using methods of machine learning, different analyses of the EEG signals can be determined. Using Discrete Wavelet Transform (DWT) and Short-time Fourier Transform (STFT), the timing of seizures can be detected and located within an EEG signal. STFT provides detailed information about the EEG signal and can be focused on specific portions of the signal. DWT decomposes the EEG signal into multiple detail vectors which can be analyzed for changepoints, allowing seizures to be specifically located within the signal. These methods can lead to significant implications in suggesting proper medical prevention and precaution with regards to seizures.

Motivation

Electroencephalogram (EEG) is a method that measures the spontaneous electrical activity of the brain. The EEG recordings helps to discover which brain waves are active based on frequencies. Approximately 1% of the world's population suffers from the brain disorder epilepsy. Seizures are a result of epilepsy, and can be monitored using the EEG. By collecting information presented by the EEG, classifiers can be identified in the hope of predicting future occurrences. In this paper, we deal with the appearance of certain patterns in EEG signals during different brain activity of the participants. The methods to be used for detecting the signals are **Discrete Wavelet Transform (DWT)** and **Short-Time Fourier Transform (STFT)**.

1 Introduction

An algorithm based on the dataset could be designed to analyze and predict information regarding detecting seizures. Using data recorded by the EEG, the goal is to identify time periods when seizures are present. If enough seizure patterns are identified, the algorithm will be able to identify similar patterns in the leading moments before an impending seizure. This identification will provide a more sufficient amount of time to prepare those with epilepsy to take the proper precautions.

Two techniques are to be used to analyze the data: Fourier Transform and Discrete Wavelet Transform. Using these Machine Learning methods, the goal is to achieve the best accuracy in classification between normal and epileptic EEG signals. The Fourier Transform decomposes a specific EEG signal into its constituent frequencies. It uses spectral graph commonly called "power spectrum", where power is square of the EEG magnitude. The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations obeying some defined rules.

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2 Data

The dataset used for this project is acquired from the UC Irvine Machine Learning Repository, and is titled Epileptic Seizure Recognition Data Set. This data is recorded in seconds and each recording has 23 seconds. We have total of 500 individual recordings with 4097 data points for 23 seconds. UCI data has total of 11500 rows as there exists 500 patient with 23 seconds of EEG recordings. There exists 179 columns where the last column 179 is the response variable. The response variable is a category of five different types of the EEG recording. The following are the original 5 different types of EEG recording:

1. EEG recording of seizure activity
2. EEG recording from the area where the tumor was located
3. Two different EEG recording: EEG recording of identification of the region where tumor was in the brain and EEG recording of the healthy part of the brain.
4. EEG recording when the patient had their eyes **closed**.
5. EEG recording when the patient had their eyes **closed**.

Visually, seizures can be identified by dense activity in the time series. The goal in this project was to show how data can be detect using some machine learning algorithms. The programming for this research was done in MATLAB. MATLAB is a programming platform that has several packages and techniques that allow the coder to easily design and produce time series visualizations in machine learning.

Data.png Data.png

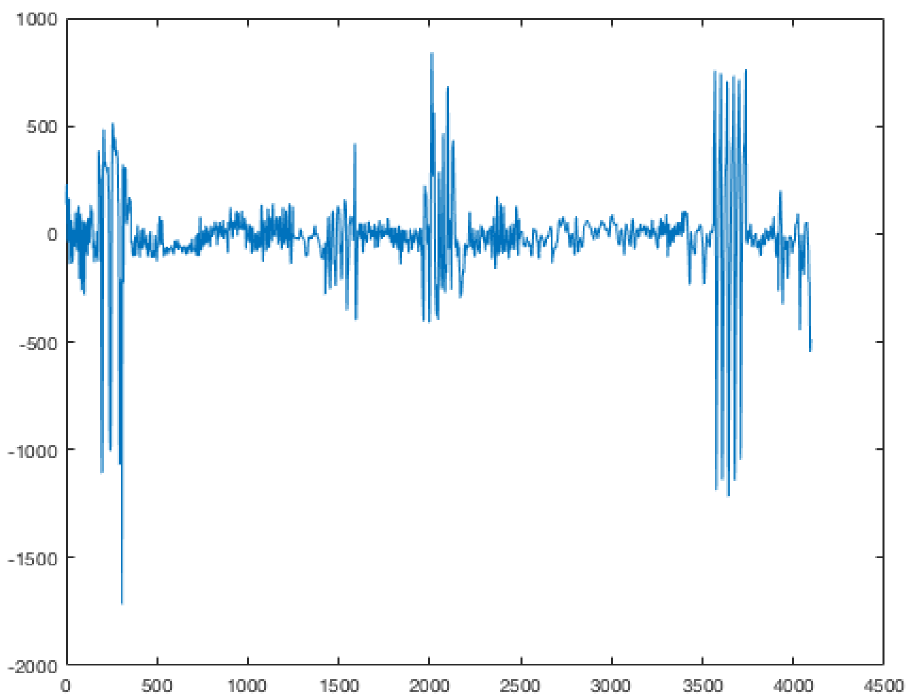

Figure 1: Sample EEG Signal

3 Feature Engineering

This section will cover the following techniques: Fourier Transform, Short-Time Fourier Transform and Discrete Wavelet Transform.
These techniques will cover:

1. Theoretical description of the technique
2. Mathematical description of the definition
3. Results of the specific technique

3.1 Fourier Transform

The Fourier Transform is very useful algorithm in machine learning, as it breaks down a signal into constituent sinusoids of a different frequency. For EEG signals as a sampled vector data we will be using the Discrete Fourier Transform (DFT). The Fourier decomposes the EEG time series into a voltage by frequency spectral graph. Spectral graph is commonly called "power spectrum", with the power being the square of the EEG magnitude, and magnitude being the integral average of the amplitude of the EEG signal. This measured positive and negative peak of each signal. The main idea of Fourier Transform is to help us visually see the structure behind each signal.

Mathematical Explanation of Fourier Transform [3]

The Fourier Transform is defined for a vector x with n uniformly sampled points by

$$y_{k+1} = \sum_{j=0}^{n-1} w^{jk} x_{j+1}$$

$w = e^{-2\pi * i/n}$ is where one of n is a complex roots of unity and i is imaginary unit. The indices j and k ranges from 0 to $n-1$, for x and y. To implement this formula we can use MATLAB Fast Fourier Transform algorithm to show the Fourier Transform of the data.

Computing Fourier Transform in MATLAB The following are the steps of Fourier Transform algorithm:

1 *Figure 2* shows x as a sinusoidal signal and that the x is the function of the time t with frequency of 15 Hz and 20 Hz. A time vector sampled of $1/13$ of a second over a period of 23 seconds.

2 Next, we will compute Fast Fourier Transform of the signal and create f to be a vector or the signal's sampling in frequency space.
Matlab code:
$y = fft(x);$
$f = (0 : length(y) - 1) * 13/length(y);$

3 In *Figure 3* the magnitude of the signal is plotted as a function of frequency. This will correspond to the signal's frequency from part 1.

3.2 Short-Time Fourier Transform (STFT)

Short-Time Fourier Transform (STFT) is very powerful algorithm for signal processing EEG recordings. STFT is basically *time-frequency distributions*. *Time-frequency distributions* is calculating amplitude versus time and frequency of any specific signal. In this project the goal was to create a window by using a spectrum in Matlab. STFT help us find the window of a specific signal where we

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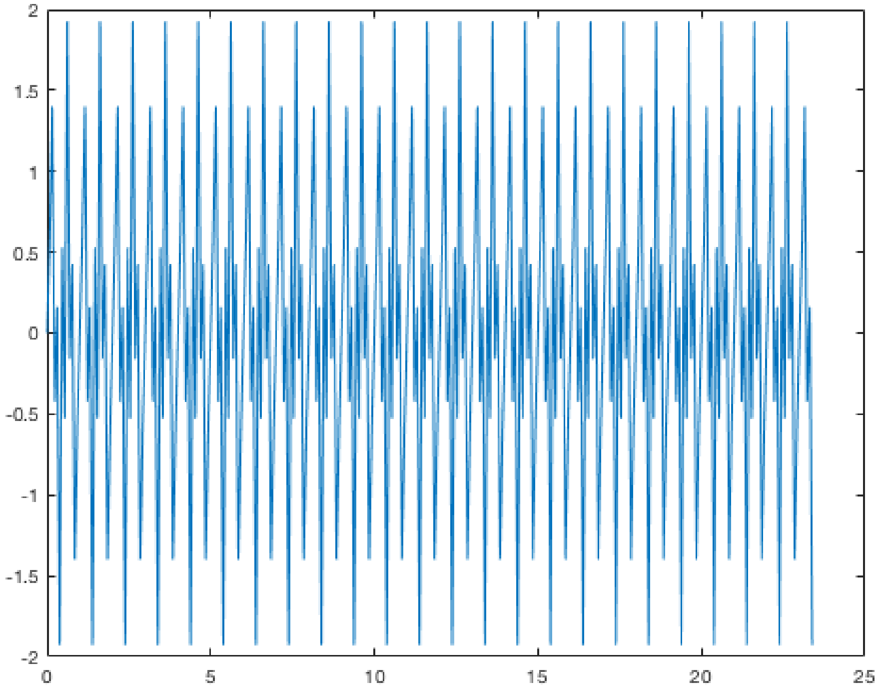

Figure 2: A Sinusoidal EEG Signal

can discover a couple seconds of a specific signal. Basically, we can zoom-in any signal we want and calculate amplitude versus time-frequency of EEG signal recording.

Mathematical Explanation of Short-Time Fourier Transform(STFT) [4]
The STFT is defined as:

$$X_m(w) = \sum_{n=-\infty}^{\infty} x(n)w(n-mR)e^{-jwn}$$
$$= DTFT_w(x * Shift_{mR}(w)),$$

where,

$x(n)$= input signal at time n

$w(n)$ = length M window function (*e.g.,* Hamming)

$X_m(w)$ = DTFT of windowed data centered about time mR

R = hop size, in samples, between successive DTFTs.

In case that the window $w(n)$ has the *Constant OverLap-Add (COLA) property* at hop-size R, *i.e.,* if

$$\sum_{n=-\infty}^{\infty} w(n-mR) = 1, \forall n \in \mathbb{Z}\ (w \in Cola(R))$$

Therefore, the sum of DTFTs over time will be equal to the whole signal $X(w)$ of the $DTFT$:

$$\sum_{m=-\infty}^{\infty} X_m w = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} x(n)w(n-mR)e^{-jwn}$$
$$= \sum_{n=-\infty}^{\infty} x(n)e^{-jwn} \sum_{m=-\infty}^{\infty} w(n-mR)$$
$$\text{where, } \sum_{m=-\infty}^{\infty} w(n-mR) = 1 \text{ if } w \in Cola(R)$$
$$= \sum_{n=-\infty}^{\infty} x(n)e^{-jwn}$$

Signal.png Signal.png

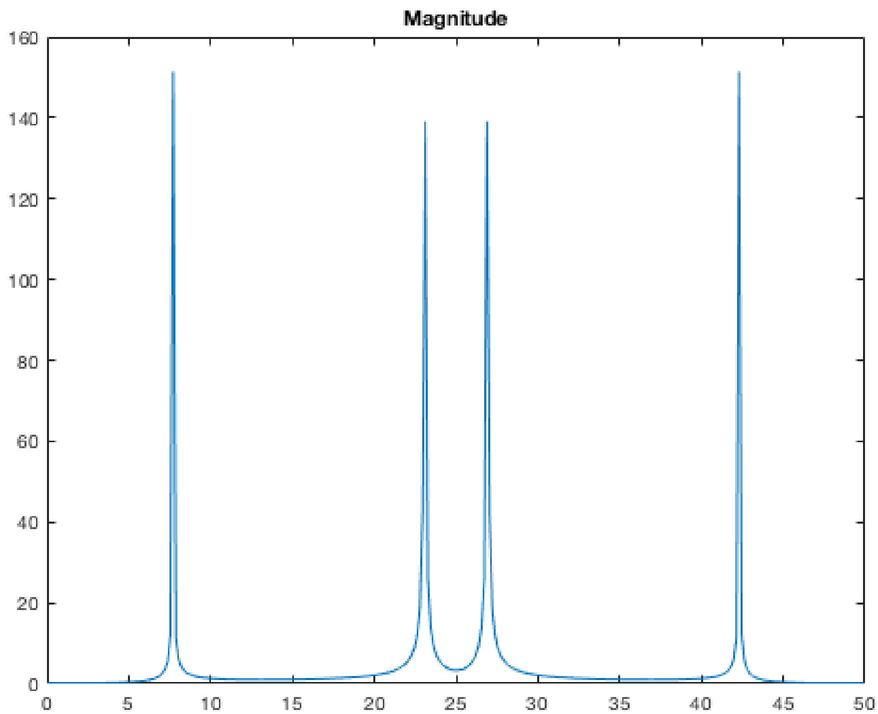

Figure 3: Magnitude of EEG Signal

$$= DTFT_w(x) = X(w).$$

To implement STFT in Matlab we can use Spectrum Analyzer to show the following analyses:

Figure 4 shows the Spectrum Analyzer with four different displays:

1. The first chart shows the row data of the signal. The raw data is data collected by the doctors (in this case) using the brain activity recorded with EEG.

2. The second chart explains the Power Spectrum of the signal. The Power Spectrum focused on the portion of a signal's power among the frequency of the signal.

3. The third chart shows the Spectrogram which explains the time-frequency of the signal. Time-frequency is used in STFT to calculate a specific window of the signal. i.e., Duration of the signal is 23 seconds for STFT is taken a frame of 1 to 7 seconds to zoom-in small parts of the whole recordings.

4. The fourth chart shows the window area that is taken from the original signal.

3.3 Discrete Wavelet Transform (DFT)

Like the Fourier Transform, the Discrete Wavelet Transform (DWT) decomposes a signal in terms of its components. While the Fourier Transform consists of sinusoidal terms, the DWT decomposes a signal into components of different bands of frequency. The DWT aims to decompose a signal into

Analyzer 2 .png Analyzer 2 .png

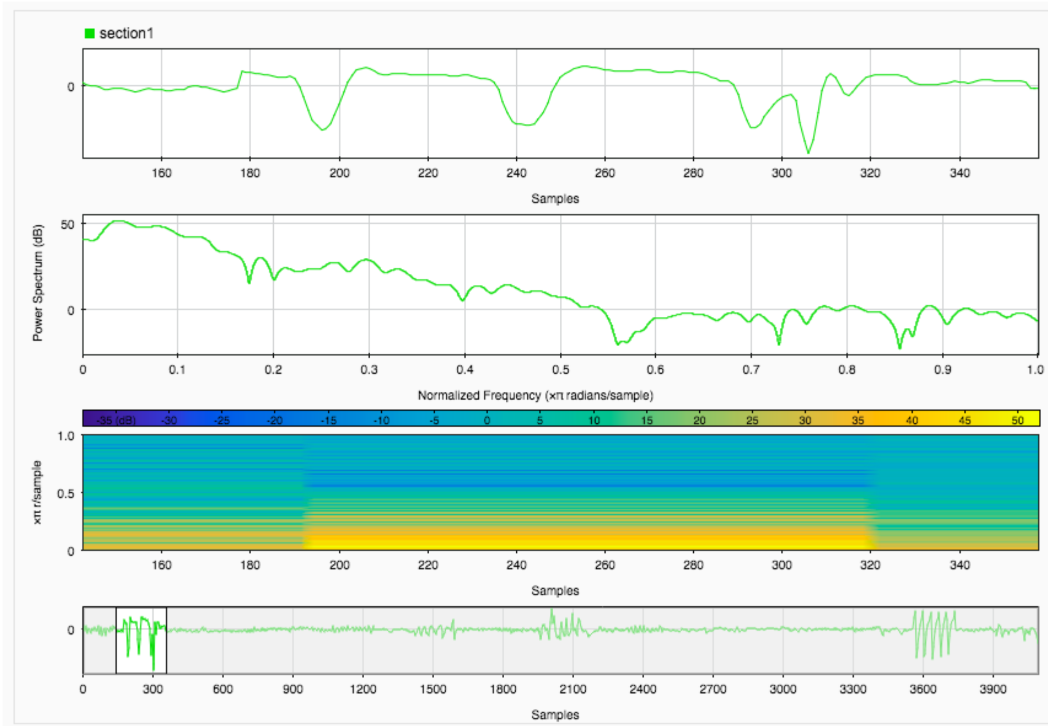

Figure 4: Spectrum Analyzer of EEG Signal

functions that have localized time and frequency, as opposed to the infinite length sinusoids which are utilized by the Fourier Transform.

Several different functions can be utilized and modified for use in the DWT. One of these functions which is found to be quite useful is the Haar function. The Haar function was first introduced in 1910 by Hungarian mathematician Alfred Haar. It is considered one of the earliest and simplest wavelet transforms. The Haar function is commonly employed in the DWT as it provides a local analysis of a signal, as is desired.

To understand it's use in the DWT, the Haar function must first be described. The function is a complete orthogonal system in the Lebesgue space $L_p[0,1], p \in [1, \infty$. It is defined as follows:

$$har(0,\theta) = \{1, 0 \leq \theta \leq 1\},$$
$$har(1,\theta) = \{1, 0 \leq \theta < 1/2 - 1, 1/2 \leq \theta < 1\}$$
$$har(2,\theta) = \left\{\sqrt{2}, 0 \leq \theta < 1/4 - \sqrt{2}, 1/4 \leq \theta < 1/20, 1/2 \leq \theta < 1\right\}$$
$$\vdots$$
$$har(2^p + n, \theta) =$$
$$\left\{\sqrt{2^p}, n/2^p \leq \theta < (n+1/2)/2^p - \sqrt{2^p}, (n+1/2)/2^p \leq \theta < (n+1)2^p 0, 0 < \theta < \tfrac{n}{2^p} and \tfrac{(n+1)}{2^p} < \theta < 1\right\}$$
$$p = 1, ...; n = 0, ..., 2^p - 1$$

This definition provides a uniformly convergent series for any continuous function on $[0, 1]$.
In order to understand how the Haar function is used in the DWT, we will look at a simple definition. The following is the definition of a 2-point single scale DWT using the Haar Transform:

$$\begin{bmatrix} X_\phi(0,0) \\ X_\psi(0,0) \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} x(0) \\ x(1) \end{bmatrix} \qquad \text{or} \qquad X = \mathrm{H}_{2,0}x$$

In this equation X represents the coefficient matrix, H2,0 the transform matrix, and x the input matrix. When using the Haar DWT, it is assumed that the length of the input is a power of 2. To show how the Haar DWT is defined for signals of longer length, the transform of an 8-point input will be defined below:

$$\begin{bmatrix} X_\phi(2,0) \\ X_\phi(2,1) \\ X_\phi(2,2) \\ X_\phi(2,3) \\ X_\psi(2,0) \\ X_\psi(2,1) \\ X_\psi(2,2) \\ X_\psi(2,3) \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} x(0) \\ x(1) \\ x(2) \\ x(3) \\ x(4) \\ x(5) \\ x(6) \\ x(7) \end{bmatrix}$$

The X_ϕ variables found in the coefficient matrix are the approximation coefficients. These coefficients correspond to low frequency components of the transform and provide an approximation of the input signal. The X_ψ variables found in the coefficient matrix are the detail coefficients, which provide a more general description of the input signal.

DWT Results

When observing a signal recorded by the EEG, it is possible to locate and identify the onset of a seizure. After years of experience, a medical professional might be able to detect a visible change in the EEG signal, and with a fair degree of certainty, identify a region as a seizure. While this identification may generally be reliable, it is highly desirable to produce as close to perfect of an identification system as possible. For this reason, several methods of machine learning have been employed to identify and predict seizures.

By using the Haar DWT on each time series, detail coefficient vectors can be produced. The detail vectors provide more concise and abrupt variance changes than the original signal, and as a result are good components to detect changepoints. By identifying common variance changepoints amongst the Haar detail coefficients, it is plausible that seizures recordings can be distinguished from non-seizure recordings in the time series.

To carry out this test, an algorithm was produced in MATLAB. The algorithm has many tasks to carry out that provides the ultimate desire of identifying seizures. Elements of the algorithm include a restructuring of data, a relabeling of chunks to 0 and 1 as described earlier, the 1-dimensional Haar transform, and a variance change detector.

Figure 5 displays a graph of the time series of an individual EEG recording along with its associated detail vectors:

The variance changepoints of these detail vectors were calculated and identified in *Figure 6*. The green lines on the top graph represent the variance changepoints, while the red lines on the bottom graph represent the actual locations in which recording of the seizures start and end:

Details.png Details.png

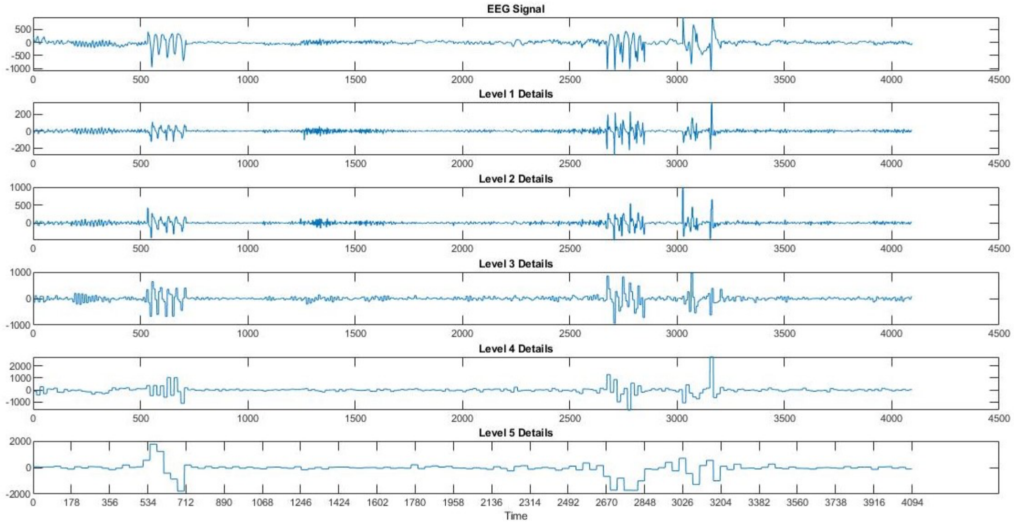

Figure 5: Detail Vectors for EEG Signal

Predictions.png Predictions.png

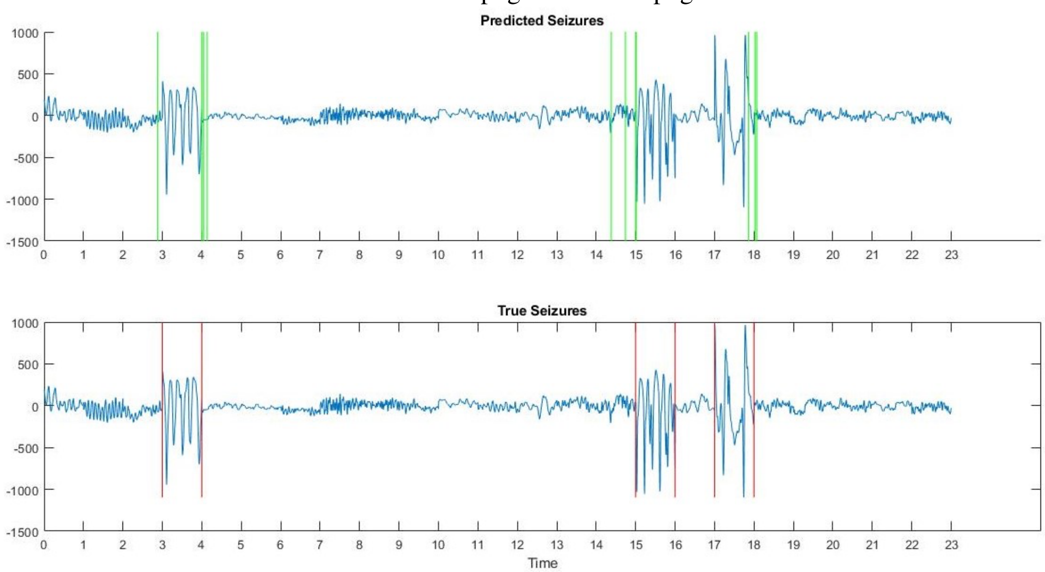

Figure 6: Predicted Seizures vs. Actual Seizures

As is evident, the predicted seizure locations are considerably accurate, however there are some concerns. When multiple seizure recordings occur with little time in between, the algorithm has trouble distinguishing them as two separate entities. In the example illustrated above, the algorithm fails to distinguish the seizures in the 15-16 range and the 17-18 range as two separate seizures. Instead it identifies one longer seizure from approximately 15-18.

4 Conclusion

After creating an algorithm that identifies seizures within the signal, the next logical step would be to create some sort of validation system which would determine whether each prediction was accurate. This could be done by checking if for each predicted seizure, there was a manually recorded seizure for the same time frame. This check would produce an output vector which would denote a value of 0 for a failed prediction, and a value of 1 for a correct prediction. Using this output, the accuracy of the algorithm could be calculated.

Considering the severity of the data being measured, as high an accuracy as possible is desired. If this algorithm were to suggest to doctors or patients when certain medications should be taken, or other precautionary measures in preparation for an oncoming seizure, decisions need to be made with the utmost assurance. Even the smallest amount of uncertainty could cause devastating consequences. As a result, should more time be dedicated to this experiment, an accuracy as close to 100% would be desired.

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