VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

Technical Answers for Real World Problems

ECE3999 – TG2

EEG SIGNAL PROCESSING FOR SEIZURE DETECTION

By

Shikhar Chandra – 18BEC0146

Submitted to

Vinoth Babu K

Associate Professor Sr.

School of Electronics Engineering

TABLE OF CONTENT

INTRODUCTION

ABSTRACT:

EEG, or Electroencephalogram, is a technique that measures the spontaneous electrical activity of the brain. It is helpful in studying brain activity and treat patients with brain disorders. One such disorder is Epilepsy, which is one of the most common brain diseases and affects people of all age groups. This disorder causes abnormal behavior and seizures. Using signal processing techniques, namely Discrete Wavelet Transform (DWT) and Short Time Fourier Transform (STFT), an EEG signal can be analyzed and the timing of seizures can be detected. The algorithm for these techniques is written in MATLAB and the EEG dataset used is Epileptic Seizure Recognition Dataset from UC Irvine Machine Learning Repository.

PROBLEM STATEMENT:

- Approximately 50 million people worldwide have epilepsy, making it one of the most common neurological diseases globally (Bose, Rama, Warangal, & Rao, 2017).
- In clinical practice, long-term EEG recording up to a few days, is usually required.
- Manual diagnosis of EEG signals of long duration may be a source of error as well as a cumbersome task. Hence automation in Seizure Detection is essential for diagnosis of Epilepsy.

LITERATURE SURVEY

Short Time Fourier Transform:

The STFT approach is to perform a Fourier Transform on only a small section (window) of data at a time, thus mapping the signal into a two-dimensional (2-D) function of time and frequency.

Mathematical Representation of Short Time Fourier Transform:

$$X(k,m)=\sum_{n=0}^{N-1}x(n+m)w(n)W_N^{nk};\ k,m=0,1,\ldots,N-1$$

Where W(n) : Window Function, m : amount of shift

The magnitude squared of the STFT yields the spectrogram representation of the power spectral density of the function.

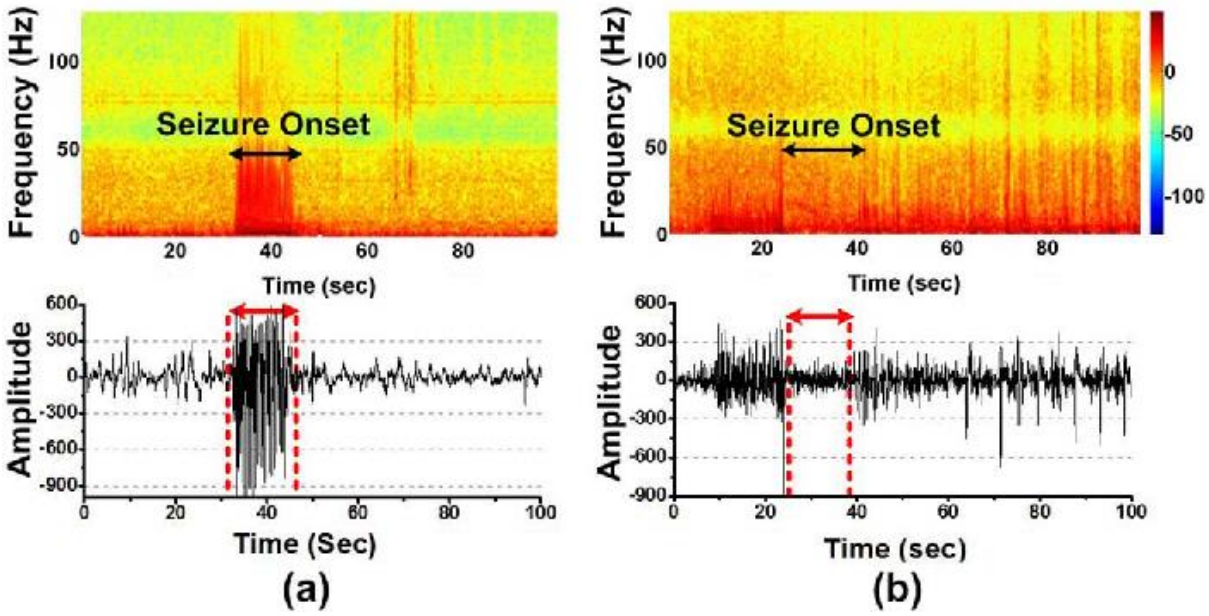


Fig. 1. EEG trace (FP2-F4) during seizure onset (in spectrogram and time domain) for (a) adult epileptic patient and (b) baby

Increasing the size of interval or the window size decreases temporal resolution while decreasing the size of interval decreases the spectral resolution. To resolve this problem, Wavelet analysis is used.

Discrete Wavelet Transform:

Wavelet transforms are very powerful compared to Fourier transform (FT) because of their ability to describe any type of signal in both time and frequency domains simultaneously, and the resolutions can also be changed unlike STFT.

In Wavelet analysis, the signal is converted into scaled and translated version of mother wavelet, which is very irregular and cannot be predicted. These are more suitable for predicting the local behaviour of the signal such as irregularities or spikes.

Examples of Mother wavelets (Chen, Wan, Xiang, & Bao, 2017):

Table 1. Fifty-four Mother Wavelets.

Wavelet family	Mother wavelet
Biorthogonal (`bior`)	bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8, bior3.1, bior3.3, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8
Coiflets (`coif`)	coif1, coif2, coif3, coif4, coif5
Daubechies (`db`)	db1, db2, db3, db4, db5, db6, db7, db8, db9, db10
Reverse biorthogonal (`rbio`)	rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6, rbio2.8, rbio3.1, rbio3.3, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8
Symlets (`sym`)	sym2, sym3, sym4, sym5, sym6, sym7, sym8
Discrete Meyer (`dmey`)	dmey
Haar (`Haar`)	haar

When running DWT using a specific basis function, the signal is fed through (inner product with) a high pass filter (difference filter) and a low pass filter (smoothing / averaging filter), each of which is unique to the wavelet basis function.

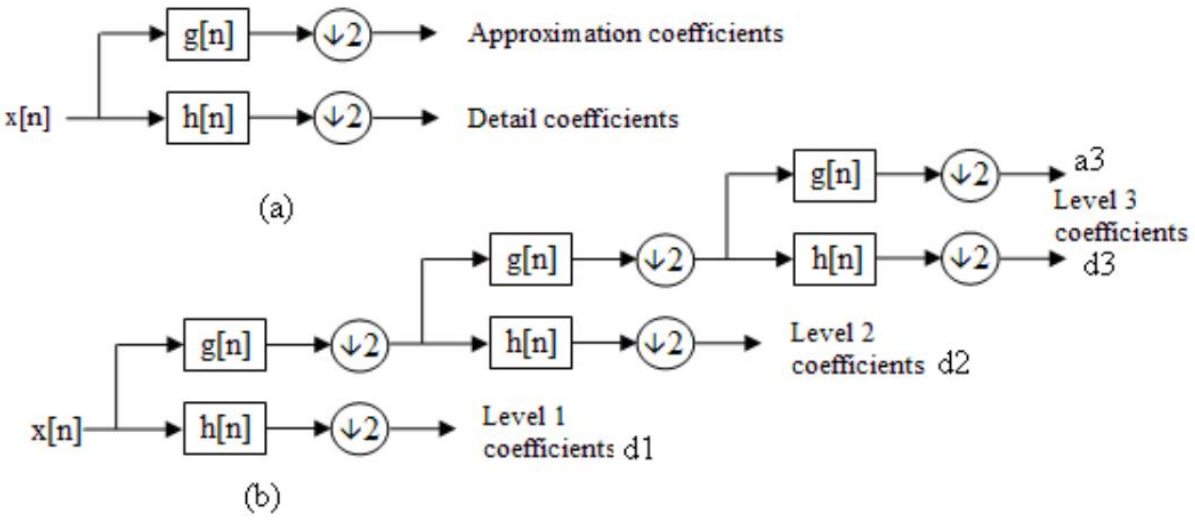
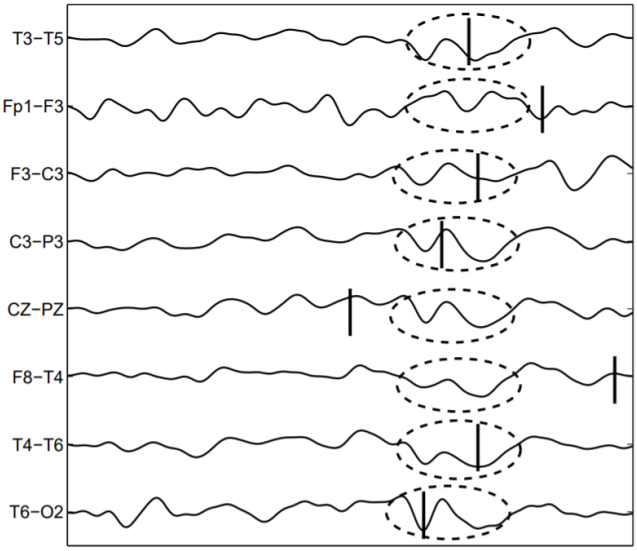


Fig.3. (a) Analysis wavelet filter banks and (b) 3-stage DWT decomposition into Approximation and Detail Coefficients

Cerquera A., Guío L.V., Buitrago E., Gutiérrez R.M., Medina C. (2011) Characterization of Focal Seizures in Scalp Electroencephalograms Based on Energy of Signal and Time-Frequency Analysis. In: Ferrández J.M., Álvarez Sánchez J.R., de la Paz F., Toledo F.J. (eds) New Challenges on Bioinspired Applications. IWINAC 2011. Lecture Notes in Computer Science, vol 6687. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-21326-7_20

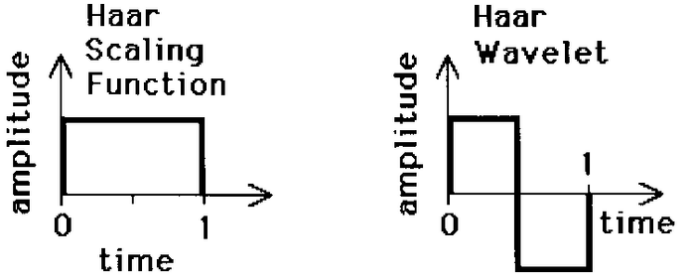
The above-mentioned Research paper employed CWT (Continuous Wavelet Transform) to detect sudden changes in frequency of EEG signal.



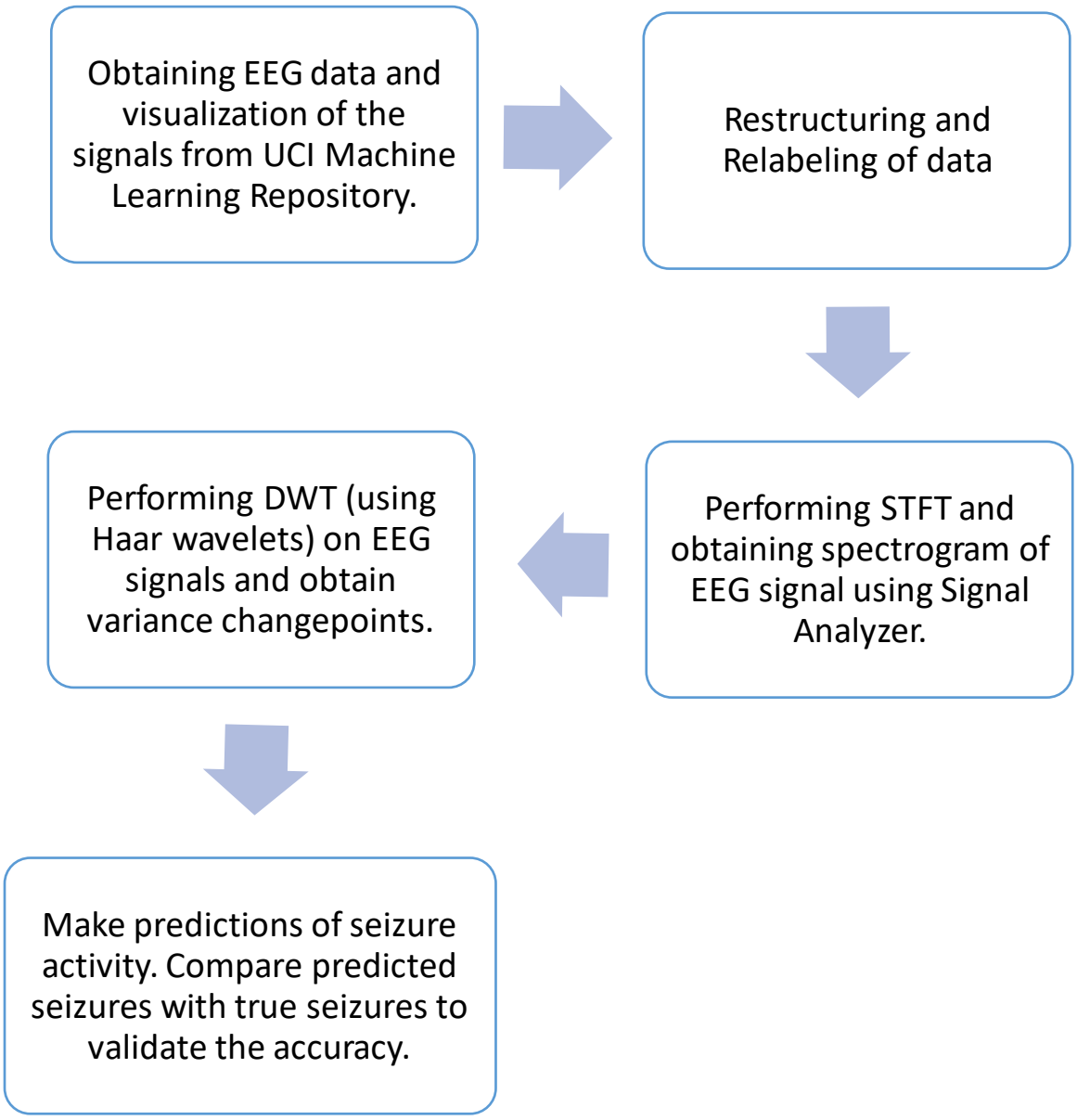
Some artifacts were identified as seizures, which is reflected in a false positives rate of about 35%.

Haar Wavelet Transform:

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.



BLOCK DIAGRAM



SAMPLE CODE

- Restructuring dataset and visualizing EEG signal:

```
load data.csv
eeg_signals = reshape((data)',178*23,500)'; %reshaping from [11500 X 179] to [500 X 4094]
time = (1:4094);
eeg_sample = eeg_signals(2:2,:);
plot(time,eeg_sample),title("Sample EEG signal"),
xlabel("Time"),
ylabel("Amplitude (uV)");
```

- Storing Seizure information from dataset:

```
load data1.csv
seizure_info = reshape(data1',23,500)';
seizure_info = seizure_info ~= 1; % storing seizure seconds in a new variable
```

- Haar Transform and obtaining detail coefficients in a matrix:

```
[a,d] = haart(eeg_signals(x,:),5); %1-D Haar Transform with level = 5; a = approximation coefficient, d = detail coefficient
u1 = repelem(d{1,1},2); % There is decimation in samples after each level, hence repeat the elements by factor of two.
u2 = repelem(d{1,2},4);
u3 = repelem(d{1,3},8);
u4 = repelem(d{1,4},16);
u5 = repelem(d{1,5},32);
umatrix = nan(4096,5);
umatrix(1:length(u1), 1) = u1;
umatrix(1:length(u2), 2) = u2;
umatrix(1:length(u3), 3) = u3;
umatrix(1:length(u4), 4) = u4;
umatrix(1:length(u5), 5) = u5;
adj_umatrix = umatrix';
```

- Finding variance changepoints in each DWT level:

```
det1 = adj_umatrix(1,:);%Getting level 1 detail coefficients in a single vector
det2 = adj_umatrix(2,:);%Getting level 2 detail coefficients in a single vector
det3 = adj_umatrix(3,:);%Getting level 3 detail coefficients in a single vector
det4 = adj_umatrix(4,:);%Getting level 4 detail coefficients in a single vector
det5 = adj_umatrix(5,:);%Getting level 5 detail coefficients in a single vector
[pts_Opt_1,~,~] = wvarchg(det1); %Finding variance changepoints in level 1 coefficients
[pts_Opt_2,~,~] = wvarchg(det2); %Finding variance changepoints in level 2 coefficients
[pts_Opt_3,~,~] = wvarchg(det3); %Finding variance changepoints in level 3 coefficients
[pts_Opt_4,~,~] = wvarchg(det4); %Finding variance changepoints in level 4 coefficients
[pts_Opt_5,~,~] = wvarchg(det5); %Finding variance changepoints in level 5 coefficients
```

- Storing all non-zero variance changepoints from all levels:

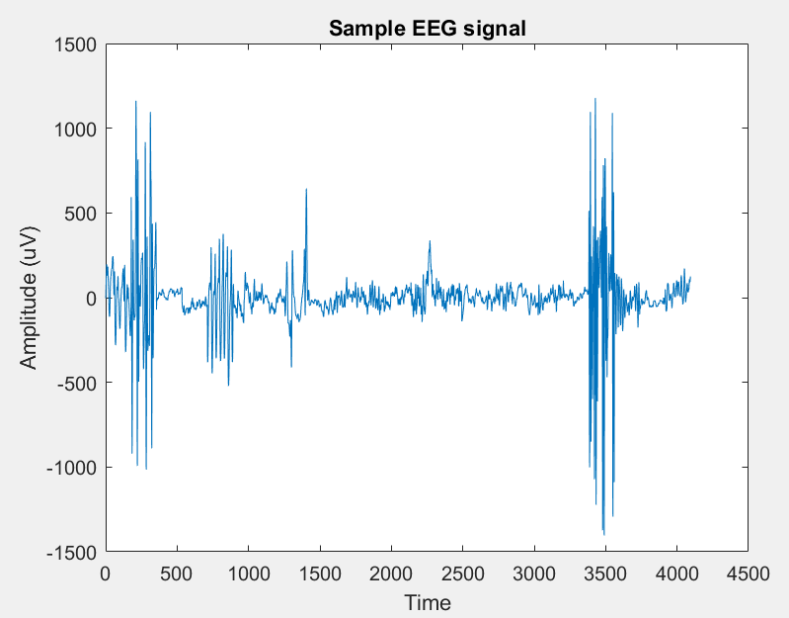
```
num_els = [numel(pts_Opt_1),numel(pts_Opt_2),numel(pts_Opt_3),numel(pts_Opt_4),numel(pts_Opt_5)];%
max_els = max(num_els);%Maximum number of variance changepoints
pts_Opt_1(1,max_els) = 0; %Array of level 1 changepoints with max number of variance changepoints
pts_Opt_2(1,max_els) = 0; %Array of level 2 changepoints with max number of variance changepoints
pts_Opt_3(1,max_els) = 0; %Array of level 3 changepoints with max number of variance changepoints
pts_Opt_4(1,max_els) = 0; %Array of level 4 changepoints with max number of variance changepoints
pts_Opt_5(1,max_els) = 0; %Array of level 5 changepoints with max number of variance changepoints
changepts = [pts_Opt_1; pts_Opt_2; pts_Opt_3; pts_Opt_4; pts_Opt_5];
changepts_v = sort(nonzeros(changepts));%all non zero variance changepoints are stored
```

- Plotting Variance changepoints and True Seizure Points:

```
AX = gca;
AX.XTick = 0:178:4094;
xlabel('Time')
changepts_plot=figure;
subplot(2,1,1)
AX = gca;
AX.XTick = 0:178:4094;
xticklabels({0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23})
hold on
plot(time,eeg_signals(x,:))
line([changepts_v changepts_v], ylim,'Color','green')
title("Predicted Seizures")
ylabel("Amplitude(uV)");
subplot(2,1,2)
seizures2 = (find(~seizure_info(x,:)))
seizures2 = seizures2*178;
plot(time,eeg_signals(x,:))
AX = gca;
AX.XTick = 0:178:4094;
xticklabels({0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23})
xlabel('Time')
line([seizures2; seizures2], ylim,'Color','red');
title("True Seizures")
```

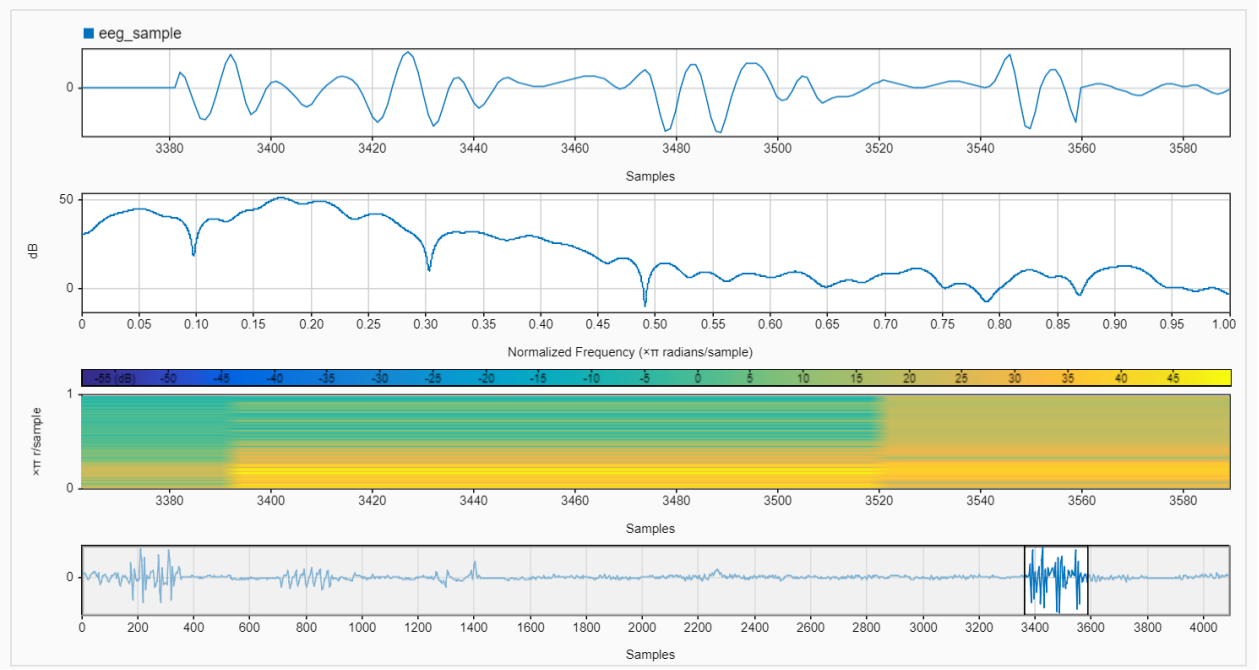
RESULTS AND INFERENCES

1. Sample EEG signal:



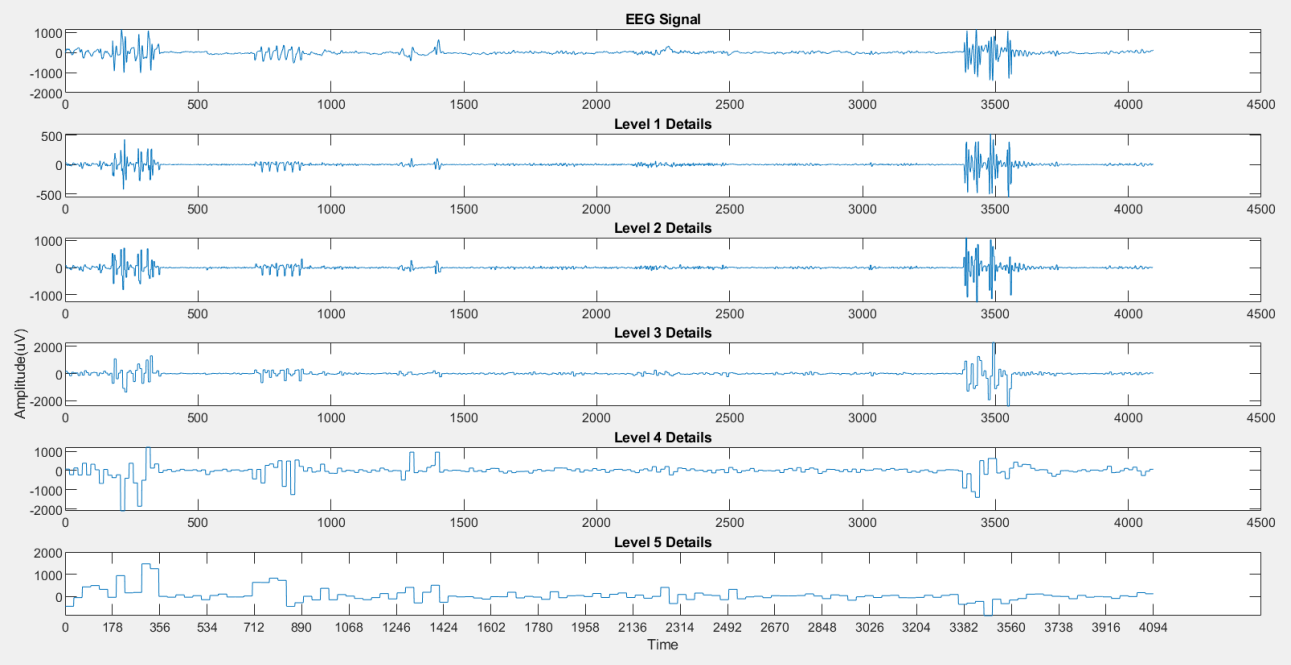
After Restructuring the dataset, we obtain the non-stationary EEG signal with 4094 data points in temporal domain.

2. Spectrogram (Using Signal Analyzer Toolbox):



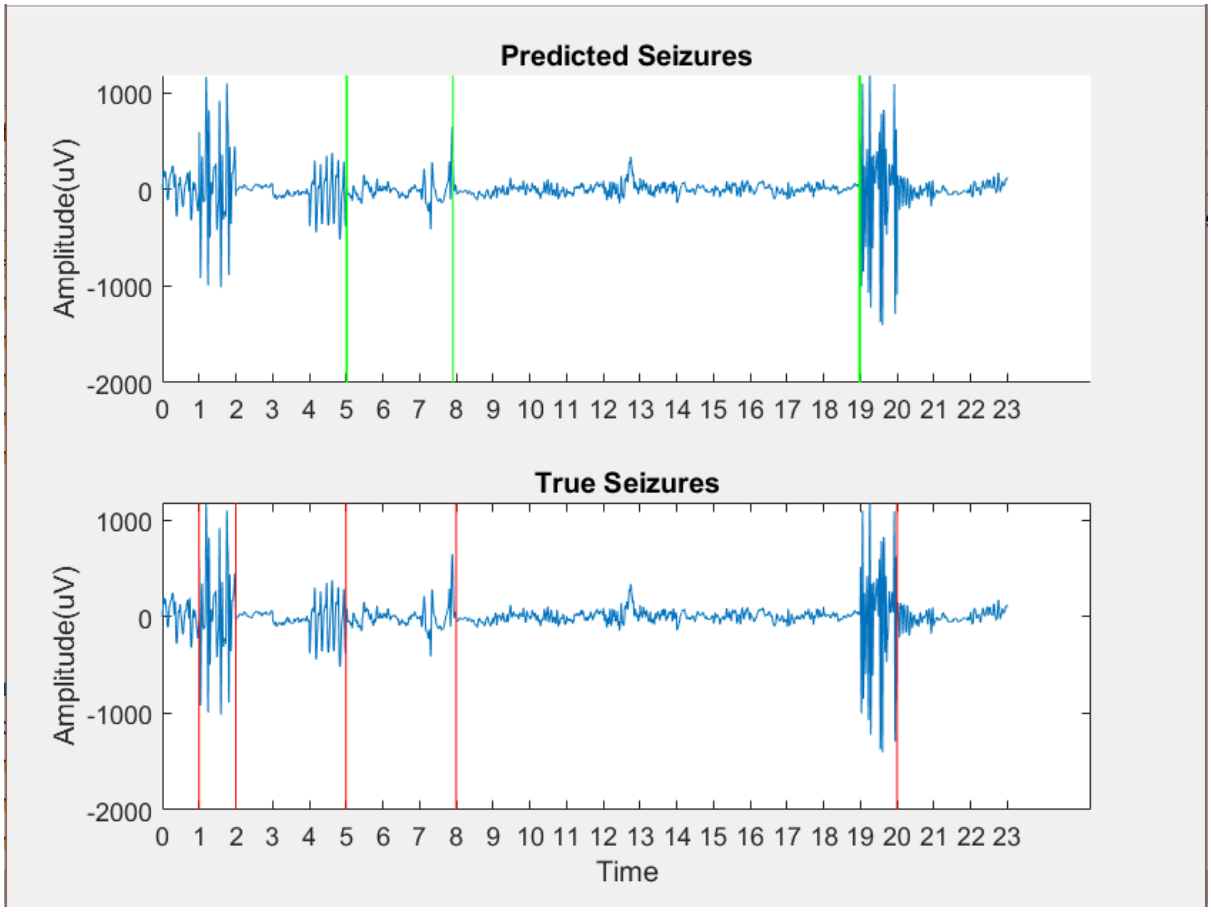
Using the Signal Analyzer App in the Signal Processing Toolbox, we obtain the Spectrum of the sample EEG signal as well as the Spectrogram. We observe the effect of changing the window size on the time-domain and frequency domain resolution. Increasing the width of the 'Panner' decreases temporal resolution while decreasing the width decreases the spectral resolution.

3. Multi-Level Detail Coefficients:



Using Haar 1D DWT, we obtain 5 levels of detail coefficients. Each level of detail coefficients is the output of a high-pass filter of the previous level's approximation coefficient. After each level, there is a decimation in samples, therefore the multi-level details represent signal decomposition from fine resolution to coarse resolution. The levels are plotted alongside the original signal.

4. Predicted Seizures VS True Seizures:



Finally, after obtaining the variance changepoints from detail coefficients, we plot these points alongside the True Seizure points obtained from the dataset.

By a visual comparison, we see that the DWT based method locates and detects the Seizure points correctly but still misses some of the points. The accuracy of the method is validated by visual comparison.

CONCLUSIONS AND FUTURE WORK

Signal processing techniques have been successfully applied to detect the seizure points in an EEG signal. Using MATLAB, a method was developed to properly pre-process the raw dataset of EEG signals from several patients. Short Time Fourier Transform was performed to observe the EEG signal in both time and frequency domain through plotting spectrogram. Drawbacks of traditional techniques like STFT and FFT for processing multi-resolution signals were investigated. An algorithm was developed for processing the EEG signals using Discrete Wavelet Transform (DWT). Using 1-Dimensional Haar Transform, the detail coefficients of the signal were obtained and observed, and using these coefficients, variance changepoints in the signal were obtained. Finally, the predicted seizure locations using variance changepoints and the True seizure locations were plotted and the results were compared.

It was concluded that Predicted seizure locations are close to the True Seizure locations. The algorithm can be further developed with a larger dataset, using Machine Learning algorithms, so as to train the model to accurately predict the Seizure location. Future work on this aspect can be done so that the accuracy of the method is improved.

REFERENCES

1. Dajana Ognjenovic and Jared Wilson, “EEG Analyses for Seizure Detection”, 32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada.
2. S. Bose, V. Rama, N. Warangal and C. B. Rama Rao, "EEG signal analysis for Seizure detection using Discrete Wavelet Transform and Random Forest," 2017 International Conference on Computer and Applications (ICCA), Doha, 2017, pp. 369-378, doi: 10.1109/COMAPP.2017.8079760.
3. Bashar Rajoub, Chapter 2 - Characterization of biomedical signals: Feature engineering and extraction, In Developments in Biomedical Engineering and Bioelectronics, Biomedical Signal Processing and Artificial Intelligence in Healthcare, Academic Press, 2020
4. Altaf, M. and J. Yoo. “A 1.83 μJ/Classification, 8-Channel, Patient-Specific Epileptic Seizure Classification SoC Using a Non-Linear Support Vector Machine.” IEEE transactions on biomedical circuits and systems 10 1 (2016): 49-60.
5. Chen D, Wan S, Xiang J, Bao FS (2017) A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG. PLoS ONE 12(3): e0173138.https://doi.org/10.1371/journal.pone.0173138
6. https://www.intechopen.com/books/wavelet-theory/time-frequency-analysis-of-wavelet-and-fourier-transform
7. https://www.cs.cornell.edu/courses/cs5540/2010sp/lectures/Lec5.Transforms.pdf
8. https://www.mathworks.com/help/wavelet/signal-analysis.html