Epileptic Seizure Detection through EEG Signal Processing

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Abstract— In the present paper, the beginning prolongation and ending of an epileptic seizure is determined through the analysis of EEG signals. The electrical activity of the brain consists of numerous classes that too with overlapping characteristics, which makes the problem challenging. Identification of features to separate the epileptic data from other kinds of brain activity was the first step in the problem solving approach. Followed by this, pre-processing and filtering techniques were applied to separate the epileptic signals from the non-epileptic ones.

Key words: Epilepsy, Seizure Detection, Signal Processing, EEG

I. INTRODUCTION

Epilepsy is a chronic disorder of the central nervous system that predisposes individuals to experiencing recurrent seizures. A seizure is a sudden, transient aberration in the brain's electrical activity that produces disruptive symptoms. These symptoms range between a lapse in attention, a sensory hallucination, or a whole-body convulsion. Epilepsy may develop as a result of inheriting a mutation in a molecular mechanism that regulates neuron behaviour, migration, or organization. Alternatively, it may develop as a result of brain trauma such as a severe blow to the head, a stroke, a cerebral infection, or a brain malignancy. Neurons are cells within the brain capable of generating, propagating, and processing electric signals. Neurons connect to other neurons in order to form functional networks, and the brain can be viewed as a collection of interacting neural networks. The inputs to a neural network can be excitatory or inhibitory. Excitatory inputs promote activity among neurons within a network and inhibitory inputs suppress it. Epileptic seizures are transient periods involving the hyperactivity and hyper synchronization of a large number of neurons within one or more neural networks. These transient states arise because of a perturbation that creates an imbalance favouring the excitation of a neural network over its inhibition. The imbalance may arise because of defects within a neuron, such as an ion channel dysfunction; defects in connections between neurons, such as deficient inhibitory neurotransmitter synthesis [1].

II. LITERATURE SURVEY

In biomedical signal processing, it is crucial to determine the noise and artifacts present in the raw signals so that their influence in the feature extraction stage can be minimized. Independent component analysis (ICA) is specifically used for artifact cancellation. ICA identifies sources, in this case artifacts present in the EEG signal, based on blind source separation (BSS) and separate them from the EEG based on their statistical independence. In time-domain techniques to detect EEG seizures, there is a need to analyze discrete time sequences of EEG epochs. This analysis can be accomplished through histograms of the epochs. In a simple time-domain seizure detection method that is based on tracing consecutive peaks and minima in the signal segment at hand and estimating the histograms for two variables: the amplitude difference and time separation between peak values as well as minima. The features used for classification of an epoch as a seizure or Non seizure are the estimated values of the histogram bins. The authors used a support vector machine (SVM) Classifier for this task and achieved an average sensitivity of about 90% on self-recorded data. Another approach to deal with the EEG seizure detection method in time domain is to compute the signal energy during seizure and non-seizure periods. A better treatment to the energy estimation approach is to estimate the energies of the signal sub-bands not the signal as a whole in order to build a more discriminative feature Vector. They used a bank of seven band-pass filters covering the frequency range from 2 to 26 Hz on eight channels of the processed EEG signals. The Fourier transform methods of automatic EEG processing are based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric methods for power spectrum estimation such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution.

III. PROPOSED BLOCK DIAGRAM

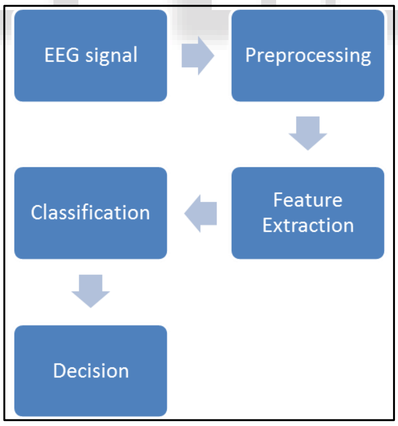

Fig. 1: Proposed Block Diagram

IV. METHODOLOGY

The raw EEG signal is displayed in Fig.2. The final target is to classify the signals as seizure and non-seizure as shown in Fig.3. Given the sample of a patient EEG data, the proposed algorithm will find out the onset, progress and end of the epileptic signal. The input data consists of the unprocessed raw EEG signals captured over a continuous time period. The epileptic seizure was detected to be in the range from 50 s to 100 s.

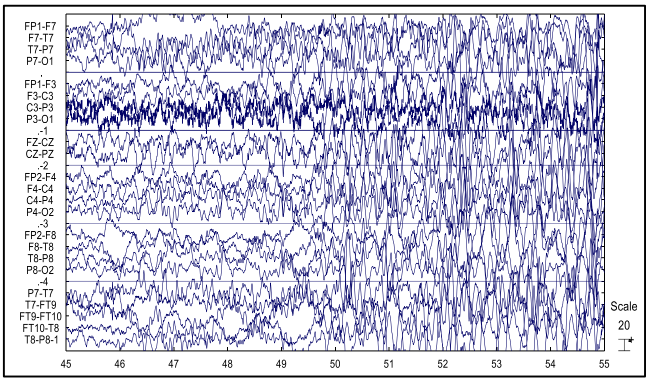
Fig. 2: Raw EEG Signal

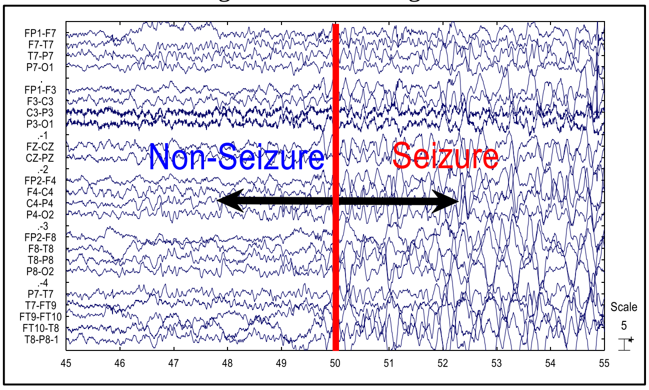

Fig. 3: Seizure- Non seizure regions

The signal could be analyzed on different time scales. Fig. 4. Displays the EEG signals scaled for 5 seconds time duration.

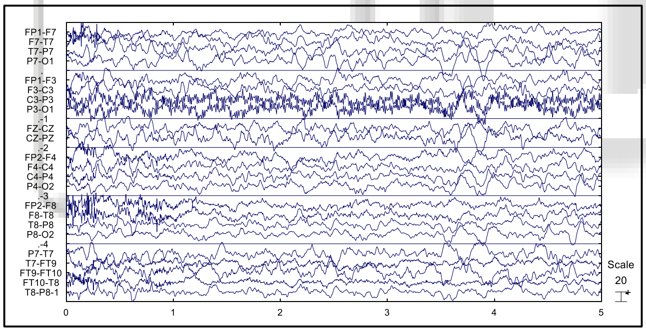
Fig. 4: Time scaling of signal

A hamming windowed FIR filter was applied on the EEG signal. The magnitude and phase responses of the filter are displayed in Fig. 5. Also, the output after the applicaion of the filter on the signal is displayed in Fig. 6. The filter specifications are as shown in Table I.

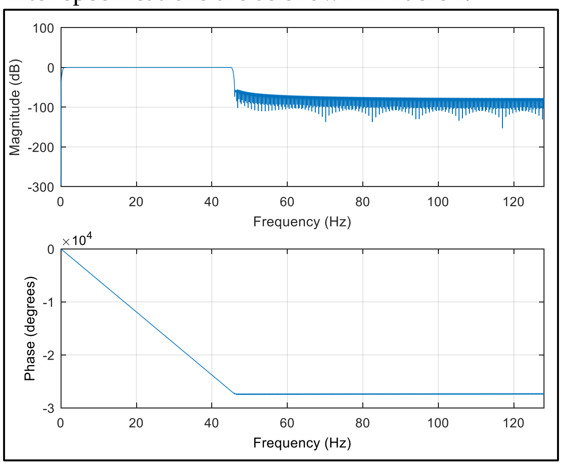

Fig. 5: Hamming windowed sync FIR filter response

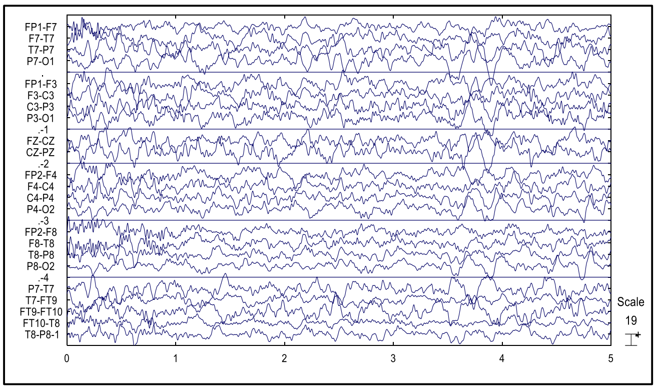
Fig. 6: Filter Output

Filter Specifications	
transition band width:	1 Hz
passband edge(s):	[1 45] Hz
cutoff frequency(ies) (-6 dB):	[0.5 45.5] Hz
performing 847 point band pass filtering.	

Table 1: Specifications of Filter

The base line wandering was removed from all the 28 channels. The output of the same is displayed in Fig. 7.

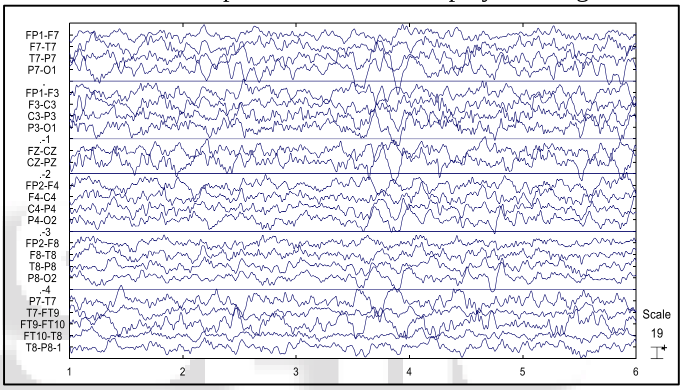
Fig. 7: Base line removal

8 bands were designed with the following specifications as given in Table 2.

Performs 425 point low pass filtering.	
transition band width:	2 Hz
Pass band edge(s):	0-2 Hz
cutoff frequency(ies) (-6 dB):	3 Hz
Performs 847 point band pass filtering.	
transition band width:	1 Hz
Pass band edge(s):	[1 5] Hz
cutoff frequency(ies) (-6 dB):	[0.5 5.5] Hz
Performs 425 point band pass filtering.	
transition band width	2 Hz
Pass band edge(s):	[4 8] Hz
cutoff frequency(ies) (-6 dB):	[3 9] Hz
Performs 425 point band pass filtering.	
transition band width	2 Hz
Pass band edge(s):	[7 11] Hz
cutoff frequency(ies) (-6 dB):	[6 12] Hz
Performs 339 point band pass filtering.	
transition band width:	2.5 Hz
Pass band edge(s):	[10 14] Hz
cutoff frequency(ies) (-6 dB):	[8.75 15.25] Hz
Performs 261 point band pass filtering.	
transition band width:	3.25 Hz
Pass band edge(s):	[13 17] Hz
cutoff frequency(ies) (-6 dB):	[11.375 18.625] Hz

Performs 213 point band pass filtering.	
transition band width:	4 Hz
Pass band edge(s):	[16 20] Hz
cutoff frequency(ies) (-6 dB):	[14 22] Hz
Performs 179 point band pass filtering.	
transition band width:	4.75 Hz
Pass band edge(s):	[19 24] Hz
cutoff frequency(ies) (-6 dB):	[16.625 26.375] Hz

Table 2: 8 Bands Specifications

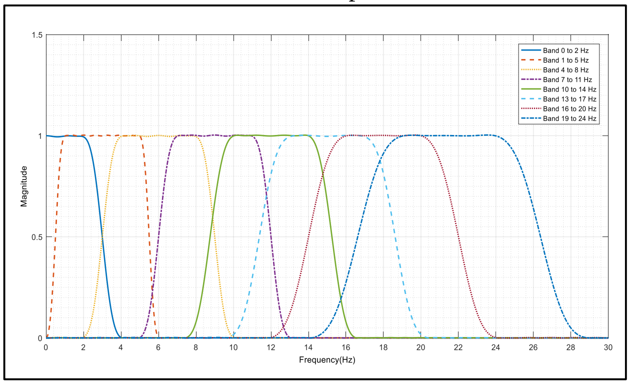

Fig. 8: Magnitude response of 8 bands

The EEG signals were then extracted from each band and the effect of each filter on seizure and non-seizure data was analyzed. The outputs should an abrupt increase in the amplitudes of seizure data. Fig. 9 Demonstrates the application on one band. Similar results were obtained for other 7 bands too. Accordingly, energy signals were also extracted from each band. One result of extracted energy output is displayed in Fig.10. Finally, the effects of band energy on seizure and non-seizure data gave a clear demarcation for classification. Fig. 11 displays one such result where the epileptic data was found to begin at time =50 seconds.

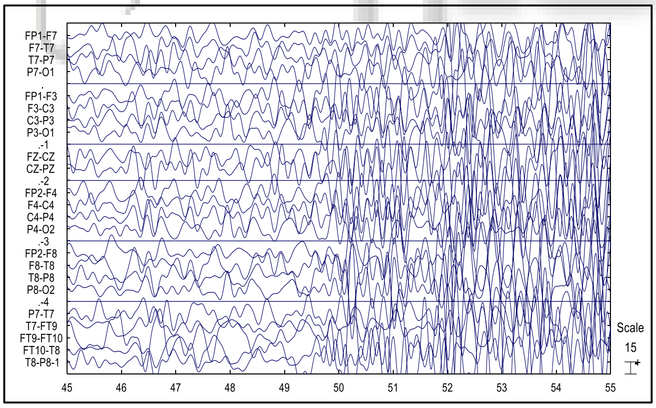

Fig. 9: Amplitude Increase in seizure data

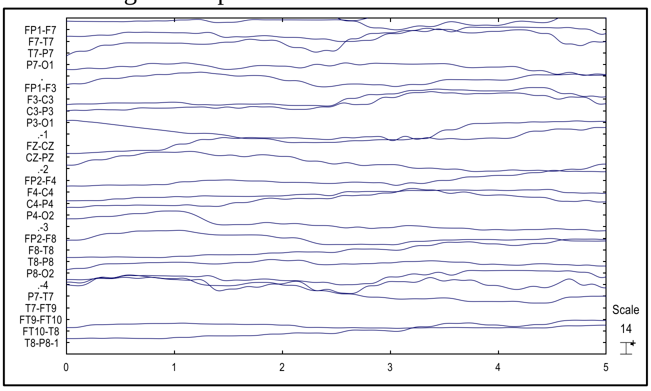

Fig. 10: Extracted Energy

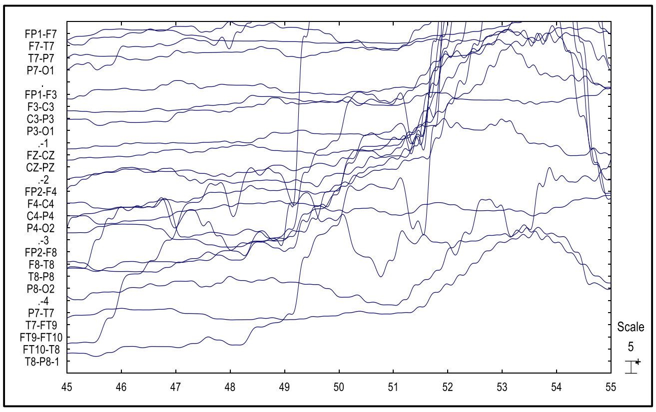

Fig. 11: Effect of band energy

V. RESULT AND CONCLUSION

The results obtained from above mentioned procedure and processing are presented in fig.12, fig.13, fig.14 and fig.15.

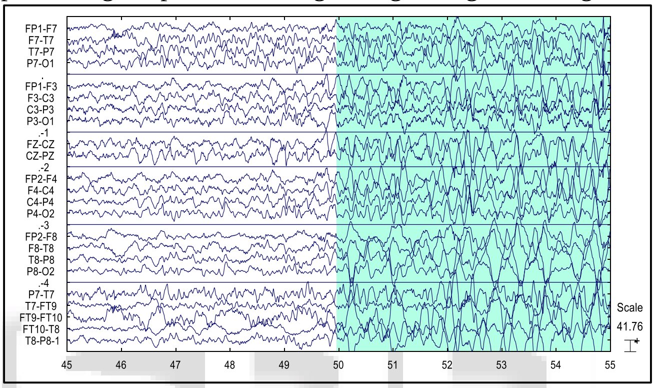

Fig. 12: Seizure- Non seizure regions

In Fig. 12 white is non-seizure and cyan is seizure, indicates the non-seizure region, starting of the seizure and the seizure region. In Fig. 13 cyan is seizure and white is non-seizure, indicates the seizure region, ending of the seizure and the non-Seizure region respectively. In Fig.14 and Fig.15 extracted only seizure region are displayed.

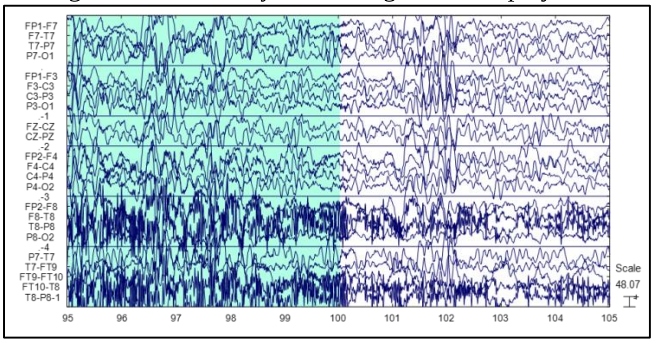

Fig. 13: Seizure- Non seizure regions

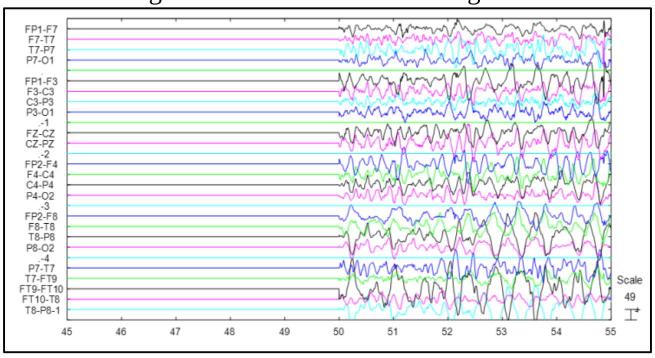

Fig. 14: Seizure- Non seizure regions

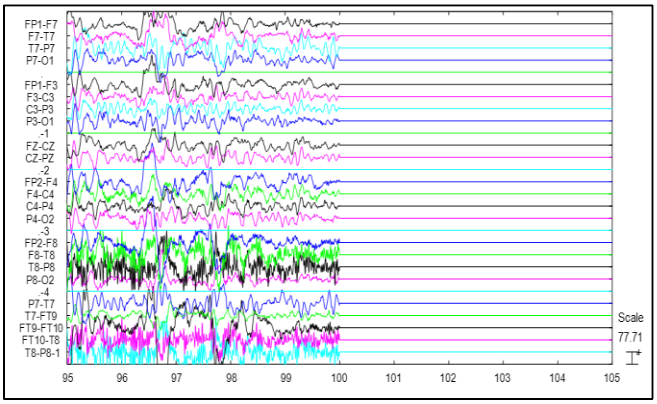

Fig. 15: Seizure- Non seizure regions

Through the application of the quadratic SVM and cubic SVM algorithms, the EEG signals were classified successfully as epileptic and non-epileptic. Also the seizure and non-seizure regions were extracted from the original signals and reproduced in separate graphs.

VI. FUTURE WORK

As a part of future work, the algorithm can be modified to give computationally fast results. Also, an effort can be made to reduce the number of features for obtaining the desired result.

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