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Identifying Pre-ictal Period of Seizure and Better Brain Lobes for Seizure Detection using EEG Biomarkers

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Abstract. Seizures are one of the serious neuropsychiatric disorders that affect 50 million people across the world, and 80% of them live in the developing countries like India. In such kind of critical care, delays in the diagnosis of neurological conditions can have a significant impact on patients with seizure. To address this treatment gap, we propose an early identificationof pre-ictal period of seizure and brain lobes for seizure detection by using electroencephalogram (EEG) biomarkers. Five subjects were voluntarily involved in this study. The raw EEG signals were filtered and decomposed using wavelet techniques and the features such as relative delta energy, relative theta energy, total beta energy, heart rate, and neuronal activity were extracted for analysis. The results showed that the relative theta activity and the neuronal activity are found to be the better features in early predicting of period of pre-ictal seizures, as both the features can be seen with significant differences among the three different time periods in all the electrode positions, which are taken into consideration. It is also evident that the occipital lobe is better in indicating the pre-ictal period earlier, as the observed data shows expected outcome from the electrode positions O1 and O2 (occipital lobe). On national level, this study will enable the primary health centres to fulfil its dream of providing basic medical facilities to serve huge sections of population with seizure.

Keywords: Seizures, Epilepsy, Brain lobes and Electroencephalogram (EEG).

1. Introduction

Seizures are temporary disruptions of brain function caused by uncontrolled excessive neuronal activity [1]. Not all the seizures are epileptic seizures. Some are temporary symptomatic seizures, which usually do not persist if the underlying disorder is corrected. In contrast, epilepsy is a chronic condition of recurrent seizures. Epilepsy is considered as a consequence of multiple malfunctioning in brain, as its clinical symptoms are heterogeneous and reflect multiple underlying causes and pathophysiological mechanisms which cause cerebral dysfunction and injury. Epilepsy is a spectrum of disorders defined by occurrence of epileptic seizures, which are characterized by abnormal firing of large populations of neurons [2].

At basic level an epileptic seizure is caused by a disruption of the normal balance between inhibitory and excitatory currents or transmission in one or more regions of the brain. Before finding a solution for epilepsy, one should understand the mechanism of seizure with the help of modelling it. It is generally assumed that seizure is a complex phenomenon. Seizure onset occurs via a bifurcation, i.e. the trajectories of brain activities need to cross a certain threshold.

Epileptic seizure can be classified based on how and where they originate. The following are the types of epileptic seizures diagnosed in the people.

- *Simple partial seizure* – seizure taking place in one part of the brain region, person is aware of his state.
- *Complex partial seizure* – seizure taking place in one part of the brain region, person losing his awareness state of awareness.
- *Secondarilygeneralized seizure* – seizure taking place in one part of the brain region and slowly spreading all over the brain region leading to tonic-clonic seizure.
- *Absence seizure* – seizure causing absence in awareness.

- *Atypical absence seizure* – seizure causing absence of awareness, but person is able to respond.
- *Tonic-clonic seizure* – seizure caused at both parts of the brain region leading to loss of awareness, muscle stiffening, and jerky movements.
- *Myoclonic seizure* – seizure causing sudden jerky movements in a muscle or a group of muscles.
- *Tonic seizure* – seizure causing sudden muscle stiffening.
- *Atonic seizure* – seizure causing loss in muscle tone or legs and arms going limp.
- *Clonic seizure* – seizure causing sustained rhythmic jerking of muscles.

More than fifty million people worldwide, approximately 1% of 40th world population, suffer from epilepsy, which is the third most 41 common neurological disorder in the United States after Alzheimer's disease and cerebrovascular events [1]. Moreover, more than 30% of the epileptic patients suffer from seizures that are refractory to medication [2]. Approximately 50 million people currently live with epilepsy world-wide. Globally, an estimated 2.4 million people are diagnosed with epilepsy each year. In India, there may be about 12 million people with epilepsy. Many people with active epilepsy do not receive appropriate treatment for their condition, leading to large treatment gap. The lack of knowledge of antiepileptic drugs, poverty, cultural beliefs, stigma, poor health infrastructure, and shortage of trained professionals contribute in the treatment gap.

To detect seizures in real time there is few modules are available in present market such as

- Infra-red cameras (unusual movements in sleep).
- Anti-suffocation pillow (SUPED).
- Mattress-(nocturnal seizures).
- Smart belt (respiration and GSR).

In clinical diagnosis, electroencephalography (EEG) plays a vital role for diagnosing epilepsy. It is assumed that EEG signals contain some type of hidden information about incoming seizures. That is to say that, with appropriate signal processing, we would be able to predict the incoming predictive markers [3].Many algorithms have been designed to facilitate the diagnosis of epilepsy. One of the methods is primarily based on the stationary wavelet transform and takes the spectral band of seizure activities into account to separate artifacts from seizures. The EEG features responsible for the detection of seizures from non-seizure epochs is found to be easily distinguishable after the artifacts are removed and also the false alarms during seizure detection are also reduced [4].

Usually doctors make use of video EEG in monitoring epilepsy. Video EEG is a technique in which the patient is induced with epileptic seizure and the EEG along with video of the patient is recorded. This is a very useful method for diagnosing epilepsy. But the workload taken by the doctor in studying the data collected will be more. To overcome the above problem, scientists have designed an algorithm, which reduces the workload through automatic seizure detection, by applying Partial directed coherence (PDC) analysis as a mechanism for extracting feature from the EEG data for seizure detection. This analysis reflects the physiological changes in the brain activity in pre-seizure episodes and post-seizure episodes [5].

Automated seizure prediction plays a major role in monitoring, diagnosing and rehabilitating epilepsy. While EEG is widely used all over the world, scientists and scholars work on improvising the selectivity of EEG towards predicting and diagnosing epilepsy. One among the designed algorithm is seizure prediction based on spatiotemporal relationship of EEG signals using phase correlation. This technique measures the relative change between current and reference vectors of EEG signals, which is then used to identify the pre-seizure episode and the post-seizure period. The EEG signal of period between two adjacent seizures isalso studied to predict the seizures [6].The multivariate oscillatory nature of the EEG signals in adaptive frequency scales is studied to investigate the occurrence of epileptic seizure. The analysis is based a moving window, with a two second long multivariate EEG signal epochs, that contains five selected channels. These signals are then decomposed from which three features have been extracted from each one second part of the two-second-long joint instantaneous amplitudes of multivariate EEG signals [7].

The heart rate variability analysis is often used for diagnosing seizures in clinical practices. The brain activity during pre-seizure episode period will be extremely active that may result in more autonomous nervous system (ANS) functions. This nervous system functions influence the heart rate to a huge level. Hence, the heart rate is widely chosen as a variable for the prediction of epileptic seizure [8]. The main objective of the present study is to identify pre-ictal period of seizure using EEG biomarkers. Also identify the lobes which are affected most predominately during seizure.

2. Materials and Methods

2.1. Subject Summary and Signal Acquisition

Five subjects (1 male and 4 female) data was considered for this study. The subjects' average age was 20 - 30 years and average weight was 68 kg (standard deviation = 5.3 kg). Electrodes were placed according to 10-20 montage. The low cut-off frequencyof the filter was set at 0.1 Hz and the high cut-off frequency was set to 70 Hz. Notchfilter permits to pass the frequency between the low and high frequency. The samplingfrequency was chosen at 128Hz.After collecting the raw EEGsignals, we export the signal into the personal computer system for further processing. The EEG signals arecaptured by expert professionals and neurologists and collected from private Neuro Hospital, located at Tiruchirappalli, Tamil Nadu, India.

2.1.1. Signal Processing

After collecting the data from the subjects, the raw EEG signals are filtered and for extraction of the features such as relative delta energy, relative theta energy, total beta energy, heart rate, and neuronal activity an algorithm is designed. Figure 1 gives a brief workflow of signal processing that is performed on the acquired EEG signals.

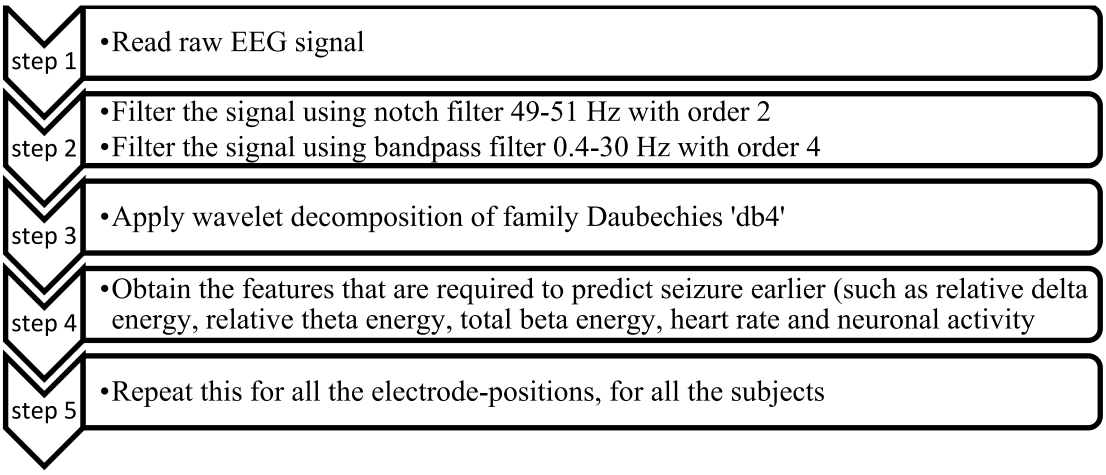


Figure 1: Workflow of signal processing on EEG signals.

Wavelet: A wavelet is a mathematical function, which cut up a data based on different frequency components, so that one can study each frequency component with a resolution that matches up to that frequency scale [9,10].
Wavelet package: A wavelet package is a package of wavelet functions for computing wavelet filters, wavelet transforms and multi resolution analyses [11].
Wavelet decomposition: A wavelet transform (Figure 2) is the one which filters the discrete-time (sampled) signals with more filters than the actual discrete wavelet transform (DWT) [12].

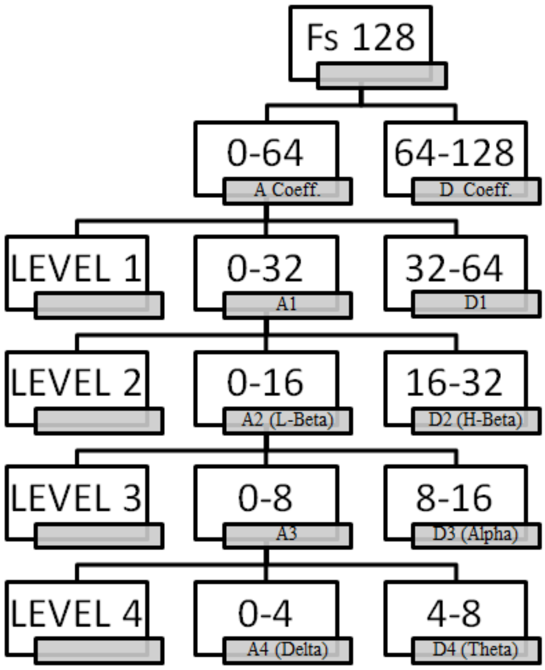


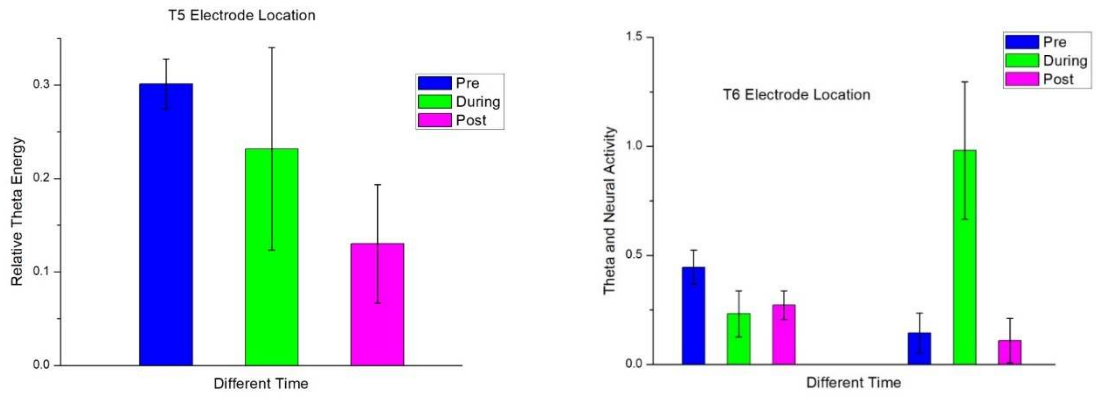
Figure2: Various levels of wavelet packet decomposition used in the study (A – approximation; D – detail; L-Beta – low beta and H-Beta – high beta).

3. Statistical Analysis

The significant difference within the groups for pre-episodic, during episodic and post-episodic period were found using the Friedman test (a non-parametric test) and the Wilcoxon signed-rank Post Hoc test was performed to find the statistically significant difference between two related groups. The alpha value was set at 0.15 and asymmetric signed (2-tailed) values were observed. The Post Hoc Wilcoxon signed rank test was performed on different combinations of related groups as the alpha value divided by three conditions (0.15/5 = 0.05). Hence, the new significance level was set at $p=0.05$. If the p value was larger than 0.05, it was not considered as a statistically significant result. The dependent variables are relative delta energy, relative theta energy, total beta activity, neuronal activity and the heart rate obtained from the brain activation using EEG signals.A single group was measured on three different conditions (pre-seizure episode, during seizure episode and post-seizure episode) at five electrode locations (temporal: T5, T6, occipital: O1, O2 and parietal: Pz).The analysis was performed using IBM SPSS Statistics for Windows, Version 20.0 (Armonk, NY: IBM Corp).

4. Results

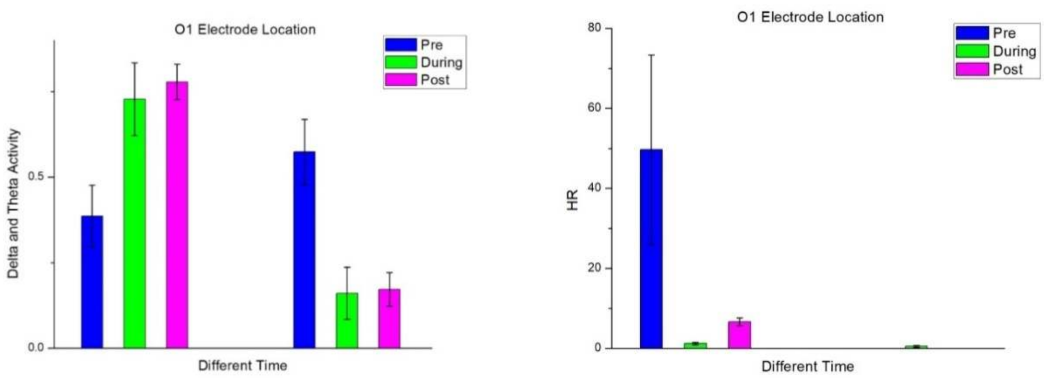
The mean and one standard error values of relative theta energy were extracted from EEG signal for five subjects at three different time intervals: pre-episodic (before the occurrence of seizure), during episode (during the seizure) and post-episodic (after the occurrence of seizure), in the T5 and T6 electrode positions as shown in Figure 3.The graphical data shows that the relative theta energy was significantly ($p<0.05$) higher in pre-episode as compared to post-episodic period in both the temporal lobes.



(a) (b)

Figure 3: Mean and standard error of relative theta energy found in the electrode locations. (a) Temporal lobe T5 and (b) Temporal lobe T6.

The neuronal activity in right side temporal lobe is found to be significantly ($p<0.05$) high during the episode than in the pre- and post-episodic period as shown in Figure 3(b). Therelative delta energy is found to be significantly ($p<0.05$) higher in post-episodic period as compared to pre-episodic period. But theta activity was significantly high in pre-episodic as compared to during, post-episodic time in left occipital lobes as shown in Figure 4(a).



(a) (b)

Figure 4: Mean and standard errorof features found in the electrode location of occipital region O1.(a) Relative delta and theta energiesand (b) Heart rate (HR).

Heart rate (HR) feature extracted from EEG signal is significantly ($p<0.05$) high in pre episodic when compared to during and post seizure interval as shown in Figure 4(b).Similarly, neural activity was significantly ($p<0.05$) high during seizure episodic time as compared to pre and post time interval in left occipital lobe.

In right occipital lobe (O2) relative delta energy was significantly ($p<0.05$) low at pre seizure interval when compared to during and post episodic time period (Figure 5). Similarly, theta activity was high significantly ($p<0.05$) in pre-seizure as compare to during and post time interval. There was no significantly difference for delta and theta parameters between during and post time period in occipital lobe.

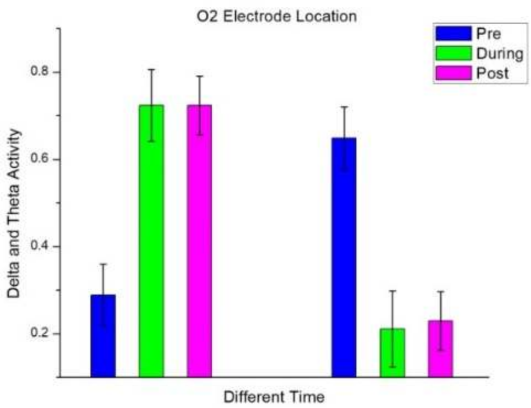
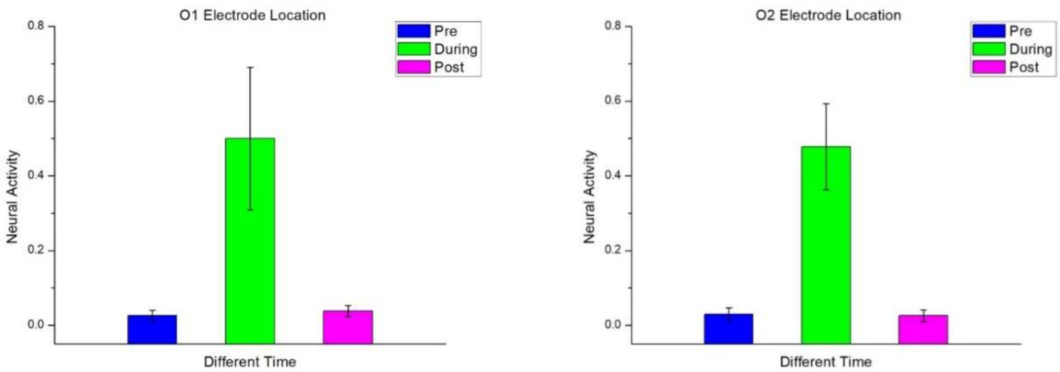


Figure 5: Mean and one standard error of relative delta and theta energies found in the location of occipital region O2.

The neuronal activity that is obtained through processing the EEG signals extracted from five different subjects significantly ($p<0.05$) high during seizure time when compared to pre and post episodic interval at right and left occipital region as shown in Figure 6.



A B

Figure6: Mean and standard error of the neuronal activity found in the location of occipital regions. (a) Occipital lobe O1 and (b) Occipital lobe O2.

5. Discussion

Many people with active epilepsy do not receive appropriate treatment for their condition, leading to large treatment gap. The lack of knowledge of antiepileptic drugs, poverty, beliefs, stigma, poor health infrastructure, and shortage of trained professionals contribute to this treatment gap [12,13]. In this study, we identify the brain activity in pre-ictal (immediately prior to a seizure), inter-ictal (between seizures) and postictal based on EEG signal. The temporal lobe is associated with hearing processing, memory, speech and olfaction [14,15]. The focal sharp waves in centro-temporal or occipital regions havecloseconnotation with active epilepsy.In present study, temporal lobe of theta activity was high during pre-ictal (immediately prior to a seizure) when compared to inter-ictal (between seizures) and postictal condition. This result supportsthe finding that temporal lobes are more affected, i.e., vision pathway and theta reduce during inter-ictal time.

The Ben Gurion University (BGU) team investigated a specific pattern of theta activity decline over time as signs of epileptic development [16].It is found that the theta and delta frequency bands have more dominancein detecting epileptic seizure. The probable reason is that these waves are found in large amounts during the ictal signs. The theta wave is predominantly seen in infants and people who are in sleep [17]. The delta wave is predominantly seen in people who are in dreamless deep sleep. The neuronal activity is the rate at which neurons fire. Therefore, it can be concluded that before he occurrence of seizure the theta activity increases significantly, the delta and the neuronal activity decreases significantly.

6. Conclusions

The importance of early diagnosis is to be aware of one's condition. Unattended medical emergency situations may lead to disastrous and tragic consequences. In the case of epilepsy, diagnosing/predicting it earlier (say an hour before), gives the patient and his/her attendant a brief time to prepare for the necessary medications. It also avoids unnecessary embarrassment faced by the patients after seizure episodes in a public place. Above all knowing about having a seizure episode earlier, may be helpful in understanding their condition and allowing them to calm themselves, so that the side effects of the episode may be reduced.The parameters, relative theta activity and the neuronal activity are seemed to be the better features in the period of pre-ictal seizures, as both the features can be seen with significant differences among the three different time periods in all the electrode positions, which are taken into consideration.From the outcome of the study, it is evident that the occipital lobe is better in indicating the early stage of pre-ictal period, as the observed data shows expected outcome chiefly from the electrode positions O1 and O2 (occipital lobe).

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