International Journal of Scientific Research in Computer Science and Engineering
Research Paper | Vol-2, Issue-1 | E-ISSN: 2320-7639

Information Theoretic Aspects for enhancement of accuracy in Epilepsy diagnosis

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Available online at www.isroset.org

Received: 12 Jan 2014 Revised: 20 Jan 2014 Accepted: 22 Feb 2014 Published: 28 Feb 2014

Abstract- An EEG recording remains a major source for analyzing epilepsy disease in the human being. There are various challenges associated with analyzing EEG signals. So we need such methods which can enhance the accuracy in analyzing these signals. We propose a technique towards enhancing diagnostic accuracy of the current state and provide a better estimation of survivability. The proposed methodology utilizes information theoretic approach associated with EEG recordings of epilepsy in developing a model with enhanced inferences with respect to current state of disease and future estimates of survivability.

Keywords - Information Theory, Electroencephalogram, Epilepsy, Shannon Entropy

I. INTRODUCTION

Analysis of EEG recordings is one of the methods which are widely used for diagnosis of epilepsy. These recordings are used for classification & assessment of patient having epilepsy. EEG signals are electrical impulses within the brain sense by the electrodes placed on the scalp. It is a recording of brain activity, which is the result of the activity of billions of neurons in the brain.

EEG signals are the measure of electric potential within the brain. This electric potential is very variable and random in nature. Analysis of these random signals obtained by EEG recordings provides a basis for clinical predictions related to epilepsy stage, type and scope of survival of the patient. In recent years, there has been a change from rule based purely clinical diagnosis to diagnostics utilizing Information theoretical methods for parametric analysis of EEG recordings.

Epilepsy is a common & diverse set of chronic neurological disorders characterized by seizures. Epileptic seizures result from abnormal, excessive or hyper synchronous neuronal activity in the brain. The occurrence of seizure is unpredictable and the process is very random in nature. The EEG signals are representation of brain activity in form of graph. The obtained EEG graph is then analyzed but the visual scanning of EEG graph is very time consuming. So Information theoretical method is used for analyzing the graph effectively.

To build a sophisticated model to analyze the EEG recordings or EEG graph has become a major need in biomedical area. The Information theoretical model can be leveraged for drawing epilepsy diagnostic inferences such as classification of epilepsy & their survival models. In this paper, we extend our work in terms quantifying results of EEG signals through entropy based statistical analysis. The research question addressed by the current work is: *"How to enhanced accuracy and reduced variability in clinical diagnostic analyzed through EEG signal in case of epilepsy & provide better model for survivability?"*

This research question has been answered in three sections in this paper.

- Section II presents the process of proposed statistical technique which is used to quantify the EEG signal by using the two real EEG data patterns of epilepsy, one is normal and other one is affected by epilepsy.
- In section III, the proposed entropy based diagnosis is presented and tested on the sample data set generated in section II. The technique has been shown to effectively provide an alternate approach towards enhancing accuracy and removing variability in the clinical diagnosis.
- The paper concludes in section IV by highlighting major implications of this work.

II. PROPOSED TECHNIQUE AN INFORMATION THEORETIC APPROACH

We are proposing a technique to quantify the EEG signals. Here we are applying Information theoretic frameworks on real EEG patterns to find out the relevance information. For quantify Epilepsy signals, following steps are performed.

- Obtain EEG patterns from patient in terms of time vs amplitude

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- Dividing this long pattern into different intervals to find out the correlation between different samples
- Each sample is plotted in terms of histogram values & new patterns is created
- Different histogram patterns were compared in terms of their shape parameters and pattern with large deviation & randomness was detected.
- The entropy for this pattern was calculated through entropy measures.

Based on entropy values the inferences are generated.
We have selected a subset of Epilepsy train and perform a statistical analysis on these samples. Further we have used those results as an approximation to the desired statistical characteristics of the epilepsy train as a whole. It is important to note that the result obtained by using this proposed methodology can be a good approximation to analyze any epilepsy pattern statistically. The problem of selecting the dataset become more difficult in our case as in most of the epilepsy pattern, the comparable datasets are unknown or too large to be analyzed. Therefore we have to rely on a more or less on a given dataset.

A critical aspect of taken any technique especially in the dataset is how well an information theoretic measure is estimated from the given pattern. A common measure used in such dataset is Entropy. This is a non parametric density estimator so that estimating entropy from small data set is not simple as there is no ideal estimator which can be applied. So the choice of selecting estimator depends on the type of data which is to be analyzed. In this work we have used an information theoretic measure such as Shannon Entropy and other Entropies to quantify the relation between different EEG patterns. The measure used in this work is adaptive in account for random changes in the pattern by Entropy measures.

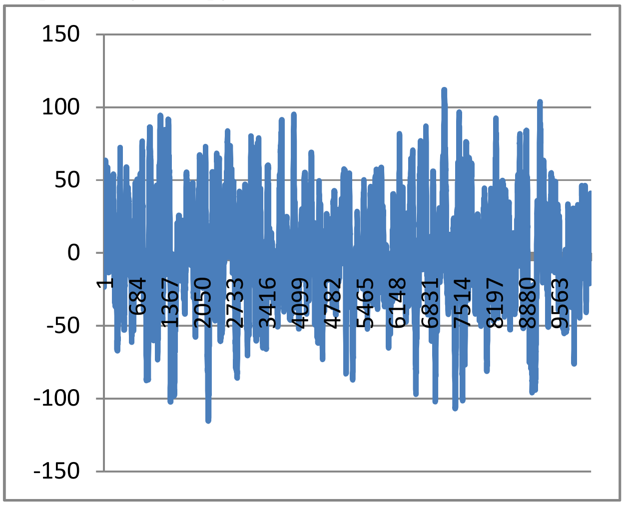

Fig 2.1(a) normal EEG pattern

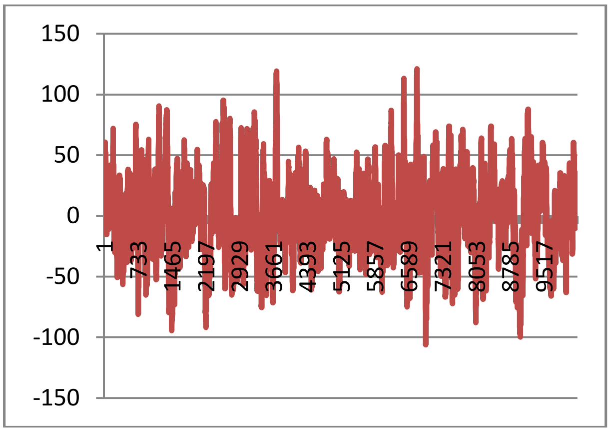

Fig 2.1(b) Affected EEG pattern

Now to analyze this pattern we are dividing this long pattern into subintervals & than plot histogram curve for each subinterval and find out the correlation among them.

III. Entropy Estimation For Eeg Data Set

In spite of several statistical models being implemented in clinical diagnosis, the information theory remains sparsely explored in this domain. In this work, we explore the concept of entropy of probabilistic data in order to compare the accuracy and reduce variability in making clinical inferences about state of disease. As a general rule of information theory, entropy is a measure of uncertainty in a random data obtained through probabilistic analysis. Given a probability p(x) of a random variable X, its entropy H(X) can be calculated as: $H(X) = - p(x) \log_2 p(x)$. The total pattern was divided into ten sub interval ranging from t1-t10. It was observed that for time subinterval t1, t3, t5, t7, t10 the normal EEG graph is uni-model where the affected EEG is bi-model for these patterns. Figure 2.2, 2.3 & 2.4 shows these model patterns for time subinterval t1, t3, t5 & t10 (both normal & affected). This leads to a new phenomenon in the pattern which clearly indicates some functional activities at the brain level.

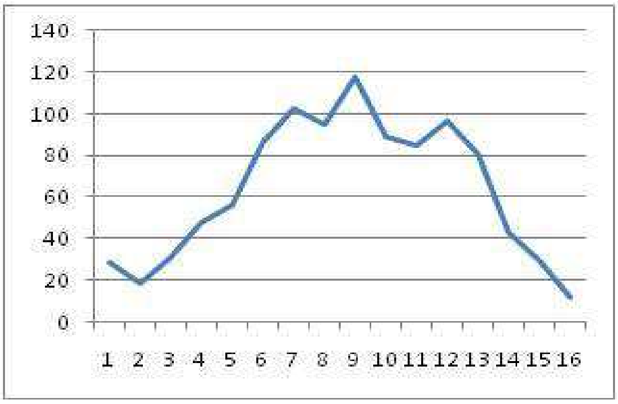

Fig 3.1(a): Unimodel Curve for t1 (normal)

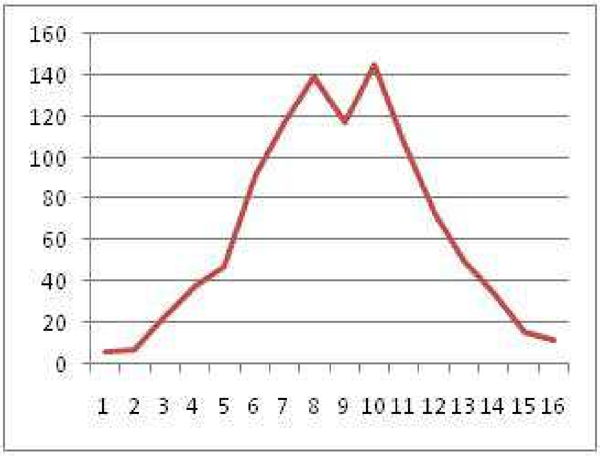

Fig 3.1(b): Bimodel curve for t1 (Affected)

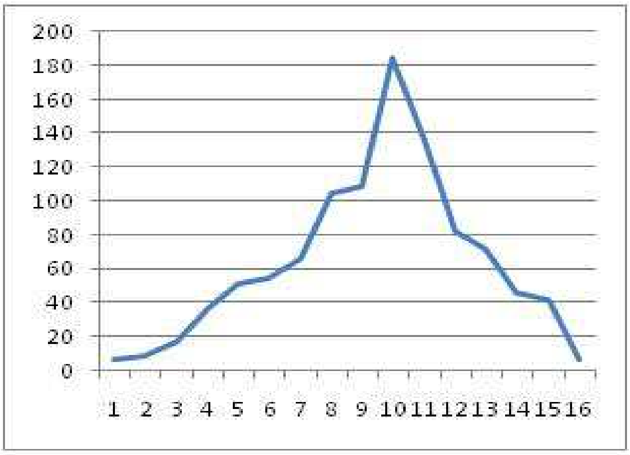

Fig 3.3 (a): Unimodel Curve for t5 (normal)

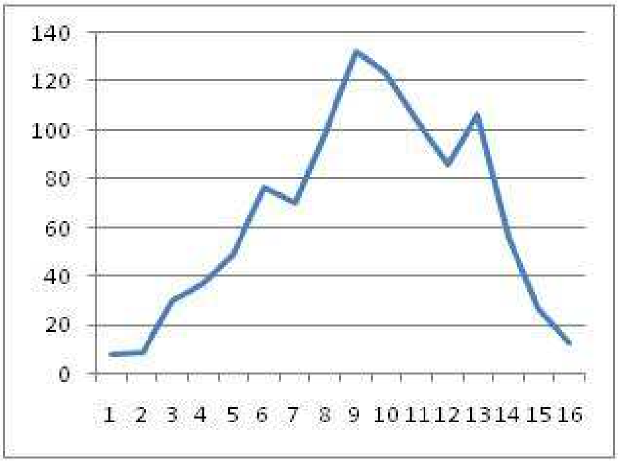

Fig 3.2(a): Unimodel Curve for t3 (normal)

Fig 3.3 (b): Bimodel curve for t5 (Affected)

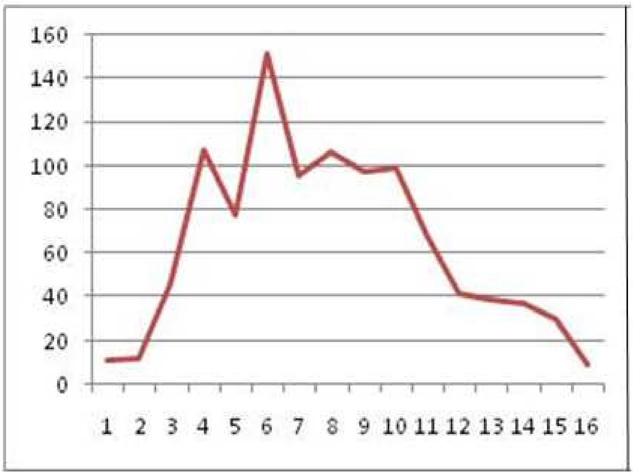

Fig 3.2(b): Bimodel curve for t3 (Affected)

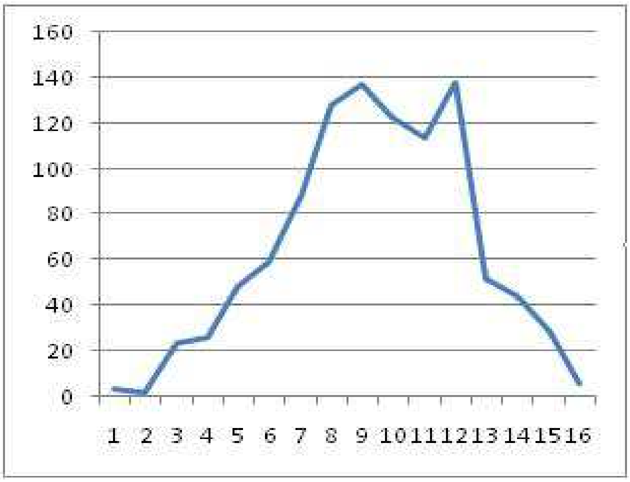

Fig 3.4(a): Unimodel Curve for t10 (normal)

Fig 3.4 (b): Bimodel curve for t10 (Affected)

Further understanding the change in complexity of EEG signal during a physiological & psychological events and its correlation with the pattern, Shannon entropy can be better measure to relate. The value shows the deviation between the normal and affected pattern is minimal. However from the table 1, it is conclusive to say that during the whole period the randomness was maximized at time interval t1 whereas it was almost minimized at time interval t10.

Table 1 gives the calculated values of these Shannon entropies and final diagnostic inference for the sample data considered in this work. This indicates the patient is suffering from epilepsy has some physiological & psychological changes which leads to these change in the randomness of the pattern.

S.No.	T.I.	NORMAL EEG	AFFECTED EEG	DIFFERENCE
1	T1	3.789760005	3.574275393	**0.21548461**
2	T2	3.690272972	3.516489367	**0.17378361**
3	T3	3.704064947	3.685392998	**0.01867194**
4	T4	3.777881722	3.624550515	**0.15333121**
5	T5	3.591922774	3.503502668	**0.08842010**
6	T6	3.591546844	3.590907753	**0.00063909**
7	T7	3.564011229	3.516386666	**0.04762456**
8	T8	3.625899967	3.610477341	**0.01542262**
9	T9	3.675765644	3.611021605	**0.06474404**
10	T10	3.54028418	3.537709686	**0.00257449**

Table 1: Shannon Entropy values different intervals

IV. CONCLUSION

In the proposed work we have introduced the information theoretic measure based on Shannon e entropy to quantify the neural activity during epilepsy. The proposed measures are shown to be effective to quantify the type of seizure based on mathematical framework over times as well as determining the difference between cognitive states.

As the Shannon entropy has given us the direction where we have found that it is clear that the affected pattern shows less randomness than the normal one. Therefore the obtained entropy measures are high in terms clinical understanding this shows that due to lower values of entropy the person is suffering from simple partial seizure.

The proposed technique enhanced the accuracy by using Shannon entropy. To find out the information present in the pulse train or in EEG recordings. By this way we can analyze the difference between the pulse train of normal patient & patient having epilepsy. One of the best implications of the proposed technique is the potential of identifying the current state of epilepsy with better accuracy and reducing the variability with respect to diagnostics and corresponding treatment.

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