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STUDY OF TWO COMMON BRAIN DISORDERS USING STATISTICAL PARAMETERS

R. KALPANA[*,a] and I. GNANAMBAL[b]

[a]Research Scholar, Anna university, CHENNAI (T.N.) INDIA
[b]Department of Electrical and Electronics, Government College of Engineering, SALEM (T.N.) INDIA

ABSTRACT

Seizures are characterized by excessive brain activity or jumpiness in the patient. Usually the patient suffers from excessive shaking of body and moments of blankness. By predicting the on-set, a physician can administer the required drugs and prevent/control the seizure thereby reducing the pain to the patients. EEG is a random process and linear analysis will not provide us with detailed information. Seizures are non-stationary in nature; therefore they are distinguished by anomalies in values of non-linear parameters such as Bi-correlation, Approximate Entropy (ApEn), Hurst Exponent. Statistical measures, time series plots are the basic ways of differentiating the changes in nature of EEG when a seizure has occurred in a subject. This methodology of analysis confirms the occurrence of this event and appropriate measures can be taken to treat the subject. We can define depression as that state of mind when we perceivably become slow in thoughts as well as action. Brain is too entangled in a maze of its own design in this state and it is among those brain disorders that lead to slow electrical activity.

Key words: Seizure, EEG, Time series analysis, Statistics, Non-stationary, Bi-correlation, Approximate entropy (ApEn), Hurst exponent, Histogram analysis.

INTRODUCTION

Electroencephalography (EEG) is the recording of electrical activity of the brain, spectral content of this wave is of utmost importance in diagnosis, that is, the type of neural oscillations that can be observed in EEG signals, tell us about the type of classification it comes under. Epilepsy is a brain disorder that causes abnormalities in EEG, which is studied in this paper. EEG can also be used as a first-line method for the diagnosis of tumors, stroke and other focal brain disorders. High quality imaging techniques have made this almost obsolete. Despite limited spatial resolution, EEG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution (not possible with CT

[*]Author for correspondence; E-mail: kalpana_suresh@yahoo.com

or MRI) is required. A seizure is the physical findings or changes in behavior that occur after an episode of abnormal electrical activity in the brain. The term "seizure" is often used interchangeably with "convulsion." Convulsions are when a person's body shakes rapidly and uncontrollably. During convulsions, the person's muscles contract and relax repeatedly. There are many different types of seizures. Some have mild symptoms and no body shaking.

EXPERIMENTAL

Materials and methods

The data set obtained from contains 5 types of EEG recordings. The sampling rate of the signals is 173.53Hz.N File-eye open of healthy subject, F File-eye closed of healthy subject, O File-epilepsy from focal region, S File-seizure Z File-epilepsy spikes from hippocampal lesion Depression data set. It’s a one channel intracranial invasive EEG data; each file contains 100.txt files. Each file contains 4096 samples of the recording. This accounts to 23.59 sec of recording. Therefore, there are about 40 minutes of data of each type the data values are stored in ASCII format.

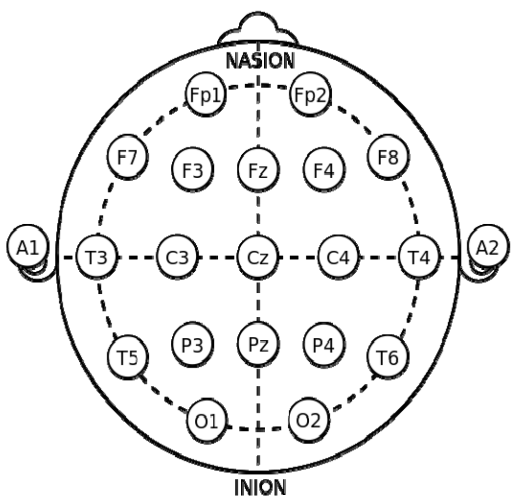

Fig. 1: 10-20 EEG Recording system

Linear measurement and analysis

Histogram analysis

A histogram is a graphical representation of the distribution of numerical data. It is an estimate of the probability distribution of a continuous (quantitative variable) and was first introduced by Karl Pearson. To construct a histogram, the first step is to "bin" the range of values; that is, divide the entire range of values into a series of intervals and then count how many values fall into each interval. The bins are usually specified as consecutive, non-overlapping intervals of a variable. The bins (intervals) must be adjacent, and are usually equal size. Histograms give a rough sense of the density of the underlying distribution of the data, and often for density estimation: estimating the probability density function of the underlying variable. The total area of a histogram used for probability density is always normalized to 1. If the lengths of the intervals on the x-axis are all 1, then a histogram is identical to a relative frequency plot.

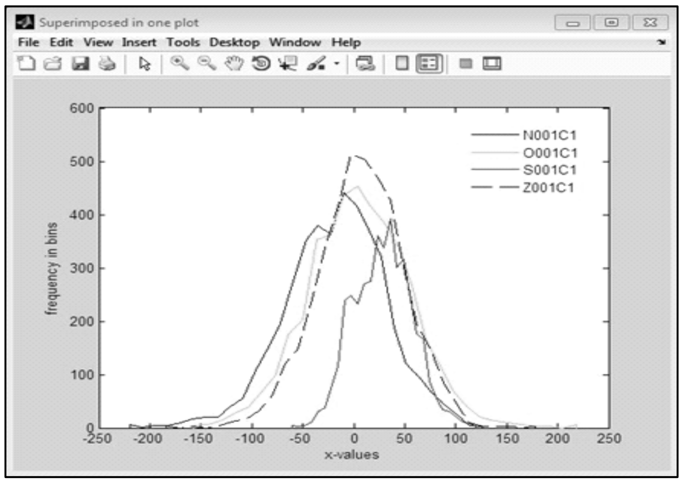

Fig. 2: Overlapped histograms

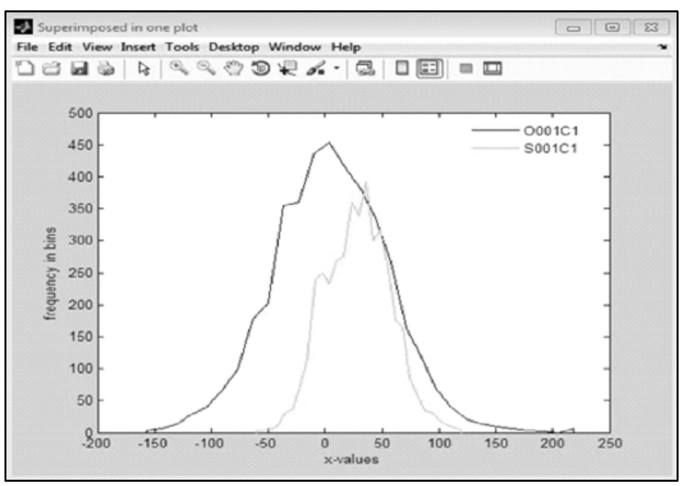

Fig. 3: Positive shift in epileptic histogram

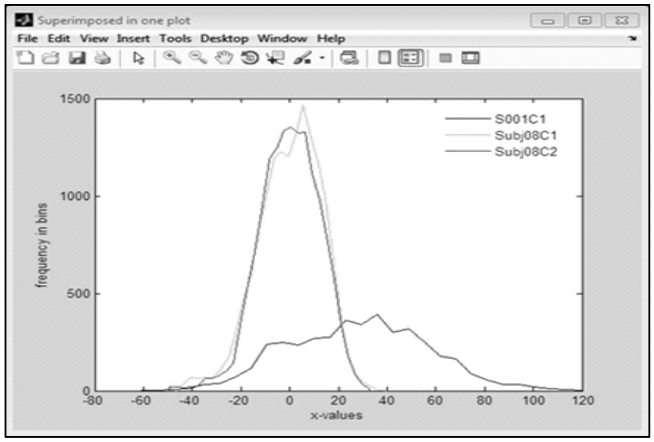

Fig. 4: Negative shift in depression histogram

Z-data set has a more concentrated histogram towards 0 x-values. S-data set shows a relative shift of nearly 50 units along x-values. Hence, seizures are indicated using this analysis. O-data set shows the next greater shift of around 20 units in x-values, hence if the recordings are showing spikes in focal region or hippocampal region of brain, then the variations are cleanly observed as shown above in histograms. Depression histogram shifts in the negative scale, indicating the alarming decrease in brain activity in the person. Seizures have the lowest standard deviation values for both maxima and minima of the EEG data for that event.

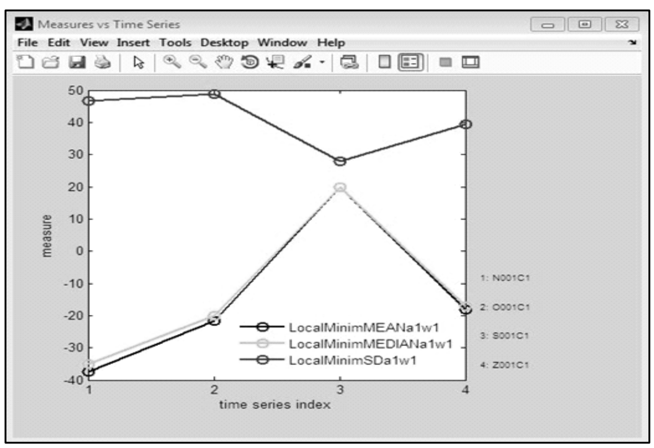

Fig. 5: Mean, median, and standard deviation for local minima values

Mean and Median values are the highest for Seizures when compared to other data-set values. These are illustrated below in Figs. 8 and 9. Low standard deviation values tell us that the Seizure EEG data is much more closely packed around the average value (mean), hence Seizures appear as narrower graphs in their time-series plots, described in Fig. 6, other data-sets show greater variations around their mean values.

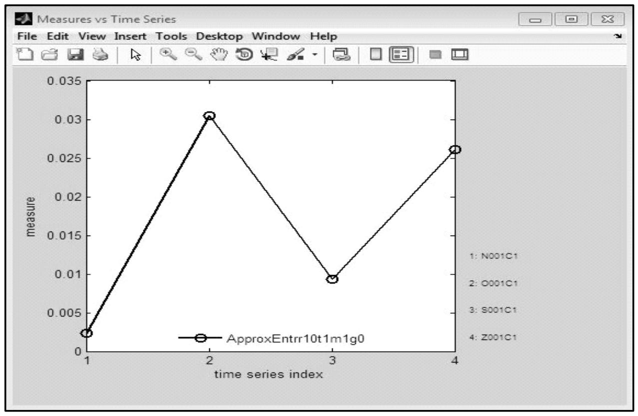

Fig. 6: ApEn Graph for data sets

Non-linear measurement and analysis

The brain is a highly complex and vital organ of a human body whose neurons interact with the local as well as the remote ones in a very complicated way these interactions evolve as the Spatio-temporal electro-magnetic field of the brain, and are recorded as Electroencephalogram (EEG). It has been established that EEG recordings exhibit chaotic behavior. The theory of nonlinear dynamical systems, also called 'chaos theory', has now progressed to a stage, w.[2-5] Here, it is possible to study self-organization and pattern formation in the complex neuronal networks of the brain. According to Kellert), chaos theory is “the qualitative study of unstable a periodic behavior in deterministic dynamical systems. Some of the common parameters are, approximate entropy, Hurst-exponent, Bi-correlation.

Approximateentropy (ApEn)

In statistics, approximate entropy (ApEn) is a technique used to quantify the amount of regularity and the unpredictability of fluctuations over time-series data.

$$\frac{1}{L-m}\sum_{i=1}^{L-m}\log C_i^{m+1}(r)-\frac{1}{L-m+1}\times\sum_{i=1}^{L-m}\log C_i^{m}(r) \qquad \ldots(1)$$

The presence of repetitive patterns of fluctuation in a time series renders it more predictable than a time series in which such patterns are absent. ApEn reflects the likelihood that similar patterns of observations will not be followed by additional similar observations[5,6]. A time series containing many repetitive patterns has a relatively small ApEn; a less predictable process has a higher ApEn. Epilepsy from the focal region has the highest approximate entropy; hence it is less predictable than the EEG from healthy subjects as indicated by the low value of ApEn is 0.032 for O-data-set much greater than 0.002 for N-data-set.

Bi-correlation

Bi-Correlation is a statistical measure that indicates the extent to which two or more variables fluctuate together. A positive correlation indicates the extent to which those variables increase or decrease in parallel; a negative correlation indicates the extent to which one variable increases as the other decreases. When the fluctuation of one variable reliably predicts a similar fluctuation in another variable, there's often a tendency to think that means that the change in one causes the change in the other. However, correlation does not imply causation. There may be, for example, an unknown factor that influences both variables similarly data set shows the highest bi-correlation value, indicating their variables are increasing over the entire duration of recording of EEG. *bicorrelation*, or three-point autocorrelation, or higher order correlation, is the joint moment of three variables formed from the time series and two delays t and s. A simplified scenario for the delays is implemented, $s = 2t$,

Formulae for calculating Bi-correlation

$$E\,[x(i), x(i+t), x(i+2t)] \qquad \ldots(2)$$

So the bi-correlation is where the mean value is estimated by the sample average. In this way, the bi-correlation is a function of a single delay t.

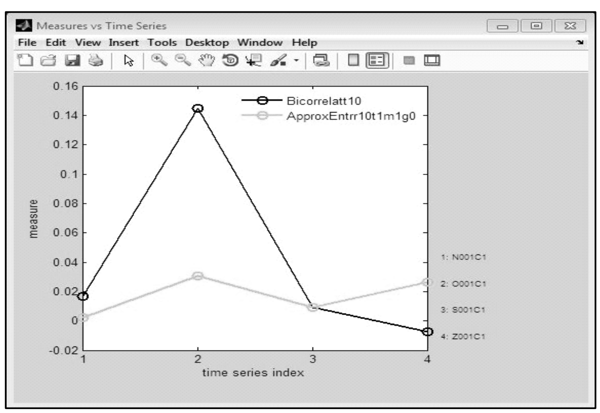

Fig. 7: Bi-correlation and ApEn comparison

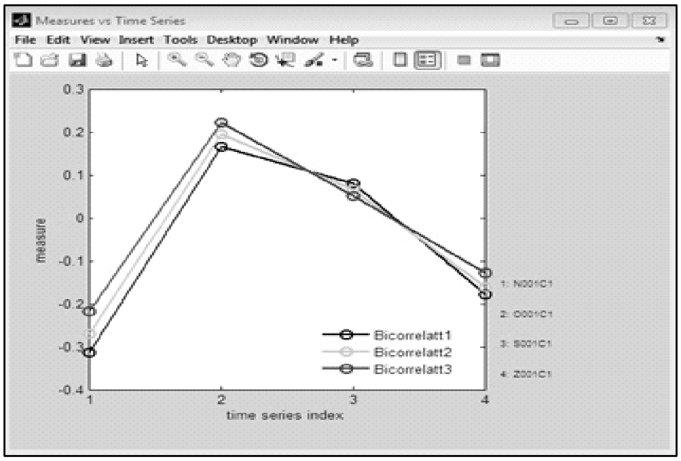

Fig. 8: Bi-correlation values

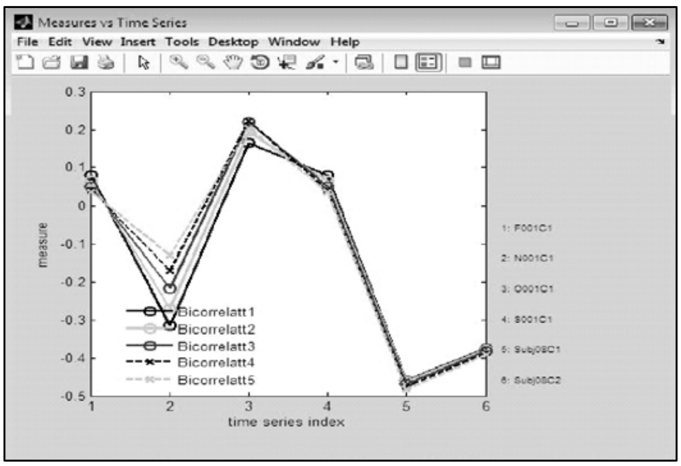

Fig. 9: Bi-correlation for depression data set

Even in the segmented time-series analysis O-data set shows the higher values of change, EEG from a healthy subject has low bi-correlation and low approximate entropy values. Observe the comparison between variations in bi-correlation and ApEn values, a small change in ApEn causes a huge change in magnitude of bi-correlation values.

Hurst exponent

The Hurst exponent is used as a measure of long-term memory of time series. It relates to the autocorrelations of the time series, and the rate at which these decrease as the lag between pairs of values increases. Studies involving the Hurst exponent were originally developed in hydrology for the practical matter of determining optimum dam sizing for the Nile River's volatile rain and drought conditions that had been observed over a long period of time. The name "Hurst exponent", or "Hurst coefficient", derives from Harold Edwin Hurst, who was the lead researcher in these studies; the use of the standard notation H for the coefficient relates to his name also[6,4,2,1].

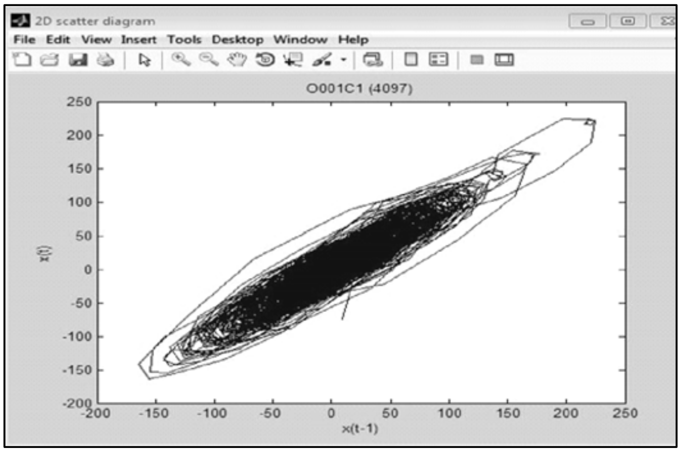

Fig. 10: Hurst exponent for epilepsy from focal region

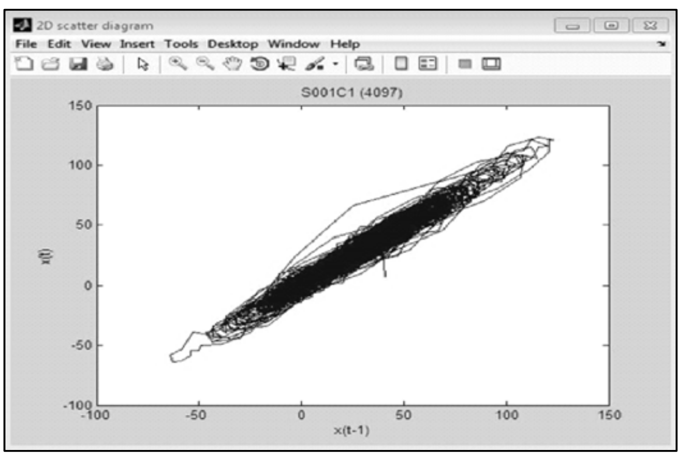

Fig. 11: Hurst exponent for seizures

The Hurst exponent is referred to as the "index of dependence" or "index of long-range dependence". It quantifies the relative tendency of a time series either to regress strongly to the mean or to cluster in a direction. A value H in the range 0.5–1 indicates a time series with long-term positive autocorrelation, meaning both that a high value in the series will probably be followed by another high value and that the values a long time into the future will also tend to be high. A value in the range 0 – 0.5 indicates a time series with long-term switching between high and low values in adjacent pairs, meaning that a single high value will probably be followed by a low value and that the value after that will tend to be high, with this tendency to switch between high and low values lasting a long time into the future. A value of H=0.5 can indicate a completely uncorrelated series, but in fact it is the value applicable to series for which the autocorrelations at small time lags can be positive or negative but where the absolute values of the autocorrelations decay exponentially quickly to zero.

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The expression for calculating hurst exponent

The Hurst exponent H is defined as:

$$H = \frac{\log\left(\frac{R}{S}\right)}{\log (T)} \quad \ldots(3)$$

Where T is the duration of the sample of data and R/S the corresponding value of rescaled range. The Hurst exponent is referred to as the "index of dependence" or "index of long-range dependence". It quantifies the relative tendency of a time series either to regress strongly to the mean or to cluster in a direction. A value H in the range 0.5–1 indicates a time series with long- A value H in the range 0.5–1 indicates a time series with long-term positive autocorrelation, meaning both that a high value in the series will probably be followed by another high value and that the values a long time into the future will also tend to be high. A value in the range 0-0.5 indicates a time series with long-term switching between high and low values in adjacent pairs, meaning that a single high value will probably be followed by a low value and that the value after that will tend to be high, with this tendency to switch between high and low values lasting a long time into the future. A value of H = 0.5 can indicate a completely uncorrelated series, but in fact it is the value applicable to series for which the autocorrelations at small time lags can be positive or negative but where the absolute values of the autocorrelations decay exponentially quickly to zero.

CONCLUSION

At first glance, the aforementioned inconsistent findings may appear discouraging because they limit the importance of those aspects of brain electrical activity that were presumed to be most relevant for a detection of an increased probability of seizure occurrence. However, these findings also indicate that seizure occurrence may not be regarded as a purely stochastic phenomenon[12,15,16]. Today, there is increasing evidence that a number of key conceptual features of nonlinear dynamic systems have particular relevance to improve understanding of the spatiotemporal dynamics of the epileptogenic process: The basic principle of almost all nonlinear time series analysis techniques is the reconstruction of the observed system dynamics in a so-called state space. Although an unknown system may well be dependent on a largeand for the EEG often unknown-number of variables, the mathematical theorem of Tokens states that the system's behavior in state space can be approximated using only a single observed variable (e.g., the EEG). If the system is governed by nonlinearity, a simple cause-effect relationship cannot be expected. Rather, nonlinear systems are characterized by a rich variety of dynamics including bifurcations that indicate abrupt state transition or intermittent behavior. EEG is of similar nature making it easier to analyze by non-linearity".[1]

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