

Non-Linear Feature Analysis on EEG Signals Under Cognition

Kalpana.R

Assistant Professor/Department of Medical
Electronics
B.M.S College of Engineering, Bangalore, India

Chitra.M

Professor/Department of Information Science and
Technology
Sona College of Technology, Salem.India

Abstract— The dynamicity of the brain can be analyzed using the Non-linear signal analysis. Non-Linear signal analysis is based on the mathematical theory of dynamical systems. Since they are complex in nature it can be both deterministic and also chaotic sometimes. If the system can be described by a set of states and some kind of transition rules which specify how the system may travel from one state to another. The significance of biological time series is mainly applied in knowing the nonlinear signals of dynamic systems, by extracting its features based on physiological phenomenon and concepts. Here the analysis is carried out for EEG signals for measuring the Nonlinear features of different cognitive tasks such as Arithmetic task, letter counting- task rotating- task, resting- task and visual counting task. The use of quantitative measures for the analysis of these systems helpful for better in sight in to system dynamics. The correlation dimension, Correlation sum, radius Correlation sum, Hurst exponent, and False-nearest neighbour are the parameters taken for measurement.

Index terms - *Electroencephalogram (EEG); Non-linear features (properties); cognition.*

I. INTRODUCTION

The [electric potential](#) generated by single neuron is far too small to be picked up by EEG or MEG. EEG activity is therefore always reflects the summation of the [synchronous activity](#) of thousands or millions of neurons that have similar spatial orientation. Specifically the significance of this work is to extract the Nonlinear properties under different cognitive states. EEG signals contain noise as a result of the movement of the electrode on the scalp is contaminated with eye blinks or other muscular activities are not stationary. EEG appears to reflect aspects of cognitive processes and may differentiate among mental activities and cognitive loads. Much research effort has focused on exploiting the information content of this signal for understanding the functioning of the brain as well as for clinical diagnostics. In particular, the focus on nonlinear properties of different cognitive states. Here, the goal is to enhance the task related performance of a human user through computer assistance based on the assessments of the user's cognitive level.

Today's cognitive psychology [21,25] differs from classical psychological approaches in the methods they use as well as in the interdisciplinary connections to other sciences. Apart from rejecting introspection as a valid method to analyze mental

phenomenon, cognitive psychology introduces further, mainly computer-based, techniques that had not been in the range of methods used by classical psychology so far. The realization that there are important links between brain activity and cognitive functions is the key assumption for present and future research. Complete psychological accounts of cognitive functioning require considerations of the computational level, algorithmic level and the brain levels, about how the representation and the algorithm be realized physically. EEG has many advantages in measuring brain activity including the convenience and low cost. However, it is very difficult to estimate cognitive or mental state from EEG signals for a number of reasons. Nonlinear dynamics theory opens new window for understanding behavior of EEG. EEG models were proposed by Freeman. The literature on the study of the application of the nonlinear dynamics theory to analyze physiological signals shows that nonlinear approaches were used for analysis of renal blood flow, arterial pressure, EEG and respiratory signals, heart rate and nerve activity.

II. METHODOLOGY

The 5 cognitive tests were administered to 7 subjects as summarized on table 1. Here we have taken five different cognitive tasks for our analysis purpose like resting or baseline task, arithmetic task, geometric task, letter composition task, visual counting task from healthy subjects with no history of neurological disorders from a age group of 22-45. Data were collected from 254 scalp, neck, face and eye locations using the Bio semi Active Two system. Data referenced to the right

An experiment paradigm was designed for the study and the protocol was explained to each participant before conducting the experiment. In this, the subject was asked to comfortably lie down in a relaxed position with eyes closed. After assuring the normal relaxed state by checking the alpha waves, the EEG was recorded for 50 sec, collecting five session of 10sec epoch each for the relaxed state. This was used as the baseline reference for further analysis of mental task. The subject was asked to perform a mental task on presentation of an audio cue. Five session of 10sec epoch for each mental task were recorded, each with a time gap of 5minute. The whole experiment lasted for about one hour including electrode placement. Feature extraction and classification of **electro-**

physiological signals is an important issue in development of disease. In this paper we propose a method based on cognitive methodology for EEG signal for classification. [21,20,24,25]

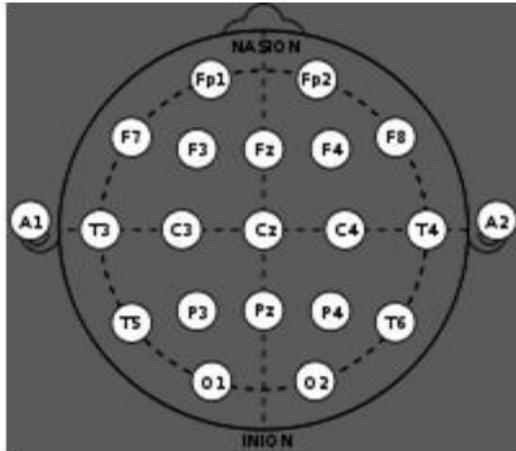


Fig. 1 International EEG Recording 10-20 system

Nonlinear features were calculated to classify EEG signal represent the Cognitive task.

III. FEATURE EXTRACTION FOR NONLINEAR ANALYSIS

A. The Hurst Exponent:

Hurst exponent is used to evaluate the presence or absence of long-range dependence and its degree in a time-series. However, local trends (non-stationaries) are often present in physiological data and may compromise the ability of some methods to measure self-similarity. The Hurst exponent is a measure of the smoothness of a fractal time-series based on the asymptotic behavior of the rescaled range of the process. The Hurst exponent is a measure that has been widely used to evaluate the self-similarity and correlation properties of fractional Brownian noise, the time-series produced by a fractional (fractal) Gaussian process,

The Hurst exponent, H, is defined as:

$$H = \log(R/S) / \log(T) \quad (1)$$

Where T is the duration of the sample of the corresponding value of rescaled range with high.

B. The Correlation dimension:

Correlation dimension (D2) describes the dimensionality of the underlying process in relation to its geometrical reconstruction in phase space. This section estimated the complexity using the approach based Grassberger-Procaccia

algorithm [3,4,1]. It estimates the average number of data points within a radius r of the data point r_{ij} as

The correlation dimension:

$$CD = \lim_{r \rightarrow 0} \frac{\log C(r)}{\log(r)} \quad (2)$$

$$C(r) = \frac{1}{(N - \eta_{\min})(N - \eta_{\min} - 1)} \sum_{x=1}^N \sum_{y=x+\eta_{\min}}^N \Theta(r - |X_x - X_y|) \quad (3)$$

Where X_x and X_y are the points of the trajectory in the phase space, for N number of data points or the radial distance around each reference point X_i , Θ the Heaviside function and η_{\min} the average correlation time.

C. The Correlation Sum

The estimation starts with the computation of the so-called correlation sum $C(r)$ which is calculated for a range of radii r. For each r, $C(r)$ is the average fraction of points within this radius r (r is referred to as radius because the Euclidean norm is used to compute the inter-point distances of all points from each reference point).

D. The Radius correlation Sum

Correlation Sum for given radius is the correlation sum computed for the given range of the delay t, the embedding dimension m, and the radii r.

E. The False Nearest Neighbor

The false nearest neighbors procedure is a method to obtain the optimum embedding dimension for phase space reconstruction. By checking the neighborhood of points embedded in projection manifolds of increasing dimension, the algorithm eliminates 'false neighbors'. A natural criterion for catching embedding errors is that the increase in distance between two neighbored points is large when going from dimension d to d+1. We state this criterion by designating as a false nearest neighbor any neighbor for which the following is valid:

$$\frac{R^2(t, r) - R^2}{R_d(t, \tau)} \Big|_{1/2=} \frac{|x(t+\tau) - x(t_r + \tau)|}{R_d(t, \tau)} > R_{\text{tot}} \quad (4)$$

Here t and t_r are the times corresponding to the neighbor and the reference point, respectively. R_d denotes the distance in phase space with embedding dimension d , and R_{tol} is the tolerance threshold

IV. RESULTS

In this work, analysis is carried out for analyzing the EEGs using various characteristic measures like Correlation Dimension, Hurst exponent, and correlation sum, radius-sum, false- nearest neighbor

trending (persistent). The Hurst exponent is limited to a value between 0 to 1, as it corresponds to a fractal dimension between 1 and 2 ($D=2-H$, where $0 < H < 1$). The Hurst exponent is limited to a value between 0 to 1, as it corresponds to a fractal dimension between 1 and 2 ($D=2-H$, where $0 < H < 1$). I often think of it more along the lines of how much space the 'wandering' fills up (between 1 to 2 dimensions) and also how jagged or noisy the process may be (more noisy \rightarrow lower Hurst, more smooth \rightarrow higher Hurst). You could calculate an $H > 1$, but it would not have any meaning using the accepted

definition and fractal dimension boundaries (fractions between integer dimensions must always be less than one).

| NO | Non-Linear Properties | Task1 | Task2 | Task3 | Task4 | Task5 |
|----|------------------------|---------|---------|---------|---------|----------|
| 1 | Correlation dimension | 0.96406 | 0.98225 | 0.9843 | 0.97737 | 0.972271 |
| 2 | Correlation Sum | 0.43237 | 0.3853 | 0.3735 | 0.3473 | 0.364029 |
| 3 | Radius Correlaton sum | 0.02336 | 0.029 | 0.02721 | 0.02818 | 0.02671 |
| 4 | False nearest neighbor | 0.99239 | 0.95 | 0.967 | 0.9872 | 0.9901 |
| 5 | Hurst exponent | 0.8367 | 0.86224 | 0.77827 | 0.85018 | 0.8444 |

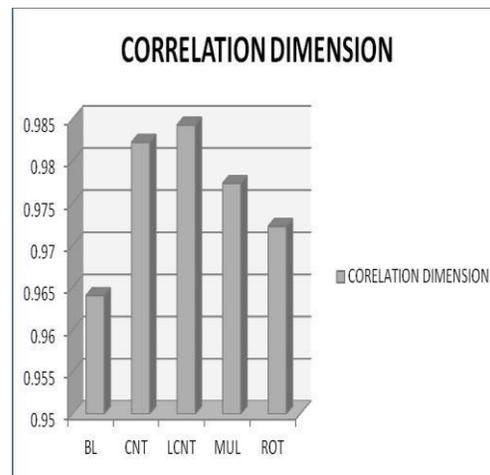


Fig. 3 Graphical representation of the Correlation Dimension of various cognitive states

From the above graph the correlation dimension of all cognitive tasks shows that for baseline task the value is significantly lower in comparison with other tas

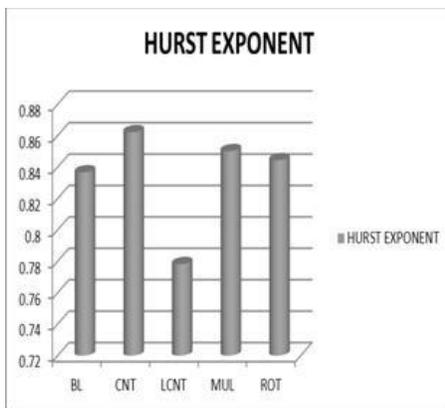


Fig: 2 Graphical representation of the Hurst exponent of various cognitive states

BL-Base line task, CNT-Counting task,LNT-countingtask
 ,MUL-Multiplicative task, ROT-rotating task

From the above graph the Hurst exponent for all cognitive tasks . A Hurst exponent, H , between 0 to 0.5 is said to correspond to a mean reverting process (anti-persistent), $H=0.5$ corresponds to Geometric Brownian Motion (Random Walk), while $H \geq 0.5$ corresponds to a process which is

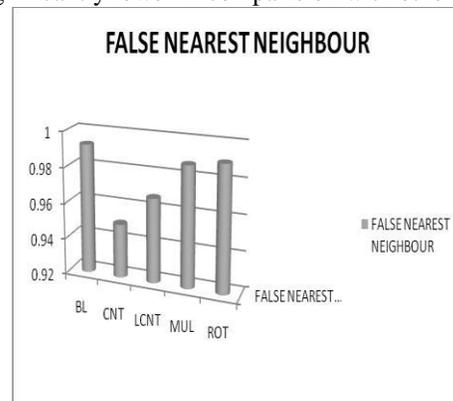


FIG. 4 Graphical representation of the False nearest neighbor various cognitive states.

The false nearest neighbor is a useful measure of nonlinearity. For more cognitive tasks the value shows low value in the base line task it shows higher value.

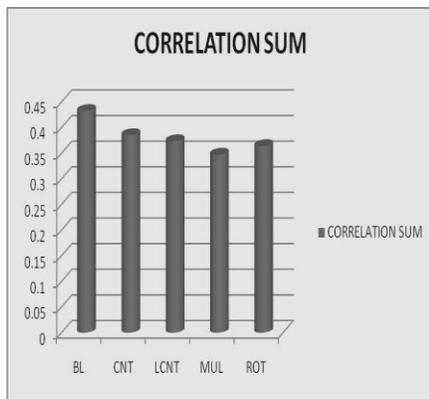


Fig. 5 Graphical representation of the Correlation sum of various cognitive states

From the above graph the correlation sum of baseline task shows 0-0.45. The other activities varies in the following order BL>CNT>ROT>LCNT>MUL. From the graph it says that for higher cognitive task the correlation dimension shows Low in value in comparison with other cognitive states

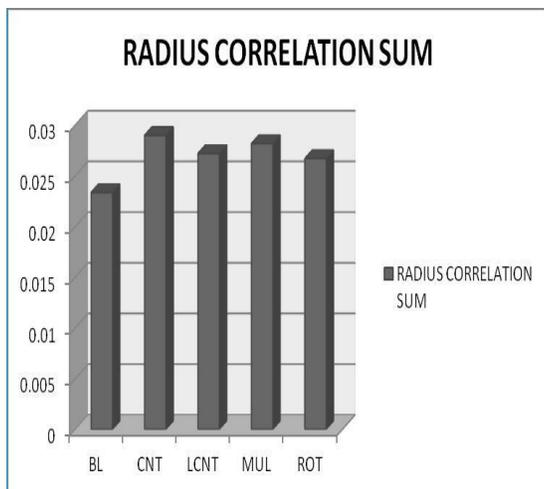


Fig. 6 Graphical representation of the Radius correlation sum of various cognitive states.

From the above diagram the Radius correlation sum of the various cognitive states are plotted it ranges form 0-0.03 for baseline task. In the same way the range varies more or less same for all the cognitive states

IV. DISCUSSION

The From this study we observe, it's possible to classify the various mental task and cognitive functions from EEG signal using Non-linear parameters and we may understand it in better way. Statistical analysis is performed by comparing

the results obtained from various mental states with respect to the normal resting state. Table 1 depicts the statistical outcome of the nonlinear analysis between the normal and other states. It is found that the measures are significantly changes when the subjects are under cognition, Compared to the normal state. It is well known that the dimension of EEG time series is closely related to the cognitive activity of the brain .The dimension increases with the degree of the cognitive activity.. From the result it can be seen that there is a distinct difference in the correlation dimension in the different mental states.. A decreased value indicates that the randomness False nearest neighbors is used for calculation of proper embedding dimension. Furthermore, one may use the algorithm to calculate simultaneously the correlation dimension. Thus, one sequence of computations will yield an estimate of both the level of chaos and deterministic signal. In this paper, we use the determinacy, the correlation dimension and the Hurst exponent method etc to study the EEG signal of 5 kinds of consciousness activities of 7 subjects. Although every method has merits and faults, the results show the nonlinear dynamic characteristics of the subject's brain from different perspective. There into, from the deterministic computation we know that the EEG signal is between random signal and deterministic signal. This indicates that the brain may be a chaotic system. The analysis of the activities well, which can better indicate the activity degree of human consciousness, The above analyses indicate: Different consciousness activities have profound nonlinear dynamic differences... The correlation dimensions show the change of chaos of different consciousness system complexity.

VI. CONCLUSION

For certain classes of problems the linear hypothesis proves false and traditional methods are modified to accommodate nonlinear behavior. From the graphs the statistical analysis of various task data's are analyzed. EEG signal can be used as a reliable indicator of the state of the mind. Ever since the birth of 'nonlinear science 'chaos ticians of physiology, biomedical engineering and theoretical biology are searching for meaningful chaotic parameters in physiological processes.. In this work, we have proposed a set of ranges for these nonlinear parameters for various mental states. [20,19,25]The above analysis is applicable for sleep data analysis, for the study of various diseases of brain disorders such as (schizophrenia, Alzemer, Demetia, epilepsyetc). The classification of various tasks taken can be classified The above techniques are helpful for comparison of higher cognitive tasks.

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AUTHORS PROFILE



Mrs. R. KALPANA received B.E degree in Electronics and communication Engineering from Hindustan college of Engineering, University of Madras, in 1992 and received M.Tech. degree in Digital Communications. from Department of Electronics, B.M.S College of Engineering, Visvesvaraya Institute of Technology in 2005, Bangalore. She has 12 years of teaching experience in field of Biomedical Electronics. Currently she is working as Asst. Prof in Department of Medical electronics. She has published 5 international research papers. Her area of Interest is in Biomedical Signal processing, Instrumentation and communication systems and Statistics.



Prof. M. CHITRA received PhD Degree in Information and communication engineering from Anna university of Technology Chennai, in the year 2009. She is currently working as Professor, Department of Information science and Technology, Sona College of Technology. Salem, Tamilnadu she has 15 years of teaching

experience in field of Information science and communication Engineering. Her Area of Interest is Mathematics, Neural networks, communication and signal processing and Image processing.. She has published more than 15 International research papers.