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The Implication of graph theory Approach with different cognitive conditions of electroencephalography Signal

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Abstract
Cognition is a branch of neuroscience which is a psychological science which is interested in various mind and brain related subfields such as the mental processes that underlie behavior, reasoning and decision making. We approach the graph theory measurements using electroencephalography (EEG) to understand the neuronal changes due to different cognitive activities. We analyze the clustering coefficient, path length and local efficiency. We found the higher clustering coefficient, path length and lower local efficiency for alpha and beta frequency bands. The fronto-temporal region show significant changes in clustering coefficients. The result shows irregular connectivity in fronto-temporal region which may significant for deficits of execution and memory components.

Keywords-graphtheory, electroencephalography, clustering coefficient, path length, Cognition.

I. Introduction

There are number of Signal processing methodologies such as fMRI (Functional MRI) and MRI to acquire the brain signal but dynamical nature and the complex nature of the brain can be analyzed very well only by EEG (electroencephalograph) rather than any other signals. Today's cognitive neuroscience is major area of research in analysis of behavior of brain activity. The cognitive functions is the key assumption for present and future research. Nonlinear methods was also another way for understanding the cognitive aspects of brain regions, Molle, M et al(1999)In this study, the performance of Sevcik's algorithm that calculates the fractal dimension and permutation entropy as discriminates to detect calming and insight meditation in electroencephalographic (EEG) signals was assessed. Chon, Ket al (2009)., the purpose of this research was to examine the robustness of these two entropy algorithms by exploring the effect of changing parameter values on short data sets. The Mathematical concepts in graph theory concepts introduced by authors came recently for the better insight into the cognitive state analysis requires a small-world analysis. The small-world models provide a powerful and versatile approach to understanding the structure and function of human brain systems.. 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 brain cognitive states, with the help of either single channel or multichannel systems. Our findings demonstrated that the brain functional networks had efficient small world properties in the healthy subjects. Whereas these properties were disrupted in the patients with different cognitive tasks performed. Our findings demonstrated that the brain functional networks had efficient small world properties in the healthy subjects. Whereas these properties were disrupted in the patients with different cognitive tasks performed. The evolution of small-world networks is discussed in terms of a selection pressure to deliver cost-effective information-processing systems, the authors consider the relevance of small-world models for understanding the emergence of complex behaviors and the resilience of brain systems to pathological attack by disease or aberrant development. Ling Li et al (2014) the author investigates phase synchrony as a neuro-marker for the identification of two brain states: coma and quasi-brain-death. Scalp electroencephalography (EEG) data the results suggest phase synchrony for coma patients has a significant increase in the theta / alpha band compared to quasi-brain-death patients. in patients with schizophrenia the small-world topological properties are significantly altered in many brain regions in the prefrontal, parietal and temporal lobes the authors found that they altered topological measurements correlate with illness duration in schizophrenia., Detection and estimation of these alterations could prove helpful for understanding the pathophysiological mechanism as well as for evaluation of the severity of schizophrenia(Aftanas, L et al. 1998). Overall, the results point to the idea that dynamically changing inner experience during meditation is better indexed by a combination of non-linear and linear EEG variables

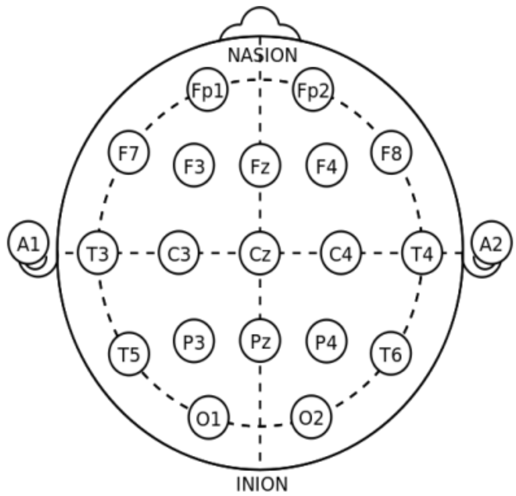


Fig1: (10-20) Electrode International Standard System

II. MATERIALS AND METHODS

Ten adult right-handed healthy people with a mean age of 28 years (SD ± 5 years) participate for electroencephalography (EEG) signal recording. The participants had no history of neurological or psychiatric disease and did not take any medication that could affect the experiment. All participants have more than five teen years of education and with IT (Information Technology) professional skill artifact and if any epochs containing voltage of more than 150 µV was manually rejected The EEG cap consisted of 31 uni polar scalp electrodes placed according to the international 10-20 system electrode placement and one additional electrode dedicated to the vertical electrooculogram (EOG) refer fig 1. Data were recorded relative to an FCz reference and a ground electrode was located at Iz (10-5 electrode system, (ostenveld and Praamstra, 2001). Data were sampled at 1000 Hz and the impedance between electrode and scalp was kept below 5 kΩ. Data was acquired in a close room with a comfort sit. The room was containing very minimum no of electronic gadget and very good grounding. The paradigm instruction was given via small mike situated inside the room. Inside the room one LCD monitor have there for visual representation.

PARADIGM FOR DIFFERENT TASKS:

Three type of cognitive task was performed fallowed to eye open and eye close at relax resting condition. Details are fallowed.

Instruction for eye open, close at rest:

Subject was instructed to be sited with relax condition, as per instruction subjects was open their eye for five minute and closed their eye for five minute. At that time instruction was given to do not do any cognitive task like language, attention, memory related or motor tasks as much as possible.

Instruction for Motor task

Subject was instructed four sections such as Relax, to squeeze right hand, relax, to squeeze left hand. Each of section was thirty second and whole cycle was repeated three times.

Instruction for Arithmetic Calculation

Subject was instructed to count the Fibonacci Sequence is the series of numbers: 0, 1, 1, 2, ……100

A. Computation of the synchronization likelihood (SL)

Functional connectivity was determined by computing the synchronization likelihood (SL) between all pair wise combinations of EEG channels, resulting in a N by N connectivity matrix (N: EEG channel). The SL is a general measure of the correlation or synchronization between 2 time series, which is sensitive to linear as well as nonlinear interdependencies. (Stam and van Dijk, 2002). Briefly, from two discrete time series *xi* and *yi* vectors are reconstructed with the method of time-delay embedding. The synchronization likelihood at time *i* is then defined as the likelihood (between 0 and 1), averaged over all *j*, that the distance between *Yi* and *Yj* is smaller than a cut off distance r_{cutoff}, given the distance between *Xi* and *Xj* is smaller than r_{cutoff}. The SL ranges between Pref (a small number close to 0) in the case of independent time series and 1 in the case of maximally synchronous signals. For the computation of SL, an average reference montage was used in order to minimize artificial sources of synchronization; SL is highest for the linked-ears montage, and substantially lower for the other types of montages. The end result of computing the SL forall pair wise combinations of channels is a square N X N matrix of size 30 (the number of EEG channels), where each entry Ni, j contains the value of the SL for the channels i and j. To convert the full connectivity matrix to a sparsely connected graph, we choose a threshold such that only pairs of channels with a synchronization likelihood above this threshold were considered to be connected by an edge; otherwise they were not considered to be connected. For the specific purposes of this study, signals were band-pass filtered (digital off-line filter with no phase-shift) in order to analyze synchronization likelihood in the following frequency bands: delta (0. 25-2. 5 Hz), theta (4. 0-7. 0 Hz); alpha (7. 0-11. 0 Hz); sigma (11. 0-15. 0 Hz); beta (15. 0-30. 0 Hz). For all analyses the threshold was chosen such that $K = 3$; in all cases $N = 30$. K is chosen such that the resulting graph is sparsely connected (thus $K \ll N$, where N = number of electrodes). The reason to keep K fixed is to compare the topological structure of the networks without bias from differences in mean synchronization likelihood (otherwise, a higher synchronization likelihood would simply result in more edges, higher Cp and smaller Lp). By fixing K, all the graphs have the same number of vertices and edges (Stam et al., 2007). For the resulting graphs, the clustering coefficient Cp and the characteristic path length Lp were determined.

B. Computation of the Cluster Coefficient C and Characteristic Path Length L:

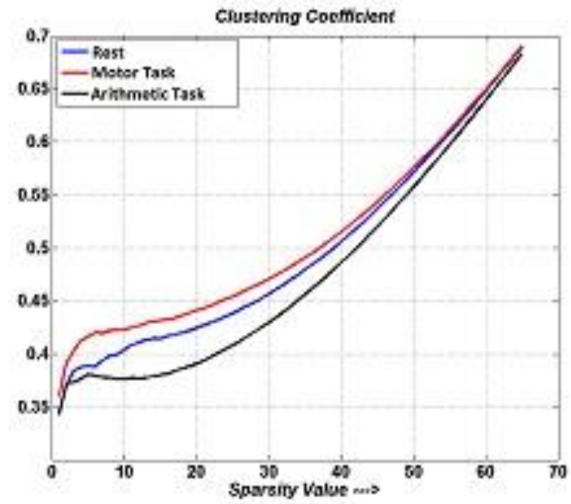
The 1st step in applying graph theoretical analysis to synchronization matrices is to convert the N X N synchronization matrix into a binary graph. A binary graph is a network that consists of elements (also called ‘‘vertices’’) and undirected connections between elements (called ‘‘edges’’). Edges between vertices either exist or do not exist; they do not have graded values. The synchronization matrix can be converted to a graph by considering a threshold T. Because there is no unique way to choose T, we explored a whole range of values of T, $0.01 < T < 0.05$, with increments of 0. 001 and repeated the full analysis for each value of T. If the SL between a pair of channels i and j exceeds T, an edge is said to exist between i and j; otherwise no edge exists between i and j. Once the synchronization matrix has been converted to a graph, the next step is to characterize the graph in terms of its cluster coefficient C and its characteristic path length L. A schematic explanation of graphs, cluster coefficients, and path lengths is given in Figure 1. To compute the cluster coefficient of a certain vertex, we first determine to which other vertices it is directly connected; these other vertices (1 edge away) are called ‘‘neighbors. ’’ Now the cluster coefficient is the ratio of all existing edges between the neighbors and the maximum possible number of edges between the neighbors; it ranges between 0 and 1. This cluster coefficient is computed for all vertices of the graph and then averaged. It is a measure for the tendency of network elements to form local clusters. The characteristic path length L is the average shortest path connecting any 2 vertices of the graph; the length of a path is indicated by the number of edges it contains. The path length L is an emergent property of the graph, which indicates how well its elements are integrated/interconnected. When C and L are computed as a function of threshold T, the results might be influenced by differences in the mean level of synchronization between the 2 groups. Because the SL is expected to be significantly lower for patients compare to healthy controls, for a given value of T, AD graphs will have fewer edges than controls graphs, and this will influence the differences in C and L between the 2 groups. To control for this effect, we repeated the analysis computing C and L as a function of degree K, which is the average number of edges per vertex. In this way, graphs in both groups are guaranteed to have the same number of edges so that any remaining differences in C and L between the groups reflect differences in graph organization. The values of C and L as a function of degree K were compared with the theoretical values of C and L for ordered (C = 3/4, L = N/2K) and random (C = K/N, L = ln(N)/ln(K)) graphs. However, statistical comparisons should generally be between networks that have equal (or at least similar) degree sequences, as these are known to affect all kinds of network measures. Because the theoretical networks have Gaussian degree distributions and may thus not provide valid controls for the experimental networks in the present study, which may have some other degree distribution, we also generated random and ordered control networks following the procedure described by Sporns and Zwi (2004) and Milo and others (2002) which preserve the degree distribution exactly. For a K value of 3, for each EEG 20 random and 20 ordered networks was generated, and the mean C and L were calculated.

STATISTICAL ANALYSIS

Statistical analysis consisted of independent samples t-tests and linear regression of the plots of C and L as a function of threshold. In order to investigate correlations between changes in topological parameters, we calculated Pearson's correlation coefficient for cluster coefficient and path lengths. A graph theory based method is newly introduced method of analyzing complexity of the brain network. It is known as small world connectivity it is totally based on mathematical modeling of graph theory concept.

V. RESULTS

The results of the Clustering Coefficient and Path-length of the measurements are shown in the graph-1and graph-2. Functional segregation in the brain is the ability for specialized processing to occur within densely interconnected groups of brain regions. Measures of segregation primarily quantify the presence of such groups, known as clusters or modules, within the network. The presence of clusters in anatomical networks suggests the potential for functional segregation in these networks, while the presence of clusters in functional networks suggests an organization of statistical dependencies indicative of segregated neural processing.

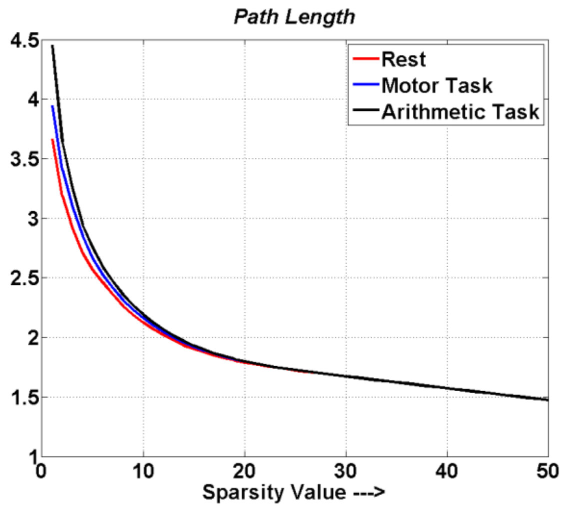


GRAPH-1

$$C = \frac{1}{n}\sum_{i \in N} Ci = \frac{1}{n}\sum_{i \in N} \frac{2t}{ki(ki-1)} \qquad (1)$$

Where C_i is the clustering coefficient of node i ($C_i = 0$ for $k_i <$ 2).

Functional integration in the brain is the ability to rapidly combine specialized information from distributed brain regions. Paths are sequences of distinct nodes and links and in anatomical networks represent potential routes of information lowbetween pairs of brain regions. Lengths of pathsconsequentlyestimate the potential for functional integrationbetweenbrainregions, with shorter paths implying stronger potential for integration



GRAPH-2

$$L = \frac{1}{n}\sum_{i \in N} Li = \frac{1}{n}\sum_{i \in N} \frac{\sum j \in Nj \neq i\, d_{ij}}{n-1} \qquad (2)$$

Where L_i is the average distance between node i and all other nodes.

IV. DISCUSSION

In this paper, we use the clustering co-efficient, path-length of different cognitive behaviors one is resting state, the arithmetic task, motor task the parametric analysis is done. The significant difference is shown in the graphs1 and 2 for all the activities with respect to sparsity value. The shorter path length signifies-resting task, the other two tasks based on the amount of higher cognitive levels it shows that motor task has increase in length in comparison with arithmetic task. With shorter paths implying stronger potential for integration. The range of the clustering coefficients shows value for each tasks, here the values are ranging between (0. 35-0. 7). The arithmetic task its higher in comparison with motor and resting tasks. The high clustering coefficient associated robustness to random error. The ratio of Normalized clustering coefficient and Path-Length gives the measure of Small worldness. The Lower value signifies that there is lower connectivity.

V. CONCLUSION AND FUTURE SCOPE

The various cognitive task data are analyzed effectively by considering the linear and nonlinear parameters. For certain analysis linear hypothesis is replaced by nonlinear behavior. The graph theory concepts are a better method in analysis in comparison with already existing methods such as linear methods such as Fourier and spectral methods The approach can be applied to ADHD and dementia Alzheimer and other cognitive disorders in the brain. Some differences are difficult to perceive, and the linear and nonlinear quantitative parameters of different individuals have great differences. Hence it is a critical problem to find a widely applicable criterion, which needs to be explored for a long time. The emerging field of complex brain networks raises number of interesting questions and gives insights into general topological principles to brain networks

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VII. REFERENCES

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