CHAPTER 5

ANALYSIS OF MULTICHANNEL EEG DATA USING 3D-CORTICAL METHOD AND GRAPH-THEORY APPROACH

5.1 INTRODUCTION

Cognition is a branch of neuroscience which is a psychological science which is dealing with mind and brain related subfields such as the mental processes that underlie behavior, reasoning, and decision making. The approach towards the graph theory measurements using electroencephalography (EEG) is to understand the neuronal changes due to different cognitive activities. The analysis of nonlinear invariants are the clustering coefficient, path length, and local efficiency. The results obtained have shown the higher clustering coefficient, path length and lower local efficiency for alpha and beta frequency bands. The fronto temporal region shows significant changes in clustering coefficients. The results shows intermittent connectivity infronto-temporal region which may be necessary for deficits of execution and memory components.

There are some Signal processing methodologies such as Functional MRI (fMRI) and MRI to acquire the brain signal but dynamical nature and the complex character of the brain can be analyzed very well only by electroencephalograph (EEG) rather than any other signals. Today's cognitive neuroscience is the major area of research in the analysis of the behavior of brain activity.
The cognitive functions are the fundamental assumption for present and future research. Nonlinear methods were also another way for understanding the cognitive aspects of brain regions, Molle et al. (1999) explained the performance of Sevcik's algorithm that calculates the fractal dimension and permutation entropy which discriminates to detect calming and insight meditation in electroencephalographic (EEG) signals was evaluated. Chon et al. (2009), the need of this research was to examine the robustness of these two entropy algorithms (Yentes et al. 2013) 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 orderliness. 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 cognitive brain states, with the help of either single channel or multichannel systems. Our findings (Liu et al. 2008) demonstrated that the functional brain networks had dynamic small world properties in the normal subjects. Whereas these properties were revealed, more information in the patients with different cognitive tasks performed. Our findings gave useful information about that the brain functional networks, which has efficient small-world properties in the healthy subjects taken for analysis? Whereas small-world properties were disrupted in the patients with different cognitive tasks performed.
The evolution of small-world networks is considered regarding a selection pressure to deliver cost-effective information-processing systems. The authors consider the significance of small-world models for understanding the emergence of complex behaviors and the flexibility 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 effects suggest phase synchrony for coma patients has a significant increase in the theta and alpha band compared to quasi-brain-death patients. In patients who has schizophrenia the small-world topological properties can show the significantly changed in several brain regions for example in the prefrontal, parietal and temporal lobes the authors have found that they developed topological measurements correlate with illness duration in schizophrenia.

Detection, and Estimation of the (Liu et al. 2008) one could prove helpful for understanding the pathophysiological mechanisms well as for evaluation of the severity of schizophrenia (Aftanas et al. 1998). Overall, the results point to the idea that dynamically changing inner experience during meditation is better indexed by Aftanas et al. (2002), combination of non-linear and linear EEG variables.

5.1.1 Motivation of using Multichannel Approach

Many complex networks have a dense local clustering networks characterizes a small-world topology. The connections of the neighboring nodes short path length between any (distant) pair of nodes due to the existence of relatively few long-range connections.
This is an attractive model for the organization of brain anatomical and functional networks of small-world topology can support both segregated and specialized and distributed/integrated information processing. Moreover, small-world networks are more economical, tending to minimize wiring costs while supporting high dynamical complexity. The authors have introduced some of the main mathematical concepts in graph theory required for small-world analysis and review how these methods have been applied for the quantification of cortical connectivity matrices derived from anatomical tract-tracing studies with animals was done.

The evolution of small-world networks is discussed regarding a selection pressure to deliver cost-effective information-processing systems. The authors illustrated how these techniques and concepts are increasingly being applied for the analysis of human brain functional networks derived from electroencephalography, magnetoencephalography and fMRI experiments.

Finally, the authors have considered 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. They concluded that small-world models provide a powerful and versatile approach to understanding the structure and function of human brain systems.

5.2 THE TOOL FOR CONNECTIVITY ANALYSIS

sLoreta and Brain Connectivity Tool Box (BCT) software tool used for the cognitive analysis.
5.2.1 Paragiram on Different Tasks (SET-1)

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

i) 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.

ii) 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.

iii) Instruction for Arithmetic Calculation

Subject was instructed to count the Fibonacci Sequence is the series of numbers: 0, 1, 1, 2…..100
5.3 METHODOLOGY OF 3D-CORTICAL METHOD

Two minute EEG data taken by concatenating the EEG segment of corresponding cognitive task stimulus

Store the EEG data in .txt format without any header or factor

Store the EEG Channel in a .txt format in the same order of EEG data recording

Note the EEG data sampling rate and total time frame (total samples)

Compute EEG Electrode Coordinates through "Electrode name to coordinate"

View EEG Electrode Coordinates through "Electrode viewer"

LORETA coordinate transformation matrix (using MNI152 template) through "Electrode coordinates to transfer matrix"

Convert EEG data to sLORETA by taking EEG data, sampling rate and LORETA coordinate transformation matrix through "EEG/ERPs to LORETA"

View Result by taking EEG data, sLORETA, sampling rate and LORETA coordinate transformation matrix through "sLORETA Viewer"

Figure 5.1 Analysis steps of sLORETA
5.3.1 Results

1) From the study under resting state high variability is seen in the frontal and occipital lobe.

2) For accomplishing complex arithmetic tasks the brain involves multifunction such as memory planning calculation and execution. The lobes involved for activation are prefrontal lobe and parietal lobe.

3) For the sensory motor task the parietal and frontal lobe is involved.

Figure 5.2 Activity maps on the different tasks
5.4 PARAGIRAM ON DIFFERENT TASKS: (SET-2)

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). data were recorded relative to an fcz reference and a ground electrode was located at iz (10–5 electrode system, (Ostenveld & Praamstra 2001).

Data were sampled at 1000 hz and the impedance between electrode and scalp was kept below 5 k. 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
5.4.1 Methodology of Graph Theory Approach

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. The analysis is carried over by taking the depressive data sets. This method could be helpful for diagnosis and evaluation of the severity of the disease, as well as understanding the pathophyslogic mechanisms underlying cognitive dysfunction of patients with depressive disorder by measuring its linear and nonlinear invariants.

We Measure:

1. Clustering Coefficient – “C”
2. Path Length – “L”
3. Global Efficiency
4. Local Efficiency

For the graph theory connectivity, signals were band-pass filtered (digital off-line filter with no phase-shift) in order to analyze synchronization likelihood in the following are the 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).

5.4.2 Functional Connectivity Matrix

Functional connectivity can be determined by computing the synchronization likelihood (SL) among all pair wise combinations of EEG channels, resulting in an N by N connectivity matrix (N: EEG channel). The SL is a general measure of the correlation or synchronization between the 2-time series, which is sensitive to both nonlinear and linear interdependencies.
Figure 5.3 Calculate graph theoretical measures representing each graph
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 result of computing the SL for all pair wise combinations of channels is a square $N \times N$ matrix of size 30 (the number of EEG channels), where each entry $N_{i,j}$ 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 synchronization likelihood above this threshold were considered to be connected by an edge, otherwise, they were not considered to be connected.

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 the $K$ value 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 $C_p$ and smaller $L_p$). 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 $C_p$ and the characteristic path length $L_p$ were determined.

Another measure of EEG functional connectivity matrix is phase lag index (PLI) which can use for EEG graph theory connectivity instead of SL. Functional connectivity between every pair of electrode by pairs was calculated using the phase lag index (PLI). PLI is a consider as the measure of asymmetry of phase differences between the pair of signals. The instantaneous phase of two signals was consider to compute phase synchronization which was accomplished by using the analytical signal based on Hilbert transformation. Followed by the PLI was measured from the time series of phase differences($t_k$), $k=1\ldots, N$ by means of-

$$\text{PLI} = \text{Sign}[ (t_k) ]$$  \hspace{1cm} (5.1)
5.4.3 Computation of the Cluster Coefficient C and Computation of Characteristic Path Length

Once the synchronization matrix has been converted to a graph, the next step is to characterize the graph regarding its cluster coefficient C and its characteristic path length L. A schematic explanation of graphs, cluster coefficients, and path lengths is given in Figure 5.2. 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 “neighbours.” Now the clustering coefficient is the ratio of all existing edges between the neighbors and the maximum possible number of edges between the neighbours; 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. Simplifying, the clustering coefficient is the ratio between all existing edges between the neighbors’ and the maximum possible number of edges between the neighbour’s. This is the range between 0 and 1.

Figure 5.4 Increasingly random connectivity

\[
(5.2)
\]
The path length \( L \) measure the no of nodes crossed to reached another node between from any source node among the \( N \) no of nodes. The characteristic path length ‘\( L \)’ is denotes the average shortest path connecting between any two nodes of the network

\[
= \quad (5.3)
\]

5.4.4 Small-Worldness

Brain functional networks have reasonable small-world properties which represents the efficient transfer of parallel information at relatively low cost. Wattz & Strogatz et al. (1998) 1st proposed the small-world network (i.e clustering coefficient and characteristic path length) parameters in neuroscience research. The small-world ness is the ratio of normalized clustering coefficient and normalized path length. The higher small world ness is represent the network towards regular network where as the lower small-world ness is represent the network as random network.

5.4.5 Local Efficiency

Efficiency quantify how efficient the connections of network for local and global level. For a graph (network) \( G \) with \( N \) nodes and \( K \) edges, the global efficiency of \( G \) was calculated as: Tun-Wei Hsu (2012).

\[
 \Omega = \quad (5.4)
\]

In the above equation, \( G \) is the shortest path length between node \( i \) and \( j \). The local efficiency of \( G \) was calculated as:

\[
 \Omega = \quad (5.5)
\]
5.5 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 a newly introduced method of analyzing the complexity of the brain network.

5.6 TABULATION OF RESULTS

Table 5.1 Tabulation of Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Delta</th>
<th>Theta</th>
<th>Alpha</th>
<th>Beta</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>C</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>0.96</td>
<td>0.037</td>
<td>0.95</td>
<td>0.039</td>
</tr>
<tr>
<td>Patient</td>
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<td>0.027</td>
<td>0.95</td>
<td>0.057</td>
</tr>
<tr>
<td>P</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>1.007</td>
<td>0.0065</td>
<td>1.008</td>
<td>0.0082</td>
</tr>
<tr>
<td>Patient</td>
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<td>0.0088</td>
<td>1.006</td>
<td>0.0073</td>
</tr>
<tr>
<td>LE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>1.048</td>
<td>0.048</td>
<td>1.045</td>
<td>0.053</td>
</tr>
<tr>
<td>Patient</td>
<td>1.037</td>
<td>0.030</td>
<td>1.050</td>
<td>0.044</td>
</tr>
</tbody>
</table>

The small-world parameters of clustering coefficient and Path-length of the measurements are shown significant differences in the alpha frequency (Figure 5.3 and Figure 5.5). Functional segregation in the brain is a significant processing to occur within the densely interconnected groups of brain regions. Measures of segregation 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 groups in functional networks suggests an
organization of statistical dependencies indicative of segregated neural processing.

\[(5.6)\]

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

![Figure 5.5 Clustering coefficient](image)

Figure 5.4 clustering coefficient of rest state (red line), motor task (blue line) and arithmetic task (black line) for alpha frequency matrices. Arithmetic task shown higher clustering coefficient, followed by motor task and list clustering coefficient found in rest state.
Figure 5.6 Motor task and list clustering coefficient found in rest state

Clustering coefficient of rest state (A), motor task (B) and arithmetic task (C) for delta, theta and alpha frequency. In Alpha frequency, the clustering coefficient shows significant changes (P<0.013), Arithmetic task shown lower clustering coefficient, followed by motor task and higher clustering coefficient found in rest state. In theta frequency, the clustering coefficient show significant changes (P<0.047), Arithmetic task shown higher clustering coefficient, followed by motor task and lower clustering coefficient found in rest state. Functional integration in the brain is the ability to fastly combine functional information from distributed brain regions.

\[ s = \ldots \ldots \ldots \ldots \ \ (5.7) \]

Figure 5.5 Characteristic Path Length of rest state (red line), motor task (blue line) and arithmetic task (black line) for alpha frequency matrices. Arithmetic task shown lower Path Length, followed by motor task and higher clustering coefficient found in rest state.
Figure 5.7 Characteristic Path Length of rest state

Figure 5.8 Characteristic Path Length of rest state (A), motor task (B) and arithmetic task (C) for delta, theta and alpha frequency. In Alpha frequency, the Path Length show significant changes (P<0.026), A task shown higher Path Length, followed by motor task and lower Path Length found in rest state.
Paths are sequences of distinct nodes and links and in anatomical networks represent potential routes of information flow between pairs of brain regions. Lengths of paths consequently estimate the potential for functional integration between brain regions, with shorter paths implying stronger potential for integration. Where $L_i$ is the average distance between node $i$ and all other nodes.

5.6.1 Results

Applied for depression sets of data:

![Normalized Clustering Coefficient](image)

Figure 5.9 Depression sets of data
DISCUSSION

In this proposed work we use the clustering co-efficient, path-length of different cognitive behaviors' one is resting state, motor task and the arithmetic task. We noted significant changes in the clustering coefficient parametric for theta and alpha frequency bands. In other hand Characteristic Path Length has shown major changes in only alpha frequency band (Figure 5.4 and Figure 5.6). The rest shown higher clustering coefficient and shorter path length where as in arithmetic task, which considers as higher cognitive task found lower clustering coefficient and higher path length. This phenomenon indicates the small world properties, at rest the brain small world properties are towards regular and when brain goes to higher cognitive state it happens with random processes with some specific patrons.

The arithmetic task it's higher in comparison with motor and resting tasks. 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

5.8 CONCLUSION

The various cognitive task data are analyzed efficiently by considering the linear and nonlinear parameters. For certain analysis linear hypothesis is replaced by nonlinear behavior. The graph theory concepts is a potential method in analysis in comparison with already existing methods such as linear methods such as Fourier and spectral methods to model brain function for cognitive state. The approach can be applied to various disorder such as ADHD, Dementia, Alzheimer, epilepsy, unconscious patients and other cognitive disorders in the brain.

5.9 SUMMARY

Graph theory method is newly introduced method in comparison with the earlier methods. The nonlinear invariants used here are clustering coefficient, Average pathlength, measure of small worldiness, local efficiency gives a clear picture of connectivity in the brain. The activity pattern gives us a clear picture of the depth of the cognitive levels of the subjects considered for the normal and depression patients. The deviations in the activity patterns of a patient with neurological disorder with reference to the normal data are not precisely visible to the naked eye. Statistical methods would render a detailed report on the several features of the activity pattern. This would help the neurosurgeon in decisions on prognosis.
The proposal on 3D visualization of EEG data at interactive depths and overlapping of healthy and patient data in 3D view to visualize the deviation extent helps in pre-surgical preparations. Brain functional connectivity abnormalities have been hypothesized to be a neurological biomarker. Here we investigated graph theory measurement of functional brain connectivity using a resting-state EEG in patients with depression and age-gender-matched healthy controls. A key finding of our study is altered graph theory measurements in patients with depression in beta frequency band, that the previously reported augmentation in this band alter temporal oscillation and frequency fluctuation which suggests for decline of higher cognitive functions.

Altered brain functional connectivity using fMRI were reported. These altered neuronal oscillatory dynamics could be indicative of aberrant neuronal maturation, an interpretation that is in line with neurobiological studies showing decline of higher cognitive functions and mental processes. It is an highly advanced method in comparison with already existing methods such as spectral and Fourier methods, the spatio temporal analysis is very well analyzed using this connectivity network. It is applicable for further study of diseases such as Alzheimer’s, Dementia, ADHD, meditation related data for better analysis in cognitive neuro science.