Brain functional network analysis using Electroencephalographic (EEG) data and graph theory in long term meditators

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Brain is the most vital organ of the human body. It is the organ which controls almost every single action we do, be it thinking, listening, reading, eating, sleeping or even breathing. It controls and coordinates every that thing which make us complete as a human being. Being concise, brain is the most complex yet intelligent organ of the human body. Brain is an arrangement of a vast network of billions of neurons supported by even multiplied number of glial cells. Bunch of neurons collectively bundled to form nuclei or brain region while their axonal processes collect together to be called as nerves. These nerves pass information in the form of electrical impulses i.e. excitation from one neuron to another neuron. Basically our brain forms the “Natural Neural Network”. The study of brain functioning and its networking has been the key interest of many scientists around the world since many years. The studies are conducted by obtaining information from the brain in the form of EEG/MEG signals or PET/fMRI scans. The analysis of the EEG data and drawing important conclusions about the Brain’s functional network can be done with the help of Graph Theory and use of Graph Algorithms.

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Abstract

The brain is the most complex yet intelligent organ of the human body. It consists of an arrangement of a vast network of billions of neurons collectively bundled to form nuclei or brain region while their axonal processes collect together forming the nerves. These nerves pass information in the form of electrical impulses i.e. excitation from one neuron to another neuron forming the “Natural Neural Network”. In general, the neurons and their processes in the brain region can be modelled as a complex brain network both anatomically as well as functionally, describing the high efficiency of information transmission in the brain. The functional connectivity network in the human brain can be visualized with the help of electroencephalography (EEG) signals obtained from the scalp. The EEG signal data obtained is preprocessed to remove the various artifacts: muscle artifact, eye movement-eye blinks artifact, head movement artifact, line noise, DC noise using Band-Pass Filter (0.05 Hz- 45 Hz), Notch Filter (50 Hz), component rejection using Independent Component Analysis (ICA), removal of bad epochs and channel rejection by visual inspection. Further, the focus is on the analysis of dynamic functional connectivity network of the brain constructed with the pre-processed EEG signal data. The brain network topology is studied using the basic principles of graph theory and network metrics – path length, clustering coefficient, modularity and betweenness centrality. The brain functional network has a small-world network topology characterized by dense local clustering and short path lengths between any pair of nodes which allows segregated yet integrated information processing in the brain. Further, the network analysis of two kinds of subjects – long term experienced meditators and non-

meditating general subjects with a particular focus on comparing the existence of small – world networks in the subjects before, during and after meditation will be explored.

Keywords or phrases:

Electroencephalography, EEG signal data preprocessing, Independent Component Analysis,

network metrics analysis, small worldness coefficient, mindfulness meditation

1 INTRODUCTION

1.1 Background/Rationale

Brain is the most vital organ of the human body. It is the organ which controls almost every single action we do, be it thinking, listening, reading, eating, sleeping or even breathing. It controls and coordinates every that thing which make us complete as a human being. Being concise, brain is the most complex yet intelligent organ of the human body. Brain is an arrangement of a vast network of billions of neurons supported by even multiplied number of glial cells. Bunch of neurons collectively bundled to form nuclei or brain region while their axonal processes collect together to be called as nerves. These nerves pass information in the form of electrical impulses i.e. excitation from one neuron to another neuron. Basically our brain forms the “Natural Neural Network”. The study of brain functioning and its networking has been the key interest of many scientists around the world since many years. The studies are conducted by obtaining information from the brain in the form of EEG/MEG signals or PET/fMRI scans. The analysis of the EEG data and drawing important conclusions about the Brain’s functional network can be done with the help of Graph Theory and use of Graph Algorithms.

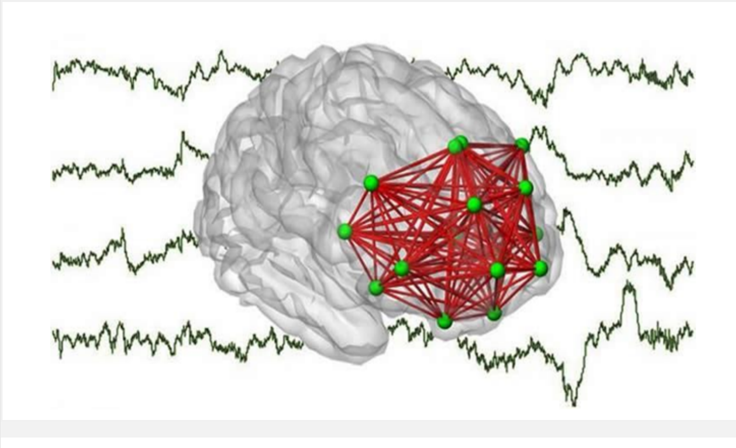


Fig 1 The functional network of the human brain represented as a graph

1.2 **Problem Statement**

The brain being a network of billions of neurons can be visualized as a graph and hence studied with the help of various graph parameters. Comparing the small-worldness index of different kinds of subjects can lead to various important conclusions about the differences in the brain functional networks in the respective subjects. The paper aims at drawing conclusions about the differences in the brain functional network in long term meditators before meditation, during meditation and after meditation.

Meditation is such an activity which has its maximum impact on the brain activity and central nervous system. It has become a focus of collaborative research of various domains of science namely: neuroscience, psychology and neurobiology. The effect of meditation on the brain's activity and hence its connectivity network is here analysed with the help of analysis of EEG data collected from long-term meditators and graph theory.

1.3 Objectives of the Research

The objective is to:

1. Preprocessing and cleaning of the EEG data from the subjects (long-term meditators)

2. Brain functional network visualization

3. Brain functional network metrics calculation and draw conclusions about the level of integration of the brain connectivity graph before and after meditation in the subjects using the graph theory parameters especially small worldness index.

1.4 Scope

The analysis done is of three different time intervals namely: before mediation (eyes opened), during meditation and after meditation (eye opened) and further the comparison is done between them in order to obtain the difference in the integration of brain functional connectivity before and after meditation i.e. impact of meditation on the human brain connectivity.

The data from meditating subjects analyzed in this study has a further scope of being compared to data obtained from non-meditating subjects and conclude the differences in their respective brain functional connectivity (meditators and non-meditators).

1.5 Limitations

The EEG data from five subjects was analyzed for three different time intervals as stated above. Out of the five subjects taken, the values of one of the subject were not falling in the general trend of values of different parameters obtained by the other four subjects. Hence, the subject was eliminated from being included in the final calculations and results.

2 LITERATURE REVIEW

2.1 Information

Electroencephalography (EEG) has been used in many studies as a primary method for evaluating the meditating brain. Electroencephalography uses electrical leads placed all over the scalp to measure the collective electrical activity of the cerebral cortex. Though EEG does not have good spatial resolution but it can be more appropriately used to evaluate the running spontaneous activity of the cortex. This spontaneous activity is classified into four main classifications based on the frequency of the activity, ranging from low frequency delta waves (< 4 Hz) commonly found during sleep to beta waves (13–30 Hz) associated with an awake and alert brain. In between these two extremes are theta waves (4–8 Hz) and alpha waves (8–12 Hz).

There have been many studies similatly done on the changes in brain functional connectivity: Connectome, few other studies also make more specific claims about trait changes in meditators versus non-meditators. Review works, however, comment on inconsistent findings as well as a lack of repeated results in this, and other studies. They further remark that some change in the electroencephalographic profile exists but with some inconsistency. It is also important to note that there are changes reported in the studies, which were observed during meditation in the functional networks by change in their encephalographic profile.

The key feature which is being compared in the different instances: before, during and after meditation is the small-worldness index. The “small-world” network model was introduced in a landmark study by Watts and Strogatz (1998) demonstrating for the first time that small-world properties exist in central nervous systems. The topology of small-world networks is characterized by high clustering (segregation) and short path lengths (integration). Segregation refers to the tendency of nearest neighbor elements to cluster together, whereas integration refers to the amount of interconnectedness and efficient information exchange within the entire network. The clustering coefficient is a measure of functional segregation or local connectedness, whereas the characteristic path length is a measure of functional integration describing global, large-scale activity. The clustering coefficient and the characteristic path length constitute properties of the small-world network model. Taken together, they are an indicator of small-worldness, an index representing the suitable balance between functional integration and segregation of dynamic system organization (Humphries & Gurney, 2008; Stam, 2010; Thatcher, 2016; van Straaten & Stam, 2013). Thus, they defined algorithmically for the first time a class of networks with topological properties similar to social networks, demonstrating both the high clustering of a lattice and the short path length of a random graph, which they called small-world networks.

Further, there are various researches illustrating how these techniques and concepts are increasingly being applied to the analysis of human brain functional networks derived from electroencephalography/magneto-encephalography and fMRI experiments. It was concluded from the researches/publications that small-world models provide a powerful and versatile approach to understanding the structure and function of human brain systems.

2.2 Summary

A human brain contains about 100 billion neurons connected by about 100 trillion synapses which are anatomically organized to form the anatomical neural network and functionally interact to form the functional brain connectivity network. Therefore, exploring the brain network and revealing its mechanism has been a challenging problem. The data that assess the brain function is obtained from Electroencephalography (EEG), functional MRI (fMRI), Magneto-encephalography (MEG) or MRI. But usually it consists of a large amount of data that poses a challenge for analysis and interpretation. One way to scale down the amount of data is to represent the data in the form of graphs. Graph theory is a valuable framework for the analysis of anatomical and functional brain networks wherein the electrodes were the signal is obtained is considered the nodes and connection links(edges) are established with the help of statistical measure i.e. correlation between the nodes and further by calculating the graph parameters: clustering coefficient and minimum path length, and thus finding the small worldness index.

3 METHODOLOGY

3.1 Concepts

3.1.1 **Electroencephalography**

Electroencephalography (EEG) has been used in many studies as a primary method for evaluating the brain connectivity graph. Electroencephalography uses electrode leads placed all over the scalp in a defined placement system to measure the collective electrical activity of the cerebral cortex. Specifically, EEG measures the electric fields of large groups of neurons. EEG has the benefit of excellent temporal resolution but doesn't have a good spatial resolution and is thus used to evaluate the spontaneous activity of the cortex. The activity in the cortex can be divided into four main classifications based on the frequency range:

1. Delta Waves(<4Hz): commonly found during sleep

2. Beta Waves(13–30 Hz): found during alert and awake brain

3. Theta Waves (4–8 Hz): important in memory formation process

4. Alpha Waves (8-12 Hz): prominent during attention disengagement

In previous studies, lower frequency Alpha and Theta waves were associated with relatively calm, decluttered and less engaged mind. While a group of researchers have prominently proved this to be a signature of meditating mind.

Throughout the research, the EEG data was used for the creation of the brain connectivity graphs followed by the graph theory-based analysis.

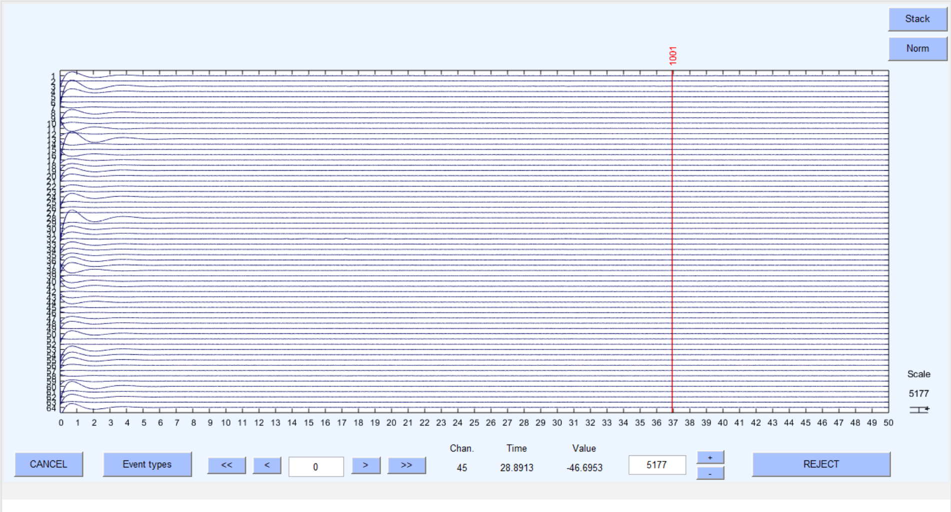


Fig 2 Illustrating sample epoch of EEG data obtained from one of the subjects

3.1.2 **Graph: Brain Network Construction**

A graph is a mathematical representation of a network which consists of a set of vertices 'V' connected by a set of edges 'E'. The connection links between the vertices i.e. edges can represent any relationship between the vertices/nodes (strength, length, weight etc) and the graph can be correspondingly form an adjacency matrix. The values is the matrix can be either 0/1 based on whether the edge exists or not (binary) and weight/strength of the edge in case of weighted graphs. The graph can be directed/undirected and weighted/un-weighted.

The construction of brain functional graphs forms a directed and weighted graph.

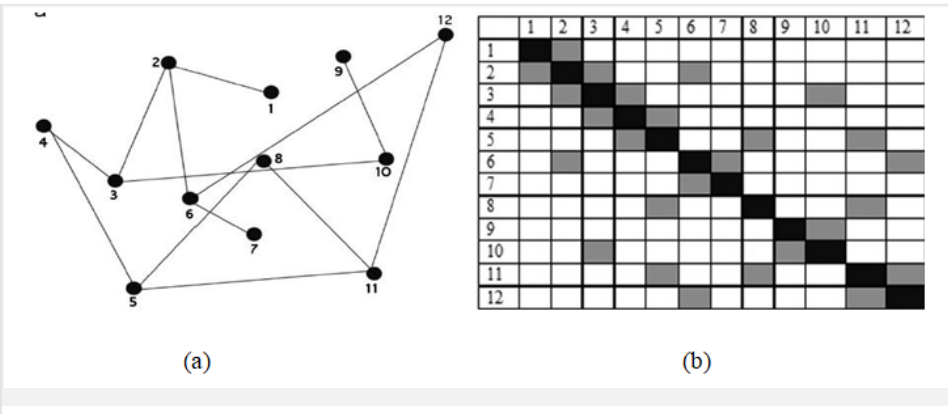


Fig 3 (a) Graph is the representation of any network consisting of a set of vertices and edges connecting the vertices (b) Any graph can be represented in the form of a connectivity matrix; here the grey boxes represent that an edge exists between that particular pair of vertices

1. **Nodes:**

In order to construct a brain network, the first step is to define nodes of the brain network. The nodes represent different, functionally similar neurons (which are grouped together to perform the same function) or brain regions.

The method followed was to consider each measurement point as a separate node i.e. different electrodes in EEG measurement correspond to different nodes in the brain graph. The advantage of this method is that no additional data processing is required to analyze the data at the original resolution or to perform further averaging or aggregating.

2. **Edges:**

The edges in the brain network refer to the connection link between two brain regions (nodes). The connectivity in the brain can be either structural or functional. The connectivity referred to here is functional connectivity which is basically statistical dependence between a pair of nodes or brain region.

3.1.3 Network Metrics:

1. **Degree**

Node degree is one of the most fundamental and important measures for a brain network and is defined as the number of edges connecting the node with other nodes in the graph. Higher the degree of the node, more the number of connections it has in the graph, higher the importance it carries in the graph.

2. **Path Length**

The minimum number of edges to be covered to reach from one node to another is called the shortest path between these two nodes. The shortest path plays an important role in the information transmission of a brain network, and it is a very important measure to describe the internal structure of the brain network. The shortest path can transmit the information more quickly and reduce brain consumption.

3. **Clustering Coefficient**

The clustering coefficient of a node is equal to the ratio of the number of the actual connected edges between its adjacent nodes to the number of all possible connection edges. It is a measure of functional segregation, which is the ability for specialized processing to occur within densely interconnected groups of brain regions.

4. **Modularity**

A module is a group of nodes with dense internal connections but sparse external connections in a network. Biological networks, including human brains, exhibit a high degree of modularity. In complex network analysis, modularity is used to measure the quality of division of a network into modules.

The modular structure also provides more detailed roles and properties of nodes dividing them into provincial hubs (node connected to other nodes in the same module) and connected hubs (node connected to nodes in the other module).

5. **Betweeness Centrality**

Betweenness centrality quantifies the number of times that a node acts as a bridge along the shortest path between two other nodes. In brain network analysis, the betweenness centrality of a brain region measures the impact of the brain region on the flow of information across the brain network.

6. **Efficiency**

The efficiency of a network (such as brain network) measures the ability of the network to exchange information. Higher the efficiency of the network, stronger is the ability of information exchange. The efficiency of a network mainly considers global efficiency and local efficiency.

The global efficiency measures the ability of parallel information exchange across the whole network, while the local efficiency measures the ability of fault tolerance of a network. Both global efficiency and local efficiency are closely related to nodal efficiency. Nodal efficiency measures how well a specific region is integrated within the network via its shortest paths.

The global efficiency of a network is the average nodal efficiencies of all nodes in the network and the local efficiency of a node can be regarded as the global efficiency of the sub network containing itself and its all direct neighbors.Summary of all network metrics is as in the figure:

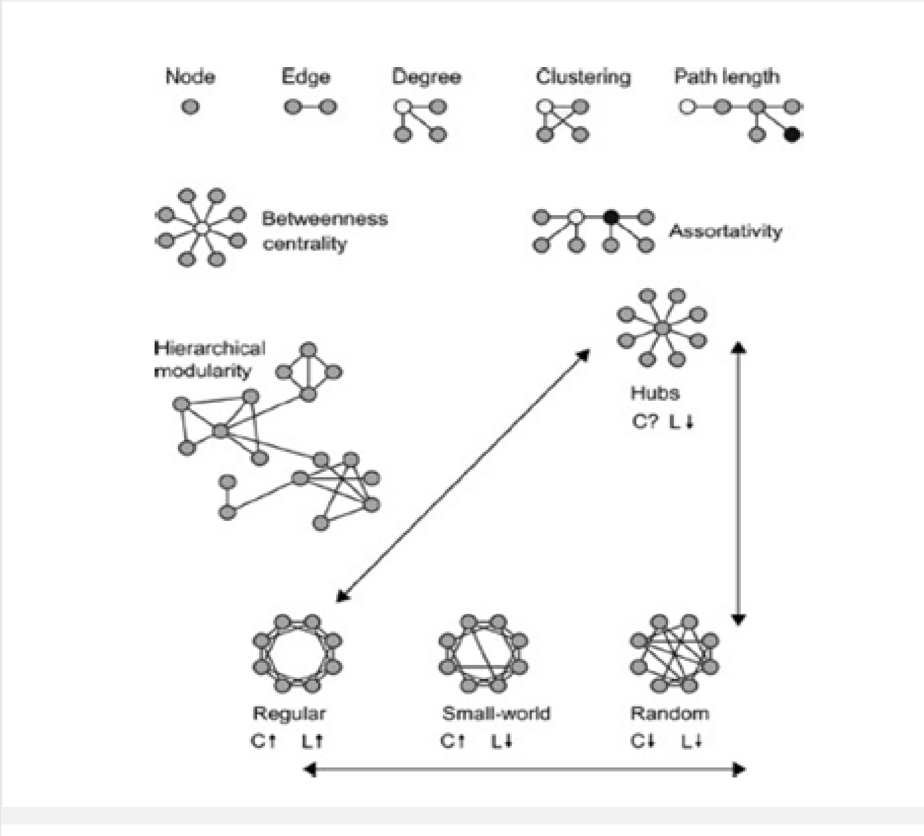


Fig 4 All the network parameters shown in the figure as labeled above; the three different types of network models are also shown in the figure

3.1.4 Different types of networks

1. **Random Network**

This kind of network consists of a set of nodes and the edges between them are totally random. If suppose the probability of an edge existing between a pair of vertices is 'p', which will be same for all pair of vertices of the network. Therefore this type of network has low clustering coefficient and low average shortest path.

2. **Regular Network**

If starting with a set of nodes represented on a circular ring and each node is only connected to its nearest neighbours. So if the node has total k neighboring vertices then symmetrically it will have k/2 on each side of the node on the ring. In this type of network clustering coefficient is high and path length is also high.

3. **Small World Network**

If on the regular network with probability ‘p’ a few random connections are rewired. This would though keep the clustering coefficient high but the path length would reduce giving rise to a distinct Small world topology comprises both high clustering (compatible with segregated or modular processing) and short path length (compatible with distributed or integrated processing).Fig: The three different types of network models with different values of clustering coefficient and shortest path length value namely: Ordered/Regular Network, Small ordered Network and Random Network

3.1.5 Brain Functional Network : Small World Network

The following criterion is followed to categorize as a network as small world network.

$$\gamma = \frac{C}{C_{\text{rand}}}$$

$$\lambda = \frac{L}{L_{\text{rand}}}$$

$$\sigma = \frac{\gamma}{\lambda},$$

Fig 5 Mathematical formula for calculation of the small worldness index of graphs: where C stands for clustering coefficient, Crand stands for clustering coefficient of random graphs, L stands for minimum path length and Lrand stands for minimum path length of random graph

A network with small-world property needs to meet two conditions:

i) **Normalized Clustering Coefficient (ϒ) >> 1**

ii) **Normalized path length of the network (λ)~1** , where ‘rand’ stands for random graph

Thus, the **small-worldness index (σ) comes > 1**; the human brain functional network satisfies this criterion.

Thus, the brain supports both segregated and integrated information processing. Small-world topology comprises both high clustering (compatible with segregated processing) and short path length (compatible with integrated processing). Therefore, for a given brain network, if the brain network is found to have small-world property, it shows that the brain has better information processing performance.

3.2 Methods

3.2.1 **Data Acquition**

EEG data was collected from experienced long- term meditators with average practice period ranging from 5-20 years. EEG data were recorded with a high- density EEG system using a Waveguard^R EEG cap with 64 active electrodes. The channel location (electrode locations) of the EEG system is as shown in the figure following the 10-20 system. The recorded EEG data files were of the extension '.cnt'. The data collected was divided into 5 major divisions namely: Before mediation with eyes open, before meditation with eyes closed, during meditation, after meditation with eyes open and finally after meditation with eyes closed.

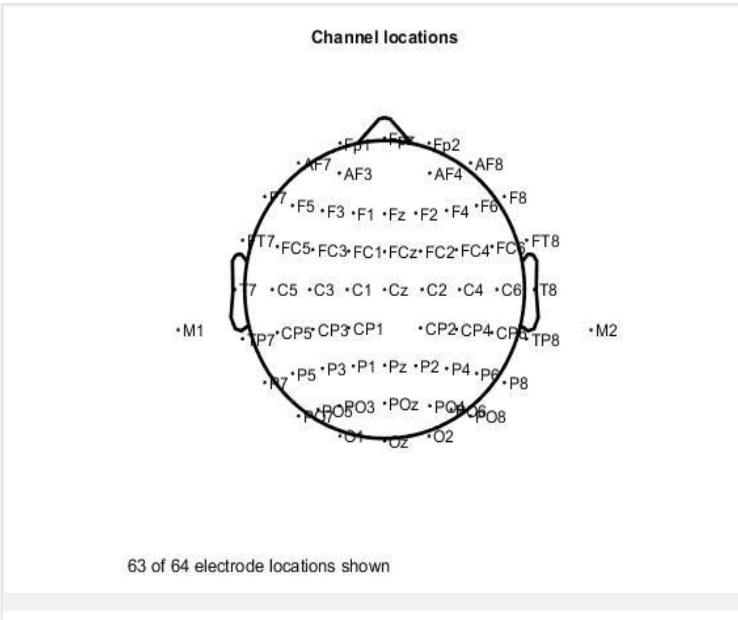


Fig 6 EEG Channel/Electrode Locations

3.2.2 Preprocessing the EEG data

The no of channels focused on were 64 channels i.e. 64 EEG scalp electrodes. The electrode was placed according to International 10−20 System nomenclature. The EEG signal was sampled at 1024 Hz. The impedance of each electrode was below 5 kΩ.

Data preprocessing was performed using the EEGLAB toolbox and MATLAB scripts. Thus the EEG data obtained from the subjects was then loaded on to the toolbox wherein the preprocessing steps of the data collected were undertaken. The EEG data consists for different types of artifacts such as:

1. Line noise (50 Hz- and higher harmonics)
2. Eye Artifact (Lateral Movement or Eye Blinks- EOG)
3. Muscle Artifact
4. Head Movement Artifact
5. Electrode Popping
6. DC removal (~0 Hz)

Removing the artifacts using the following measure:

1. Band pass Filter (0.05-45/72 Hz) – For required frequency band and removing DC Noise
2. Notch Filter (50 Hz,100Hz)- For removal of Line noise
3. Run Independent Component Analysis and removal of components when identified with eye/muscle artifact
4. Automatic removal of bad channels and artifact effected data
5. Reject data manually – by setting a particular threshold and visual inspection

First of all the data collected was visually inspected for bad channels. Subsequently, the bad channels hence found were rejected from the data. Data was then filtered between 0.5 and 72 Hz using a Butterworth Impulse Response (IIR) (Band pass filter). The artifact due to the eye blinks were detected by running ICA on the dataset and the components which showed resemblance to any artifact were rejected either. Secondly, all the components that survived the automated artifact rejection were visually inspected for undetected artifacts and thereafter the artifact-free segments per subject were selected for further analysis.

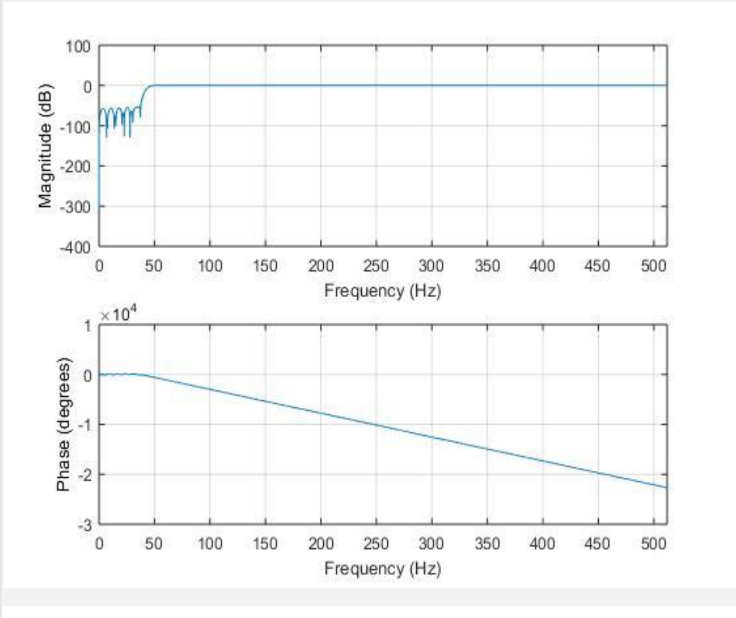


Fig 7 Notch Filter of 50 Hz for the removal of the line noise from the data

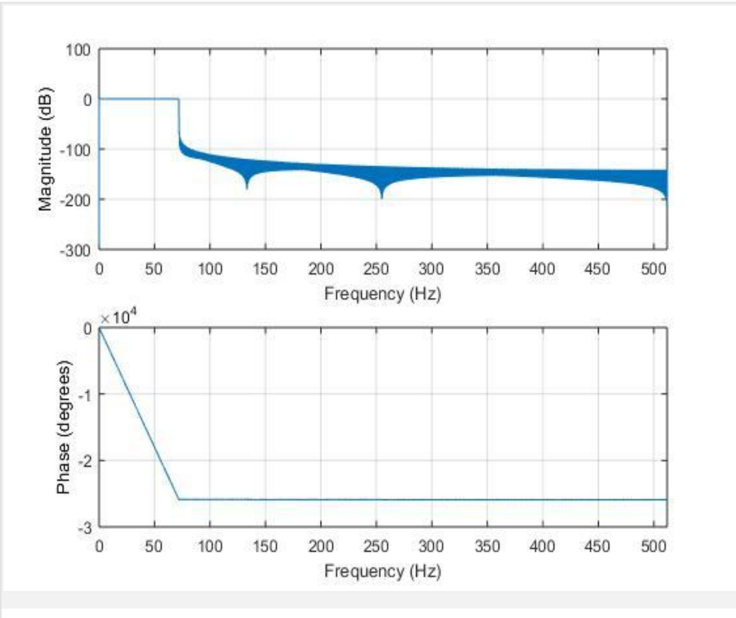


Fig 8 Pass Band Filter (0.05-72 Hz)

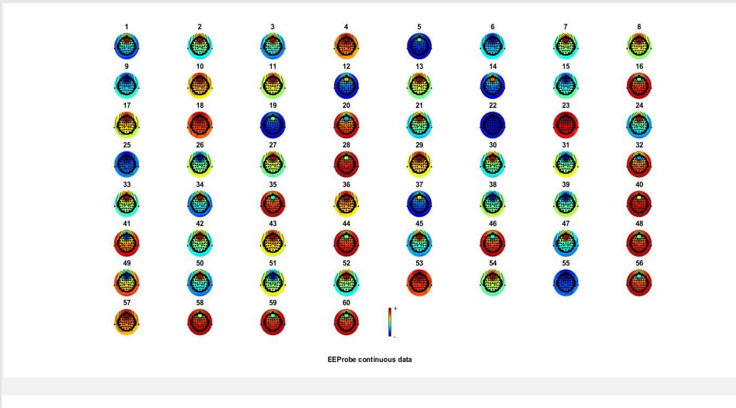


Fig 9 Independent Component Analysis for rejection if any artifacts are found

3.2.3 Functional Connectivity Analysis

The functional connectivity network of the human brain was visualized and statistically studied with the help of the MATLAB-based software with Graphical User Interface (GUI), EEGNET. EEGNET is a useful processing pipeline to identify, visualize and characterize brain networks from M/EEG recordings. It can perform all steps including the estimation of brain sources, the computation of the functional connectivity and the mapping of brain networks at scalp level and/or at source level. This pipeline includes: 1) loading and filtering the EEG signals, 2) the computation of the functional connectivity, 4) the calculation of the network measures and 5) the visualization of 2D (scalp level) and 3D (cortex level) brain networks and associated measures.

To compute the functional connectivity (FC) matrices, there are four methods are available: the cross-correlation, the mean phase coherence (MPC), the mutual information (MI) and the Phase Locking Value (PLV). The connectivity values can be computed over scalp signals (generating 2D networks) according to the method chosen. Here, the Phase Locking Value (PLV) was computed between scalp electrodes as well as between sources as the connectivity measure. The PLV is a part of the method from PS family. It was initially proposed by Lachaux et al. and its main advantage is the possibility of computing FC matrix at each instant as the method look at the inter-trial information.

3.2.4 Network Metric Analysis

To characterize the obtained networks, graph theory based analysis was widely used and proved its high performance and usefulness. A graph is a simple model of a system that are based on a set of nodes (electrodes used for EEG) and the edges between them (functional connectivity values). Using EEGNET, several graph metrics can be computed and can be divided into three categories:

A. Global features

- **Density**: It is the fraction of present edges to all possible connections. If the density of a graph is 1 then it is a complete graph (every vertex is connected to every other vertex).
In the observed values using EEGNET, the density of the graph was 1 for all the subjects over all the time sections.

- The **characteristic path length** is the average shortest path lengths in the network

- The **global efficiency** is inverse of the average shortest path length in the network

- The **radius** of a graph is the minimum graph eccentricity of any graph vertex in a graph. A disconnected graph therefore has infinite radius. Eccentricity is the maximum graph distance between a vertex v and any other vertex u of the graph.

- The **diameter** is the largest number of vertices which must be traversed in order to travel from one vertex to another.

B. Node parameters

- **Node degree** is the number of links connected to the node. In case of directed graph, the indegree is the number of inward links and the outdegree is the number of outward links, and the total degree is the sum of both indegree and outdegree.

- The **clustering coefficient** is the fraction of triangles around a node i.e. the fraction of node's neighbors that are neighbors of each other.

-**Node betweenness centrality** is the fraction of all shortest paths in the network that contain a given node. Nodes with high values of betweenness centrality participate in a large number of shortest paths.

- **Participation Coefficient** compares the number of links (degree) of node i to nodes in all clusters with its number of links within its own cluster. The participation coefficient plays an important role in classifying the nodes of a graph as connector hubs and provincial hubs.

C. Edge parameters

- **Edge betweenness centrality** is the fraction of all shortest paths in the network that contain a given edge. Edges with high values of betweenness centrality participate in a large number of shortest paths.

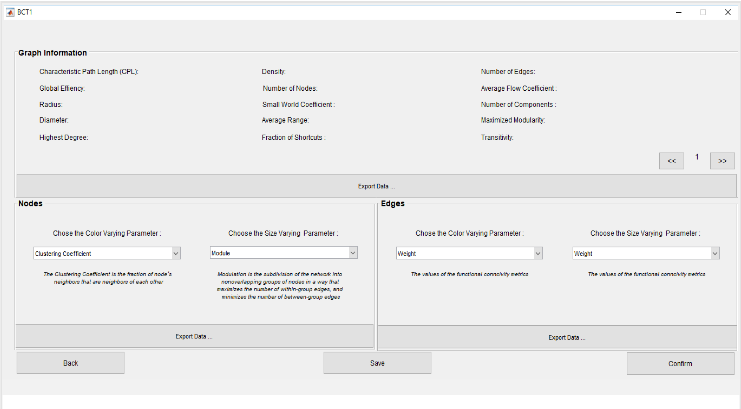


Fig 10 Illustrating the Graphical User Interface of the Toolbox EEGNET for calculation of the network metrics

SNO	BEFORE MEDITATION Eyes open	DURING MEDITATION	AFTER MEDITATION Eyes open
1. CHARACTERSTIC PATH LENGTH	1. 1 2. 1 3.1 4.1 5.1	1. 1 2. 1 3.1 4.1 5.1	1. 1 2. 1 3.1 4.1 5.1
2. GLOBAL EFFICIENCY	1. 1 2.1 3.1 4.1 5.1	1. 1 2.1 3.1 4.1 5.1	1. 1 2.1 3.1 4.1 5.1
3. RADIUS	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1
4. DIAMETER	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1
5. DENSITY	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1	1.1 2.1 3.1 4.1 5.1
6. MAXIMUM DEGREE	1.60 2.60 3.60 4.60 5.60	1.60 2.60 3.60 4.60 5.60	1.60 2.60 3.60 4.60 5.60

Fig 11 The graph network parameters using EEGNET

7. NO. OF NODES	1. 61 2. 61 3. 61 4. 61 5. 61	1. 61 2. 61 3. 61 4. 61 5. 61	1. 61 2. 61 3. 61 4. 61 5. 61
8. NO. OF EDGES	1. 1831 2. 1831 3. 1831 4. 1831 5. 1831	1. 1831 2. 1831 3. 1831 4. 1831 5. 1831	1. 1831 2. 1831 3. 1831 4. 1831 5. 1831
11. CLUSTERING COEFF.	1. 0.73545 2. 0.708453 3. 0.723623 4. 0.86836 5. 0.737451	1.0.724588 2.0.741913 3. 0.744678 4. 0.864784 5.0.746516	1. 0.727353 2.0.738165 3. 0.725342 4. 0.87195 5.0.729052
10. AVERAGE NODES EFF.	1. 0.73545 2. 0.735667 3. 0.723623 4. 0.86836 5. 0.730875	1.0.724588 2. 0.741913 3.0.744678 4.0.864784 5.0.746516	1. 0.727353 2.0.738165 3. 0.725342 4. 0.87195 5.0.729052
10. AVERAGE PARTICIPATION OF NODES	1. 44.16835 2. 44.17915 3. 43.4818 4. 52.15824 5. 44.30823	1.43.51765 2. 44.54874 3.44.70177 4. 51.94209 5. 44.83238	1.43.68067 2.44.34452 3.43.57994 4.52.36742 5.43.80185
10. AVERAGE NODE STRENGTH	1. 10 2. 10 3. 10 4. 1 5. 10	1. 10 2. 10 3. 10 4. 1 5.10	1. 10 2. 10 3. 10 4. 1 5. 10

Fig 12 The graph network parameters using EEGNET

3.2.5 **Brain Network Visualization**

In this study only analysis of scalp networks was required,so only the EEG data was loaded at first. The functional connectivity was then computed among scalp signals with the parameter, in this case PLV. For visualizing the network and computing the network measures, the channel file was required. The channels position is a file with four columns, the first for the node number or label, the next three for x, y and z positions. This part supports the static and dynamic options of visualizing the brain network. Here, only the static visualization was done for all the subjects over the three intervals of time. The graph calculated and the adjacency matrix for subject 5 for the three sections is as shown below:

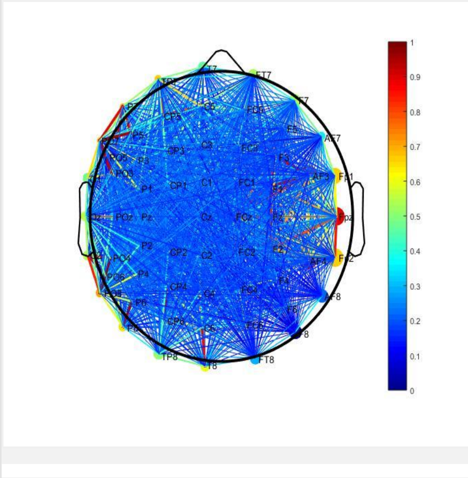


Fig 13 The figure shows the graph i.e. connectivity (1830 edges) between the 61 nodes and their strengths established in the subject 5, before meditation with his eyes open

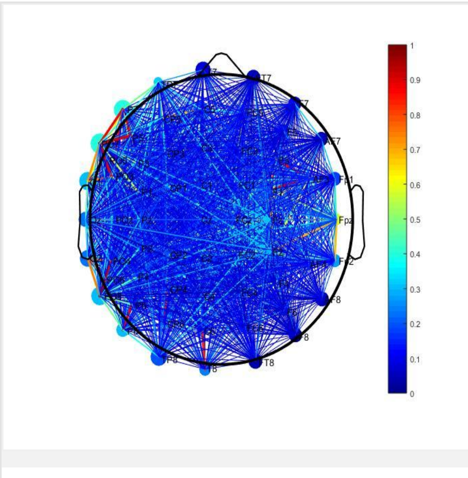


Fig 14 The figure shows the graph i.e. connectivity (1830 edges) between the 61 nodes and their strengths established in the subject 5, during meditation

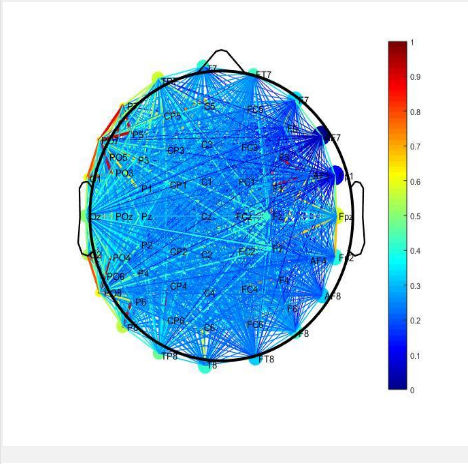
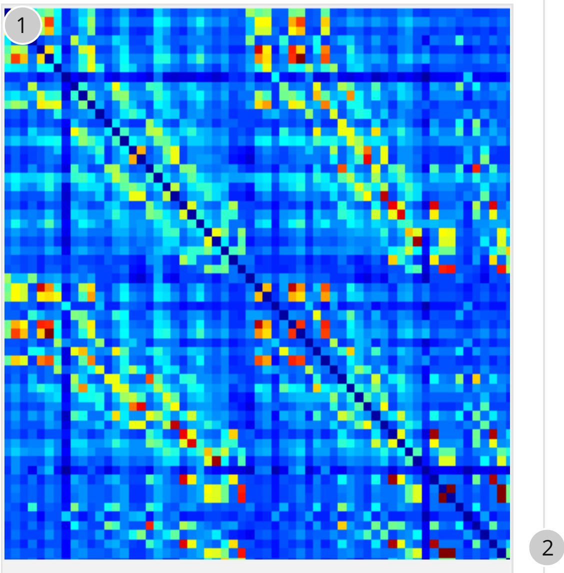


Fig 15 The figure shows the graph i.e. connectivity (1830 edges) between the 61 nodes and their strengths established in the subject 5, after meditation with his eyes open



1 Y-Axis : 61 Nodes/ EEG Electrodes

2 X-Axis : 61 Nodes/ EEG Electrodes

Fig 16 The adjacency matrix of the brain functional network of subject 5, before meditation with eyes open

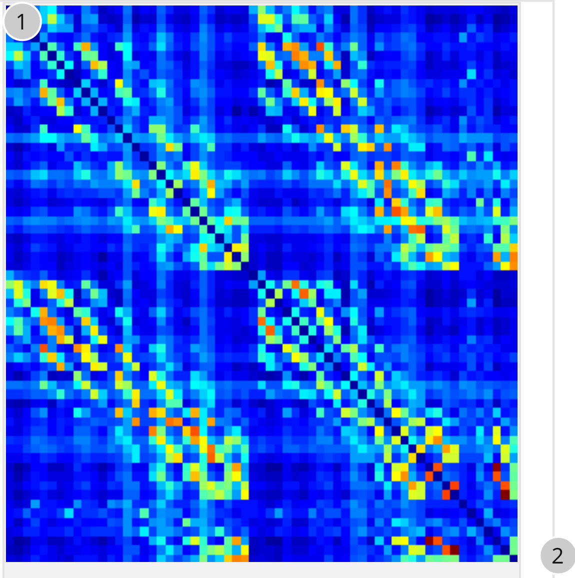


Fig 17 The adjacency matrix of the brain functional network of subject 5, during meditation

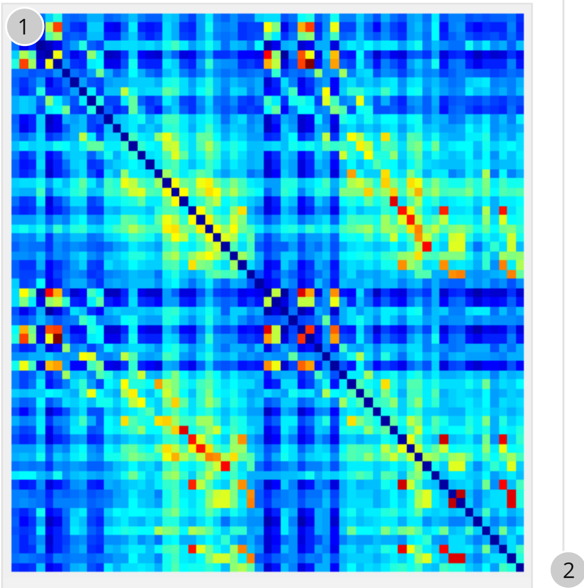


Fig 18 The adjacency matrix of the brain functional network of subject 5, after meditation with eyes open

4 RESULTS AND DISCUSSION

The graph network parameters which were statistically analyzed using EEGNET are: Clustering Coefficient and minimum path length for five long-term meditators as subjects divided into three events namely : Before meditation- eyes open, during meditation and after meditation-eyes closed for defined time intervals.

The values obtained after the statistical graph theory analysis of the EEG data collected is as follows:

Table 1 Observations of characterstic path length and clustering coefficient for five long tern meditators as subjects

SNO	BEFORE MEDITATION Eyes open	DURING MEDITATION	AFTER MEDITATION Eyes open
CHARACTERSTIC PATH LENGTH	1. 1 2. 1 3. 1 4. 1 5. 1	1. 1 2. 1 3. 1 4. 1 5. 1	1. 1 2. 1 3. 1 4. 1 5. 1
CLUSTERING COEFF.	1. 0.73545 2. 0.708453 3. 0.723623 4. 0.86836 5. 0.737451	1.0.724588 2.0.741913 3. 0.744678 4. 0.864784 5.0.746516	1. 0.727353 2.0.738165 3. 0.725342 4. 0.87195 5.0.729052

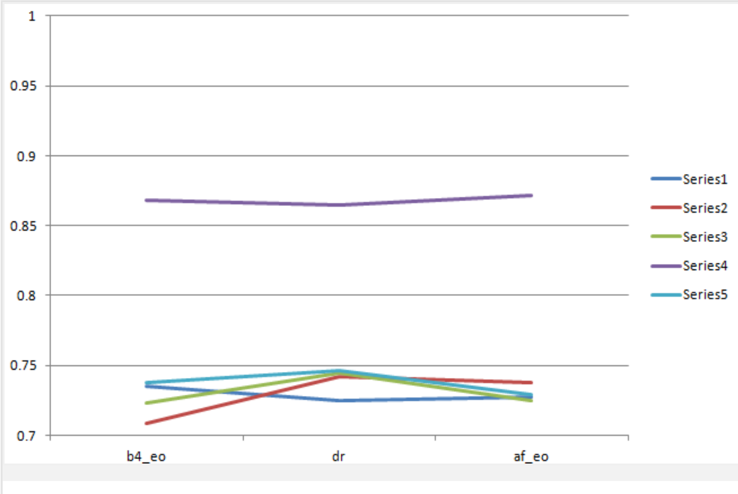


Fig 19 Plot considering only three time intervals (Before, during and after meditations- Eyes Opened)

The graph as shown here plots the variation of clustering coefficient of the five different subjects across the given events. Since the 4th subject has shown out-valued data which doesn't go along the general trend expected in all the subjects, is therefore eliminated from the further analysis.

Table 2 Observations of the clustering coefficients of the four meditating subjects (after elimination of the 4th subject)

Clustering Coefficient	Before Meditation (Eyes opened)	During Meditation	After Meditation (Eyes opened)
1	0.73545	0.724588	0.727353
2	0.708453	0.741913	0.738165
3	0.723623	0.744678	0.725342
5	0.737451	0.746516	0.729052

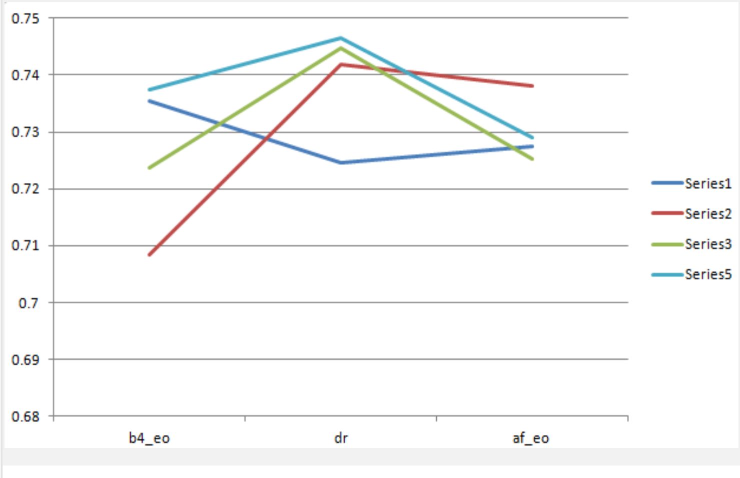


Fig 20 Plot considering only three time intervals (Before, during and after meditations- Eyes Opened) after elimination of the 4th subjects because it was out-valued compared to the other subjects

In order to compare the brain connectivity network before, during and after meditation, small worldness index is taken as the key-parameter. According to the mathematical formula of small worldness index, for its calculation, the values of minimum path length and clustering coefficient of the corresponding random graph is required.

Hence, calculation of the required parameters of the random graph is as follows:

$$L_{rand} \approx \frac{\ln(N)}{\ln\left(\left(\frac{K}{N}\right)-1\right)} \tag{1 a}$$

$$L_{rand} \approx 1.00000000559$$

$$C_{rand} \approx \left(\frac{K}{N}\right)/N$$

$$C_{rand} \approx 0.01612469 \tag{1 b}$$

The calculated value of minimum path length for all the subjects at all intervals of time is 1 as seen from the table. Using the parameters of the random graph, we can thus find the normalized values of minimum path length and clustering coefficient of the graph given as follows:

$$\lambda = \frac{L}{L_{rand}}$$

$$\lambda = \frac{1}{1.00000000559} = 0.9999999944 \quad (1\,a)$$

$$\gamma = \frac{C}{C_{rand}} \quad (1\,b)$$

Table 3 Calculated values of ratio of Clustering Coefficient of the experimentally observed graph and a corresponding random graph

Value of ratio of C and Crand	Before Meditation (Eyes opened)	During Meditation	After Meditation (Eyes opened)
1	45.61015739	44.93653236	45.10800844
2	43.93589345	46.01097111	45.77853264
3	44.87668628	46.18244719	44.98329293
5	45.73425274	46.29643382	45.21337476

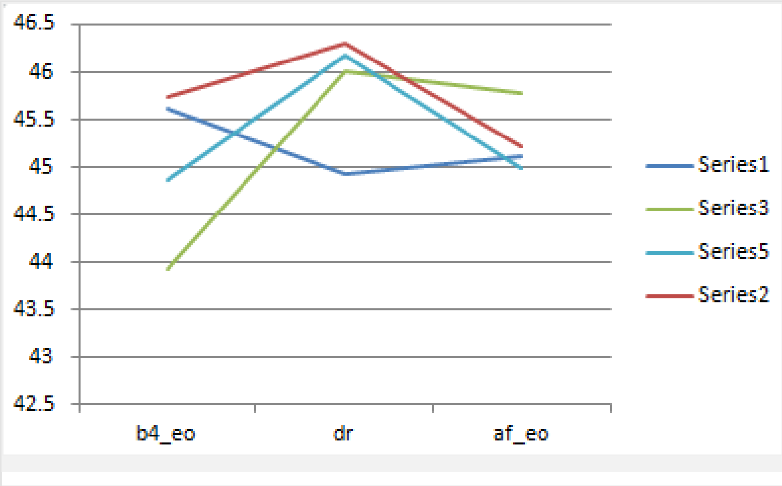


Fig 21 Plot showing the values of the normalized clustering coefficients of the functional networks of the subjects only consiering the time intervals with eyes-open

Upon calculations of the normalized parameters of the functional networks of the four subjects under consideration, it is followed by finding the ratio of the two, hence finding the small worldness index for the 4 subjects.

$$\sigma = \frac{\gamma}{\lambda} \tag{1}$$

Table 4 Calculaed values of the small worlness index for the four subjects

Small Worldness Index	Before Meditation (Eyes Opened)	During Meditation	After Meditation (Eyes Opened)
1	45.61015765	44.93653261	45.1080087
2	43.93589369	46.01097137	45.7785329
3	44.87668653	46.18244745	44.98329318
5	45.734253	46.29643408	45.21337501

The following plot shows the small-worldness index of the long term meditators:

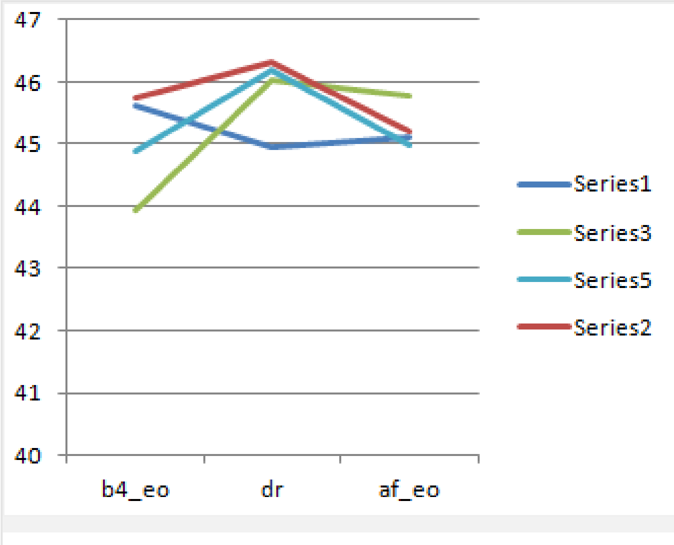


Fig 22 Plot showing the small worldness index variation when only three time sections are considered

From the various plots shown above: the small worldness coefficient and the normalized clustering coefficient follows the same trend i.e. iniially increasing in the before meditation phase till the meditating phase followed by decrease in the after meditation phase.

The network metric values calculated from the data obtained from the meditator subjects show large clustering coefficient, global and local efficiency, and shorter average path length. The shorter average path length and larger global efficiency indicates more efficient parallel information transfer in the brain, while higher clustering coefficient and local efficiency reflect the different regions of brain being fired on together.

It can also be observed that the average path length decreased and clustering coefficient increased in brain networks due to meditation practice, by comparing the the values calculated using EEGNET in the three given time intervals(events). Since we know average path length is inversely related to the global efficiency, it can be easily concluded that decreased average path length of a network node means increase in its network efficiency.

The values of the ratio of minimum path length and the minimum path length of a random graph (i.e. normalized minimum path length) came approximately 1, same in all the subjects while the ratio of clustering coefficient and the clustering coefficient of a random graph (i.e. normalized clustering coefficient) is stated in the tables above.
The ratio of the above two normalized quantities, i.e. the small worldness index is much larger than 1, which was the criterion to be statisfied to possess the small-world property. Thus we can conclude that the human brain also follows the small-world topology.

The meditation process also has an impact on the small-worldness index of the human brain, as the value varies from before meditation to during meditation to after meditation. The index is maximum at the time of meditation which signifies the perfect balance between the high segregation and integration property of the human brain.

5 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

From the graph plotted on the various parameters of clustering coefficient, normalized clustering coefficient and small worldness index, we can conclude that meditation very evidently has an impact on the human brain functional network in terms of connectivity strength and level of integration.

In addition to that, the network parameters obtained from the brain functional networks of the subjects satisfy the conditions of normalized minimum path length being approximately equal to unity and the normalized clustering coefficient as greater than 1. Thus making the small worldness coefficient much large than 1, therefore we can conlude that the human brain indeed follow the small world topology.

Not only that, but since the small-worldness index increases during the before meditation event to its maximum duting the meditation phase, we can conclude that mediation does improve the overall cognitive performance with the strong network connectivty during meditaton.

The brain thus is likely to support both segregated and distributed information processing and is evolved to maximize efficiency and/or minimize the costs of information processing. Small-world topology is associated with high global and local efficiency of parallel information processing sparse connectivity between nodes, and low wiring costs.

Apart from the conclusive results obtained from the study, there were shortcomings, one of them can be stated as: the fourth subject out of the 5 subjects under consideration was out-valued, due to which it was eliminated from the result and calculations. Also, the values obtained for the small worldness index needs to be verified, even though it successfully suggests that small-worldness topology exists in the brain functional networks.

Futher, the study can be extended to more number of long-term meditators as well as non-meditating subjects as it can be used to study how is the brain functional network of the mediatating subjects different from that of the non-meditating subjects and how can meditation have an impact on the small world topology from a non-meditator to a long term meditator.

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Source

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2. Fig 2: EEGLAB Toolbox (MATLAB)
3. Fig 3: · Connectome: Graph theory application in functional brainnetwork architecture. *Clinical neurophysiology practice*, *2*,206-213.
4. Fig 4: · Connectome: Graph theory application in functional brainnetwork architecture. *Clinical neurophysiology practice*, *2*,206-213.
5. Fig 6: Google Images
6. Fig 7: EEGLAB (MATLAB)
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