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A Review Technique for Graph Theoretical Approach Applied for EEG Features Identification

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Abstract: **In recent decades it has been a flow of analysis of brain model in terms of network Technologies. This review is basically concerned with the analyzing the functional Connectivity network of brain with the help of various images like EEG or MEG etc. Graph Theoretical approaches are in current trends to find out principle of brain network. It is a mathematical representation of a network by establishing a relationship among Vertices (electrodes) and edges (relation between electrodes). We have implemented algorithms of graph theory on MATLAB and done comparative analysis. We have compared algorithms for efficiency for shortest path computation, clustering coefficient, motifs, sub graphs, path length and efficiency. These properties are used to identify information processing, propagation of information over paths in network, occurrence and existence of neural diseases and cognitive abilities on different brain connectivity levels. This approach is applicable for ten to hundreds of nodes because the graph parameter estimates differ as the network size changes. Also accordingly association matrix is created by assigning pair wise associations between nodes and a threshold value is applied to each element of the matrix to generate an adjacency matrix. According to the relationship between nodes, matrix can be weighted or un-weighted. Weighted graphs have more information than un-weighted. Hence the ultimate goal is to demonstrate the possible applications of graph theoretical approaches in the analyses of brain functional connectivity networks from Electroencephalography (EEG) signals.**

1. INRODUCTION

Graph theory

Graph theory is a branch of mathematics that deals with the formal description and analysis of network kind of architecture made up of set of nodes and edges.

Complex network

A network consists of dense structure of node and edges also having high degree of node are considered as complex network. These type of networks are used to identify various characteristics such as clustering coefficient, high degree of node, small world, modularity etc.

Graph structure in terms of matrix is represented by using adjacency matrix as binary –that is, element will be 1 if there is an edge between corresponding nodes otherwise 0. Here for weighted graphs the elements will be in terms of their corresponding assigned weights. By using graph approach we can represent complex brain network in terms of nodes and edges hence in complex brain network electrodes can be replaced by nodes and also connectivity among them can be replaced by edge representation.

2. PURPOSE OF THIS REVIEW

This review presents analysis and study on network modelling brain connectivity such as functional or structural in different regions and states. This is done by capturing EEG/MEG/ fMRI images of brain .This review will focus mainly on recent findings concerning graph theoretical analysis of human brain networks with a variety of images including structural MRI, diffusion MRI, functional MRI, and EEG/MEG.

3. RECENT FINDINGS

Recent studies have utilized graph theoretical approaches to investigate the organizational principles of brain networks. These studies have consistently shown many important statistical properties underlying the topological organization of the human brain, including modularity, small-worldness, and the existence of highly connected network hubs. Importantly, these quantifiable network properties were found to change during normal development, aging, and various neurological and neuropsychiatric diseases such as Alzheimer's disease and schizophrenia. Moreover, several studies have also suggested that these network properties correlate with behavioural and genetic factors.

Structural and functional connectivity of the brain

Structural and functional connectivity are the two main types of brain connectivity. Structural brain connectivity represents structural associations among different neuronal elements, which includes both the morphometric correlation and true

anatomical connectivity . Functional brain connectivity shows functional associations among brain regions and can be obtained by measuring the temporal correlations between spatially remote neurophysiological events from fMRI and EEG/MEG data. Once the brain connectivity information is extracted from the neuro-imaging data, graph theoretical approaches can be further applied to model brain networks and analyze their underlying topological properties.

4. GRAPH THEORETICAL APPROACHES

Graph theory is a mathematical representation of complex networks. Recently, graph theory has attracted considerable attention in brain network research because it provides a powerful way to quantitatively describe the topological organization of brain connectivity. The brain architecture can be depicted as graphs composed of nodes representing regions and edges representing structural or functional connectivity among the nodes. Graph theory is mainly focuses on topology architecture of brain rather than anatomy. The clustering coefficient and characteristic path length are two basic measurements of a network.

The clustering coefficient is the average of clustering coefficient of all the nodes in the network. the clustering coefficients over all nodes in the network, where the clustering coefficient of a node is the number of existing connections among the node's immediate neighbours divided by all of their possible connections (Fig. 1). It quantifies the extent of local cliquishness or local efficiency of information transfer of a network.

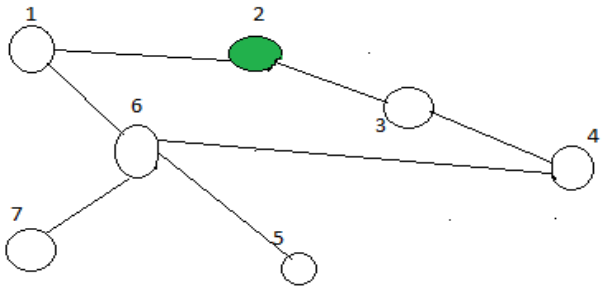

Fig. 1. Calculating Clustering Coefficient

The characteristic path length of a network is the average minimum number of connections that link any two nodes of the network (Fig. 2). It quantifies global efficiency (in terms of inverse path length) or the capability for parallel information propagation of a network. The two metrics can be used to distinguish different classes of network such as regular, small-world, and random networks. A small-world network has a shorter characteristic path length than a regular network The small-world model not only supports both specialized/modularized and integrated/distributed information processing but also maximizes the efficiency of information transfer at a relatively low wiring cost.

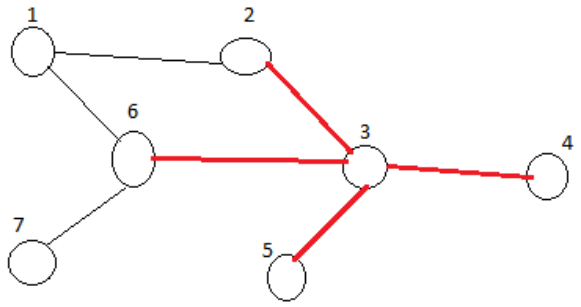

Fig. 2. Calculating Average path length

Another important network metric is the modularity, which identifies modules of linked nodes that work together to achieve distinctive functions . Connections are usually denser within modules than between them (Fig. 1). Detecting and characterizing modules of the brain can allow us to identify groups of anatomically and/or functionally associated components that may subserve specific behavioural functions.

5. BACKGROUND

The implementation concept of graph theory is very simple. To implement the simplest graph one should start with the basic building blocks of graph theory the nodes and the association between them called edges. The assignment of weights gives a topological structure which demonstrates a more general as well as simple network than the ontological modeling.

The degree of graph is defined as number of edges incident or adjacent to it. Average node degree is calculated by the average of number of edges divided by number of vertices in graph [Fig. 3].

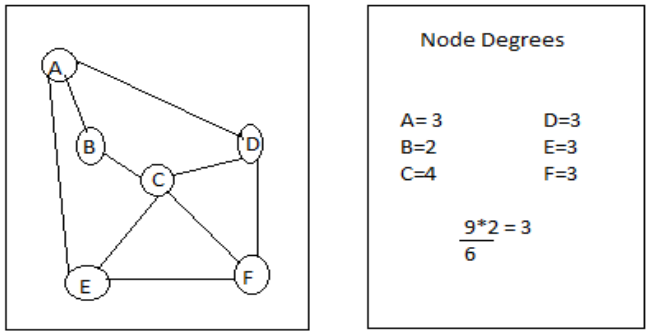

Fig. 3. Average Node Degree. The Degree Of node 2 is 2 and node 3 is 4. The average Node degree of graph is 3

To clearly understand the graph theory concepts, some characteristic graph parameters are required to be understood on which graph theoretic approaches are based, these parameters are called signature measures of the graph topology.

The average shortest path length also known as the as the average path length is the average of the distance between any two nodes of the graph.

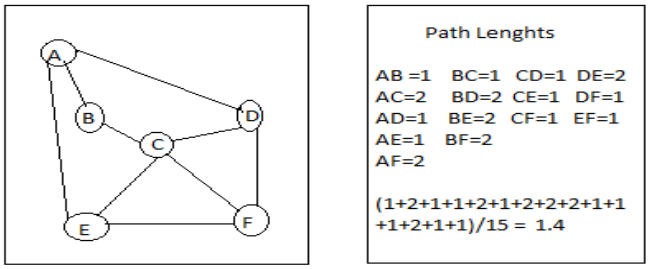

Figure 4 Average Path Length. The distance between node A and node F is 2. The average Path Length of graph is 1.4

Clustering Coefficient is the number of edges between the node and its adjacent node. Its value lies between 0 and 1, after calculation which is then averaged over all nodes in the graph. It can be high or low depending on the strong or weak clustering of the nodes respectively. Basically clustering coefficient is as the extent to which the neighborhoods of two neighboring nodes overlap. In a fully connected graph, or a graph in which each node is connected to every other node, the clustering coefficient is 1.

Graphs can be either directed or undirected. If the direction of edge is defined than it is called a directed graph otherwise undirected graph. A directed graph can be converted into undirected by removing directionality of edges. A graph is connected if there exists at least an edge between any two nodes; if an edge is removed it becomes an undirected one.

Motifs are defined as the simple building blocks of the complex networks. They represent a particular brain state with respect to reference states. It is a new approach to represent a complete functional connectivity by its increase or decrease among the brain regions at a particular state.

6. ELECTROENCEPHALOGRAPHY

The electrical activities occurring inside the brain are captured by electroencephalograph (EEG) signals. Study of such signals gives significant information about many neurological diseases (i.e. epilepsy, Alzheimer). To record EEG signals, electrodes are placed on the subject scalp using the standardized electrode placement scheme. EEG signals are characterized by several waveforms defined separately based on frequency ranges. The graph theoretic approaches clearly distinguish them using several graph features. Correlation and coherence is computed from association matrix of pair wise of functional connectivity.

7. CONCLUSION

Such graph theoretic approaches are found to be very effective and efficient for feature extraction from EEG data. The analytics provides a brief on change detection between various states of EEG data analysis. Shorter average path length and larger clustering coefficient represent more parallel information transfer between the electrodes representing different brain regions. Thus graph theoretic approaches are found to be more useful to detect more functionality between several brain regions[2]. The major challenge is of better representation of functional space and specification of anatomical network with respect to functional connectivity.

8. FUTURE SCOPE

Graph based approaches are applied to the network topologies to identify various characteristics. As graph based representation is used to represent these topologies the information flow via different path can be examined. Flow of information in region based network can be determined by using different images. It is already proved that network nodes can be defined using both anatomical and/or functional brain image voxels by using structural, functional and diffusion MRI. But still there is lot of work to be done in order to represent a network in graph format so that it can be fully utilized to extracts appropriate information. Another important challenge which is a question that how does the topology of a brain network can be relate to anatomy and also to the function and dynamics. The main systematic methodology is to be designed so that by using graph theory the brain network can be analyzed.

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