Functional brain networks underlying cognitive control processes have been of central interest in neuroscience. A great deal of empirical and theoretical work now suggests that frontal networks in particular the medial prefrontal cortex (mPFC) and lateral prefrontal cortex (lPFC) are involved in cognitive control. The most common way to study functional brain networks has been through measures of connectivity such as coherence, synchrony and mutual information. However, it has been noted that functional connectivity measures are limited to quantifying pairwise relationships between brain regions and do not describe the overall organization of the brain network. Recently, researchers have adapted tools from graph theory to address this issue.

Graph theory can model a network by a set of vertices and edges upon which complex network analysis may be applied. With respect to the functional brain network, the vertices represent the individual neural assemblies and the edges are weighted by their pair-wise phase synchrony. The connectivity of the brain can therefore be modeled by a fully connected weighted matrix upon which graph measures may be applied. Most graph theoretic measures, however, are limited to sparsely connected unweighted graphs. Therefore, some of the conventional graph measures, such as small world measures and centrality measures,
cannot be directly applied to the fully connected weighted graphs.

In this thesis, existing graph measures and graph theoretic approaches are modified specifically for the analysis of the functional brain network. First, a new weighted clustering coefficient and path length measure are introduced for quantifying the local weighted ‘small-world’ index of the brain. These measures are based on modeling the edge weights as probabilities which represent the reliability of information flowing across these edges. These measures differ from conventional measures by considering all possible connections with varying strengths of connectivity between nodes instead of focusing on only the directly connected or highest weighted pairs. This approach outperforms other measures because it does not require arbitrary thresholding of the weighted connectivity matrix to obtain a binary graph and thus can be applied directly to a fully connected weighted graph.

In addition to the modified conventional graph measures, concepts from signal processing and information theory are adapted to graphs to identify central vertices and anomalies within a network. These measures include new graph energy and entropy measures which are extended to weighted graphs. The proposed graph energy measure outperforms existing definitions of graph energy for local anomaly detection because it is computed from the most relevant spectral content extracted from the graph’s Laplacian matrix. The largest eigenvalues of the Laplacian matrix have been shown to provide a more complete representation of graph structure. A new definition of entropy rate based on modeling the adjacency matrix of a graph as a Markov process is introduced to quantify the local complexity of a weighted graph. The proposed method outperforms existing definitions of graph entropy by providing a value of entropy correlated to the graph’s structural complexity and being generalizable across multiple graph structures.

Multivariate relationships between neural assemblies of the brain can shed light upon the organizational principles of functional segregation and functional integration. Community detection algorithms provide a way to detect the underlying modular patterns of networks.
The study of modules for functional brain networks poses multiple challenges including the network being represented by a fully connected graph, the lack of a priori information about the number of communities and the need to identify communities across multiple subjects. In order to address these challenges, we introduce a hierarchical consensus clustering algorithm. This algorithm uses the well-known Fiedler vector based bi-partitioning of the graph to reveal a hierarchical structure of the brain network across various modular resolutions. Moreover, new measures of clustering quality are introduced to determine when to stop partitioning the network. Finally, a common community structure representative of the organizational principles shared across multiple brain networks is obtained through a consensus approach.

The proposed methods are applied to error-related negativity (ERN) data, a response-locked negative deflection of the brain event-related potential that is observed following errors in performance tasks, and is a reliable index for the self-monitoring process of the brain. Previous research shows that the primary neural generator of the ERN is the anterior cingulate cortex (ACC) and there is significant difference in connectivity patterns between mPFC and lPFC for error and correct responses. The proposed graph theoretic approaches give a succinct representation of the functional networks involved during action-monitoring and cognitive control and provide insight into the reorganization of the neural networks during error processing. The 'small-world' measures reveal there is increased local functional segregation and integration among electrodes in the mPFC and lPFC during error responses compared to correct responses. Also, the mPFC region of the brain network demonstrated increased energy and complexity indicating the presence of an anomalous perturbation located around the FCz. Finally, the hierarchical consensus clustering algorithm revealed an increase in modularity across the mPFC during error responses indicating a reorganization of the underlying functional network in response to error processing.
Journals Submitted:


Journals To Be Submitted:


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