Evaluating Brain Networks and Connectivity Measures from Models of EEG Data

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Abstract
Evaluation of the connectivity and dynamic interactions between areas in the human brain can lead to a better understanding of mental health disorders such as depression, autism spectrum disorders, post-traumatic stress disorders, Alzheimer’s disease, and many others (Bassett et al., 2009). However, current metrics to measure brain networks have not been thoroughly evaluated. This study evaluates different network metrics used for analyzing complex brain networks and compares them using synthetic brain network models simulating seizure activity. Synthetic electroencephalogram (EEG) data of an individual experiencing a seizure was evaluated using metrics from the Brain Connectivity Toolbox (BCT) by Rubinov and Sporns, 2010. Our results show metrics that were tested increased in value as a result of the increase of electric brain activity during the seizure. These results suggest that simple measures of changes in connectivity may be useful for characterizing changes in brain state. A more comprehensive study comparing behavior in other models and in real data is needed.

Objectives
• To evaluate some of the metrics in the Brain Connectivity Toolbox used for analyzing complex brain networks (Rubinov and Sporns, 2010).
• To determine if metrics in the Brain Connectivity Toolbox support hypothesis that each metric should increase during seizure phase because more electrical activity is taking place.
• To witness how these metrics change over time with different conditions applied to dataset (e.g., change over time with seizure).

Methods
• Obtain EEG dataset. Our data was synthetically generated EEG data from a Matlab toolbox called Source Information Flow Toolbox (SIFT) (Mullen, et al., 2014). The EEG data used was 300 seconds long, sampled at 150 hertz (Hz) per second. Between the first 40-60 seconds, a seizure takes place.
• Separate the dataset into three sections: pre-seizure, seizure, and post-seizure.
• Transform each phase of dataset into an adjacency matrix. We used the phase shift index (PSI) proposed by Nolte et al., 2007. Following the instructions from PSI index, Nolte et al., we used the brain frequencies ranging from 5-10 Hz.
• Apply a threshold to zero out edges of the adjacency matrix. The threshold method we used was obtained from the Brain Connectivity Toolbox by Rubinov and Sporns, 2010, and called the absolute threshold method. We used — 0.0001, 0.001, 0.01, and 0.1 — for our threshold values.
• Choose a metric to be used to analyze the matrix. For our experiment, we used degree value, clustering coefficient value, strength value, and betweenness centrality value.
• Once metric is computed, find the average metric value for each phase.
• Finally, plot each average metric phase value as a function of threshold.

Conclusion
Preliminary results show the complex brain network measures tested above from the Brain Connectivity Toolbox are able to distinguish fundamental changes in network structure when a model seizure occurs. As predicted, the values of each metric increased as the electrical activity in the EEG results from the seizure increased. Future work needs to be completed to evaluate these metrics in more computationally heavy metrics found in the toolbox and to apply the metrics to actual EEG data, especially from EEG results from individuals with mental health disorders. Understanding complex brain network structures from mental health disorders may lead to an improved diagnostic tool for confirming an encephalopathy.

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