Variation of Brain Network Dynamics Across Subjects Using EEG Data

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Abstract
We are not certain how the human brain operates during a task or how different areas of the brain interact during that task. EEG is one of the only feasible means to non-invasively access the brain at work in the real world. In this work we seek to establish methods for evaluating baseline connectivity in brain networks derived from EEG data. This baseline can then be used to interpret what is happening inside each individual’s brain. We have been able to view several different individuals’ data side-by-side as an average of their degree, clustering coefficients and efficiency while they were performing a specific task. We are in the process of developing views of the data as a function of time to provide information about network evolution during tasks. Our research is ongoing.

Goals
• Generate network models from EEG data.
• Determine how network connectivity varies with threshold across subjects.
• Use results to better characterize brain networks generated from EEG data.

Methods
Data Generation Data Decomposition Source Localization Create Network Nodes
Gather EEG Data Run independent component analysis (ICA)
Find the dipoles using DIPFIT Extract dipoles

Figure 1: Summary of the workflow for connectivity analysis

• Perform independent component (ICA) analysis (Delorme et al. 2011).
• Find dipoles that fit components to within 25% residual variance using EEGLAB DIPFIT (Oostenveld et al. 2003).
• Extract the dipoles as the nodes of the network.
• Extract the time courses of these dipoles.
• Calculate the connectivity using phase slope index (PSI) with a frequency of 5 to 10 hertz (Nolte et al. 2008; Haufler et al. 2013).
• Apply thresholds to the resulting adjacency matrix.
• Apply network measures to the adjacency matrix from the Brain Connectivity Toolbox (BCT) (Rubinov et al. 2010).

Data
The data used in this work was acquired using a 64-channel Biosemi EEG headset and consists of 18 subjects performing a visual oddball task (VEP). This collection was a part of a larger, multi-headset and consists of 18 subjects performing a visual oddball task. EEG was recorded using the Brain Science System from Biosemi, with dipoles that fit components to within 25% residual variance using EEGLAB DIPFIT (Oostenveld et al. 2003). Scalp maps of the independent components detected with residual variance less than 0.25 when fit to a dipole. Results were from subject 1.

Results
The graphs that follow show the degree, clustering coefficient and efficiency for the PSI method after decomposing EEG data for VEP subjects 1-6.

Network measures
The graphs that follow show the degree, clustering coefficient and efficiency for the PSI method after decomposing EEG data for VEP subjects 1-6.

• Results (Continued)

Conclusion
Utilizing this method and averaging the data, we can see trends in the data decomposition. The goal is to find a way to see clear data flow in the brain. We are also hoping to find better threshold values to use. Our next step is to analyze small windows of data over time. Our research is still ongoing.

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References

Figure 2: Component Maps and DIPFIT For vep_01 Data Set with a Residual Variance of <0.25.

Figure 3: Change in network degree as the edge weight threshold varies.

Figure 4: Clustering coefficient and efficiency as a function of threshold.

Figure 5: Efficiency Change with Increasing Threshold

Results

Averaged Degree Change with Increasing Threshold

<table>
<thead>
<tr>
<th>Subject</th>
<th>Degree Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2.3</td>
</tr>
<tr>
<td>B</td>
<td>1.2</td>
</tr>
<tr>
<td>C</td>
<td>3.5</td>
</tr>
<tr>
<td>D</td>
<td>0.8</td>
</tr>
<tr>
<td>E</td>
<td>1.9</td>
</tr>
<tr>
<td>F</td>
<td>2.1</td>
</tr>
</tbody>
</table>

With the averaged clustering coefficient we can see that initially the increasing threshold increases the average, but it summarily drops off.
• The clustering coefficient relates to how likely the nodes around a node are connected to one another.
• Efficiency relates to how easily a node can reach another node in the entire network.
• Subject six appears to be an anomaly.