Graph Visualization for Brain Connections

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Abstract—In this paper, we compare 9 visual encodings along with 3 layout methods for brain functional connection network visualization via a user study. 9 encodings, including angle, slope, length, density, shape, area, texture, hue and lightness are used to encoded the centrailty of a node in the network. 3 layout methods are horizontal projection, circular and matrix layout. 4 tasks developed from the domain was used for the experiment. Participants' performance results indicate the circular layout overall outperforms other layouts and lightness encoding have relatively the worst performance. Our study results could provide guidlines for developping visualization for complex network.

Index Terms—Keyword1, keyword2

1 Introduction

The complexity of brain connection and insufficient knowledge to computationally model the brain make visualization a valuable tool for brain scientists to understand the important feature that exists in the connection and generate hypotheses. Visualizing complex network on the other hand, proves to be difficult task itself. The lack of understanding of what kinds of graphics representation are best suitable at demonstrating the connection feature must be filled before we can build useful visualization tools to understand human brain.

Human brain functions as a large, sparse and complex network [23]. It consists of billions of neurons and tens of trillions of neuron connections [20]. The axons that connect the neurons are responsible for conducting most of the brain's signal transmission. The recently popular diffusion Magnetic Resonance Imaging (dMRI) technique could image the axons by measuring the anisotropy of water molecule movement in the axon fibers. By using tractography technique [3], the three dimensional structure of those fibers could be constructed from slices of two dimensional images. Those fibers connecting different brain regions forms the brain anatomical connectivity network.

Many visualization techniques exist yet guidelines for choosing the appropriate techniques almost do not exist; expect the most recent studies[2]. Functional MRI technique tends to study the brain by reflecting the functional behaviors of brain regions. By measuring the blood oxygenation level-dependent (BOLD) factor over time, correlation between different regions of the brain could be constructed and thus forming the functional connectivity graph of the brain. Interactions between the two networks is intricate and mutual. The anatomical constructions of brain though are the determinant could also be shaped during one's development [25].

Brain circuit visualization has been applied in brain research literatures to illustrate interregional connections using graph visualization techniques. The purpose of including such visualizations are presenting the results discovered from statistics. The regions are represented by node with related characteristics encoded as size or color. The connections exist between regions after filtering with selected threshold are expressed as straight line edges. The nodes are usually placed in two dimensional space consistent to their corresponding locations in brain from a fixed viewing point with transparent brain cortex model supplied as landmark. The goal of this work, is to experiment with graph visualization design choice and discovered the best suitable graph representation choice for brain connection.

Through our paper, we use *region* to indicate an anatomical structure of human brain. *link* to denote one existing connection between two different regions. In the connectivity graph, *node* is the geometrical representation of node in the node-link diagram, which usually represents one corresponding brain region and *edge* is the line that connects two nodes in the diagram.

Our contributions of this work include:

1. We compare different network representation techniques and discovered that a ring layout is best suited for most of our selected tasks.

2. We demonstrate the usability of different visual encodings to complex network representation such as a brain functional connection network.

2 Related Work

2.1 Brain Functional MRI Measurements

Degree Centrality Degree Centrality of a node equals the number of neighbors of it. The degree property of a node is the most local and direct measurement[28]. The distribution of node degree is also a good indicator of the network resilience [**?**, **?**].

Betweenness Centrality Betweenness centrality is defined as the fraction of all shortest paths in the networks that passes through the given node. Betweenness centrality is a good measurement that can be used to indicate hub node that plays a role that transmit communications between communities. Therefore it is natural to extend its definition to links and thus detecting important anatomical of functional connections. [6] Similarly, *closeness centrality* is defined as the inverse of the average shortest path length from one node to all other nodes in the network.

Eigenvector Centrality Eigenvector Centrality of a given node i is defined as the i-th element of the first eigenvector of the adjacency matrix which corresponds to the principal eigenvalue. It measures the influence of a node in by assigning relative scores to all nodes so that connections to high scoring nodes contribute more to the score of the given node than that to low-scoring nodes.[**?**] Eigenvector centrality captures the global feature of the graph.

Subgraph Centrality of a given node indicates its participation in all subgraphs of a network [**?**]. It takes into account all possible subgraphs.

Leverage Centrality Leverage Centrality aims at finding the local important node in the concept that an important node is one that feed most information to the neighboring nodes. [17]. This metric may be used to discover important nodes within the network.

Page-rank Centrality Google page-rank centrality is a variant of eigenvector centrality. It adds a small random damping factor

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Manuscript received 31 March 2013; accepted 1 August 2013; posted online 13 October 2013; mailed on 4 October 2013.
For information on obtaining reprints of this article, please send e-mail to: tvcg@computer.org.

to avoid walking traps on a graph [**?**]. It has been shown to be similar to degree centrality and examined in the functional connectivity context [6].

Closeness Centrality It is defined as the inverse of the sum of its distances to all other nodes. Thus, the more central a node is the lower its total distance to all other nodes. Closeness can be regarded as a measure of how long it will take to spread information from s to all other nodes sequentially.

Markov Centrality This centrality interprets the network as a Markov process, and can be understood intuitively as the amount of time an imaginary token performing random walks spends on each node. It is similar to eigenvector centrality in many cases.

Katz Centrality Unlike typical centrality measures which consider only the shortest path between a pair of actors, Katz centrality measures influence by taking into account the total number of walks between a pair of actors. Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors. Connections made with distant neighbors are, however, penalized by an attenuation factor alpha.

Alpha Centrality It is an adaptation of eigenvector centrality with the addition that nodes are imbued with importance from external sources.

Those centrality measurements are used to determine the important hub regions. In [1], regional characteristic path length is used to define hub regions. Hagmann et al. [12] define hub node with high degree and betweenness centrality and discovered a structural core within posterior medial and parietal cerebral cortex, as well as several distinct temporal and frontal modules. In a project searching for functional hubs [**?**], nodes with high connection degree across subjects are considered hub nodes.

2.2 Brain Functional MRI Data Visualization

With the application of Principle-Component Analysis (PCA) [11] and Independent-Component Analysis (ICA) methods [4], brain functional connectivity from fMRI data could be constructed. Given the large amount of connection existed in human brain, analyzing the data proposes difficult tasks for brain researchers.

Visualizing the brain connectome [24] has been popular method to presenting the change of brain due to injury, aging or diseases. Many useful metrics have been proposed in graph theory perspective [14, 28]. For example clustering coefficient and characteristic path length are combined used to derive a character factor to identify hub nodes [27] and the small-worldness has been demonstrated by using cortical thickness measurements [13].

3 Graph Based Brain Connectivity Analysis

3.1 Brain Functional MRI Visualization

Based on a previous survey on graph visualization taxonomy [18], we discuss the centrality mapping below. Degree centrality, eigenvector centrality and betweenness centrality are three essential important measurements of a given node in a connection network. *Degree centrality* is the most direct and local attribute of a node. A higher degree indicates a region that is highly connected to other regions. It has been used in many studies [13, 14, 28]. The centrality is a measurement of a node that describes its importance in a graph. In this paper, we experiment with different visual mapping methods for the centrality measures. Since degree, eigenvector and betweenness centrality are the most commonly used measurement, our visualization focuses on the mapping of these three values.

Visualization design space. The basic elements are nodes and links in a node-link diagram. The glyph representation of a node could be used to encode information and information that related to connectedness might also be inferred from the links. According to the taxonomy of Mackinlay's [19], several properties of the glyph could be used to encode quantitative value. The effectiveness of the encoding, ranked by perceptual tasks, differs. It is reported that position encoding is the most effective, followed by length, angle, size, saturation and hue. Texture and shape is not appropriate for quantitative value encoding.

Degree Centrality Reading degree centrality is basically a task that requires counting number of links connected to a node.

Betweenness Centrality In order to derive the degree centrality, it is required to counting the number of shortest paths. This, however is a very difficult if not impossible for human without appropriate representation of the topology implemented. A clever way [7] to present this measurement is to draw all the shortest paths in the node-link graph instead of every individual links. In such way, the betweenness centrality is effectively converted to a task similar to degree centrality reading task. In addition to avoid confusion for reading the number of links to infer the degree centrality, the links between nodes are grouped into a band whose width will be used to encode the number of path on the link.

Eigenvector Centrality The eigenvector centrality, by its definition, is an iterative computation that assign node importance so that node connected to importance nodes is also of high importance score. This process, however, is not appropriate for human mind. So computation should be done first to get the centrality measure and visual mapping should be applied to convey that information to the human user.

Since both degree centrality and betweenness centrality could be encoded on and read from the link, we could use the glyph representation of node to encode eigenvector centrality.

Each existing link between any two nodes is always the shortest path between them, so every direct connection between two node will be preserved. As paths are drew instead of links, more than one paths might exist between two nodes, which causes confusion for degree centrality reading. To solve this, we group links between two nodes into a band whose width indicates the number of paths pass on. Based on this, we experiment with the encoding methods and see how to encode eigenvector centrality on a node glyph representation will be the most effective.

As circle glyph is mostly used and not biased to any direction, it will be our baseline for encoding design. *Position* is usually fixed for a node-link diagram by the layout constrains, so it is not suitable for quantitative encoding. For encoding with *length*, we draw a thin bar within the circular node with indicates the value. The *angle* encoding involves using a bar chart to convey the centrality value. The *size* of the node could be well matched to Machinley's terminology to encode quantitative value as well. *Saturation* and *hue* of the node will also be tested and is commonly used for visualization is the medical domain. These are in total 5 conditions to test with.

3.2 fMRI Analysis Tasks

Several high-level brain connection analysis tasks has been proposed by Alper et al. [2]. We've also reconfirmed the validity of these tasks applied to fMRI dataset alone with our collaborating medical doctors. Following are our selections of the fMRI analysis tasks.

Degree Reading *What is the degree centrality of the highlighted node?*. This task asks the participant to read the centrality value encoded in the marker that represents a brain region.

Degree *Which of the two highlighted regions has higher connection strength*. For the brain connection data, the overall connection strength of a region is defined as the sum of connection strengths (covariance) off all edges of it. The degree property of a node is the most local and direct measurement[28]. In a visualization perspective of view, the degree measurement is also the easiest perceivable property for graph reading task, compared to other measurements. Severe degree change might indicate disease or lesion of the given region. To complete this task, the user are required to count the number of links of the given regions and do a comparison. If the difference is huge, the counting might be not necessary.

Variation *Of the 2 highlighted brain areas, which one has more link number change from brain on the left to the the brain on the right?*. This task requires the participant to compare the amount of change between 2 brain lobes. The brain areas are grouped to 8 lobes, including Parietal L, Parietal R, Frontal L, Frontal R, Occipital L, Occipital R, Tempareil L and Tempareil R. It is actually four areas separated into L(left) and R(right) since our brain is left-right symmetrical. Each of the region will be indicated by a bounding box. the participant need to judge which area has more variation than the other in terms of link number change. To make this task simpler, 2 brain lobes are pre-highlighted and the participants only need to compare this 2 highlighted ones.

Hub *Of all the regions that are connected to the highlighted region, which one is most likely to be a hub region*. The hub region is mostly characterized as a regions that connects highly connected sub-regions. The most significant measurement of it is that having high betweenness centrality, so this task essentially ask the user to find the neighboring nodes that has the highest betweenness centrality as encoded by the total link width.

3.3 Data

Our connection dataset is from the NBS website. It is consists of 27 subjects' brain connection matrices. The matrices describes a weighted graph of the brain functional connection. We generated the experiment dataset by the following procedure. First, we generate a mean connection matrix by averaging all the 27 matrices. Then we randomly select subject matrices along with the mean matrix for the each task. If the task only requires one graph to be visualized, only the mean graph will be used. Following are the process we used to generate experiment data for each trial.

For the degree reading task, we ask the participants to read node degree on the mean graph. The difficulty is controlled by sample nodes from the node degree distribution histogram in 3 ranges: 0 25, 25 75 and 75 100 percentile, with each corresponding a difficulty index (1 to 3).

For the degree compare task, the participants need to compare the value of the same node in the mean graph and a randomly selected graph. We control the difficulty by selecting nodes with centrality difference in the 3 percentile range as we used for the degree reading task.

For the variation task, we grouped the brain regions into 8 clusters based on their anatomical positions, including frontal(left and right), parietal(left and right), occipital(left and right) and tempareil(left and right) lobe. The participants are required to compare the change of each lobe from the mean graph, which represent the mean brain to a randomly selected graph.

For the hub node task, the hub nodes are first detected in the mean graph by using betweenness centrality measures in the mean graph. All nodes that are connected to at least one hub node are selected as candidates. We control the difficulty by selecting candidates with 2, 3 or 4 neighbors, with each corresponding to a difficulty index.

There are in total 4 tasks * 3 layouts * 9 encodings * 3 difficulty indices = 384 combinations. We reduced the number of trials for each participants to 108 trials by using a Latin square. The Latin square reduces the combination of 3 layouts and 3 difficulty indices to 3 combinations for each participants.

Projection+D1	Treering+D2	Matrix+D3
Matrix+D2	Projection+D3	Treering+D1
Treering+D3	Matrix+D1	Projection+D2

4 HYPOTHESES

H.1 For the 9 encoding methods, length, angle, slope will show better performance than area,density, hue, lightness, texture and shape for all tasks that requires value reading, i.e. degree reading, comparison and hub node task. This ranking is adopted from [19]. Since the experiment uses this encoding for the value reading and comparison, the ranking shall still stand correct.

H.2 Among the 3 layouts,projection layout will show the worst performance for the variation task and for hub node task, treering will outperform other layouts. The reason is that variation task requires the comparison of link changes. The three-dimensional nature of the brain makes the brain lobes overlap in the projection view and thus making the task difficult. Treering and matrix view arrange node positions according to brain lobes and will not have such problems. Hub node task requires finding neighbor and comparing the values. Treering layout arranges the node in a linear way and the links directly connects to all the node's neighbors.

H.3 Encoding will have no significant effect on variation task and layout will not significantly affect degree reading and degree comparison task. This is because the variation task does not actually use the information encoded on the node and degree reading and comparison task provide information form node encodings.

5 EXPERIMENT

5.1 Participants

All participants are UMBC students. Their average age is X to Y with N females. They were recruited as volunteer participants for visualization study and paid for 12 dollars per hour. The longest completion time is less than 1.5 hours and no fatigue has been reported during the experiment.

5.2 Procedure

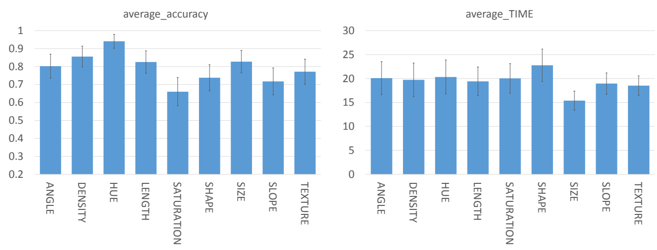
The experiment was conducted in our lab at UMBC. The display is DELL 24 inch monitor with Nvidia XX Graphics card. The anti-aliasing is implemented by using the hardware feature. The screen resolution is 1920*1200. The size of the visualization is controlled so that it can occupy as much screen space as possible.

Each participant was asked to fill the consent form and an anonymous geographical survey before the experiment starts. We will give he/she a training section which lasts for about 20 minutes before the former experiment starts. During the training sections. All the visualization options and parameter of the all tasks has been introduced to them. The training session won't continue until the participants has fulling understand the meaning of the visualization and know how to get to the right answer. The experimenter will stay next to the participant and answer questions if he/she has any and at the same time make sure the participants understand the questions and visualizations. The performance data during the training session is recorded but not used.

After the training section, the participants proceed to the former experiment. During which the participant was told to complete all trials of the experiment alone. The task trials include all encoding and visualization combinations.Each participant complete part of all combinations according to the latin square. The latin square is balanced as we use 3*N participants. The order that each participant completes the trials is randomized so the learning effect can be countered. After the experiment, the participants is asked to rate their preference for each visualization set and give their confidence score for each task. After this, they are paid and done for the experiment.

5.3 Results

User study results. Statistics and subjective feedbacks.



(a) average accuracy

(b) average time

Fig. 1: Overall performance for 9 encodings.

6 Discussion and Future Work

7 Conclusion

Acknowledgments

The authors wish to thank A, B, C. This work was supported in part by a grant from XYZ.

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