AUTOMATIC DATA EXTRACTION IN ANALYSIS OF BRAIN CONNECTIVITY USING GRAPH THEORY

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Abstract: This paper describes one of the methods used for analysis of the brain connectivity – the graph theory focused on network topology and node significance. Brain connectivity is evaluated on the functional magnetic resonance imaging (fMRI) data, which is well established modality for imaging brain activity. Using graph theory in analysis of brain connectivity is a recently developed approach and offers many possibilities for comparing the results among individuals and characterizing different types of graphs.

Keywords: functional magnetic resonance imaging, functional connectivity, graph theory

1 INTRODUCTION

Brain connectivity describes how one neural population (an area of neurons with similar behavior) relates to the other. Especially in the state of rested mind without any stimuli, particular networks are activated – they are called the *resting-state* networks and well-known is the *default-mode* network. From that point of view the use of graph algorithms is convenient to consider. Taking the tools from the complex network analysis and applying them to neural data, we can estimate the plausibility of individual brain areas (the present of the given area together with its significance in the network) and describe the topology of the connectivity [1]. This work groups the activated neurons according to their classification to Brodmann anatomical areas and introduces the software that performs the network analysis defined above these clusters.

2 BRAIN CONNECTIVITY

This work concentrates on mapping the simultaneous coactivation of brain areas; it does not say anything about the causality of the relationship, or the direction of influence. This concept is called *functional* connectivity and it describes the statistical dependencies between the areas. The structure of the connectivity – distinct areas connected with mutual statistical dependencies – inspired the application of the graph theoretical approach, which can reveal some information that cannot be captured by standard methods.

3 FUNCTIONAL MAGNETIC RESONANCE IMAGING MEASUREMENTS AND DATA PRO-CESSING

The data to this work are obtained from the measurement of an fMRI experiment. The fMRI measurement in a strong magnetic field records the changes in the ratio of oxygenated and deoxygenated hemoglobin. The subject may perform a given task, or lay at awake rest depending on the experiment design. The data pass the preprocessing steps, then they are statistically processed, and the spatial activity distribution is assessed. However getting the connectivity data just requires preprocessed scans followed by extraction of the functional dependencies: the data are parceled to Brodmann areas according to anatomical template, then a representative of every area is selected and correlation between every two representatives is computed (a representative is set to be the average of the area activity or its first principal component). Some studies suggest to perform the correlations between every pair of functional voxels but this approach is computationally very demanding.

4 USING GRAPH THEORY IN ANALYZING BRAIN CONNECTIVITY

The approach to the neural connectivity data is highly similar to the network analysis previously applied in different fields (social networks, epidemiology, system biology, etc.); the emphasis is put on the topology and its description by various metrics. The neural network is classified as a *large scale* network. First of all there is a hypothesis that the network is different from the random network. It was found that the neural graphs have the characteristics of *scale-free* and *small world* networks [1] – shown in the figure 1. The small world network is typical by the large amount of connections between neighboring nodes and only a few links going to distant nodes, the scale-free network is characterized by *hubs* – highly connected nodes.

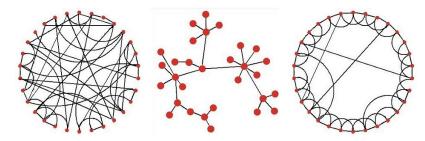


Figure 1: Random network, scale-free and small world network [2].

The network can be described by many parameters; all of them create the complex information about the topology. The centrality is determined, among the others, by the degree of the node, *betweenness*, *closeness* or *eigenvector centrality* [1]. The degree informs about the number of connections to the node *i*, betweenness centrality describes the fraction of the shortest paths $g_{jk}(i)$ between nodes *j* and *k* passing through the node *i* of all the shortest paths g_{jk} . The node with high betweenness centrality connects different clusters which may not be activated in the same time; the quantity is specified by the equation 1 [3].

$$C_b(i) = \frac{1}{(n-1)(n-2)} \sum_{j \neq k, j \neq i, k \neq i} \frac{g_{jk}(i)}{g_{jk}}$$
(1)

$$C_{c}(i)^{-1} = \frac{n-1}{\sum_{j \neq i} d(i,j)}$$
(2)

The closeness centrality informs about closeness of the node to the graph center and does not deal with the connectedness. The closeness is based on the average path length d between the node i and every other nodes j and is defined by the equation 2 [3]. The last mentioned parameter, the eigenvector centrality, specifies how central the node is depending on the centralities of its neighbors.

Evaluation of these parameters for every node in the graph can bring us the information about the node involvement in the task and its significance. The functional connectivity, therefore also this work, use only undirected connections. According to the measured correlations between voxel values, the weight of the connection can be added to the evaluation, or the relationship can be binar – the link is present or not.

5 IMPLEMENTATION AND CHALLENGES

As mentioned before, this work uses anatomical atlas for parcellation of the cortex. The brain atlas can be potencial source of errors – the areas in the atlas are statistically created and do not exactly fit to the given personal data. According to the recently published papers, e.g. [4], wrongly parceled data can cause highly varied results. On the other hand basing the parcellation on the voxel-wis correlations of the activity would be more precise but also very difficult to implement in the practice.

The output of this work is a software that uses the fMRI resting-state data and computes and visualizes the functional network as its output. The correlation matrix is computed from the representatives of the areas, then (optionally) thresholded, and it is passed to the graph algorithms processing – this work implements the Brain Connectivity Toolbox [3]. The software presented in this paper uses the Toolbox functions which work with the binary or weighted networks with undirected links between nodes. The advantage is that the user can choose the method depending on what he wants to examine. Then the result (the graph description) is visualized with the aid of the framework The Connectome Viewer [5]. The example of the result is shown in the figure 2 – this figure comes from the Connectome Viewer dataset.

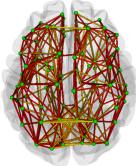


Figure 2: Visualization of the connectivity by The Connectome Viewer.

6 CONCLUSIONS, ACKNOWLEDGEMENT

The paper presents an introduction to theoretical background for the analysis of brain connectivity using the graph theory. This is followed by short description of the software, applying the graph algorithms to neural data to get better view of functional integration.

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