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Brief Note on Detecting AD and ASD Using Ambivert Degree of Autism Spectrum Disorder

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Abstract

It is known that hubs help the brain process information, and changes in the functional connectivity of hubs have a global effect on the network and function of the brain. Brain functional hubs are disproportionately and significantly affected by a variety of neurological conditions, including Alzheimer's disease (AD), schizophrenia, and autism spectrum disorder (ASD).

Keywords: Alzheimer's disease; Brain modules; Functional connectivity

Introduction

The high level of information processing at the hub regions, which results in high baseline activity and metabolic requirements of the hub regions may be the cause of these disruptions in hub connectivity, making the hub neurons susceptible to metabolic stress or degeration as a result of high activity [1]. Multiple resting state functional MRI (rs-fMRI) studies have found widespread impairment in intrinsic functional connectivity in ASD, a developmental disorder characterized by a variety of heterogeneous symptoms of varying degrees of severity (for a review, see Hull et al., 2017), particularly in the centers [2]. Similarly, research suggests that Alzheimer's disease (AD) affects highly active heteromodal regions in a preferential manner. Buckner and others 2009) utilized node degree centrality to identify brain hubs and demonstrated that healthy human hubs overlap with AD patient regions with higher A deposition. Discovered that hub vulnerability in AD may be caused by excessive neuronal activity that led to degeneration. According to Sheline and Raichle (2013), the Amyloid-(A) cascade hypothesis, A disrupts the normal functioning of adjacent neurons and synapses in AD [3].

We hypothesized, based on previous research, that AD and ASD subjects could be distinguished from their respective healthy subject cohorts by using nodal hub scores. Using rs-fMRI data from people with AD and ASD, we demonstrate how brain hubs can help diagnose brain diseases [4]. Due to the availability of large data sets for deep neural network modeling and examples of hub disruption, we chose AD and ASD for our analysis. From functional scans, we discovered that AD and ASD patients had brain hubs that were distinct from cognitively normal controls. We trained neural networks and SVM classifiers with the nodal hub scores and functional connectivity as input features, and we demonstrate that using hub scores resulted in significantly higher classification accuracy with a significantly lower number of trainable weights.

Let's use =G W(,) to represent the functional brain network (connectome), where denotes the set of brain regions of interest (ROI) or nodes and is the matrix of edge weights of the network with wi, denoting the weight between brain ROI. Previous research has used a subject averaged functional connectivity matrix to identify brain modules and hubs; however, numerous studies have highlighted a variety of individual differences in the functional connectome. When looking for functional modules (and, consequently, network hubs), it is necessary to take into account differences in functional architecture between subjects and report combined group results from all subjects [5].

Discussion

Therefore, we employ the Iterative Consensus Spectral Clustering (ICSC) algorithm, which iteratively increases the similarity of subject-level and group-level modules by maximizing their similarity. The ICSC algorithm identifies a modularization that divides brain ROIs into modules with higher connectivity between modules' ROIs than with other ROIs. In order to identify subject-level modularizations Wk of subject k, the ICSC reduces the normalized cut objective function. Consensus clustering on subject-level modules provides the group-level modularization By maximizing =S, where the Adjusted Mutual Information is used to measure similarity between modularizations, the ICSC algorithm then greedily refines the subject-level modularizations so that they are most similar to the group-level modularization. Consensus clustering, for example, is used to derive group-level modularizations from the newly obtained subject-level modularizations until the given similarity cost function remains unchanged. Each subject's modular labels were aligned with those at the group-level modularization after ICSC provided subject-level modularizations [6]. Using the Jaccard Index (JI) matching method, we match the group-level modules with the subject-level modules. If for both the group-level module a, and a module with index b in k, the label a of the module at the group level. Our modularization technique takes into account weighted, unthresholded subject-level networks, but weak connections are most affected by experimental noise. The stability of derived topological features over a variety of thresholds has been demonstrated by performing analyses across a variety of densities. However, weak correlations may still contain significant functional information; consequently, it is essential to employ techniques that determine the optimal trade-off between the formation gain from the removal of noisy edges and the loss due to the re- moval of potentially useful weak edges. In order to demonstrate this, researchers utilized synthetic networks that were comparable to brain functional networks in terms of their modular structure and noise. They also demonstrated

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that percolation analysis preserves the minimum number of edges necessary to keep the network connected while maximizing information on the modular structure of brain functional Additionally, maintaining the same edge density in subject-group brain functional networks may result in the inclusion of spurious and weak connections in a subject-group with impaired functional connectivity and the absence of strong connections in another subject-group. Since we conduct analysis on a subject-by-subject basis rather than a group-by-group basis, the latter becomes particularly significant in our situation. Each subject's functional network is subjected to percolation analysis to determine the ideal weights threshold t and zero weights for connections with weights below t.

Conclusion

A large number of weak or strong intra-modular weights determined by cor-relations of brain activations—or a combination of the two characterize nodes with a high intra-modular degree. Even though nodes with a lot of weak correlations between brain activations do not convey meaningful information, these nodes are still categorized as modular hubs using the methods that are currently in use. In social networks, these nodes are thought to be extroverts because they have a lot of weak ties to other nodes. On the other hand, we are inter- ested in ambiverts, which means that we are nodes that not only connect with a sufficient number of other nodes but also share meaningful relationships with those nodes. We propose an ambivert degree measure to identify high intra-modular degree nodes that are synchronized with multiple nodes in the same module for this purpose. In module S, the ambivert degree of node is specified.

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