Brain network from sparse and topological point of view

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Introduction:

The sparse brain network is usually obtained by two different ways : thresholding of connectivity matrix and imposing the sparseness constraint in the connectivity matrix estimation. However, it is not yet known what threshold or sparseness level is best in determining the hidden connectivity structure of the brain. In this work, we show the equivalence between sparseness and threshold and propose to look at the topological changes by varying the threshold/sparseness, instead of using the fixed threshold/sparseness. For visualizing and comparing the topological changes, we borrow a barcode provided by the persistent homology. As an illustration, we apply the proposed method to construct the FDG-PET based functional brain networks out of 24 attention deficit hyperactivity disorder (ADHD) children, 26 autism spectrum disorder (ASD) children and 11 pediatric control (PedCon) subjects.

Methods:

Sparse Network Construction:
Suppose that a data matrix $X=\{x_1,\ldots,x_p\}$ consisting of n-dimensional data vector measured at the p selected regions of interest (ROIs) is given. The connectivity matrix C is usually constructed by the correlation matrix Σ or the partial correlation matrix Σ^{-1}. For simplicity of visualization and computation, it is natural to find sparse connectivity matrix in two ways : constructing an adjacency matrix by thresholding C with the cutoff value ε and imposing the sparseness by minimizing the l_1 norm of C, $|C|$.

Thresholding and sparseness:
To show their equivalence, we introduce the penalized linear regression to estimate the correlation (1) and partial correlation (2) as follows [1,2]:
(1) the a_{ij} of which objective function is to minimize
$\Sigma\ (x_i - a_{ij}\, x_j)^2 + \lambda|a_{ij}|$
(2) and the β_{ij} of which objective function is to minimize
$\Sigma\ (x_i - \Sigma_j\, \beta_{ij}\, x_j)^2 + \tau|\beta_{ij}|$
λ and τ are parameters controlling the sparseness. We can solve two objective functions by gradient descent, then the obtained sparse correlation and partial correlation are forms of thresholded standard correlation and partial correlation with cut off values, functions of λ and τ.

Barcode :
The sequence of networks varying the threshold/sparseness is persistent and it is directly connected with the persistent homology of Rips filtration [3]. Thus, we can borrow a visualization tool, a barcode, for the evolutionary changes of the topological structures from the persistent homology [3].

Results:

All PET scans were obtained from ECAT EXACT 47 (Siemens-CTI, Knoxville, USA) PET scanner with an intrinsic resolution of 5.2 mm FWHM. PET images were preprocessed using Statistical Parametric Mapping (SPM) package. After spatial normalization to the standard template space, mean FDG uptake within 97 ROIs were extracted and globally normalized to the individual's total gray matter mean count.
We examined the persistence of thresholded networks by increasing the threshold/sparseness in Fig.

1. The denser networks persistently include the sparser networks.
The barcodes of ADHD, ASD and PedCon networks for the connected components are shown in Fig. 2 and their differences are compared by 1000 permutation test. They are significantly different between ADHD-ASD, ADHD-PedCon and ASD-PedCon at level 0.05. The bars are merged faster into a bar in PedCon than other groups. It means that the brain networks of ASD and ADHD groups might be more difficult to be merged into a component due to common underconnectivity and local overconnectivity [4,5].

Conclusions:

We show the equivalence between sparsity level and threshold of the network and propose to seek the topological changes of network varying the sparseness/threshold using the barcode.

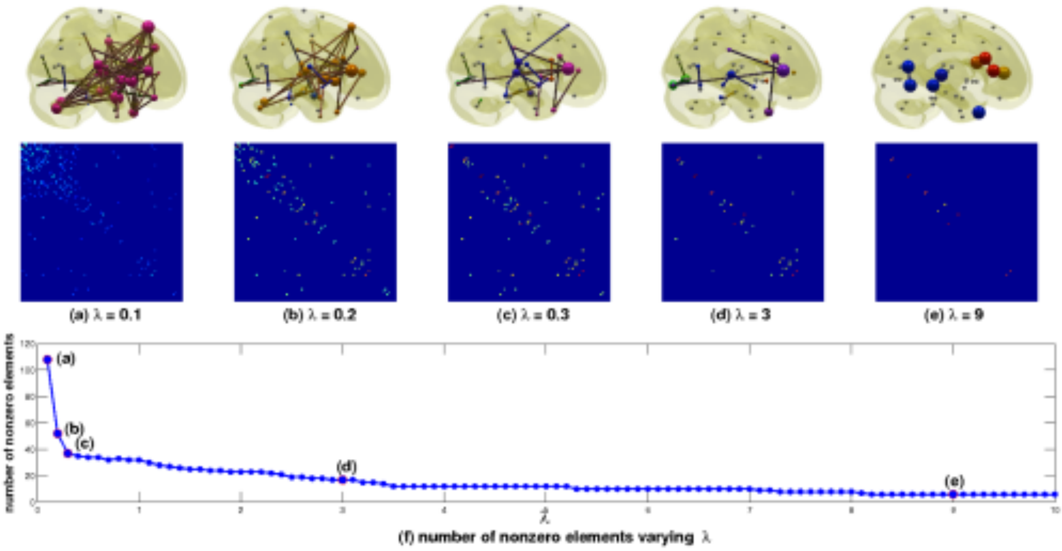

Figure 1. (a)-(f) The connectivity matrix based on the partial correlation with the sparseness constant λ = 0.1, 0.2, 0.3, 3, 6 and 9 and (g) the number of nonzero elements varying λ. In (g), the vertical axis means the number of nonzero elements and the horizontal axis means λ.

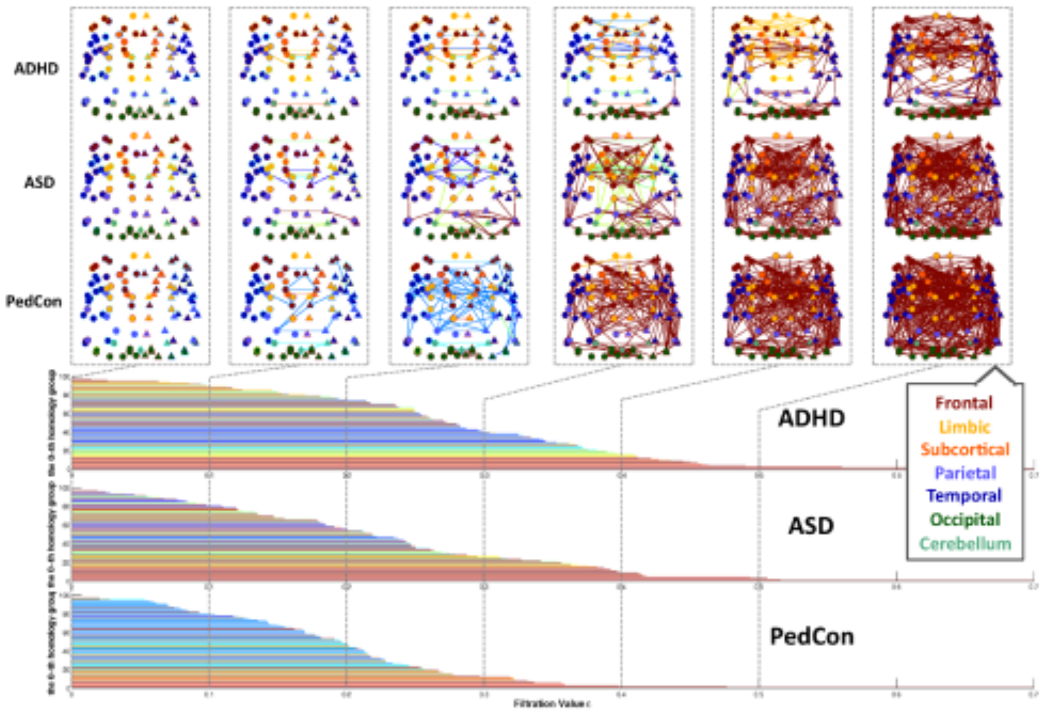

Figure 2. Barcodes of the connected components and their corresponding ADHD, ASD and PedCon networks when the thresholds are 1,0.9,...,0.5 from left to right. (The filtration values are one minus thresholds.) The marker face color of nodes represents lobes and the marker edge color of nodes and edges represents their corresponding clusters. When the threshold becomes smaller, the nodes are connected more and the number of clusters becomes one.

Modeling and Analysis Methods

PET Modeling and Analysis

Abstract Information

References

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