Edge selection preserving the topological features of brain network

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Introduction:

To determine the edges of brain networks, it is general to estimate the connectivity matrix using the correlation and threshold it into the adjacency matrix. However, the obtained network changes depending on where to threshold the correlation. In this work, we propose the edge selection method which preserves the topological features of brain network based on the computational topology.
In the topology, the topological space is characterized by the Betti number. The 0th and 1st Betti numbers, β0 and β1, are the number of connected components and holes (Zomorodian, et al., 2005). The persistent homology, a branch of the computational topology, looks at the changes of the topological features (β0 and β1) of the network when varying the thresholds. This procedure is called as a graph filtration. We collect the edges which contribute the changes of β0 and β1 during the filtration. The proposed method is similar to find the minimum spanning tree (MST) in the network (Lee, H., et al. 2011). MST basically finds how nodes are connected to each other. However, MST does not find holes present in the network. We minimize the loss of topological information by considering both connected components and holes.
As an application, we used the FDG-PET data set: 24 attention deficit hyperactivity disorder (ADHD), 26 autism spectrum disorder (ASD) children and 11 pediatric control (PedCon) subjects. We showed that our edge selection method finds the minimum number of edges minimizing the information loss in the given distance matrix.

Methods:

Graph Filtration:
Given a node set X consisting of p regions of interest (ROIs), the binary brain network, B(X,ε) is constructed by connecting two ROIs i and j by an edge if their distance d(i, j) = 1-corr(i,j) is smaller than ε. A sequence of binary networks for increasing ε is called a graph filtration. During the filtation, the topological characteristics of binary network, B(X,ε), is quantified by the 0th and 1st Betti numbers, β0

and $\beta 1$, and visualized by the barcode as shown in Fig. 1 (b) and (c).

Edge Selection Procedure:
By increasing ε, the edge is added one by one and the binary network, $B(X, \varepsilon)$ and its Betti numbers, $\beta 0$ and $\beta 1$ are estimated. If $\beta 0$ and $\beta 1$ are changed when the edge is added, it is collected (See Fig. 1 (a)). Then, the set of selected edges can represent the topological characteristics of network as shown in Fig. 1 (d). And the shortest path lengths along the selected edges approximates the original distance matrix in (e-g).

Results:

FDG-PET images were preprocessed using Statistical Parametric Mapping package. After spatial normalization to the Korean standard template space, mean FDG uptake within 103 regions of interest were extracted (Lee, J.S., et al., 2004). The values of FDG uptake were globally normalized to the individual's total gray matter mean count. Using the general linear model, we factored out the effects of age.

We illustrated the graph filtration and barcodes of ADHD, ASD and PedCon in Fig. 2. The total number of selected edges of ADHD, ASD and PedCon are 144, 136 and 148 in Fig. 3. The ADHD, ASD and PedCon networks have 42, 34 and 46 holes. The hole is generated when the edges connect between the connected components, rather than within a connected component.

To check whether the selected edges preserves the original distance, we estimated the least square errors between the distance matrix, $D=[d(i,j)]$ and the shortest path lengths along the selected edges by our method and between D and one by previous thresholding method which uses the sparsity (Basset, D.S., et al., 2006) in Fig. 4. Then, we found that the proposed method approximates the original distance matrix better with the smaller number of edges.

Conclusions:

We proposed the edge selection method using the graph filtration. The selected edges preserve the topological features of brain network such as the connected components and holes, but reduces the number of edges to represent the given network.

Modeling and Analysis Methods:

PET Modeling and Analysis

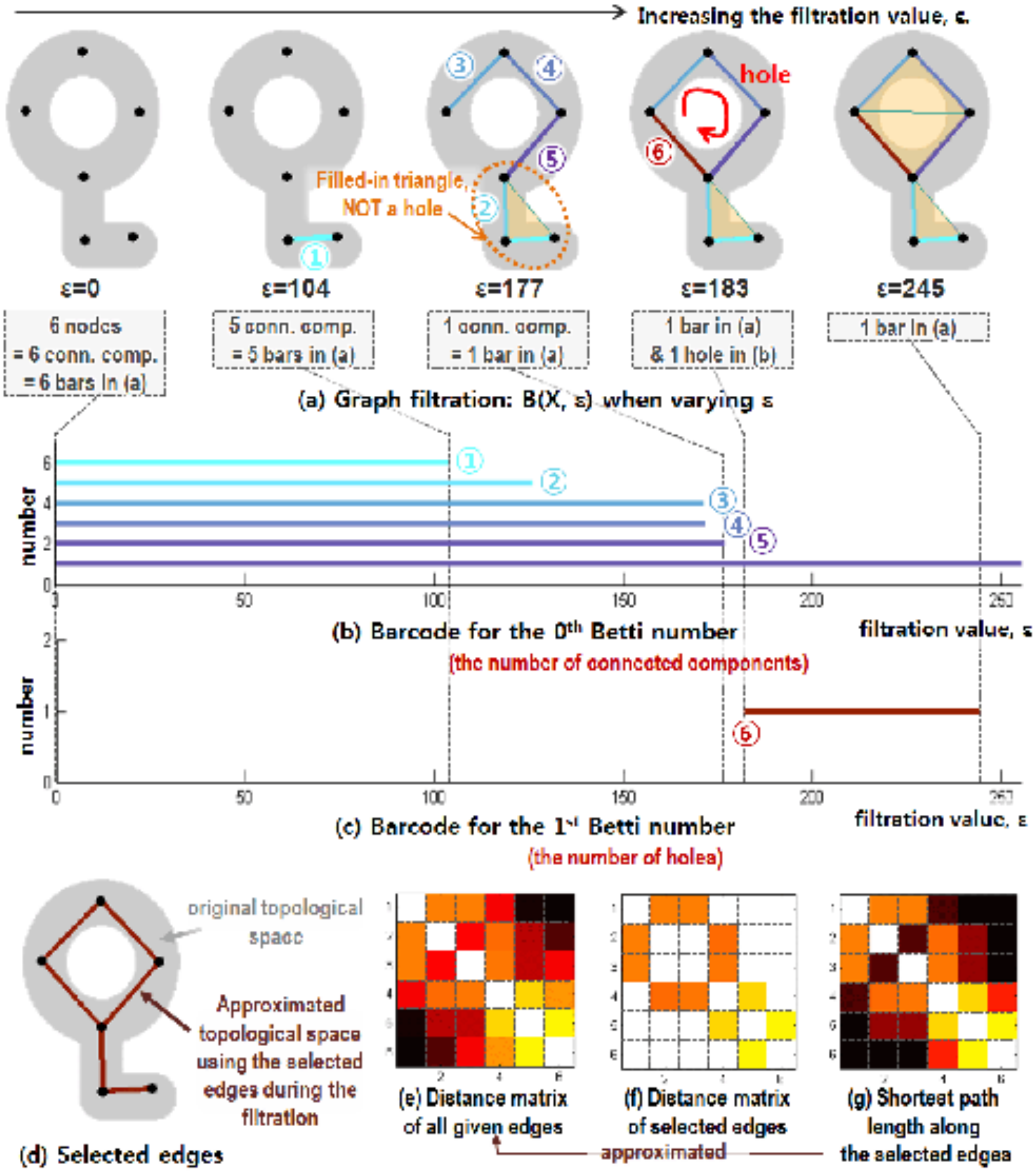

Figure 1. Toy example for edge selection procedure

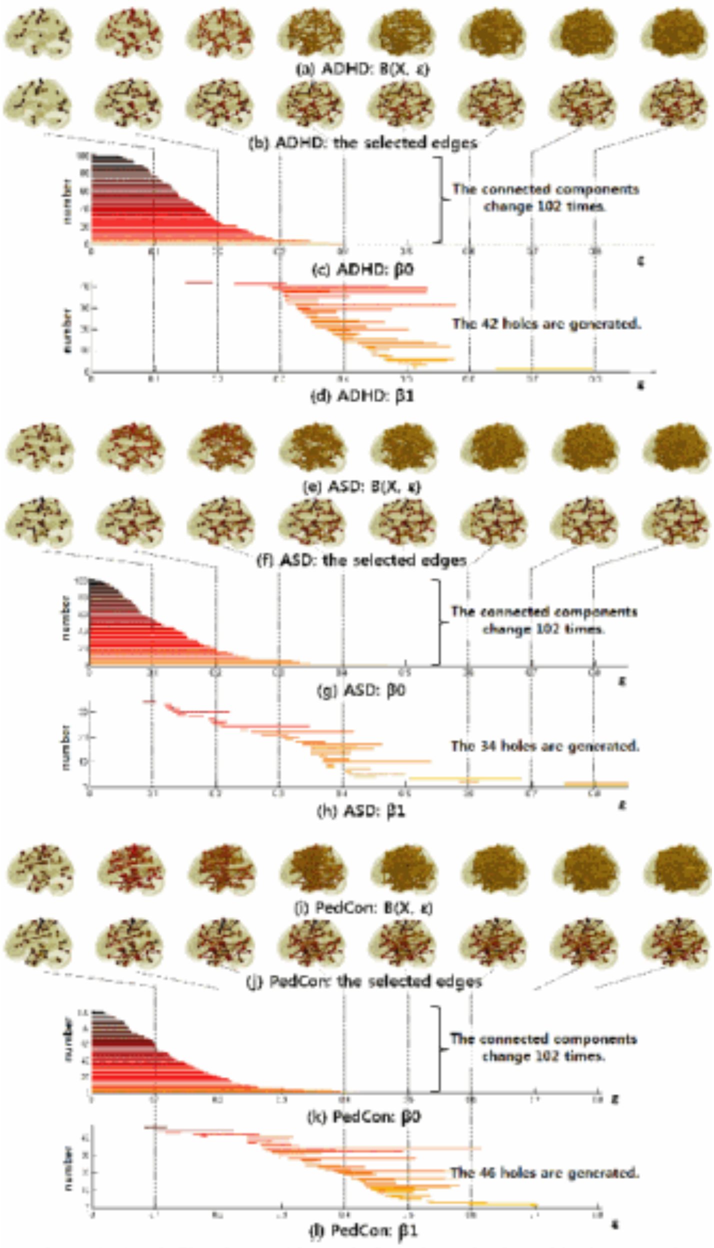

Figure 2. Graph filtration and barcode for edge selection of brain network

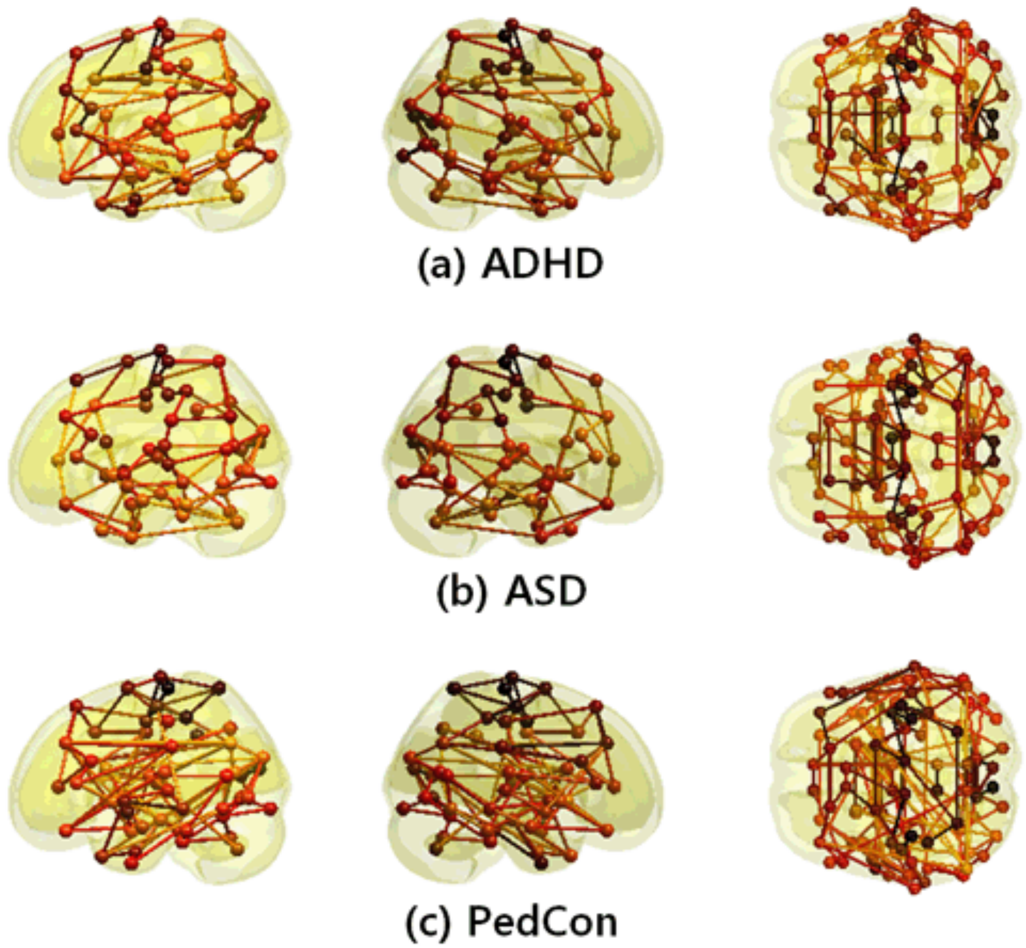

Figure 3. Selected edges during the graph filtration

		ADHD	ASD	PedCon
Number of selected edges	using our method	**144**	**136**	**148**
	using MST (Lee, H., et al., 2011)	102	102	102
	using the thresholding (Basset, et al., 2006)	822	823	826
	all positive correlated edges	2518	2574	2602
Error between the given distance matrix and the shortest path lengths along the selected edges	using our method	**0.0441**	**0.0784**	**0.0603**
	using MST (Lee, H., et al., 2011)	1.8031	1.7069	1.3430
	using the thresholding (Basset, et al., 2006)	0.0719	0.1073	0.0803

Figure 4. Comparison of the number of selected edges and mean error to the given distance matrix to the previous methods. The smaller error is, the better representation of the given distance matrix is. Our edge selection method finds the smaller number of edges with the smaller error.

Abstract Information

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