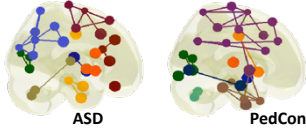


Persistent Network Homology from the perspective of Dendrograms

Hyekyoung Lee¹, Moo K. Chung^{1,2}, Hyejin Kang¹, Boong-Nyun Kim¹, Dong Soo Lee¹

¹Seoul National University, Seoul, Republic of Korea, ²University of Wisconsin, Madison, WI

Introduction



ASD PedCon
Modular structure with the fixed scale

• The **modular structure** of brain connectivity helps to understand from the local module information to their global relationships of brain network [1,2].

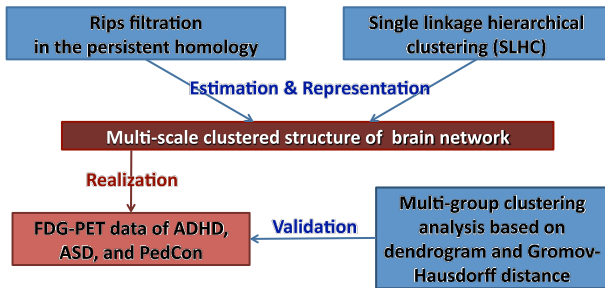
• Usually, we select only one optimal modular network by maximizing the predefined metric such as a modularity. But the optimal network can be changed depending on the metric and it is not yet known which network is truly modular.

• In this study, we seek the evolutionary changes of modular structures when the threshold in correlation matrix increases, instead of choosing a fixed modular structure. It can be directly related with the **hierarchical clustering** with the **persistent property** and visualized by a **dendrogram**.

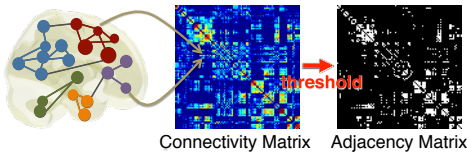
• As an application, we constructed the brain networks using the FDG-PET data of 24 attention deficit hyperactivity disorder (ADHD), 26 autism spectrum disorder (ASD) children and 11 pediatric control (PedCon) subjects.

• The difference between the changes of the modular structures was compared by **Gromov-Hausdorff distance** [3,4], which measures the distance between dendrograms.

Outline

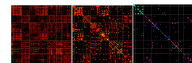


Network Construction



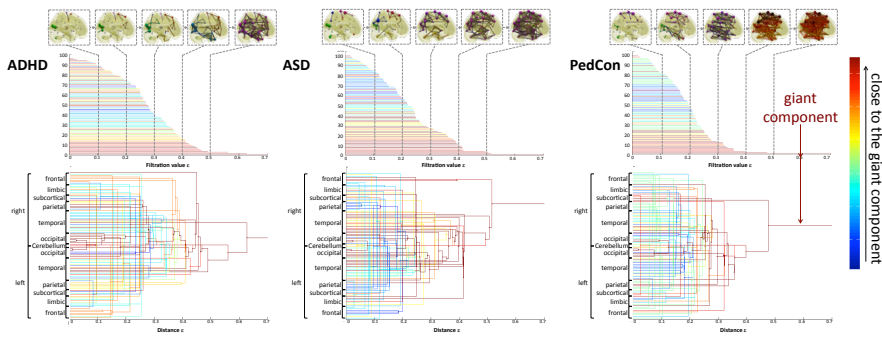
Distance = 1 – positive correlation

Different adjacency matrices are constructed depending on the thresholds.



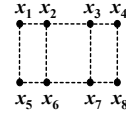
Which one do you prefer?

Multi-scale modular structure of brain networks



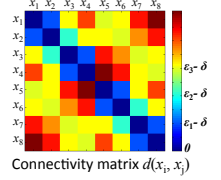
Persistent Homology

Given point cloud data X & their metric $d(x_i, x_j)$,



$$X = \{x_1, x_2, \dots, x_8\}$$

$$\begin{cases} d(x_1, x_2) = d(x_3, x_4) = \dots = \varepsilon_1 - \delta, \\ d(x_2, x_3) = d(x_6, x_7) = \varepsilon_2 - \delta, \\ d(x_1, x_5) = d(x_2, x_6) = \dots = \varepsilon_3 - \delta \end{cases}$$



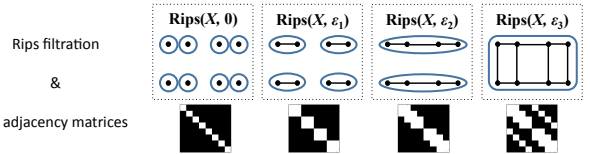
• **Rips complex, $Rips(X, \varepsilon)$**

approximate the topology of the point cloud data by connecting two point cloud data, x_i and x_j , if $d(x_i, x_j) < \varepsilon$

• **Rips filtration**

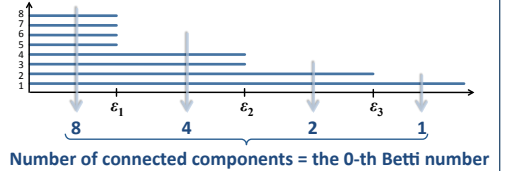
the sequence of Rips complexes satisfying the persistent property such as

$$Rips(X, 0) \subseteq Rips(X, \varepsilon_1) \subseteq Rips(X, \varepsilon_2) \subseteq \dots \subseteq Rips(X, \varepsilon_n) \text{ for } 0 \leq \varepsilon_1 \leq \varepsilon_2 \leq \dots \leq \varepsilon_n$$



• **Barcode**

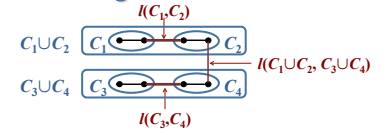
visualize the changes of the connected components during the filtration



Single Linkage Hierarchical Clustering

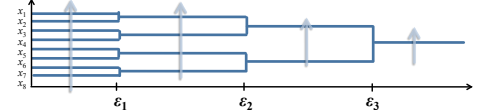
• **Single Linkage Distance**

$$l(C_i, C_j) = \min_{x_i \in C_i} \min_{x_j \in C_j} d(x_i, x_j)$$



• **Dendrogram**

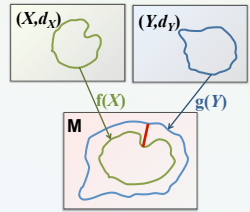
rearrange the barcode according to the index of nodes



Gromov-Hausdorff Distance

We constructed 61 dendrograms using 24 ADHD, 26 ASD and 11 PedCon jackknifed resampled datasets and estimated their pairwise differences based on Gromov-Hausdorff distance.

1. Different shapes (dendrograms of brain networks) in the different metric spaces



smaller distances within a group and larger one between groups

2. Mapping into a common space and estimating the Hausdorff distance

Gromov-Hausdorff distances between dendrograms (clustering accuracy = 100%)

References

- [1] Bassett, D. (2006), The Neuroscientist, vol. 12, pp. 512-523.
- [2] Chen, Z.J., et. al. (2008), Cerebral Cortex, vol. 18, pp. 2374-2381.
- [3] Carlsson, G. and Memoli, F. (2010), JMLR, vol. 11, pp. 1425-1470.
- [4] Lee, H., et. al. (2011), MICCAI2011.