Shape variability in the dynamics of resting-state functional network and relationship with age

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Introduction

Resting-state functional brain connectivity

fMRI data
6.7 minutes
116 volumes

Sliding-window analysis

Nodes
90 regions of interest based on the AAL

Edge weights
Correlation-based Gaussian kernel

PSS kernel matrix
Persistence scale-space (PSS) kernel

Difference between two persistence diagrams

Persistence scale-space (PSS) kernel

k₁(F, G) = \frac{1}{8\sigma^2} \sum_{p \in P \cap G} \exp\left(-\frac{||p-F||^2}{8\sigma^2}\right) - \exp\left(-\frac{||p-G||^2}{8\sigma^2}\right)

Data set

Resting-state fMRI in normal brain aging

Network
Nodes and edges
Clique complex
Nodes, edges, faces, triangle

Subject
Age
20 25 30 35 40 45 50 55 60 65 70
38 normal healthy subjects

Shape in Algebraic Topology

● Determines and discriminates the shape of topological space including object, network
  • Topological invariant = Betti number
  - 0'th Betti number = number of connected components
  - 1'th Betti number = number of holes

Methods

Persistent homology

1. Connect edges by varying threshold and fill the inside of every triangle

2. Find the homology groups at every thresholded network

Persistence diagrams

Barcodes

P₀

Connected component

Hole

P₁

Shape variability in the dynamics of resting-state functional network

We computed the sequence of functional brain networks per subject using the sliding-window analysis (the window size was 40 images and 3D images were overlapped). Then, 8-dimensional functional brain networks, N₀, ..., N₄ were constructed for each subject.

The shape information of connected components and holes in each network was encoded in the persistence diagrams P₀ and P₁, respectively.

Subjects

Age

0.05
0.1
0.17
0.34
0.65

Classification accuracy

87.95% (p < 0.0005)

References


Clustering state of network topology and classification of young (age < 45) and old (age > 45) groups

Probability map of persistence diagram, P₀ and P₁

Transition probability

Classification accuracy

78.95% (p < 0.0005)

Results and conclusions

Shape variability with respect to age

by kernel principal component analysis (PCA) of K

The functional brain network changes over time. In this study, we propose a new method to measure the change of shape of functional brain network during the resting-state. By introducing the persistence diagram and multiple PSS kernel, we can visualize the trajectory of dynamic resting-state functional brain network. By applying hidden Markov model to the trajectories, the state of network can be classified in the perspective of both connected components and holes and the trajectory of network can be classified into young or old group.

Trajectory of dynamic resting-state functional brain network

by kernel principal component analysis (PCA) of K

K = \begin{bmatrix}
α & 1 - α
\end{bmatrix}

K = 304 \times 304 matrix

α = 0.2 (find the multiple kernel that has the most correlated trajectory with age)

K₁ = 304 \times 304 matrix

β = 0.2 (find the multiple kernel that has the most correlated trajectory with age)

K₂ = \begin{bmatrix}
1 - α & α
\end{bmatrix}

K₀ and K₁ are two 8x8 kernel matrices K₀ and K₁ between N₀, ..., N₄ were calculated based on the PSS kernel. K₀ and K₁ are a kernel matrix of P0 and P1, respectively.

Because the kernels are additive, we added two kernels by K = αK₀ + (1-α)K₁ (Lin's product).

Subject

State 1

State 2

State 3

State 4

State 5

P(state) = 0.07
0.13
0.17
0.01
0.62

Transition probability

State 1

State 2

State 3

State 4

State 5

P(state) = 0.27
0.26
0.08
0.34
0.05

Classification accuracy

75.95% (p < 0.0005)