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

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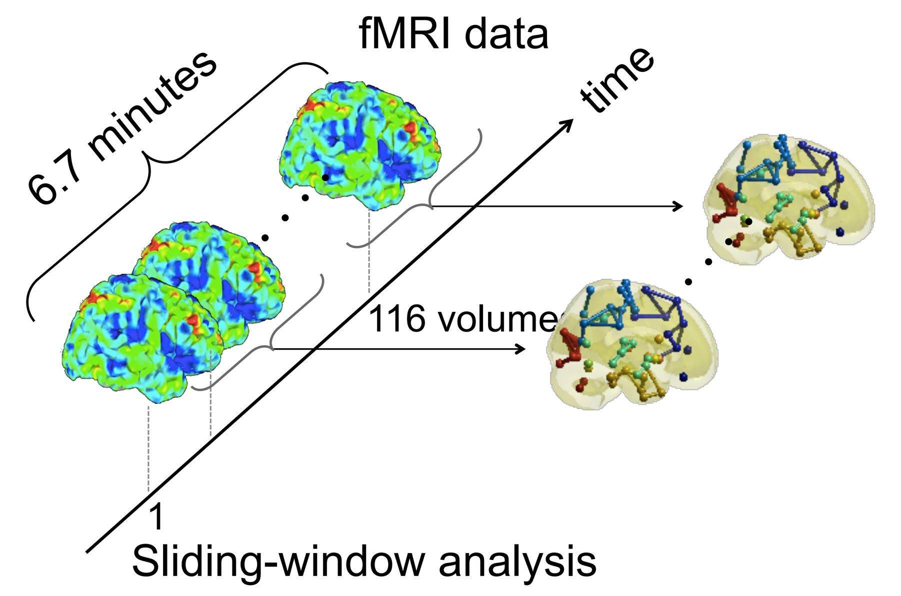
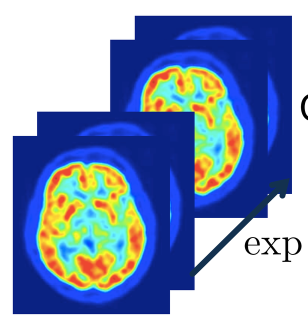
Introduction

Resting-state functional brain connectivity



Nodes

90 regions of interest based on the AAL



Edge weights

Correlation-based Gaussian kernel

$$\exp\left(-\frac{2-2\mathrm{corr}(x,y)}{2\sigma^2}\right)$$

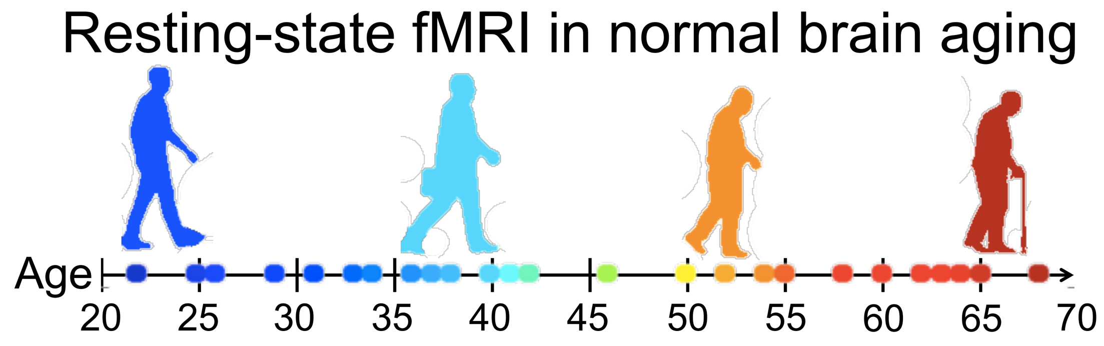
Functional network dynamics

How can we measure the change of network?

→ We measure the shape of network based on persistent homology and draw the trajectory of shape change.

Data set

Resting-state fMRI in normal brain aging



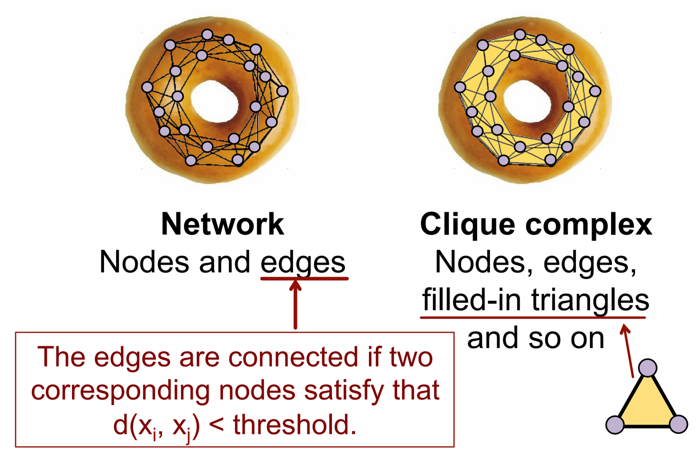
38 normal healthy subjects

Shape in Algebraic Topology

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

1 connected component
1 hole

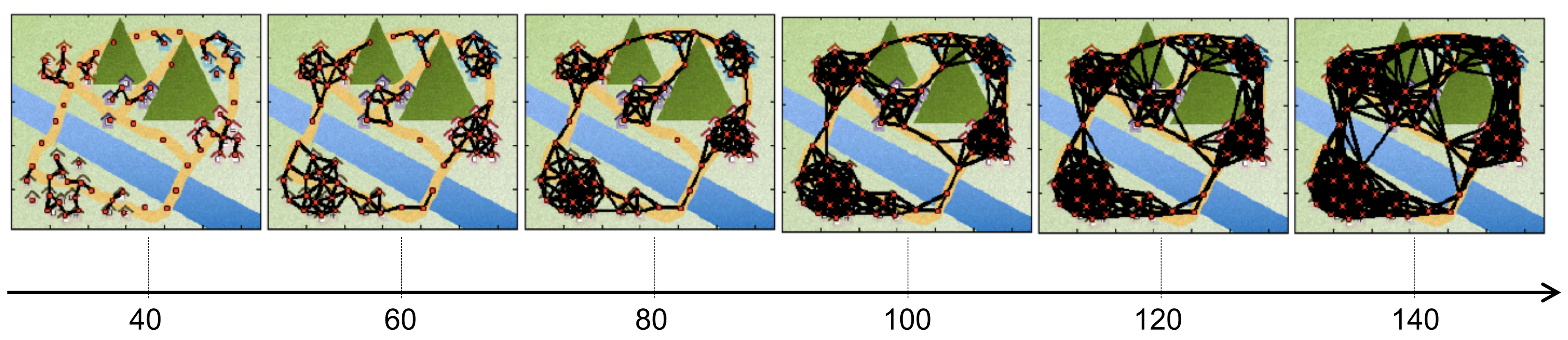
homology group



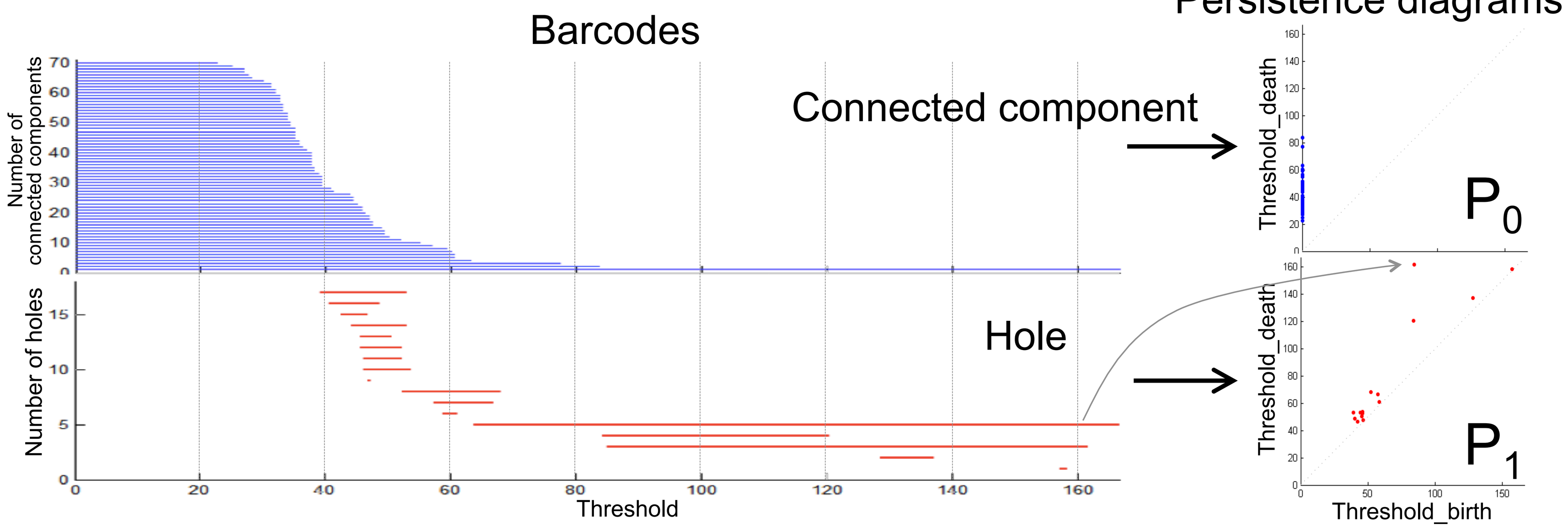
Methods

Persistent homology

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

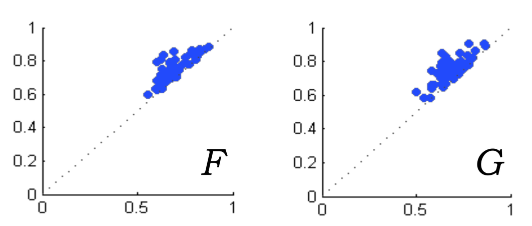


2. Find the homology groups at every thresholded network



Difference between two persistence diagrams

Persistence scale-space (PSS) kernel [1]



$$k_\sigma(F,G) = \frac{1}{8\pi\sigma}\sum_{p\in F, q\in G} \exp\left(-\frac{\| p-q \|^2}{8\sigma}\right) - \exp\left(-\frac{\| p-\bar{q} \|^2}{8\sigma}\right)$$

Shape variability in the dynamics of resting-state functional network

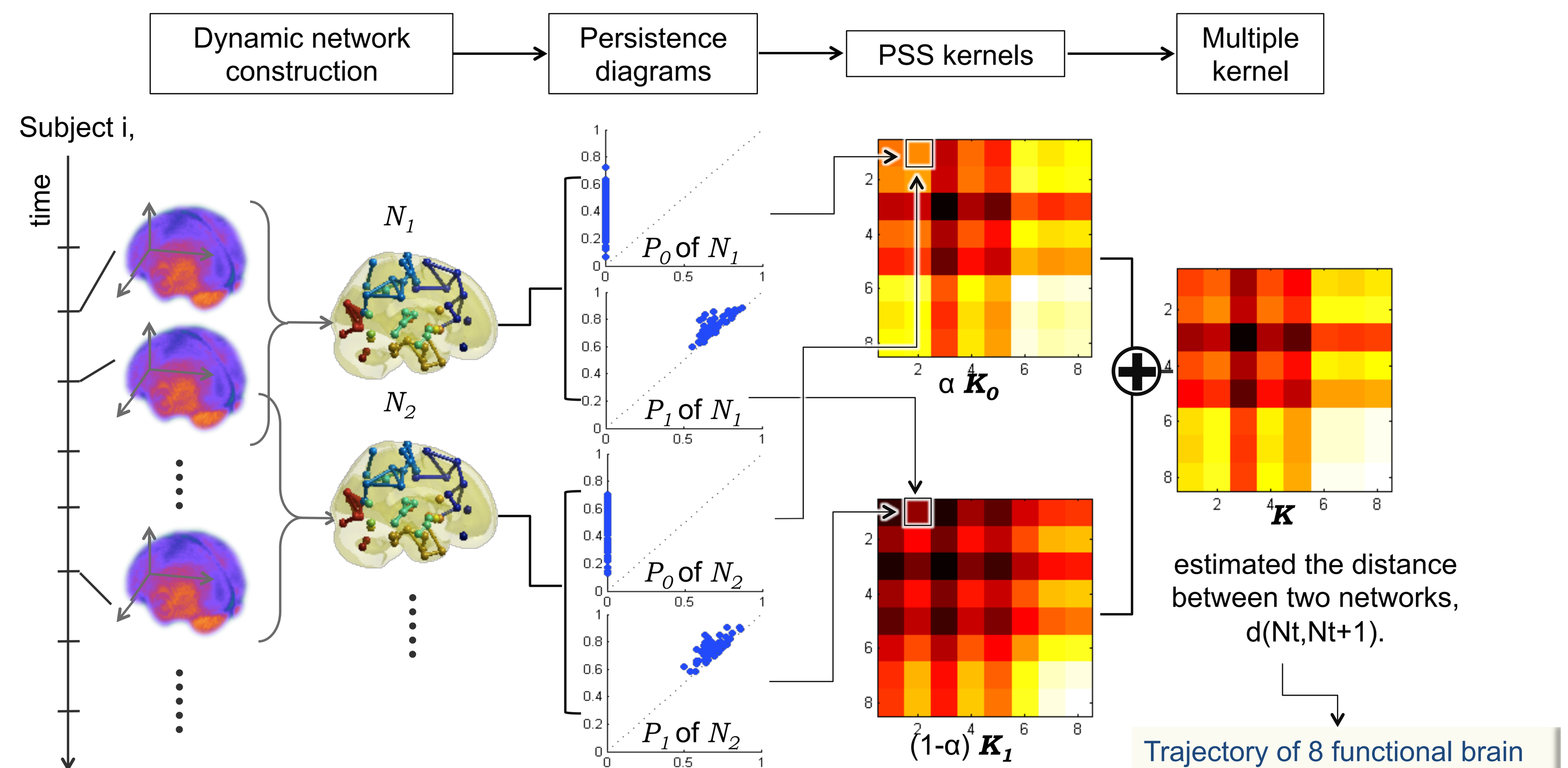
We computed the sequence of functional brain networks per subject using the sliding-window analysis (the window size was 40 images and 30 images were overlapped). Then, 8 dynamic functional brain networks, $N_1, \ldots, N_8$ were constructed for each subject.

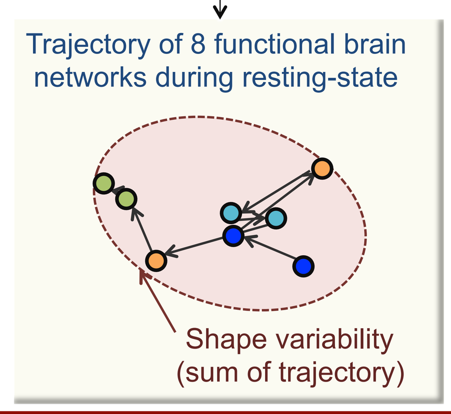
The shape information of connected components and holes in each network was encoded in the persistence diagrams P_0 and P_1, respectively.

Two 8X8 kernel matrices K0 and K1 between $N_1, \ldots, N_8$ were calculated based on the PSS kernel [1]. K0 and K1 are a kernel matrix of P0 and P1, respectively.

Because the kernels are additive, we added two kernels by

$$K = \alpha K0 + (1-\alpha)K1 \quad (0 \le \alpha \le 1).$$

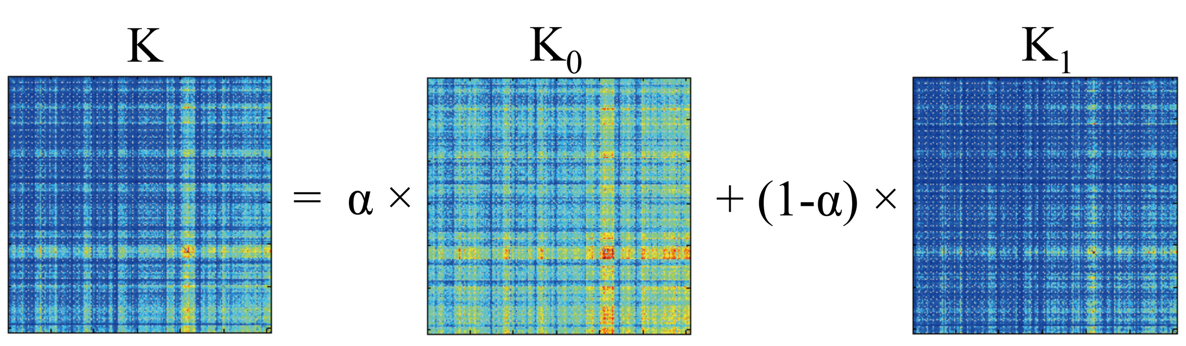




Using kernel K:
- We can visualize the trajectory of dynamic resting-state functional brain network in 3-dimensional space using kernel pricipal component analysis (PCA).
- The shape variability is defined by Σt d(Nt,Nt+1). The larger the shape variability is, the more the shape of functional network changes during the resting-state.
- By applying hidden Markov model to the trajectories, the state of network can be clustered in the perspective of both connected components and holes and the trajectory of network can be classified into young or old group.

Results and conclusions

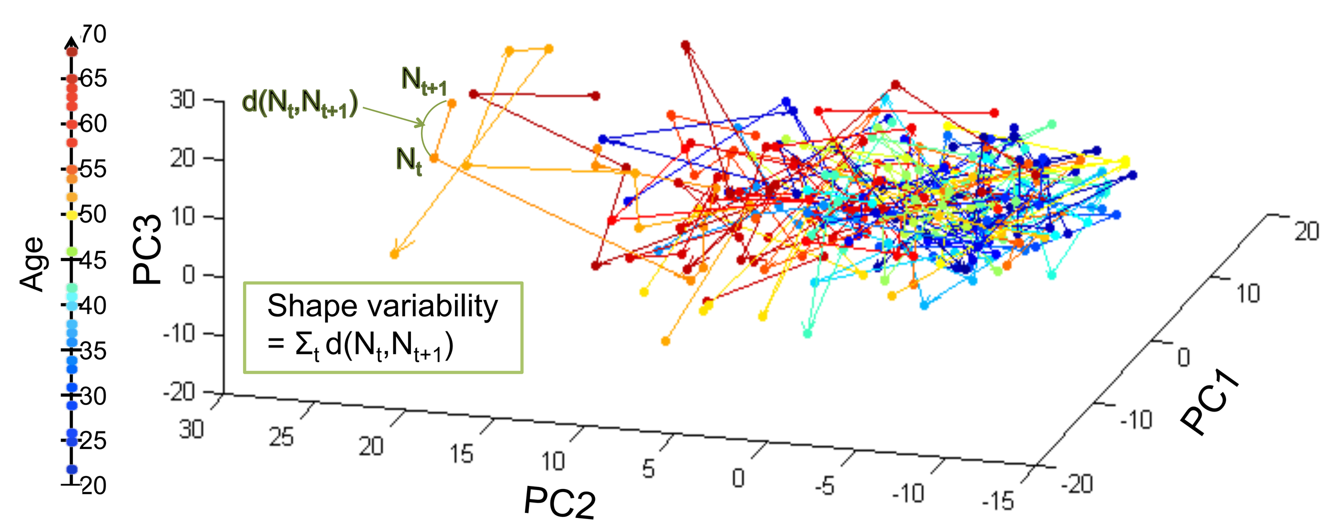
PSS kernel matrix



K = 304 × 304 matrix (8 networks/subject * 38 subjects)

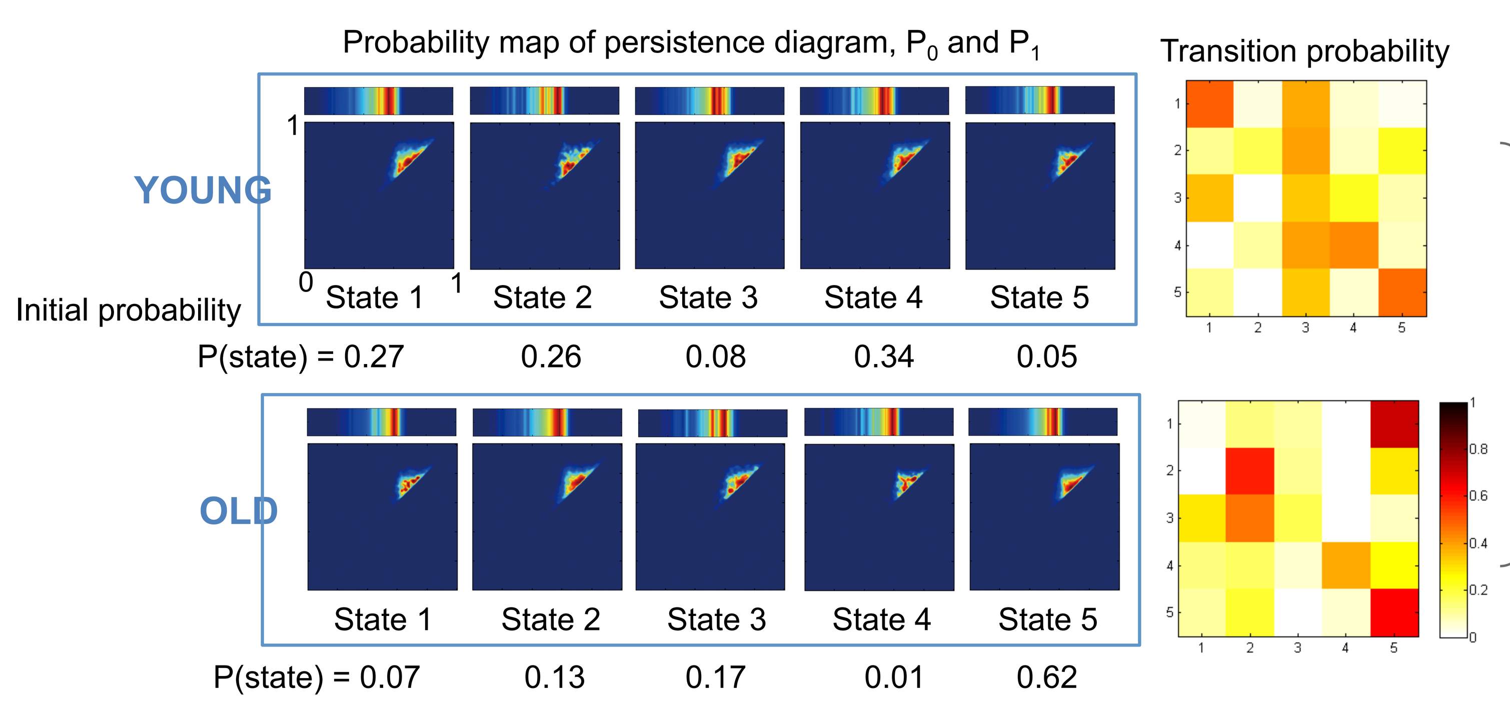
α = 0.2 (find the multiple kernel that has the most correlated trajectory with age)

Trajectory of dynamic resting-state functional brain network



by kernel principal component analysis (PCA)[2] of K

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



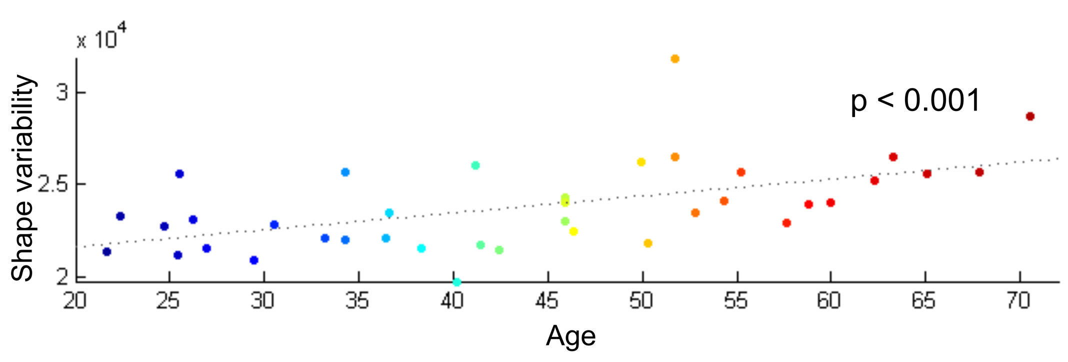
Classification accuracy = 78.95 % ($p < 0.0005$)

References

[1] R. Reininghaus, U. Bauer, S. Huber, and R. Kwitt. 'A stable multi-scale kernel for topological machine learning', In CVPR, 2015.

[2] Schölkopf B, Smola AJ, Muller K-R,. 'Kernel principal component analysis', In: Bernhard S, Christopher JCB, Alexander JS, editors. Advances in kernel methods: MIT Press. p 327-352, 1999.

Shape variability with respect to age



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 visualise the trajectory of change of shape and measure the shape variability with respect to the age. We also find that as the subject gets old, the shape of functional connectivity changes more during the resting-state. It is known that the normal aging is related to a decline in information processing of brain. In the future, we will try to find the relationship between shape variability and inefficient information processing of functional brain network.