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

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E-Poster

Introduction:

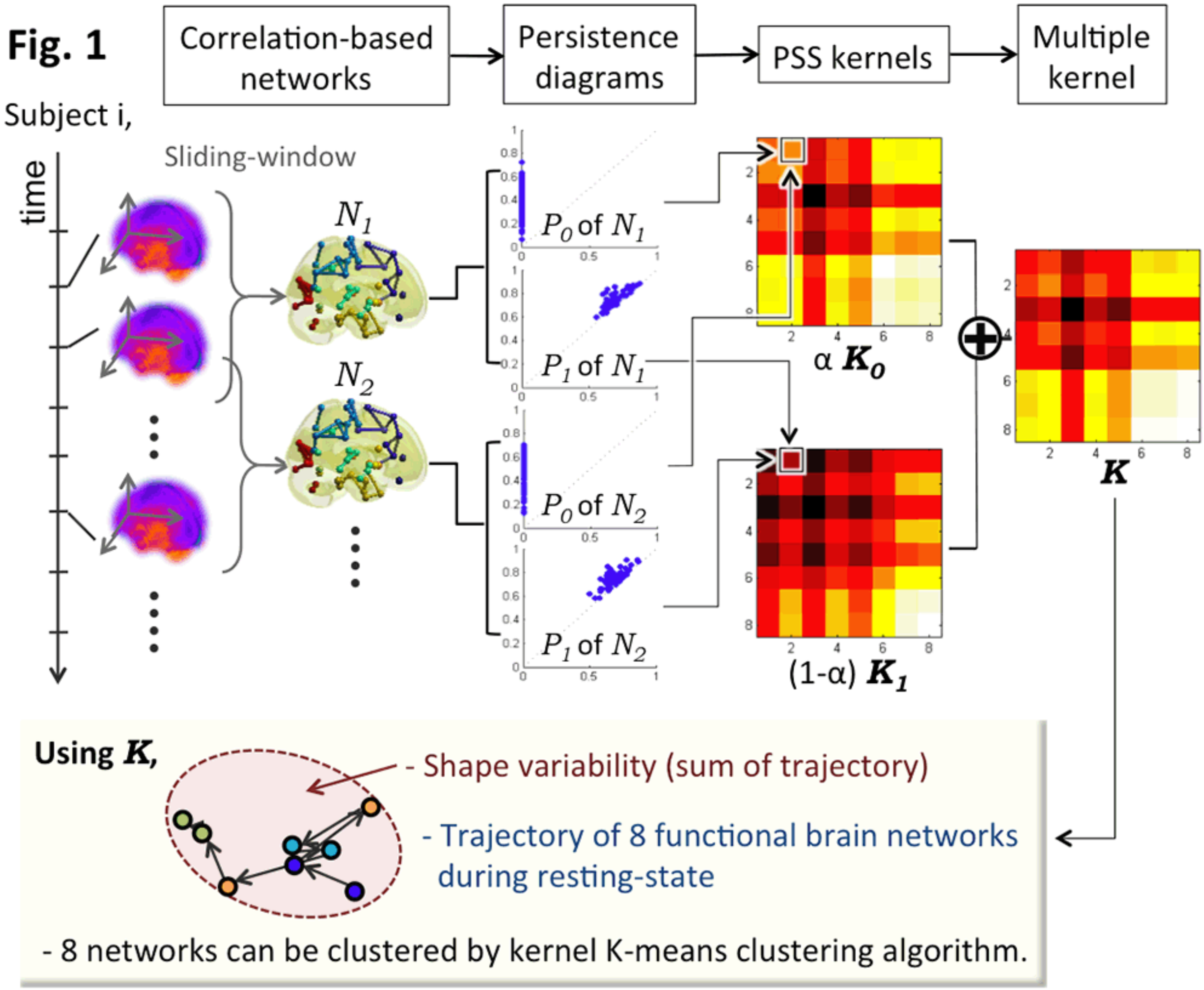
The functional brain connectivity changes over time even during rest. This change of network depends on the individual characteristics such as age and disease severity. In this study, we assume that the change of shape in the dynamics of resting-state functional connectivity is associated with age. The topological data analysis can quantify the shape of network by mapping into persistence diagrams (PDs). It also provides a tool for measuring the difference between shapes, called persistence scale space (PSS) kernel [1]. We extend the PSS kernel to multiple PSS kernel by combining two different kernels that have different shape information of connected components and holes. Using the multiple PSS kernel, we define a new measure, called shape variability, to estimate how much the network changes during the resting-state. The larger the shape variability is, the more the network changes during the resting-state. In experiments, the proposed method is applied to resting-state fMRI data of 38 healthy normal subjects from 20s to 60s. The result shows that as the subject gets old, the functional brain network changes more during the resting-state.

Methods:

Datasets:
The fMRI data set consists of 38 (M\F: 19\19, age: 43.85±13.86) healthy normal subjects. 112 volume of MR images were acquired from each subject for 6.7 minutes (Siemens Biograph mMR 3T scanner). After preprocessing by AFNI and FSL, the mean BOLD signals in 90 regions of interest (ROIs) defined by automated anatomical labeling (AAL) template were estimated.

Overall procedure of the proposed methods are shown in Fig. 1.
* Dynamic brain 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.
* Persistence diagrams: The shape information of connected components and holes in each network was encoded in the PDs P_0 and P_1, respectively.
* PSS kernels for connected components and holes: Two 8X8 kernel matrices K_0 and K_1 of $N_1, \ldots, N_8$ were calculated based on the persistence scale space (PSS) kernel [1]. K_0 and K_1 are a kernel matrix of P_0 and P_1 of 8 networks, respectively.
* Multiple kernel: Because the kernels are additive, we added two kernels by $K = \alpha K_0 + (1-\alpha) K_1$ ($0 \le \alpha \le 1$) and estimated the distance between two networks, $d(N_t, N_{t+1})$.

* Using the kernel K and the distance D:
- We can visualize the trajectory of dynamic resting-state functional brain network by transforming the networks into points in 2-dimensional space (Fig. 2(a)).
- 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 (Fig.2(b)).
- By applying kernel k-means clustering, the networks can be clustered according to their connected component and hole structures.

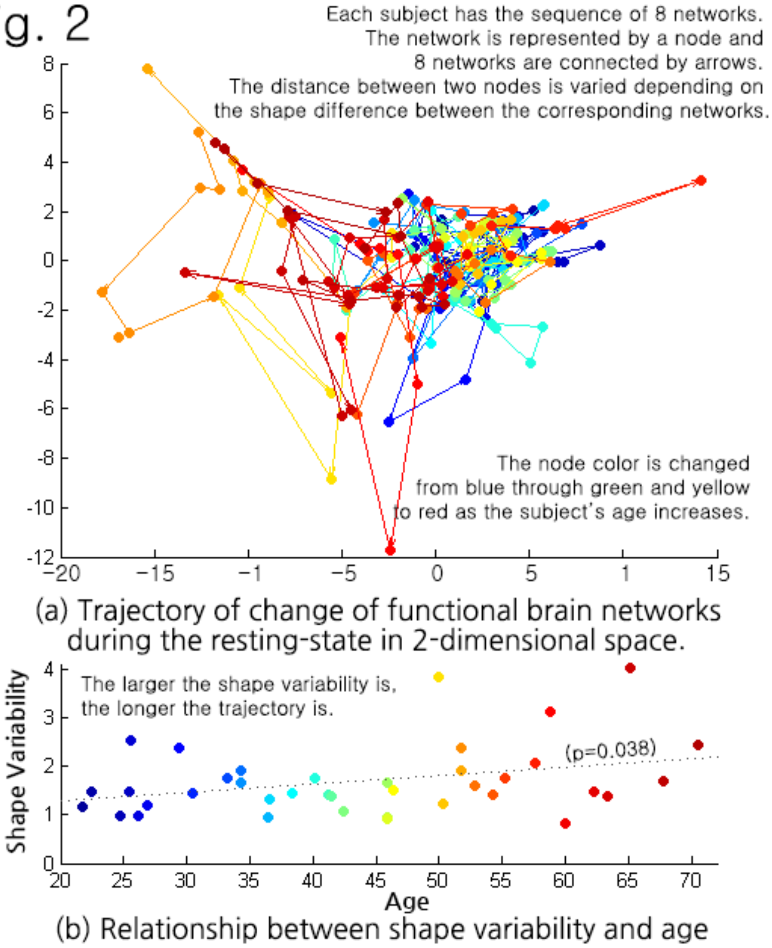


·Figure 1. Overall procedure of the proposed method

Results:

Using the multiple PSS kernel K with α=0.2, we drew the trajectory of change of brain network during rest in the 2-dimensional space (Fig.2(a)). The larger the shape variability is, the longer the trajectory is. The shape variability is proportional to age ($p = 0.038$, Fig.2(b)).

Fig. 2



·Figure 2. (a) Trajectory of dynamic functional brain networks, (b) Relationship between shape variability and age

Conclusions:

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 of networks and measure the shape variability during rest. The shape variability is related to age. It means 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.

Imaging Methods:

BOLD fMRI

Lifespan Development:

Aging [2]

Modeling and Analysis Methods:

fMRI Connectivity and Network Modeling [1]
Task-Independent and Resting-State Analysis

Poster Session:

Poster Session - Wednesday

Keywords:

Aging
Data analysis
FUNCTIONAL MRI

NORMAL HUMAN
Other - Connectivity

[1|2]Indicates the priority used for review

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Please indicate below if your study was a "resting state" or "task-activation" study.

Resting state

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Please indicate which methods were used in your research:

Functional MRI

For human MRI, what field strength scanner do you use?

3.0T

Which processing packages did you use for your study?

AFNI
FSL

Provide references in author date format

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