How to Represent Subregions in a Parcellated Brain for fMRI Analysis?

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Highlights

- We systematically compare different strategies to represent subregions in an fMRI network analysis.
- We introduce a new representation based on voting.
- We measure the performance in terms of reproducibility and functional homogeneity with a set of 100 subjects.
- Averaging time series yields more robust and functionally homogeneous parcellations compared to other strategies.

Introduction

Network analysis applied on the parcellated fMRI data is commonly used to identify the brain function and behavior. The effectiveness of an analysis is highly dependent on how reliably the parcels are represented. Several strategies have been proposed to solve this problem including but not limited to averaging, seed vertices/ROIs [1], and principal component analysis (PCA) [2]. In this study, we compare these techniques to each other and discuss their effects on the parcellation performance. We also propose a simple voting-based representation strategy and include it in our comparisons.

Data

We conducted our experiments on the rs-fMRI datasets, containing two 30-minute scans from 100 different subjects (54 female, 46 male adults, age 22-35); acquired, pre-processed and de-noised as part of the Human Connectome Project (`www.humanconnectome.org`). For each subject, gray matter voxels were mapped to the native cortical surface and registered onto the 32k standard triangulated mesh with no topological defects to establish correspondences. Each time series was temporally normalized to zero-mean and unit-variance.

Representation Strategies

- **Averaging:** The average of the time series in a subregion is used for representation.
- **Stable seeds:** Stability maps are computed based on the root mean square error between the time series of each vertex and all time series of its adjacent vertices. Seeds are identified as the local minima within each subregion and their time series are used for representation [1].
- **Stable seeds with ROIs:** Seeds to represent subregions are selected using the stable seeds approach, but this time the average time series within a ROI centered on the seed vertex is used for representation [1].
- **Voting-based:** The proposed method, in which a representative vertex is selected by cross-correlating the time series within a subregion (after applying Fisher's z-transformation). The vertex with the highest correlation sum represents the whole subregion with its time series.
- **Voting-based with ROIs:** A representative vertex is selected using the voting-based approach, but this time the average time series within a ROI centered on the voted vertex is used for representation.
- **PCA:** The first principle component of the set of time series in each subregion is used for representation [2].

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LaTeX poster template modified from *Jacobs Landscape Poster* version 1.1.

References

[1] Blumensath et al., "Spatially constrained hierarchical parcellation of the brain with resting-state fMRI," 2013.

[2] Friston et al., "A critique of functional localisers," 2006.

Processing Pipelines

For a systematic comparison, we use the same set of clusters with the same parcellation algorithm throughout the pipelines, only changing the representation strategy at each run. An overview of the pipelines is demonstrated in Fig. 1 and each step is summarized below.

1. A spatially constrained k-means is applied on the rs-fMRI data to obtain non-overlapping, highly homogeneous clusters.
2. A strategy is picked to represent the time series in each cluster.
3. Clusters are combined into a hierarchical tree using Ward's linkage rule.
4. Final parcellations are generated by prunning the tree at different levels.
5. Resulting parcellations are evaluated.
6. Steps 2-5 are repeated by changing the representation technique each time.

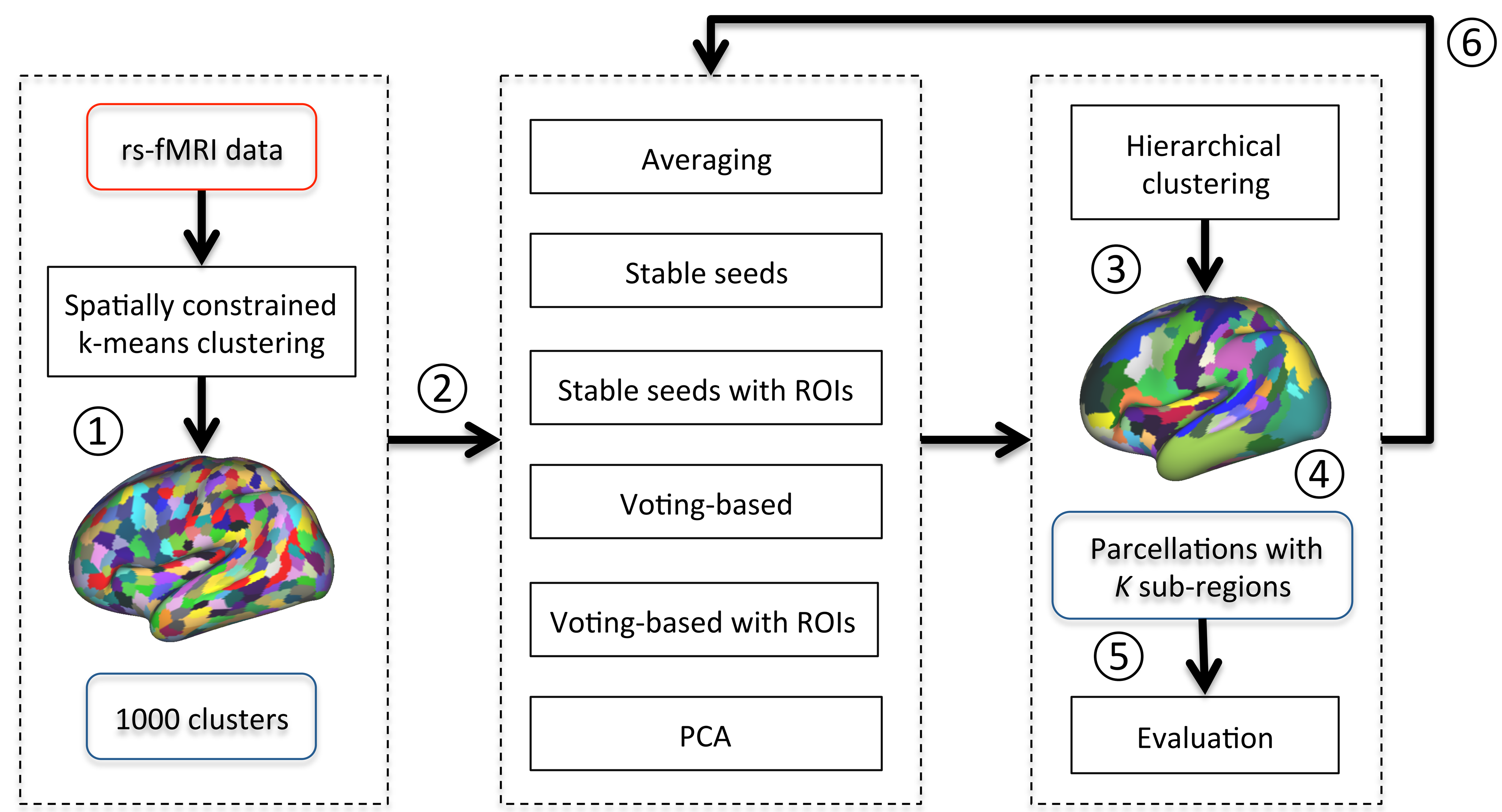

Figure 1: Visual representation of the processing pipelines.

Quantitative Results

The evaluation is performed by means of scan-to-scan reproducibility and functional homogeneity, based on a hierarchical tree of 1000 clusters, being cut at different levels in decrements of 100. Results are presented in Fig. 2 and summarized below.

- Averaging yields more reproducible and homogeneous parcellations at all resolutions.
- The proposed voting-based technique performs similar to the averaging in terms of reproducibility, but generates the least homogeneous parcellations.
- Seed-based approaches suffer from a lack of reproducibility, but are almost as effective as the averaging by means of functional homogeneity.
- ROI variants perform better than their base methods, which can be attributed to the fact that time series in ROIs are also averaged.
- For both experiments, PCA performs around on average of all methods.

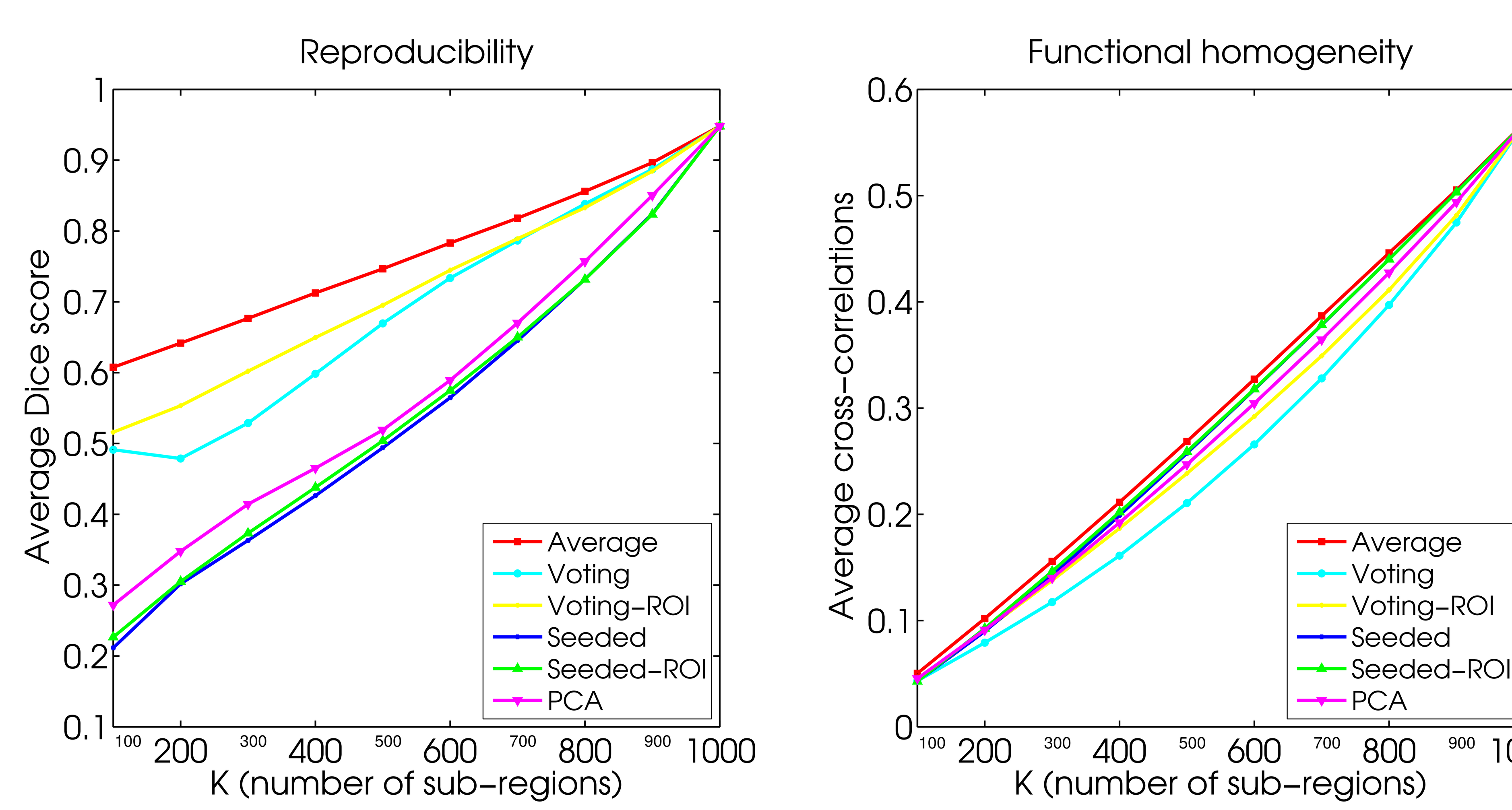

Figure 2: **Reproducibility** results obtained by computing Dice scores after matching parcellations of each subject and averaging across the whole cortex. **Functional homogeneity** results obtained by computing the average cross-correlations between rs-fMRI time series within each subregion (after applying Fisher's z-transformation) and averaging across the whole parcellation.

Discussions

Averaging would be the most effective strategy in a similar parcellation setting. Its superiority can be attributed to the clustering algorithm we used for pre-parcellation, since in a similar study based on region growing [1], the seed-based technique using ROIs has been shown to produce more reproducible parcellations compared to the averaging and PCA. Therefore, one should pick the right technique by considering the needs of the target application as well as the internal dynamics of the preprocessing and parcellation pipelines.