Resting State Network Detection with Searchlight on Functional MRI

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Introduction: Studying the resting state networks (RSNs) can serve as functional biomarkers for disease diagnosis, such as Alzheimer's disease[1] and Parkinson's disease[2], which are difficult to detect by structural imaging until irreversible brain damage. The conventional techniques to detect RSNs, such as the seed-based correlation analysis[3] and the data-driven independent component analysis[4], assume a voxel-to-voxel functional connectivity and require a spatial smoothing step to increase the signal-to-noise ratio (SNR) and alleviate the individual differences in group analysis. However, these assumptions along with spatial smoothing are still under debate in the literature.[5,6] In this work, we assume the functional connectivity is a region-to-region connection and it carries information from one brain region to another. We present a seed-based multivariate regression with searchlight[7-9] method to detect this mutual information directly. The proposed method is able to identify different resting state networks with different seed region setups even on unsmoothed or slightly smoothed resting-state functional MRI (rs-fMRI) data.

Methods: For the volume-based searchlight, we collected T1-weighted structural data and rs-fMRI data with a spatial resolution of $0.9\times0.9\times0.9\text{mm}^3$ and $2\times2\times5\text{mm}^3$, respectively. The temporal resolution for fMRI was 2s and the duration was 8 minutes. We performed standard preprocessing steps as in 1000 Functional Connectomes Project preprocessing pipeline[10] except the global signal regression. For the surface-based searchlight and the group analysis, we used 18 subjects from the Human Connectome Project (HCP) Q-3 dataset for which preprocessing was performed according to the minimal preprocessing pipelines.[11] In particular, we considered the data that had been registered onto 32k Cento69 surface mesh[12] and slightly smoothed with 2mm FWHM kernel. After setting a seed region with 4mm radius, a whole brain searchlight with 4mm radius was conducted and the voxels or vertices inside the searchlight were regressed to the signal from the seed region. The first half of the time acquisitions was used for training the regression parameters, whereas the second half was used for testing (i.e., to evaluate the performance of the linear regression and support vector regression (SVR), and thus generating the informative maps.) We assume that the brain region which interacts more with the seed region has more information from the seed region and thus will perform better when being regressed to the seed region signal. The most important difference between the surface-based and volume-based searchlight is the distance metric: Instead of the Euclidean distance, the surface-based searchlight uses the geodesic distance.[13] The searchlight method employed herein was based on the Surfing toolbox[14] with some modifications.

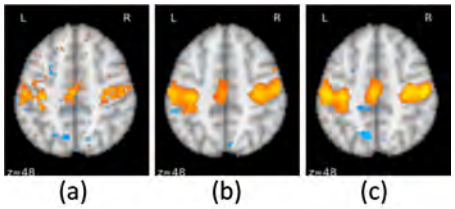

Fig. 1. Volume-based searchlight on unsmoothed data of a single subject. a) conventional univariate linear correlation; b) searchlight + linear regression; c) searchlight + SVR.

Results and Discussions: In Fig. 1, motor networks detected by the volume-based searchlight methods (Figs. 1b, 1c) are smooth even if it is conducted on unsmoothed data of a single subject. Since the proposed method was conducted on a small region and the weights of voxels inside the searchlight were optimized in the regression procedure, the searchlight could be viewed as a spatial smooth kernel with flexible weights. This property enables searchlight to serve as an alternative to spatial smoothing without scarifying image details for SNR. Furthermore, as shown in Fig. 2, the fuzzy boundary given by the correlation analysis (Fig. 2a) was due to low SNR and high individual differences, while the surface-based searchlight was able to derive smooth RSNs (Figs. 2b, 2c). Some RSNs detected by searchlight also cover more brain regions. For example, the visual network (Fig. 2III) derived by the surface-based searchlight includes the intraparietal sulcus (IPS), a node of the dorsal attention network, while correlation analysis does not. This co-activation of visual and attention network has also been reported in the literature.[15,16]

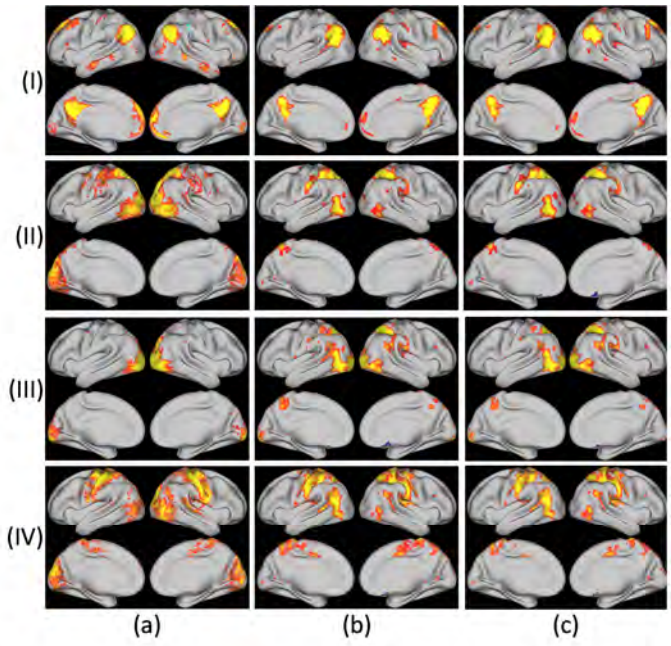

Fig. 2. Surface-based searchlight for a group study. a) conventional univariate linear correlation; b) searchlight + linear regression; c) searchlight + SVR for I) default mode network; II) attention network; III) visual network; IV) motor network.

Conclusion: We developed a seed-based multivariate regression with searchlight method to detect the mutual information between a seed region and other brain areas. This method can be used to derive different resting state networks with different seed region setups. Furthermore, it can be applied to both volumetric and surface-based data and serve as an alternative to spatial smoothing to compensate the low SNR of fMRI data and the individual differences in group analysis.

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