

An objective autoselection of resting-state networks based on time course correlation

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Introduction

Independent component analysis (ICA) has recently been employed in the detection of several different networks in resting-state (RSNs) which are consistent and highly reproducible across healthy subjects [1-3]. However, the identification of RSNs often involves visual inspection of the spatial maps and power spectra [4] and/or correlating spatial maps derived from ICA with templates or seed-based results [5]. Here, we employed a more objective and template-free approach to select and classify RSNs to avoid the visual inspection bias.

Methods

40 young healthy right-handed adults were recruited in the study (age: mean=26.2, SD=6.3; 16 males). Scanning was performed with a 32-channel head coil on a 3T MRI scanner. All participants were asked to lie still with eyes closed, not to fall asleep, and think of nothing during 6-minute scanning. A GRE-EPI sequence was used to acquire resting-state fMRI data (TR=2000ms, TE=24ms, FA=90, Thickness=3mm, FOV=256mm, matrix size=64x64, Slices=34). For registration purpose, high-resolution T1 weighted images were acquired with a MPRAGE sequence (TR=2000ms; TE=2.98ms; 1x1x1mm, FOV=256mm). The images were preprocessed using SPM8. The first three functional volumes of each time series were discarded. The preprocessing steps were applied as follow: slice-timing correction, motion correction, coregistration and normalization to the MNI template, removal of nonbrain structures from the EPI volumes, high-pass temporal filtering using 6-order Butterworth for removing drift (<0.008 Hz), spatial smoothing using a Gaussian kernel of 8 mm FWHM, and mean-based intensity normalization. The Group spatial ICA was applied to decompose the datasets into 70 maximally independent spatial maps and their corresponding time courses (TCs) using infomax approach repeated for 20 times via GIFTv1.3i. The results of GICA were sorted according to the low frequency to high frequency power ratio (P_{LF}/P_{HF}) in the descending order (max=89.88; min=0.99) [4]. The Pearson's correlation coefficient and partial correlation coefficient between pairs of sorted TCs were then calculated.

Results

The RSNs (large P_{LF}/P_{HF} and DR) and noisy components (small P_{LF}/P_{HF} and DR) can be easily determined because they were significantly negatively correlated ($p<0.0005$) [Figure 1]. Based on the partial correlation results [Figure 2], the strong component pairs obtained by partial correlation ($p<0.0005$) were found to belong to the same networks such as visual network (IC8&IC13&IC16, IC2&IC4, IC13&IC28) and sensorimotor network (IC1&IC10, IC3&IC35) [Figure 3].

Conclusions

Without subjective selection and templates, RSNs can be distinguished from nuisance signals such as CSF and physiological noise based on the P_{LF}/P_{HF} , DR and Pearson's correlation coefficient. Based on the partial correlation coefficient, resting-state components can be classified and the relationship between RSNs can also be defined. The strong component pairs obtained by the partial correlation can be clustered in the same network. Our proposed method adds value to the data-driven approach in defining RSNs, and is potentially useful in the connectome research.

References

- [1] J. S. Damoiseaux et al., Proc Natl Acad Sci U S A 103, 13848 (Sep 12, 2006)
- [2] S.M. Smith et al., Proc Natl Acad Sci USA (PNAS), 106(31):13040-13045 (Aug 4, 2009)
- [3] Van Dijk et al., J Neurophysiol 103: 297-321, 2010
- [4] E. A. Allen et al., Front Syst Neurosci. 2011; 5: 2 (Feb 4, 2011)
- [5] M. D. Greicius et al., Proc Natl Acad Sci U S A 101, 4637 (Mar 30, 2004)

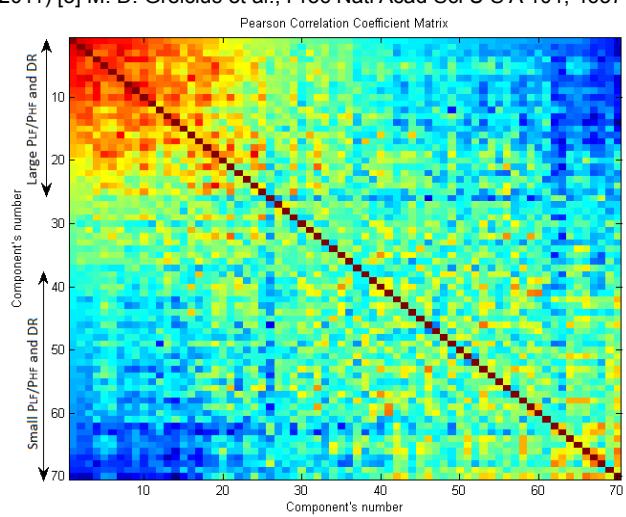


Figure 1. Color-coded Pearson's correlation coefficient matrix. X and y labels are components' number, which were sorted by P_{LF}/P_{HF} and DR.

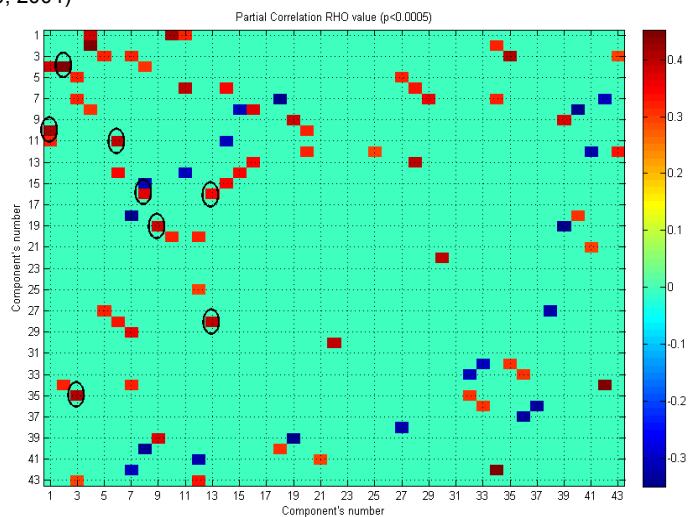


Figure 2. Color-coded partial correlation coefficient matrix. Those correlation coefficients are set to zero if p value ≥ 0.0005 . X and y labels are components' number, which were sorted according to P_{LF}/P_{HF} in the descending order.

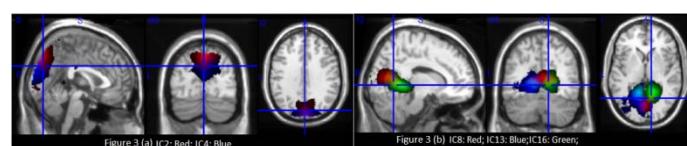


Figure 3. (a) IC2 (red) & IC4 (blue);
(b) IC8 (red) & IC13 (blue) & IC16 (green)