Automatic Resting State Network Decomposition using ICA and Classification in a Clinical Population

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Target Audience

This work is intended for neuroimaging researchers and clinicians who study functional connectivity of healthy and patient populations. Particularly, this will be of interest to researchers who use multivariate pattern analysis (MVPA) on resting state functional MRI data.

Purpose

Resting state functional MRI (rs-fMRI) is a powerful technique for studying whole brain neural connectivity, and allows examination of the dynamics of activity within large scale networks potentially affected by pathologies. Our goal is to decompose a subject's functional time series signal into independent components that are anatomically and functionally representative of known resting state networks (RSNs) and then accurately classify each component as belonging to one out of seven RSNs as defined by a template previously compiled by Allen et al. [1] The overall goal is to create a clinically oriented, automated component classification method using rs-fMRI that could complement or substitute task fMRI for patient diagnostic and pre-surgical procedures.

Methods

rs-fMRI scans from 23 patients (17 epilepsy, 6 vascular/tumor, 10 male, mean age = 39 years) were acquired on GE MR750 3T and GE MR450 1.5T scanners with a gradient echo EPI sequence (28 slices, 150 volumes, 2s TR, 30ms TE, 3.75×3.75×5 mm). Data were preprocessed, consistent with Allen et al.'s study, using AFNI [2] and FSL [3] which included slice-timing correction, motion correction, transformation into standard MNI space (3×3×3 mm), and spatial smoothing (Gaussian 10 mm FWHM). The patients had no gross structural abnormalities and the resultant registration was satisfactory. Data were decomposed into functional networks using individual, spatial independent component analysis (ICA), a MVPA technique, implemented in the GIFT toolbox [4] (Figure 1). Components for the visual, sensorimotor, default-mode, and auditory networks were visually identified. Each resultant component was spatially correlated with 28 ICs of the template (Figure 2) and a ranking by correlation was used for the classification step (using MATLAB). The most correlated component was chosen to represent the subject's component, and its network membership was inherited. The metric used for measuring classification performance was a matching rate to the researcher's network identification.

Results

The analysis of the patient data set revealed clear and adequate functional components. For the components which the researcher identified as the visual network, the classifier achieved 88.7% agreement (of 62 visually-identified network components, the classifier matched 55, p-value $< 1 \times 10^{-16}$ [binomial test]). For the sensorimotor network, the classifier was in 57.9% agreement (38 visually-identified components, 22 classifier matched, p-value $< 1 \times 10^{-6}$). For the default-mode network, the classifier was in 48.9% agreement (139 visually-identified components, 68 classifier matched, p-value $< 1 \times 10^{-16}$). For the auditory network, the classifier was in 65.2% agreement (46 visually-identified components, 30 classifier matched, p-value $< 1 \times 10^{-16}$).

Discussion

Allen et al. showed that an ICA method is able to produce robust and reliable normal brain RSNs that are in great agreement with networks identified by previous studies. With clinical motivation in mind, we extended the analysis to a patient population and developed an automated network classification method. The results show a promising classification rate that is significantly better than random guessing (roughly 1 out of 7, ~15%).

Conclusion

The automated classifier showed promising performance for the visual, sensorimotor, default-mode and auditory networks of clinical patients. Further development and validation will be done to make this method available as a clinical software tool for automated functional network component extraction and classification.

References

1. Allen, E.A., et al. A baseline for the multivariate comparison of resting-state networks. Front. Syst. Neurosci. 2011; Vol 5:2
2. http://afni.nimh.nih.gov/afni . Accessed November, 2013
3. http://fsl.fmrib.ox.ac.uk/fsl/fslwiki/FSL . Accessed November, 2013
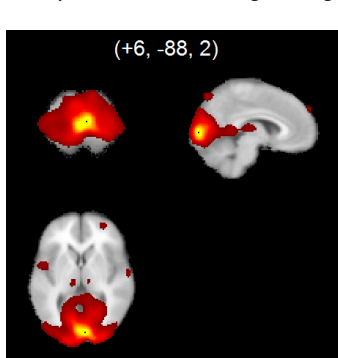4. http://icatb.sourceforge.net/groupica.htm . Accessed November, 2013

Figure 1. A spatial map (plotted as a t-statistic) of an example component identified as a visual network by both the researcher and classifier.
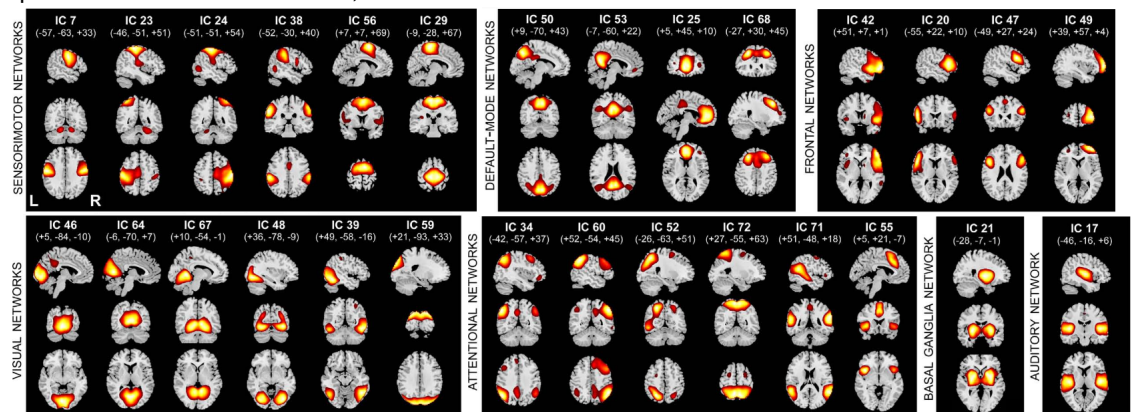

Figure 2. The 28 components organized into 7 RSNs (spatial maps plotted as t-statistics) from Allen et al. used as the template.