Automated procedure for identifying stable brain states with independent components analysis (ICA)

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Introduction

Independent components analysis (ICA) can be applied to fMRI data in order to identify spatial distributions of voxels that share a common time-varying pattern of activity. Many components are generated. Some of them bear resemblance to activation patterns arising from model-driven analyses, while others reflect physiological sources, subject motion, or acquisition artifacts. Thus, one is left with the problem of identifying reliable/stable components using a heuristic that is no better than, "Gee, that component looks like it makes sense."

Here I illustrate a method for automated identification of recurring spatial activation patterns within individual subjects, across multiple functional runs within a scanning session and across multiple scanning sessions.

fMRI Data

BOLD data were collected on a 1.5T GE Signa scanner in 14 subjects who participated in 2-4 scanning session each, typically separated by one week. In each of four functional runs during a session, 194 whole-head image volumes (27 slices) were acquired (TR=3 s) while subjects performed musical target detection tasks (1). Resting state data were collected for 1 minute at the beginning and end of each functional run. Respiratory data were collected with chest bellows, and cardiac data with a pulse oxymeter attached to a finger.

Preprocessing

All analyses were performed in Matlab, with calls to FSL utilities as needed.

Motion correction of EPI runs was performed with FSL's flirt. The mean EPI image was calculated. Using FSL's film_gls, the variance associated with movement parameters and physiological (respiration, heart rate) parameters was modeled on a slice-by-slice basis and removed (**Figure 1)**. The residuals were repacked into a 4D volume, to which the previously calculated mean was added.

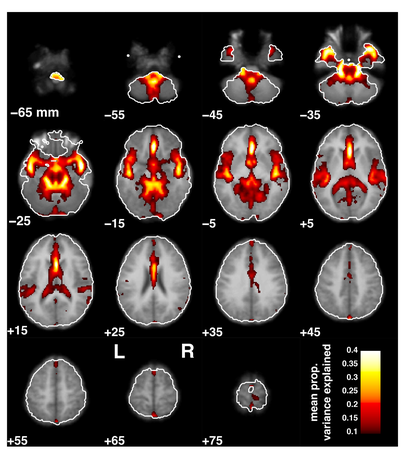


Figure 1. Spatial maps of the proportion of variance explained by cardiac and respiration regressors. N=14.

Independent Components (IC) Estimation

FSL's MELODIC program (2) was used for the independent components analysis (ICA).

Within-session analyses

For each functional run (194 volumes), the residuals from the preprocessing step were analyzed using default options in Melodic, including automatic dimension estimation. The number of estimated dimensions is shown in **Figure 2**.

Between-session analyses

A single collection of ICs was estimated for each scanning session consisting of 4 runs. The residuals for each run in a session were first transformed to z-scores. The z-score images were rotated into the space of the first run and concatenated. The composite file was given a positive offset so that brain voxels could be readily identified, and then passed to Melodic for IC estimation.

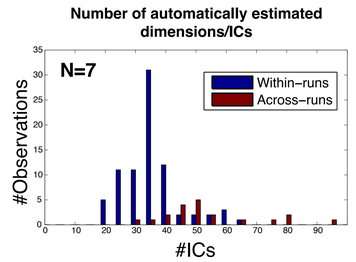


Figure 2. Distributions of the number of estimated ICs for individual runs (blue) and concatenated runs in sessions (brown).

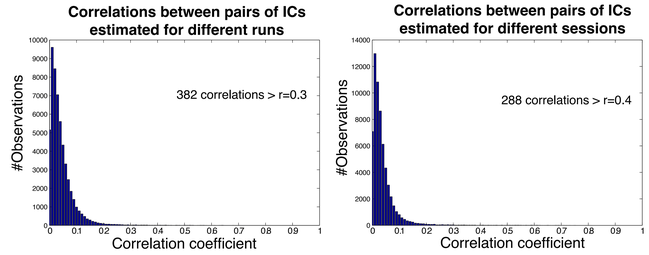


Figure 3. Distributions of IC correlations calculated between runs (top) and between sessions (bottom). Data pooled for 7 subjects. A relatively small number of correlations exceed the (arbitrary) cutoff criteria of 0.3 and 0.4.

Identification of Stable Components

Stable components were defined as those that showed up in every run for "within-session" analyses and every session for "between-session" analyses. This process was automated in several steps. First, the estimated ICs from each run/session were rotated into a common space. Next, each IC from each run/session was correlated with every IC in every other run/session using FSL's avwcc utility and a correlation coefficient criterion (**Figure 3**). Corresponding ICs were matched up by following the "correlation chains" through the between-run/session correlation matrices (**Figure 4).** Whenever chains of correlations could be followed through to the originating IC, the set of participating ICs was declared a "stable set." Individual ICs in stable sets were thresholded with the standard mixture model threshold of 0.5, and averaged together to produce the spatial map corresponding to the stable set (**Figure 5**). The number of stable sets was approximately 10-20% of the original number of estimated ICs (**Figure 6**).

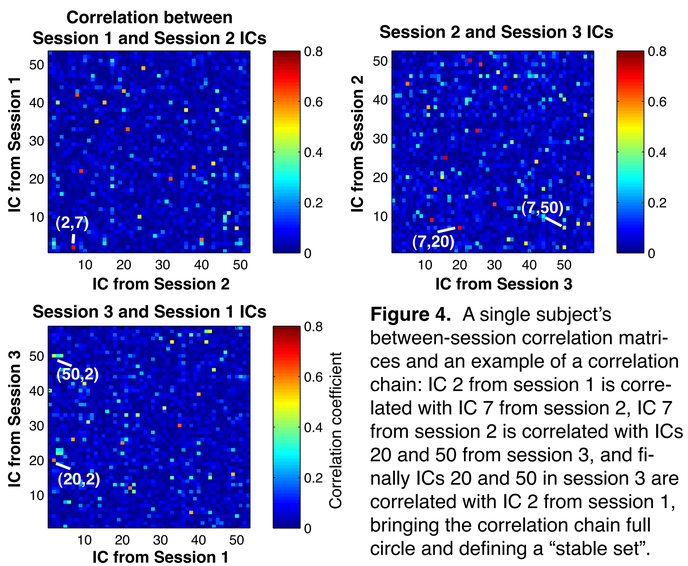


Figure 4. A single subject's between-session correlation matrices and an example of a correlation chain: IC 2 from session 1 is correlated with IC 7 from session 2, IC 7 from session 2 is correlated with ICs 20 and 50 from session 3, and finally ICs 20 and 50 in session 3 are correlated with IC 2 from session 1, bringing the correlation chain full circle and defining a "stable set".

Figure 5. Stable sets of ICs for a single subject. Both within and between session analyses identified similar sets, though the between session method yielded a larger number. With the exception of Set 1 in both analyses (which may reflect residual physiological or movement variability), the "activated" areas reflected activation patterns observed in the model-driven analyses of the data (1).

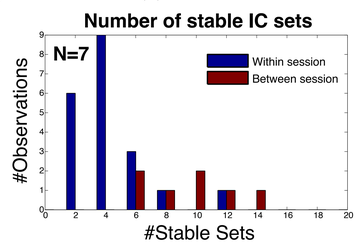
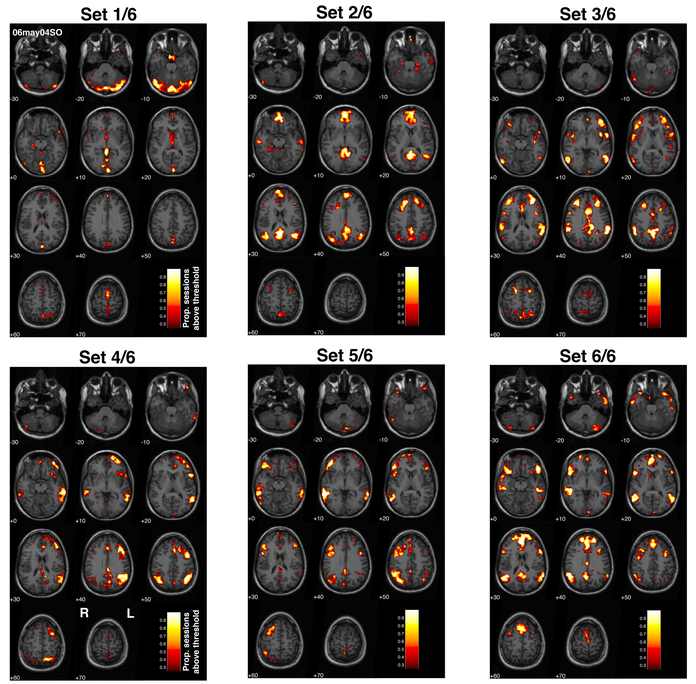
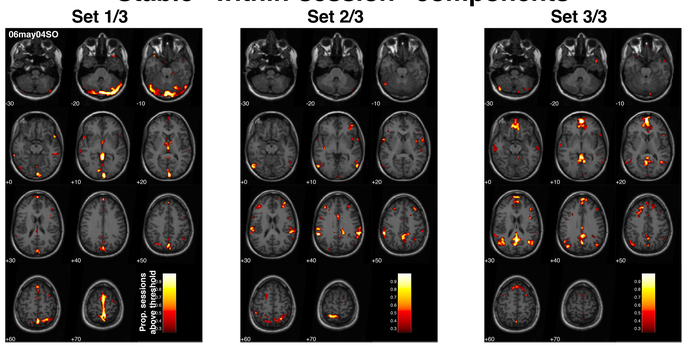


Figure 6. Between session analyses resulted in a larger number of stable sets, due perhaps to the greater number of time points entering into each analysis, or due to the subtle task differences between runs which would be lost in the within session analyses given the criteria for defining a stable set.

Stable "between-session" components



Stable "within-session" components



Conclusions

Repeatedly occuring ICs can be identified in an automated manner by calculating the correlations among sets of estimated ICs and then extracting those sets that share correlations exceeding a desired threshold.

References

1. Janata, P., Birk, J. L., Van Horn, J. D., Leman, M., Tillmann, B., & Bharucha, J. J. (2002). The cortical topography of tonal structures underlying Western music. Science, 298(5601), 2167-2170.
2. Beckmann, C.F. & Smith, S.M. (2004). Probabilistic independent component analysis for functional magnetic resonance imaging. IEEE Trans. on Medical Imaging, 23(2):137-152.