Independent Component Analysis of fMRI Data - Assessing Reliability

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Objective

Analysis of an fMRI block-based visual stimulation paradigm was comparatively performed by selected algorithms implementing spatial independent component analysis (sICA). In contrast to inferential approaches, exploratory analysis like ICA reveals task-related, transiently task-related, and function-related activity without reference to any experimental protocol, including unanticipated activations. The study covered the stochastic neuromorphic (Infomax [1]) and batch-type (FastICA [2]), as well as the deterministic (JADE [3] and SIMBEC [4]) algorithms. Validation of the results was carried on both synthetic data and by resampling-based techniques [5]. In each case, *whitening*, *Fourier*, and *wavelet transforms* were employed. Surrogate fMRI-like time series were generated and by evaluating the test statistic for each one, the probability of observing a test statistic higher than a certain threshold was estimated.

Methods

ICA is a data-driven multivariate exploratory analysis based on the covariance paradigm and formulated as a generative linear latent variables model. Noise in fMRI data is spatially correlated, but noise and data are assumed uncorrelated. Non-square ICA model alleviates data overfitting and allows statistical assessment of the estimated independent components (ICs) but inevitably deviates from the best linear fit. Though sICA model enforces a stringent statistical-independence requirement on the estimated spatial maps, their associated time courses (TCs) of activation result separable but not necessarily independent. Data model selection was performed in compliance with a structural measure introduced in projection pursuit [6]. Synthetic and real fMRI data were used to quantitatively analyze and rank the algorithms based on their power of minimizing the mutual information between the estimated ICs [7].

Results

12 healthy subjects were selected for single-shot gradient-echo MR EPI scanning at *1.5* T magnetic field during *12* identical sessions. Acquisition and reconstruction matrices were $64 \times 64 \times 35$ with voxel size $3.8\text{mm} \times 3.8\text{mm} \times 3.75\text{mm}$. Sessions consisted of *72* volumes acquired at $TR = 3$ s. All data were subject to some data preprocessing: (*i*) acquisition time correction, (*ii*) realignment (movement correction and unwarping), (*iii*) coregistration, and (*iv*) spatial normalization. The separated components were sorted and the algorithms ranked by temporal regression of their activations with the model TC in the primary visual cortex (WFU PickAtlas) generated by Waver. All algorithms, after identically thresholding the estimated maps, identified a set of cortical bilateral visually responsive regions; one single IC showed activity in bilateral cerebellum (Fig.1) and a highly time-correlated TC ($r > 0.92$) with the experimental paradigm. The first most energetic 6 ICs were used to artificially generate back *6* independent clusters, each consisting of *12* components obtained by resampling and used to assess the reliability of ICA projections (Fig. 2).

Conclusion

All ICA algorithms comparably performed brain source separation and found task-related components in both left and right hemifields. JADE slightly outperformed all others in terms of convergence and discrimination power, followed by SIMBEC. Infomax and FastICA with *tanh* nelinearity performed quite similarly, with FastCA being faster. SIMBEC best detected the number of spatially independent clusters [8], whereas the stabilized version of FastICA efficiently avoided trapping in local minima.

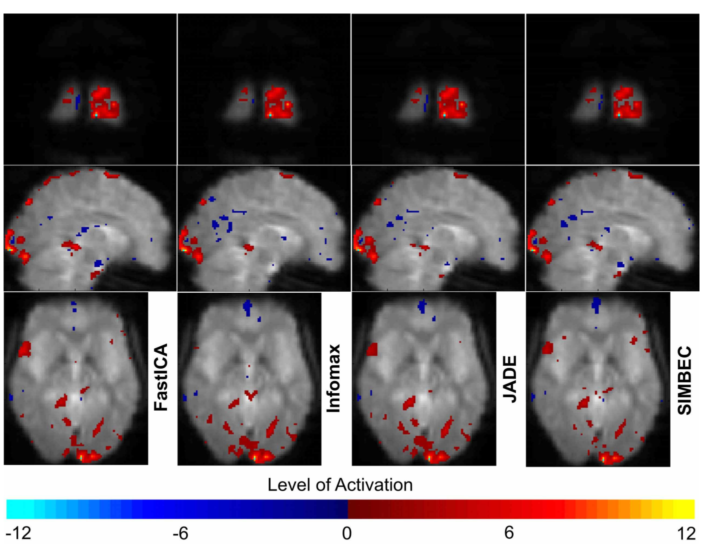

Fig. 1 – Maps of the best time correlated independent components.

References

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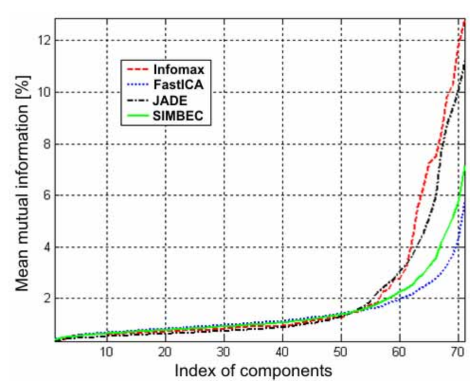

Fig. 2 – Separation power determined on synthetic data.