Semi-Blind ICA Of fMRI: A Method For Utilizing Hypothesis-Derived Time Courses In A Spatial ICA Analysis

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Introduction

Independent component analysis (ICA), a blind, data-driven approach utilizing high-order statistical moments to find maximally independent sources, has found fruitful application in functional magnetic resonance imaging (fMRI). In some cases, it would be useful to incorporate paradigm information into the ICA analysis. In this paper, we present an approach for constrained or semi-blind ICA (sbICA) analysis of fMRI data. We demonstrate the performance of our approach using simulations and fMRI data of an auditory oddball paradigm. Results suggest that 1) a regression approach slightly outperforms ICA when prior information is accurate and ICA outperforms the general linear modeling (GLM) approach when prior information is not completely accurate, 2) prior information improves the robustness of ICA in the presence of noise, 3) ICA analysis using prior information with weak constraints can outperform a regression approach when the prior information is not completely accurate.

ICA has been shown to be useful for characterizing data sets for which a specific *a priori* model is not available [1], however, a limitation of the existing ICA models that have been applied to fMRI data is the lack of ability to incorporate information about the fMRI paradigm into the algorithm. Because ICA is a blind source separation technique, no information is assumed about the time courses. Paradigm information is typically applied after the ICA algorithm in selecting the components of interest through sorting the component time courses according to some spatial or temporal criteria [2]. In our case, we are interested in performing spatial ICA, but applying constraints to the time courses (*i.e.* the mixing matrix). The ability to incorporate prior information directly into the algorithm has several potential advantages. First, the performance of the algorithm may improve by providing information about the mixing properties of a known signal. Secondly, components that are constrained to have a particular time course can be directly compared in an analysis of multiple data sets (*e.g.* a group analysis) [3].

In this paper, we demonstrate a simple, but effective approach for incorporating information about the fMRI paradigm into an ICA algorithm based upon the infomax principle [4]. We propose a component selective constraint of the ICA model mixing matrix such that one or more specific components are constrained to be "close" to a paradigm-derived time course. The degree of closeness is specified by the user based upon amount of confidence placed in the information provided. Using simulations, we compare our sbICA approach to standard ICA and also to a linear regression-based analysis. Finally, we demonstrate the performance on two runs of fMRI data collected on twenty participants performing an event-related auditory oddball experiment.

Theory

The ICA models fMRI data, X, as independent sources, S, mixed linearly as X=AS. Our approach involved constraining the columns of the A matrix such that they are "close" to pre-specified time courses at each update of the weight algorithm. We utilize correlation as the distance metric (although other metrics, such as Kullback-Leibler divergence, could be used instead). The tolerance for each constraint is specified vector $\mathbf{t}$ containing a tolerance value for each column of the mixing matrix and a design matrix $\mathbf{D}_i$ for each column $\mathbf{A}$ (*i.e.*, each component) containing regressors and nuisance criteria. The $\mathbf{D}_i$ matrix thus contains the prior information about the fMRI time courses for each component i. At each iteration of the algorithm, alternating with the infomax update steps, we 1) compute a multiple regression upon the estimated columns of $\mathbf{A}$ (the fMRI time courses) to produce the parameter estimates and 2) apply the distance criteria to update the weights according to the constraint. The above approach can be formalized using the Lagrange framework.

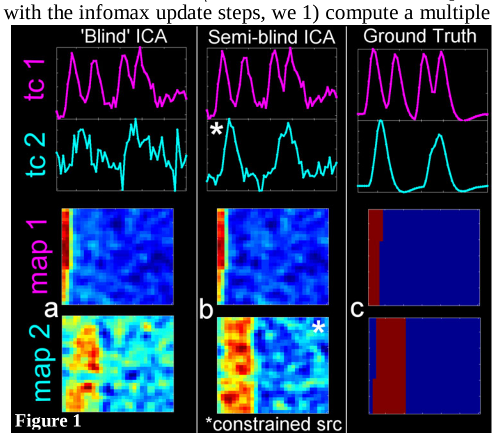

Figure 1

Methods

We first tested whether the sbICA constraint would negatively impact the unconstrained components. Figure 1 shows (a) blind ICA, (b) semi-blind ICA, and (c) ground truth time courses and images for two sources. The data set consisted of a 30×30 image with 60 time points and 40 simulated sources. The data were first reduced to 40 dimensions using PCA, then processed using our sbICA algorithm using the same parameters as for the fMRI data analysis. One of the sources (colored in magenta) was constrained for the sbICA analysis and another one, overlapping with the constrained source (colored in cyan) and correlated temporally with a value of 0.46, was not constrained. Twenty healthy participants each provided written, informed, IRB approved consent at Hartford Hospital. An auditory oddball paradigm was presented to the subjects as described in Kiehl, *et al.* (2001) [5]. Scans were acquired at the Olin Neuropsychiatry Research Center at the Institute of Living on a Siemens Allegra 3T dedicated head scanner equipped with 40mT/m gradients and a standard quadrature head coil. Gradient-echo echo-planar-imaging functional scans were acquired (TR=1.86s, TE=30ms, FOV=24cm, matrix=64×64, flip=60°, slice thickness=3mm, gap=0.5mm, 36 slices, ascending acquisition). Scans were motion corrected, spatially normalized, and smoothed using SPM2. Regressors for the target and novel stimuli were created in SPM2 and used as constraints.

Results

The semi-blind ICA results (Figure 1b) show marked improvement for the constrained source and no apparent degrading of the unconstrained source. Auditory oddball task performance was as follows: reaction time 436.8 ± 14.52 ms, accuracy for target detection 99.6 ± 0.54 percent, novel false alarms 0.46 ± 0.28 percent, standard false alarms 0.15 ± 0.10 percent. A comparison of ICA and sbICA for one participant is presented in Figure 2. For the blind ICA analysis the component-of-interest was selected by performing a multiple regression of the target/novel regressor upon the ICA time courses. The component which was most highly correlated with this regressor was selected. The blind ICA tends to capture temporal lobe regions into a separate component, but is not strongly correlated with the task. The sbICA approach includes temporal lobe regions and also includes expected motor and parietal regions and the correlation value is significantly higher (0.51 vs. 0.33), as expected. The average correlation with the target/novel regressor across the 20 participants and 2 runs was 0.53. The average ratio of target to novel stimuli weights estimated by the sbICA approach was 1.7, thus the target stimuli were contributing about 2/3 of the amplitude to the final component and the novel stimuli about 1/3 of the amplitude on average.

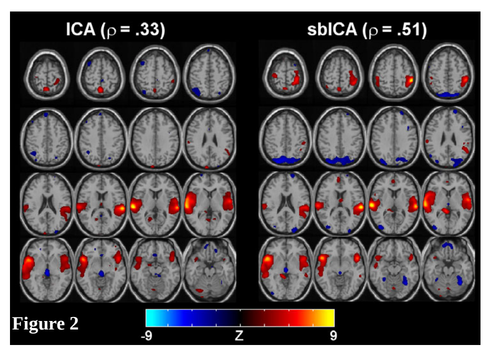

Figure 2

Discussion

We have demonstrated an approach for incorporating information about the fMRI paradigm into an ICA analysis which has a number of advantages over blind ICA. Our findings suggest that imposing constraints can improve the robustness of ICA in the presence of noise. Secondly, we have demonstrated that sbICA can in some cases outperform a traditional GLM approach for the task-related component, while still enabling a fully data-driven approach to unknown components. Thirdly, constrained components can now be readily compared in a group analysis. Finally, the sbICA approach provides a representative time course which may be useful for interpretation and/or subsequent analyses.

References

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Acknowledgment

Supported by the National Institutes of Health under grant 1 R01 EB 000840-01 (to VC).