A novel variational Bayesian method for spatiotemporal decomposition of resting-state fMRI

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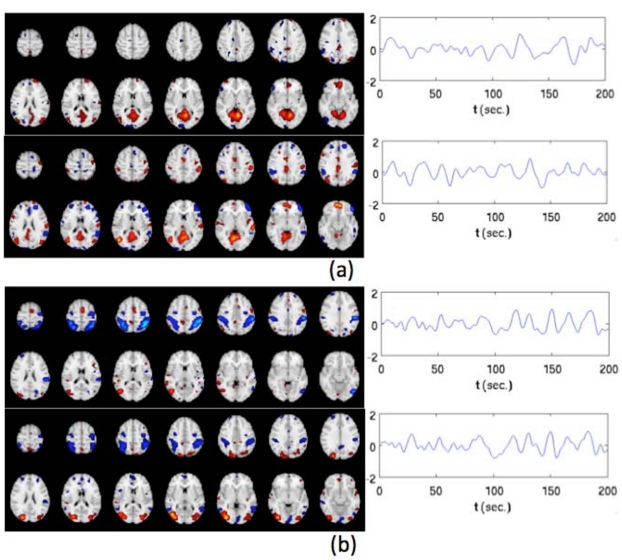
Introduction

We apply a new variational Bayesian factor partition (VBFP) method to the sparse spatiotemporal decomposition of resting state fMRI data. The VBFP method estimates sources with sparse distributions in both spatial and temporal domains and incorporates automatic relevance determination in a fully Bayesian inference framework. Hence it achieves dimension reduction as an integrated part of the inference. We apply VBFP to resting state fMRI data and compare it with a maximum likelihood independent component analysis (ICA) algorithm [Bell and Sejnowski, 1995] and show that VBFP identifies similar functionally coherent brain networks and their temporal fluctuations. The potential advantages of VBFP on the integrated inference of the noise model and on robustness for small sample sizes motivate further investigation.

Methods

Image acquisition: Ten healthy young adult subjects were studied on a 3T Signa EXCITE MR scanner (GE Healthcare, Waukesha, WI) using an 8-channel phased-array radiofrequency head coil. BOLD fMRI images of the supratentorial brain were obtained using a 2D multislice gradient echo echoplanar acquisition with FOV 22x22 cm, 64x64 matrix, 4 mm interleaved slices with no gaps, and TR of 2 sec and TE of 28 sec. After 10 dummy brain volume scans to reach equilibrium magnetization, two hundred (T=200) brain volumes were collected over a period of 7 minutes with eyes closed to minimize exogenous visual activation. ASSET parallel imaging with a reduction factor of 2 was used to reduce the distortion.
Preprocessing: (a) Motion correction was applied to fMRI volume data by registering each scanned volume data with the median volume using the MCFLIRT function in FSL (http://www.fmrib.ox.ac.uk/fsl). (b) In-brain voxels were extracted by the BET function in FSL. (c) Spatial smoothing was applied by convolving each scanned volume with an 8x8x8mm Gaussian kernel, using the "fslmath" function in FSL. (d) Temporal filtering was applied to each voxel time sequence by regressing out the linear trend and performing temporal smoothing using a Gaussian kernel with σ = 2.8 sec.
Data analysis: (a) The global baseline (i.e., the grand mean of the dataset), the global spatial map (i.e., the mean of time sequence at each voxel), and the global time course (i.e., the mean of in-brain volume at each time point) were removed from the dataset. (b) ICA and VBFP were applied to the fMRI data to achieve a spatiotemporal decomposition as $Y = AHX$ where Y is the TxN spatiotemporal fMRI data matrix with N in-brain voxels in each row and T time points. For ICA, "A" contains the eigenvectors obtained by principal component analysis and "H" is the lower dimensional mixing matrix estimated by the Information maximization (Infomax) algorithm to maximize statistical independence of the sources in X [Bell and Sejnowski, 1998]. For VBFP, "A" contains temporally sparse sources in its column, "X" contains spatially sparse sources in its row, and "H" is a low-dimensional non-sparse mixing matrix. For fMRI analysis, the spatial and temporal sources can be constructed in two different ways from the above decomposition. (i) "X" is output as the set of decomposed spatial activation maps, correspondingly, the matrix product of "AH" is deemed to be the time course matrix containing the temporal fluctuations of the sources in X. (ii) "A" is output as the sparse temporal response sequences and the matrix product "HX" is deemed to be the activation maps. In this work, scheme (i) is adopted for the correspondence between statistical independence (achieved by Infomax) and sparsity (achieved by VBFP) in the spatial domain. A total of thirty components were estimated using both algorithms. The spatial sources were normalized to unit variance and thresholded at 1.5 standard deviations with the supra-threshold voxels displayed on the brain anatomy. The estimated spatial maps between ICA and VBFP are matched by the overlap between the activation regions.



Results

Figure 1 shows two pairs of connectivity maps and their time courses estimated by ICA (top) and VBFP (bottom), as these results are representative to characterize the difference between the two algorithms. It can be observed that (i) both algorithms identify similar suprathreshold regions during the resting state and capture similar temporal fluctuations of those regions. (ii) VBFP tends to include both positive (red) and negative (blue) regions in the same connectivity maps, indicating anti-correlated networks. On the other hand, ICA estimates maps are less inclusive of both positive and negative regions, thus showing only the positively correlated brain networks.

Figure 1. (a) Connectivity of bilateral posterior cingulate gyri during the resting state and their time course. The top panel shows the results of Infomax ICA and the bottom panel shows the results of VBFP, which includes anti-correlation with a parietal lobe network. (b) Connectivity of bilateral superior parietal lobes and their time course. The top panel shows results of Infomax ICA and the bottom panel shows results of VBFP. The VBFP map includes more anti-correlated networks in the bilateral posterior parietal and lateral occipital regions.

Discussion

Since ICA assumes a noiseless mixing model, a dimension reduction has to be applied to separate the noise subspace from the signal subspace before estimation of statistically independent sources. This is in order to avoid overfitting of the independent component decomposition model. In VBFP, since the noise is incorporated as part of the model, dimension reduction becomes an integrated part of the inference. VBFP is developed based on the sparsity assumption in both spatial and temporal domains; a similar idea was proposed in [Stone, et al., 2000] where the estimation is achieved by a heuristic coupling between the spatial and temporal mixing matrices. In contrast, VBFP achieves the spatiotemporal decomposition through a fully Bayesian inference.

References and Acknowledgements: [1] Bell, A. J. and Sejnowski, T. J. (1995). An information-maximization approach to blind separation and blind deconvolution. Neural Computation 7(6):1129-59 [2] JV Stone, et al., "Spatiotemporal ICA of fMRI Data," Computational Neuroscience Report, 2000. This study was funded by U.S. National Institutes of Health.