Comparison between Spatial and Temporal Independent Component Analysis for Blind Source Separation in fMRI Data

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***Abstract*— Independent component analysis (ICA) is an exploratory method for analyzing spatial and temporal properties of fMRI data and requires no explicit temporal model, necessary for conventional fMRI analysis. Two varieties of ICA are employed to achieve maximal independence component in space or time yields for functional MRI (fMRI) analysis: spatial ICA (sICA) and temporal ICA (tICA). sICA is widely studied and used in signal separation of fMRI data. In this study, we compared the performance of sica and tICA to extract and separate signals with spatial and temporal independence based on simulated data. Our results reveal that sICA is able to extract and separate relatively highly independent signals. tICA can fulfill the separation of mutually independent component signal in time course and classify the temporally corresponding signal as one group in spite of having a spatially independent component. The results suggest that tICA can be applied to detect a special signal overlapping with the physiological signals by evoking other activations using the special signal.**

Keywords- independent component analysis; sICA; tICA; signal separation; fMRI

I. INTRODUCTION

Functional magnetic resonance imaging (fMRI) is a technique for inferring information about neuronal activity by directly or indirectly measuring regional magnetic changes caused by neurons fire. In fMRI, a set of slices are acquired over time (3D space + 1D time). The signal responding to changes of neuronal activity over time, a mixture of underlying source signals, are recorded in the 4D data.

Independent component analysis (ICA) is a technique that recovers hidden signals, assumed to be nonguassian and mutually independent, from linear mixtures of some unknown latent signals with an unknown mixing system. The hidden signals to be separated are called the independent components (IC) of the observed data [1]. ICA can be used in two complementary ways to decompose an image sequence (4D) into either spatially or temporally independent components. Each choice yields a set of component maps or a corresponding time courses. Spatial ICA (sICA) and temporal ICA (tICA) are two methods of computing the desired information. sICA can find a set of mutually IC images and a corresponding set of unconstrained time course, whereas tICA can find a set of IC time course and a corresponding set of unconstrained images. sICA or tICA requires no reference function (explicit temporal model) or predefined seed, which is one advantage of application of ICA to fMRI data compared with other conventional fMRI analysis methods (e.g. cross-correlation analysis - CCA).

The first application of ICA to fMRI data was sICA to determine spatially distinct brain networks. For fMRI data, it is more common to use sICA to extract a particular component using a model or to find anatomically meaningful maps using knowledge of brain structure and function. tICA is more commonly applied in EEG and ERP data analysis. The application of tICA in fMRI data is rarely reported in literature. James J. Pekar, Vince Calhoun, James V Stone, et al. studied the performance of sICA and tICA to fMRI data. Some results have suggested that sICA and tICA yield similar results for experiments with task-related component [2, 3]. To our best knowledge however, an in-depth performance evaluation of sICA with tICA in signal separation and extraction from fMRI data has not been performed especially when there is one predictable component mixed with other composite signal and noise which have varying degrees of spatial or temporal dependence. This situation can appear when a researcher attempts to detect a useful signal overlapping with some physiological signals (e.g. heartbeat, breathing) in spatial location or indentify one region responding to multiple tasks which have high correlation in temporal dimension. In this study we evaluate performance of sICA and tICA in separation of signals with varying spatial or temporal independence using simulated data. In addition, we compare performance of different types of ICA in accuracy of space position and timing for signal detection. Finally, we explore a strategy to detect a particular signal from source data in which components have different temporal independent and same spatial independent.

II. MATERIAL AND METHOD

A. *Simulation*

Simulated data were generated to test effect of different types of ICA over ICs separation and evaluate performance of sICA and tICA. A volume of one-slice EPI scans (64×64 voxels) was replicated 700 times to simulate 700 time points of noise-free fMRI data. TR was 0.3s, and the temporal waveforms were 210 second in duration. Two simulated signals

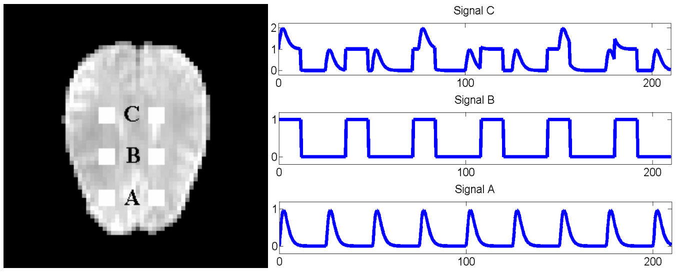

Figure 1. EPI scan image, regions of interest and simulated fMRI signals. Signal A (0.13 Hz) is series of gamma variate functions simulating event-related design fMRI signal. Signal B (0.09 Hz) is a square wave simulating a block-design fMRI signal. Signal C is sum of signal A and signal B.

were created to represent event-related brain hemodynamics. One consisted of repeat patterns of gamma wave with 0.13Hz frequency (signal A), and another consisted of repeat patterns of block wave with on for 1.2 second then off for 2.4 second (0.09 Hz frequency)(signal B). Signal A and B are uncorrelated signals (correlation = 0.0043). The linear combination of two signals formed third signal (signal C), which correlated with signal A and B (correlation between A and C = 0.54, correlation between B and C = 0.85). Each signal was added to two volumes of interest (VOIs; each with a size of 4×4×1 voxels). The order from bottom to is top signal A, B and C. The simulation mode was shown in Fig. 1. To simulate the noisy environment in the brain, we added random noise to the simulated data (all voxels in the brain area). The random noise data (64×64×1×700) follows a Gaussian distribution with a mean of 0 and a variance of 1. The contrast-to-noise ratio (CNR, magnitudes of the signals to the noises) was assigned 10.

B. *Independent Component Analysis*

ICA was performed following principle components analysis (PCA), which reduced simulated data in dimension based on assumption of fewer independent sources than time points (sICA) or spatial voxels (tICA). Twenty components were selected in PCA for a good trade-off between information preservation and data set reduction.

For the sICA analysis, data was a $N \times M$ matrix where N was the number of time points ($N = 700$ for the simulated data) and M was the number of voxels ($M = 64 \times 64$ for the simulated data). The output was 20 statistically independent components which contained M spatial voxels in each. For the tICA analysis, the input was a $M \times N$ matrix where M, N were also the number of voxels and the number of time points. The output was still 20 temporally independent time courses/components. The independent maps of ICA were converted to z maps for thresholding and were then overlaid on EPI image. In both cases, ICA was performed using Infomax [4], Combi [5], FBSS [6] and ICA-EBM [7] algorithms in turn.

III. Results

The performances of different sICA algorithm for the simulated data are summarized in Fig. 2. Infomax, Combi, FBSS and ICA-EBM algorithms were all capable of detecting gamma wave (signal A) in spatial domain, but they failed to separate block wave (signal B) and mixed signal (signal C) in spatial domain. Infomax, FBSS and ICA-EBM algorithms detected signal B and C as an independent component (see Fig. 2. a, c, d), while Combi algorithm considered that signal A, B and C aren't mutually dependent (see Fig. 2. b). The results from the simulated experiment using four tICA algorithms are shown in Fig. 3. Infomax, Combi, FBSS and ICA-EBM algorithms all detected regions containing gamma wave (signal A). Combi, FBSS and ICA-EBM algorithms were able to successfully detect regions containing block wave (signal B) (see Fig. 3. b, c, d), expect that Infomax analyzed signal A, B and C as highly dependent signals (see Fig. 3. a).

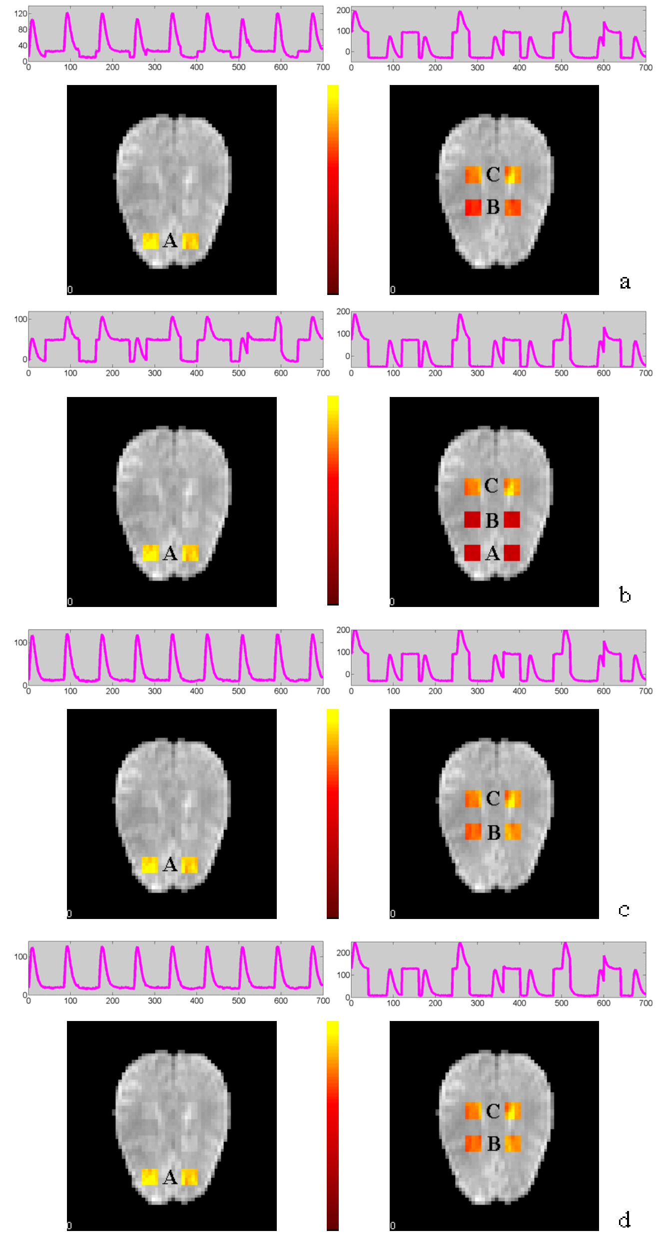

Figure 2. The results of sICA for simulated data. **a**) results using Infomax, signal A is one IC, signal B and C are one IC; **b**) results using Combi, signal A is one IC, signal A, B and C are one IC; **c**) results using FBSS, signal A is one IC, signal B and C are one IC; **d**) results using ICA-EBM, signal A is one IC, signal B and C are one IC.

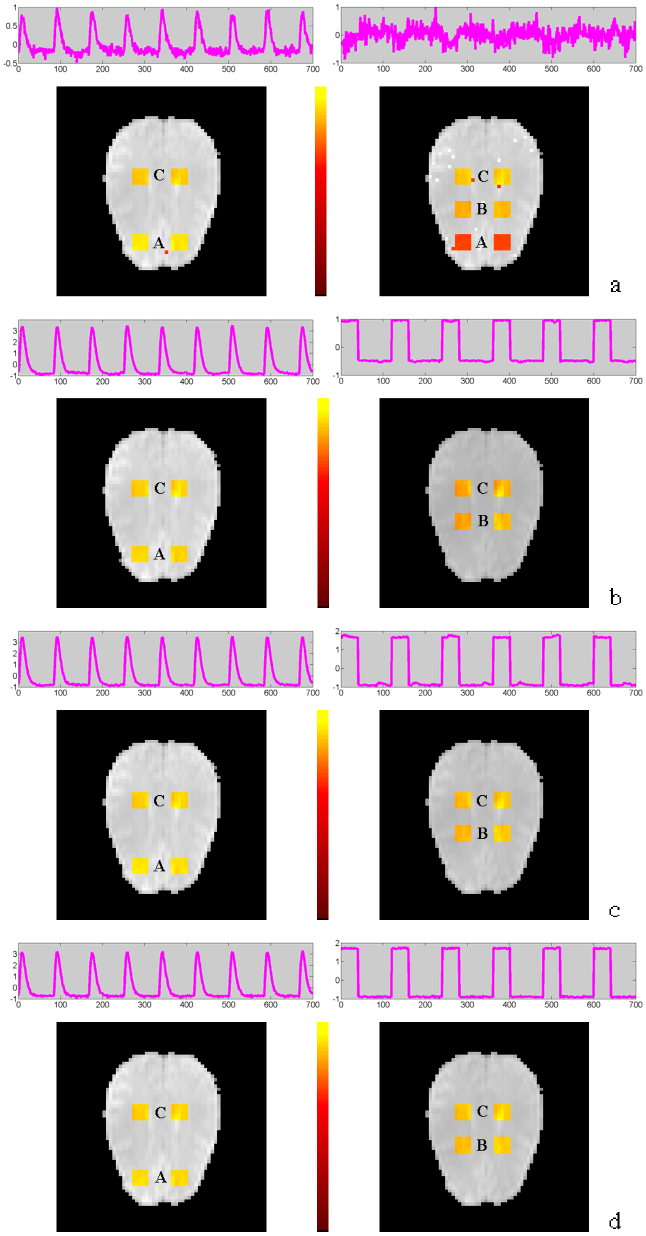

Figure 3. The results of tICA for simulated data. a) results using Infomax, signal A and C is one IC, signal A, B and C are one IC; b) results using Combi, signal A and C is one IC, signal B and C are one IC; c) results using FBSS, signal A and C is one IC, signal B and C are one IC; d) results using ICA-EBM, signal A and C is one IC, signal B and C are one IC.

IV. Conclusion and Discussion

sICA and tICA are both capable of separating supposed mutually statistically independent signals. However, when the assumption of spatial or temporal independence is violated to a certain degree (e.g., the signals are dependent spatially or temporally, respectively), the performances of sICA and tICA are not necessarily always the same. sICA is able to separate highly independent signals (separated signal A from signal B and C, Correlation(A, B) = 0.0043, Correlation(A, C) = 0.54, Correlation(B, C) = 0.85). The results demonstrated that the value 0.54 is a relatively low correlation coefficient, and 0.85 is a high correlation coefficient. sICA fail detection of all regions containing same signal (detected signal A and C at the same time). For sICA method, Combi algorithm performed poorly compared with Infomax, FBSS and ICA-EBM algorithms (see Fig. 2. b). tICA can not only separate statistically independent signals, but can also extract all correlated signals even with medium correlation (separated signal A and C from signal B and C). This characteristic provides us an important method for detecting a desired signal from blind mixed source by evoking other activation using the desired signal. For tICA method, the performance of Combi, FBSS and ICA-EBM algorithm were relatively stable compared with Infomax.

From the above analysis, we can draw a conclusion that tICA can be used to detect a desired signal overlapping with some physiological signals in spatial position, which is useful in small signal detection for brain functional connectivity. Compared comprehensively, FBSS and ICA-EBM tICA algorithm provide more stable properties.

Acknowledgment

The work was financially supported by the NIH (Grant R21 MH 082187-01). The authors thank Ph.D. candidate Hongcheng Yang for partial data visualization.

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