Robust Ordering of Independent Components for Temporal Event-Related fMRI Data Analysis

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Synopsis

We present a robust method for ranking the outcome of independent component analysis (ICA) of fMRI data based on canonical correlation analysis. The new method works by observing the correlation between the initial components and a special function derived from the activation paradigm.

Introduction

The application of ICA to fMRI data has been proven useful (1). The main advantage is that ICA requires no prior assumption about the neuronal activity or the noise structure, which are usually unknown in fMRI. Unlike principal components analysis (PCA), ICA attempts to find the statistically independent components and has no natural ranking schema for them. Even though the higher order statistics taken into account in ICA have been shown to be valuable, the fact that the resultant component from ICA are not ranked makes its use dependent on a human observer to discern the significant components, which is always a cumbersome task. In this work, we introduce a simple yet robust technique for ranking the resultant independent components (ICs) with the aid of prior information about the activation paradigm.

Methods

ICA works by recovering source signals S from their observed mixture X. In its most common form, ICA assumes that there exists a mixing matrix A such that X = A·S and that the sources are mutually independent. By constructing a suitable measure of independence among the components of S, we may estimate S by optimizing this measure. This procedure involves a whitening step that makes the variance in the whitened space unity in all direction, and this leads to the difference between ICA and PCA in ranking the components. Usually, some of the components of S come from the neuronal activity while others from physiological and random noise. Attempts to rank these components by the correlation with activation paradigm are usually not robust due to the inherently low signal-to-noise ratio in fMRI signals. Here, we propose to use the canonical correlation (CCA), a well-known statistical analysis tool developed by Hotelling (2). CCA is a way of measuring the linear relationship between two multidimensional variables. It finds two bases, one for each variable, that are optimal with respect to correlation. Moreover, it finds the corresponding correlation values at the same time. Consider two multidimensional random vectors x and y. CCA try to find linear combinations

$$X = a_1x_1 + a_2x_2 + a_3x_3 + ... + a_mx_m = w_x{}^T x \quad \text{and} \quad Y = b_1y_1 + b_2y_2 + b_3y_3 + ... + b_ny_n = w_y{}^T y \qquad [1]$$

which are chosen so that X and Y correlate the most. In our experiments, we apply CCA between all the components of S as vector *x* and a model for the activation signal as vector *y* in Eq. [1]. This model is chosen depending on the symmetric square wave paradigm of the activation signal. It is then possible to assume that the response will have the same fundamental frequency as the paradigm. Therefore, it is suitable to include components with frequencies equal to the first few harmonics of the Fourier series expansion of the symmetric square-wave. In this work, we have chosen the following simple basis:

$$y(t) = (\sin(\omega t) \quad \cos(\omega t) \quad \sin(3\omega t) \quad \cos(3\omega t) \quad \sin(5\omega t) \quad \cos(5\omega t))^T \qquad \omega = \frac{2\pi}{T}, \qquad t = 1,2,...,N \quad . \qquad [2]$$

The CCA results in a six-tuple correlation (r_i) corresponding to the six transformation vectors in both w_x and w_y. It is clear that the higher the r_i, the higher the relation between the activation paradigm and the corresponding w_x. Moreover, the higher a certain coefficient in w_x, the higher the relation between the activation paradigm and the IC that corresponds to this coefficient. Based on this note, a certain score can be assigned for each IC based on its relation with the activation paradigm as:

$$M = \sum_{i=1}^{n} w_x^T \cdot r_l \qquad [3]$$

Also, to avoid our basis being correlated with random noise just by chance, we apply a mean square test between the projection of the paradigm on the chosen basis and the projection of each component on them (2). Hence, our rank equation is modified to include a term that contains a diagonal matrix with elements equal to this mean square error.

$$M = \sum_{i=1}^{n} w_x^T \cdot \left(DIAG\left(\ MSE\left(w_{yi} - w_{y0}\right) \ \right) \cdot r_i \right) \cdot \qquad [4]$$

Results

The present technique was applied to ICA results for event-related fMRI data. The data were obtained from an activation study performed on a volunteer using a Siemens 1.5T clinical scanner. In this study, an oblique slice through the motor and the visual cortices was imaged using a T2*-weighted EPI sequence (TE/TR= 60/300 ms, Flip angle=55°, FOV=22cmx22cm, slice thickness=5 mm). The subject performed rapid finger movement cued by flashing LED goggles. The study consisted of 31 epochs, with 64 images per epoch (3). Temporal ICA was applied to process groups of pixels within a user-specified region of interest of variable size between 4×4 to 16×16. The proposed ranking method based on CCA was used to order the outcome of ICA, which came in different order each run (as in Figs. 1-2). The technique was found to be consistent in all the experiments providing the signals representing the true activation and physiological noise at the same order every time.

Conclusions

A new technique for ordering the outcome of temporal ICA is proposed. With the aid of CCA, our method attempts to distribute noise in fMRI signals to many projections so its effect on the overall decision of ranking is minimal. Our experiments suggest this technique to be highly robust, which makes it suitable as a postprocessing step after ICA to make its results easier to evaluate.

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References

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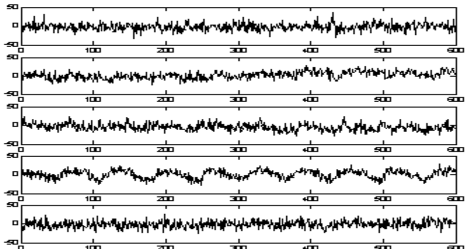

Fig. 1: Initial independent components

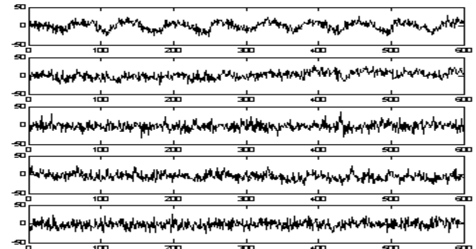

Fig.2: Ranked independent components.