Comparison of Orthogonal and Independent Component Analysis on Dimension-Reduced fMRI Data in Patial Least Squares Framework

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Introduction

Partial Least Squres (PLS) [1,2] has been introduced in the analysis of human brain function to reveal distributed activity patterns that support behavior and cognition. Beyond the emphasis on distributed function, a benefit of this multivariate statistical method is that it contains hypothesis-driven and data-driven features. The possible contrasts in the data are encoded in the contrast matrix. The cross product of the contrast matrix and the spatiotemporal brain images matrix results in the effect space with the reduced data dimension.

In the usual application of PLS, singular value decomposition (SVD) is used to generate orthogonal latent variables. Recently, independent component analysis (ICA) [3, 4] was developed to decompose matrices for maximizing mutual information among components. ICA thus identifies independent, but not necessarily orthogonal activity patterns. Based on the framework of PLS, we report here the comparison of these two decompositions approaches on the effect space. The difference and similarity of the decomposed components are quantified in multi-dimensional vector space for both simulation and a real fMRI motor experiment data.

Methods

Simulation

The data matrix was created as 120 time points and 10,000 voxels from Gaussian distribution N(0,1). Two to six orthonormal time courses were created as patterns of simulated activated voxels. Non-orthonormal time courses were also generated by different time shift of the orthonormal time courses. Twenty voxels were randomly selected for each orthonormal and non-orthonormal activation.

All orthonormal time courses simulating active voxels were chosen as contrast vector in PLS. Effect space was constructed by the cross product of data matrix and the contrast matrix. SVD decomposes the effect space into orthonormal latent variables. Fast-ICA [4] algorithm was used as an alternative to decompose the effect space. Similarity between the estimated brain activation maps by SVD and ICA were quantified as the inner-product of two unit-length vectors which produces the cosine of the angle between vectors. This cosine is the correlation between the activation maps between the approaches. Estimation power was calculated as the ratio of the most dominant detected active voxel numbers given the total number active voxels.

Different signal-to-noise ratios (SNR) were applied for each active pattern simulation. 100 iterations of each condition were performed on PC Intel Pentium-III (Santa Clara, CA) platform using Matlab (Natick, MA).

Experiment

A right-handed subject executed a left hand button press in response to a visual stimulus appearing at 1 Hz in this block design experiment. Multislice echo-planar image (EPI) acquisition was used. The details of imaging parameters and post processing including spatial normalization and spatio-temporal filtering are described in [5].

9 orthonormal contast vectors were created in contrast matrix in this 10-block experiment. One contrast vector matches the on-off paradigm was included. SVD and PCA are performed for the estimation of activated brain area.

Results

The angles between the most dominant estimated brain activation maps by SVD and ICA are almost zero (inner-product=1) in simulations with six orthonormal activation pattern with 2 to 6 non-orthonormal ones, as the SNR of the active voxel higher than 0.1. The simulated brain maps diverge as the SNR drops down. SVD and ICA have similar power of detection rate at different SNR. These are shown in figure 1.

In figure 2, the brain activation maps from the experimental data by SVD and ICA are shown. The two methods estimate similar activation areas in contra-lateral motor cortex, ipsi-lateral cerebellum and superior parietal lobule with different predicted areas on ipsi-lateral occipital lobe and cerebellum.

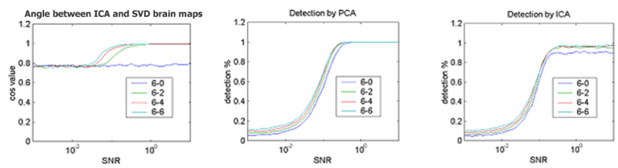

Fig. 1 The angle and detection rate of simulation including 6-orthornormal contrasts and 0 to 6 time delay shifts as non-orthonormal contrast at different SNR

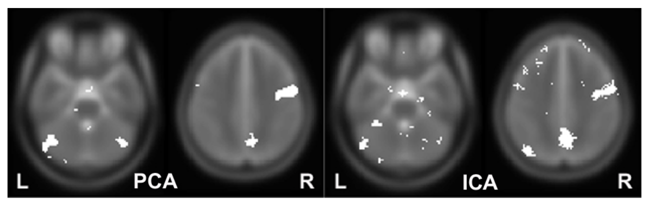

Fig. 2 The brain activation maps estimated by SVD and ICA on effect space in PLS

Discussion

From the simulation, SVD and ICA predict similar brain maps and detection power for different SNR, as the degree of freedom for decomposition is less than 12. In real fMRI data, these two decomposition schemes predict similar activation map with minor difference, which may be physiological and instrumental noise or missing brain activity estimation. SNR changes the similarity of the brain maps by both methods. There may be more divergence of SVD and ICA decompositions are the number of degrees of freedom increases and the effects are non-orthogonal, but this requires further study. From a practical perspective, the main difference between SVD and ICA was computational cost. Even with the improved fast-ICA algorithm, ICA costs approximately ten fold more of computational resources than SVD. SVD provides a fast prediction of paradigm related component, while ICA is the alternative to reveal transient responses in the brain. Both methods should be utilized interchangeably depending on experiment design and data quality to understand the brain functions, which give no biological preference to either mathematical model.

References

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