

A new Dimensional Estimation Method for Group fMRI Data Reduction at Multiple Levels

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Introduction

Data driven methods, e.g. independent component analysis (ICA), have been used in fMRI data analysis without a priori knowledge [1]. However, determination of the data dimensions has a significant impact on ICA results [2]. For group ICA, data reductions are generally required based on an appropriate dimensional estimation of the fMRI datasets [3]. Previous studies have shown that traditional methods, e.g. the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Minimum description length (MDL), overestimate the dimensions because white noise was generally assumed in the analysis [4]. Cordes et al. [5] proposed an improved method for individual dataset but it still overestimates the dimensions of the group MRI data. A new method has been developed for more reliable dimensional estimation for group fMRI at multiple levels of data reduction.

Methods

14 healthy right-handed volunteers (all male, 30±6 yrs) participated in 5 session, resting-state fMRI scans (EPI: 35 slices covering whole brain, FOV=22 cm², matrix size=64×64, TR=2160ms, TE=27ms, 86 timepoints) on 5 different days over two weeks. All datasets were spatially normalized to Talairach space. Principal Component Analysis (PCA) based data reductions were performed on group data (concatenated along time) at 3 levels in “individual-session-subject” or “individual-subject-session” order. The AR(1) noise fitting technique as described in [5] was implemented, and the divergent point of the fitted noise spectrum from the actual fMRI data spectrum was used to indicate signal dimensions. To obtain an improved estimation, colored noise was added into the group fMRI data to blur the signal variation that contributes to the overestimation. The colored noise was generated by another AR(1) model with an autoregressive coefficient (ϕ) that was set as the average ϕ values fitted from all fMRI datasets in the group, and the noise ratio (nr) that was determined by minimizing the sum of square error (SSE) between the pre- and post-noise PCA eigenspectra.

Results

In Fig.1 and Fig.2, red, blue, and black curves represent the pre-noise, post-noise, and AR(1) fitted noise eigenspectrum, respectively. Fig.1 shows the noise ratio effect (nr = 1~2) on dimensional estimation. The optimized nr value is determined by the minimum of SSE between the pre- and post-noise spectrum. Fig.2 shows the dimensional estimations at 3 levels in “individual-subject-session” order. It is shown that the estimated dimensions of the group fMRI data are significantly reduced after adding colored noise of appropriate ϕ and nr. In Fig.3, different estimation methods are compared at the 3 levels in 2 different group orders. Compared to post-noise MDL method (snMDL), the pre-noise AR(1) method (sAR) has less dimensional overestimation. The proposed post-noise AR(1) method (snAR) significantly reduced the dimensional overestimation at all 3 levels. AIC, BIC, and regular MDL methods did not report dimensions fewer than the total time points for Level 2 and 3, and thus are omitted. It is noted that different group orders show consistent estimation results at Level 3 for the proposed method.

Discussion and Summary

Previous methods substantially overestimate the dimensions of group fMRI data. The small variations of the signal components within a group contribute to the overestimation. Instead of using spatial smoothing as suggested in [6], the present work solves this problem by adding appropriate colored noise generated from an AR (1) model to the group data to blur the signal variants. The proposed method has been tested on group fMRI data reductions at multiple levels for the application of group ICA analysis to reveal resting-state functional networks in the human brain.

References

[1]. Brown GD, et al., Trends Neurosci 24:54-63. [2]. Calhoun VD, et al., MRI 22:1181. [3]. Calhoun VD, et al., HBM 14:140-151. [4]. Hansen LK, et al., NeuroImage 9:534-544. [5]. Cordes D, et al., NeuroImage 29:145-54. [6]. Friston KJ, et al., NeuroImage 12:196-208.

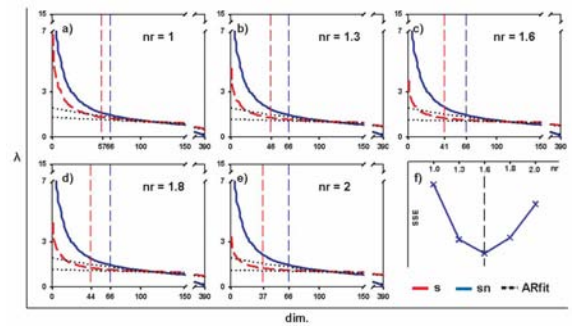


Fig.1: Noise ratio (nr) optimization and the dimensional estimation

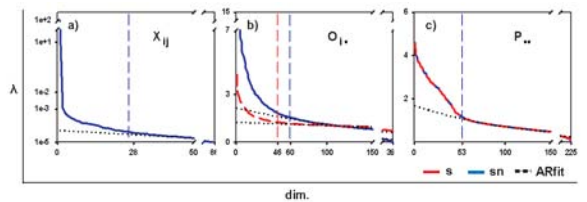


Fig.2: Dimensional estimation at multiple levels of data reduction

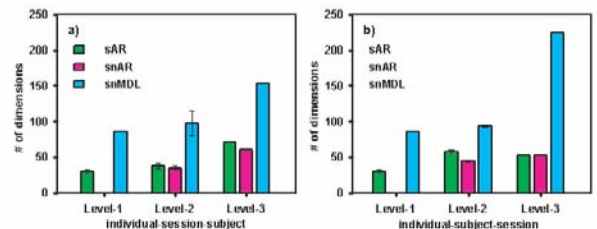


Fig.3: Comparing methods at multiple levels of data reduction