Principal component projections achieve frequency decomposition on resting-state fMRI data

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Introduction

We observe that the projection vectors associated with spatial principal component analysis (PCA) of resting-state fMRI data have their frequency spectrum shifting from low to high frequency as the variance of the spatial principal components decreases. This trend becomes more significant after the fMRI data is treated with temporal smoothing using a Gaussian kernel. This observation indicates that, after the typical preprocessing procedure including motion correction, spatial smoothing, temporal smoothing, and global signal removal, the variance of resting-state fMRI data is dominated by the lowest frequencies within the 0.01 to 0.1 Hz range associated with BOLD signal fluctuations. The decomposition of signal variance at different temporal frequency bands can be achieved by PCA, indicating that PCA provides the basis for order selection of fMRI data not only by ranking the variance of the principal components, but also by the ranking their frequency concentration. As a result, dimension reduction of fMRI data using PCA is a valid procedure for removing high frequency signal fluctuations irrelevant to the hemodynamic response.

Methods

Image acquisition: Ten healthy young adult subjects were studied on a 3T Signa EXCITE HDx MR scanner (GE Healthcare, Waukesha, WI) using an 8-channel head 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 the subject's eyes closed to minimize exogenous visual activation. ASSET parallel imaging with a reduction factor of 2 was used to reduce 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) are removed from the dataset. (b) PCA is applied to each dataset to achieve the spatiotemporal decomposition, i.e., the TxN fMRI data matrix Y, where T is the total number of time points and N is the total number of in-brain voxels, is decomposed into a TxT projection matrix E and a TxN component matrix Z, i.e., Y = EZ. Discrete Fourier transform was applied to each column of E to obtain the frequency spectrum of each PCA project vector.

Figure 1. The principal component magnitudes (top panel) and the center frequencies of their projection vectors (bottom panel). Mean and standard deviation are taken across resting state fMRI datasets from all ten subjects.

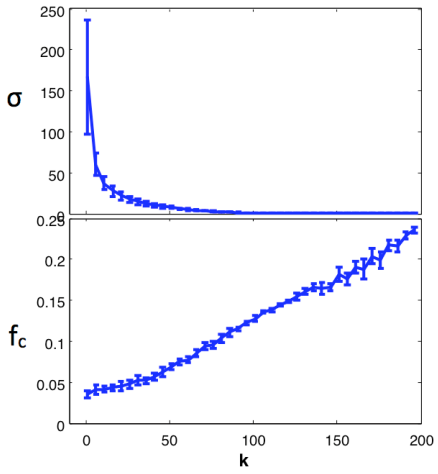

Fig. 1

Figure 2. Frequency spectrum plots of ten representative principal component projection vectors from one resting state fMRI dataset.

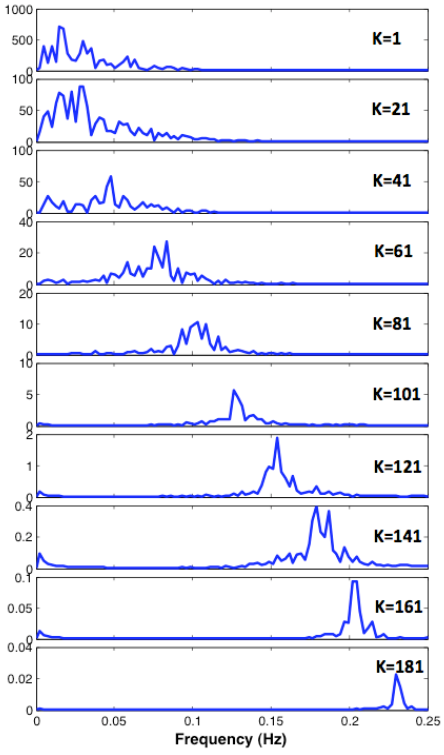

Fig. 2

Results

Figure 1 shows that, as the magnitude of the principal component decreases, the frequency spectral power tends to shift from low frequency to high frequency. The BOLD fluctuations are captured within the first 70—80 principal components. Figure 2 shows the frequency spectrum plots of 10 projection vectors sampled evenly from the full temporal dimension of the fMRI data (k = 1, 21, …, 181). It is observed that as the dimension index k increases, the frequency band segregation across the PCA projections become more clear. We also compared the results on the same dataset without temporal smoothing, i.e., step (d) in the preprocessing procedure, and observe that the dynamic range of the magnitudes of the principal components increases after temporal smoothing is applied.

Discussion

We observe that PCA on fMRI data not only decomposes the signal fluctuations into principal components ranked by the variance contribution, but also decomposes their temporal dynamics into ordered frequency bands, even within the 0.01–0.1 Hz BOLD frequency range. After the typical preprocessing and removal of global signals, the major contributor to signal fluctuation in fMRI is the BOLD signal, which has its frequency concentration from 0.01 to 0.1 Hz due to the effect of the hemodynamic response [Martino, 2007]. Through investigation on the effect of temporal smoothing with a Gaussian kernel, we find that PCA projection of temporally filtered data gives more significant contrast on the magnitudes across different principal components and their temporal frequency bands are more clearly separated. These observations indicate that (i) order selection criteria for fMRI data based on PCA can be cross-validated by observing the frequency shifting trend of the PCA projection vectors and (ii) temporal filtering may aid estimation of the intrinsic dimension of spatiotemporal fMRI data.

References and Acknowledgements: [1] Martino FD, et al., "Classification of fMRI independent components using IC-fingerprints and support vector machine classifiers," NeuroImage, 34:177–194, 2007. This study was funded by the U.S. National Institutes of Health.