BASELINE DRIFT AND PHYSIOLOGICAL NOISE REMOVAL IN HIGH FIELD FMRI DATA USING KERNEL PCA

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ABSTRACT

Baseline drift and physiological (cardiac and respiratory) fluctuations are among major sources contaminating blood oxygenation level dependent (BOLD) signals in high field functional magnetic resonance imaging (fMRI). Automatically detecting and removing them have been long-standing problems. We propose here a new method, utilizing kernel principal component analysis (KPCA) and frequency analysis, to detect and remove the noise from fMRI data. Differing from thermal noise, the main energy of baseline drift and physiological noise are characterized by the most significant kernel principal components that also contain information on brain structure. To maintain the details of brain anatomy, we filter the feature projections to the components that are found to contain significant baseline drift and physiological noise. This approach is different from most discriminant analysis-based denoising methods that remove insignificant or noisy components before the reconstruction. Experimental results show that the proposed method increases the BOLD contrast and the detection sensitivity of activated voxels.

Index Terms— Drift, cardiac rate, respiration, aliasing.

1. INTRODUCTION

Detecting activated brain regions is the fundamental task of fMRI data processing. However, machine thermal noise, heartbeat and respiration linked physiological noise, baseline drift, and subject movement can significantly affect the detection of BOLD signal. High field ($> 4\ T$) scanners provide fMRI data not only with increased spatial resolution and BOLD contrast, but also with increased physiological noise. Thus, removing the noise is imperative when processing high field fMRI data.

Reducing baseline drift might not be difficult because it has the lowest frequency compared to BOLD signals and physiological noise, and can be attenuated by a highpass filter. It is not easy to detect cardiac and respiratory noise in fMRI data because their frequencies and intensity could considerably change with different conditions. Simultaneously recording respiratory and cardiac rates with fMRI is not technically difficult and has been used in fMRI studies [1]. Provided the temporal resolution of fMRI is sufficient to critically sample signal and physiological noise, BOLD signal could be separated from physiological noise in the frequency domain. However, the repetition time (TR) of most multi-slice fMRI experiments is relatively long (over 2 s) in order to obtain sufficient spatial coverage. This results in physiological noise aliased into the frequency band of BOLD signal. This aliasing happens in both human and animal studies. Fourier or wavelet transform-based frequency analysis cannot always guarantee a clear separation between BOLD signal and aliased physiological noise.

Principal component analysis (PCA) and independent component analysis (ICA) project fMRI data into different subspaces that may distinguish different sources of signals and noise [2, 3]. PCA decomposes data into uncorrelated components, and ICA performs the decomposition by removing high order dependencies among the components. PCA was applied to denoising and detrending in [4, 5]. ICA was suggested for denoising and motion correction in [6, 7]. While PCA and ICA show potential to separate aliased physiological noise from BOLD signal, fMRI data usually does not satisfy the fundamental assumptions that lead to optimal solution for PCA or ICA. Consequently, the estimated components may contain multiple sources of signals and noise and therefore are difficult to interpret. Thus, it is not sufficient to separate individual signal or noise by discriminant analysis alone.

Since either frequency analysis or discriminant analysis along is not sufficient to separate the baseline drift and physiological noise from BOLD signals, in this work, we propose to combine nonlinear discriminant and frequency analysis to detect and reduce their effects. Specifically, kernel PCA (KPCA) [8] is used to decompose fMRI data into multiple components, and the feature projection to each component is further analyzed using frequency analysis. After detecting the projections containing significant energy of baseline drift and physiological noise, digital filters are designed to attenuate them in these projections. fMRI data are reconstructed using the method proposed in [9]. Reconstructed data are evaluated using several numerical approaches, including the number of voxels correlated with the experimental paradigm, and the skewness and kurtosis of the distribution of BOLD contrast sensitivity (CS) values [10]. Compared with the original fMRI data, the data processed by the proposed method shows increased BOLD contrast, leading to higher sensitivity of activation detection.

We first briefly review KPCA, and then introduce the proposed detection and denoising method. Experimental results are described next, followed by the conclusions.

2. KERNEL PRINCIPAL COMPONENT ANALYSIS

KPCA is an unsupervised method that uses kernel trick to implement nonlinear PCA. Given a set of q-dimensional data $\mathbf{x}_i \in R^q$, $i = 1, 2, \cdots, n$, the kernel principal components (KPC) are obtained by calculating the eigenvalue $\lambda > 0$ and corresponding eigenvector $\mathbf{V}$ so that:

$$\lambda \mathbf{V} = \frac{1}{n} \sum_{i=1}^{n} (\Phi(\mathbf{x}_i) \cdot \mathbf{V}) \Phi(\mathbf{x}_i), \tag{1}$$

where Φ is a nonlinear mapping from R^q to a higher dimensional feature space F. We have $\mathbf{V} = \sum_{i=1}^{n} \alpha_i \Phi(\mathbf{x}_i)$ because $\mathbf{V} \in$

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span$\{\Phi(\mathbf{x}_1), \cdots, \Phi(\mathbf{x}_n)\}$. If we define a $n \times n$ matrix K where each entrance is: $K_{i,j} = (\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j))$, and replace the inner product with a kernel function $k(\mathbf{x}_i, \mathbf{x}_j)$, then the original eigenvalue problem becomes:

$$\lambda\alpha = K\alpha, \tag{2}$$

where $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_n)^T$. After normalizing λ and α in F, we can compute the feature projections onto the extracted KPCs:

$$(\mathbf{V} \cdot \Phi(\mathbf{x})) = \sum_{i=1}^{M} \alpha_i^k k(\mathbf{x}_i, \mathbf{x}) \tag{3}$$

From experimental studies we found that the polynomial kernel is appropriate for our analysis. The polynomial kernel is defined as:

$$k(\mathbf{x}, \mathbf{y}) = (\mathbf{x} \cdot \mathbf{y} + 1)^m, \tag{4}$$

where m is the kernel order.

The reconstruction of KPCA, which is called the pre-image problem, is more difficult than that of linear PCA. It is typically not possible to obtain a full and unique reconstruction for KPCA, and several approximation techniques have been proposed [8, 9]. Here we use a method developed in [9] to reconstruct fMRI data.

3. THE PROPOSED METHOD

We describe here a KPCA-based method we developed to detect and remove baseline drift and physiological noise. KPCA can extract nonlinear structures in fMRI data and overcome the limitations of linear PCA and ICA for fMRI data analysis [11]. Linear PCA only considers the second order statistics and cannot account for the higher order dependencies that usually exist between brain functional units. In ICA, the assumption of statistical independence in spatial or temporal domain is not always true, and some signals and noise are not mixed in a linear way.

For denoising, discriminant analysis typically removes less significant components before the reconstruction. These are primarily components related to thermal noise. Components corresponding to baseline drift and physiological noise are usually the most significant and contain primary information on brain structure. They cannot be simply removed or the brain structure information would be lost. Therefore, we propose to filter the projections to KPCs instead of removing the corresponding eigenvectors before the reconstruction.

3.1. Detecting Kernel Principal Components of Interest

Prior information, such as the temporal sampling rate (1/TR) of fMRI time series, the period of each trial, and simultaneously recorded cardiac and respiratory signals, can be used for automatic detection and recognition of KPCs that are related to BOLD signal, baseline drift, and physiological fluctuations. In this work, these KPCs are detected by evaluating the feature projection to each of them using the power spectrum.

Multiple trials are often implemented in task-related or event-related fMRI experiments. The period of each trial determines the central frequency of expected BOLD signal, denoted by f_{BOLD}. The shapes of BOLD responses, which are usually unknown, only affect the bandwidth of corresponding power distribution. In the power spectra of feature projections to KPCs, we first locate the frequency point that is closest to f_{BOLD}, then sum the power of this and the two neighboring (one lower, one higher) frequency points. Finally, the feature projections are ranked in descending order of the summed power.

f_{BOLD} implies an upper bound frequency that can be used to design a filter to remove slow baseline drift, which is usually characterized by the most significant KPCs. In the power spectra of feature projections, the energy of baseline drift is estimated by summing the power from zero frequency to the one closest to $0.5f_{BOLD}$. The projections are ranked in descending order of the summed power.

The simultaneously recorded cardiac and respiratory data are used to detect their effects on fMRI time series. The recorded data are first re-sampled at the sampling rate as that of the fMRI data, and the aliased power spectra are then calculated. After locating the frequency of the highest power, denoted by f_{alias}, from the calculated spectra, we find the closest frequency point to f_{alias}, and its lower and higher neighboring frequency points in the power spectra of the feature projections. The feature projections are ranked in terms of the summed power of these three frequencies. This process is implemented individually for cardiac and respiratory data.

3.2. Filtering and Reconstruction

We heuristically select the first three projections that are most significant in terms of baseline drift, cardiac and respiratory effects. Finite impulse response (FIR) highpass or bandstop filters are designed to remove low frequency drift or aliased physiological noise from these projections. All other projections are untouched. If some projections are simultaneously ranked in the top three in terms of BOLD and noise power, then the filter band should be carefully considered to guarantee that energy of BOLD signal will not be attenuated. The method proposed in [9] is used for the data reconstruction. This method aims to estimate a pre-image as the reconstructed one by utilizing distance constraints in input and feature spaces.

3.3. Objective Evaluation

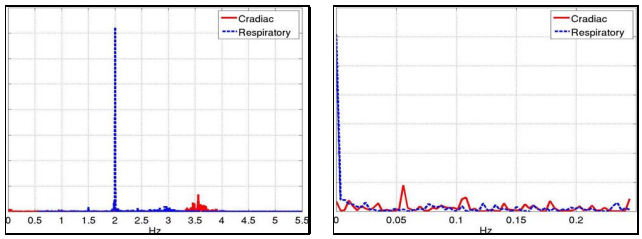
Several approaches are used to measure the improvement achieved by the KPCA and filtering processes. The first one is the number of activated voxels detected by correlation analysis. The second is the contrast sensitivity (CS) of BOLD response [10]:

$$CS_{BOLD} = \Delta S / [(SE_{base} + SE_{stim})/2], \tag{5}$$

where ΔS is the signal intensity change in response to the stimulus. SE is the standard error of intensity in baseline or stimulation period, and is defined as: $SE = SD/N^{0.5}$, where SD is the standard deviation of the average intensity during baseline or stimulation period, and N is the number of images during the baseline or task period. Additionally, the skewness and kurtosis of the distributions of CS values are calculated. Given N CS values $CS_n, n = 1, \cdots, N$, the k^{th} order central moment C^k is computed as:

$$\hat{C}^k = \frac{1}{N} \sum_{n=1}^{N} (\frac{CS_n - \hat{\mu}}{\hat{\sigma}})^k, \tag{6}$$

where $\hat{\mu}$ and $\hat{\sigma}$ are the estimated mean and standard deviation. Skewness and kurtosis are the 3^{rd} and 4^{th} order central moment, respectively. A positive or negative skewness indicates an asymmetric distribution of CS values with long right or left tail. A positive or negative kurtosis means more peaked or flat distribution compared to a normal distribution. Increased skewness and decreased kurtosis are expected because of increased and more concentrated positive CS values after the proposed processing that can attenuate drift and physiological noise.



(a) (b)

Fig. 1. Power spectra of cardiac (solid line) and respiratory (dotted line) noise. (a) Sampling rate: 200 Hz, heart rate: around 3.5 Hz, respiratory rate: around 2 Hz, (b) Sampling rate: 0.5 Hz.

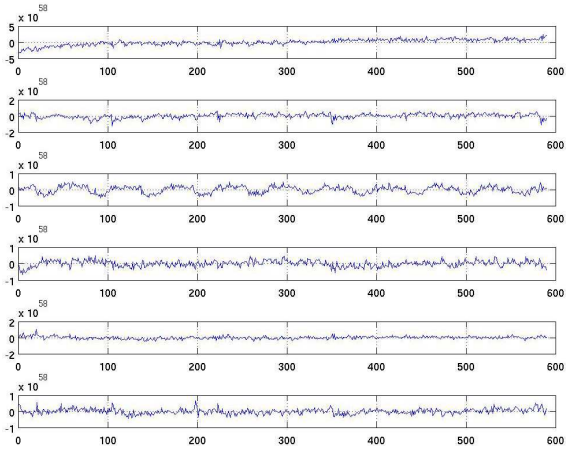
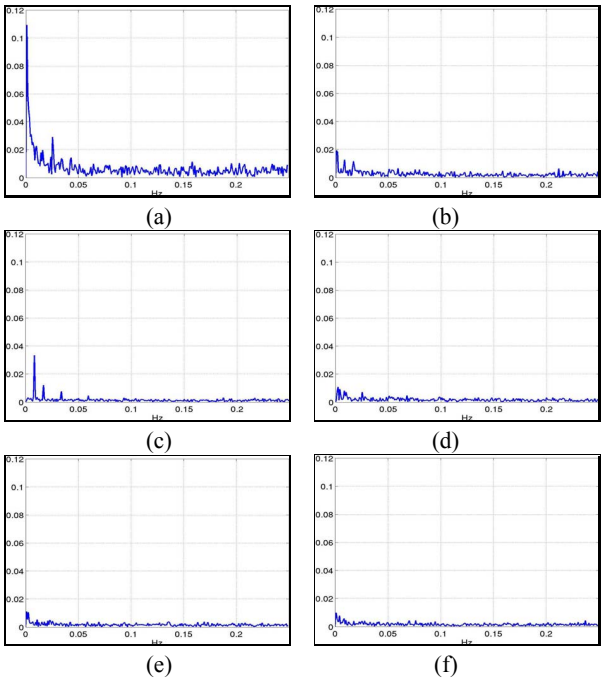


Fig. 2. The projections to the first six KPCs of data.

4. EXPERIMENT AND RESULTS

fMRI data were acquired from a Dutch-belted rabbit brain using a 4.7T Bruker Avance imaging spectrometer. Four contiguous 1 mm thick slices were acquired using a single-shot gradient echo EPI with a 48×48 mm^2 FOV and a 128×64 matrix size, corresponding to a voxel size of 375×750 μm, a 2 second TR and a 20 ms echo time (TE). The stimulation paradigm was designed to characterize the BOLD response to a whisker stimulus (65 Hz sinusoidal vibration of whisker rows D through F) and consisted of 22 images off, 20 on, and 20 off. The initial three images were deleted to allow for longitudinal relaxation equilibration, and ten trials were repeated. The electrocardiogram (EKG) was recorded by a modified precordial lead using two surface electrodes on either side of the chest wall close to the heart. The respiration recording was acquired using a pneumogram sensor on the chest wall where the respiration movement was apparent. The sampling rate for both traces was 200 Hz.

Based on the paradigm and TR, the central frequency of BOLD response is around 0.0085 Hz. The frequency distributions of the recorded cardiac and respiratory data are shown in Fig. 1 (a). The central heart rate is around 3.5 Hz. Rabbit respiratory rate ranges from 0.5 to 1 Hz, but under stress it could be much higher, e.g., 2 Hz in this experiment. After re-sampling them at the rate of 0.5 Hz, the temporal sampling rate of the fMRI data, the aliased spectrum was calculated as shown in Fig. 1 (b). The highest power of the aliased respiratory noise is at 0.0035 Hz, possibly mixed with frequency band of baseline drift. A highpass filter can remove their effects in fMRI data. The highest power of the aliased cardiac noise is at 0.059 Hz, which is away from the central frequency of BOLD. Its



(a) (b) (c) (d) (e) (f)

Fig. 3. (a)-(f) Power spectra of the feature projections to the first six KPCs of data.

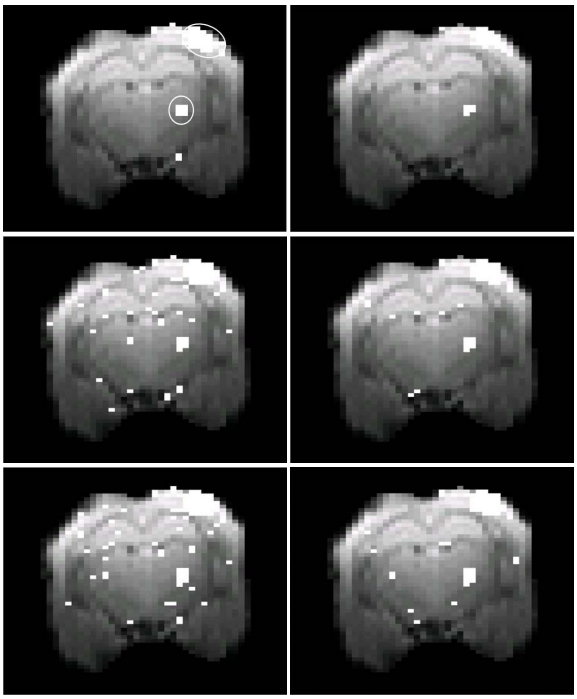
potential effects in fMRI data can be removed by a bandstop filter.

When processing fMRI data, the affine transformation-based registration was first performed to remove subject motion. KPCA was then applied to all ten trials of data with a 11^{th} order polynomial kernel, which is experimentally determined. After ranking the KPCs in descending order according to their eigenvalues, the projections to the first six KPCs are shown from top to bottom in Fig. 2. The first projection shows a long-term slow baseline drift, and the third projection is clearly related to the BOLD response. The power spectra of these projections are shown in Fig. 3. The power of the first projection is most significant, and the baseline drift and possible aliased respiration in this projection result in strong frequency components below 0.005 Hz. The largest peak in Fig. 3 (c) corresponds to the BOLD response, and it is the same as the estimated central frequency of BOLD signal.

Based on f_{alias} estimated from the power spectra of aliased physiological noise, we summed the power around f_{alias} in the way described in section 3.1, and found the top three ranked projections. For cardiac noise, the projections are, in a descending order of power, 2, 1, and 3. A bandstop filter was designed to attenuate them. For respiration and baseline drift, they are projections 1, 2, and 5. Since the effects from both respiration and drift are below the central frequency of BOLD signal, we designed a highpass filter to remove them in projections 1, 2, and 5.

After filtering, the Matlab toolbox *Spider* [1] was used to implement the reconstruction method described in [9]. We applied correlation analysis to the reconstructed data with a significance level of 1% and the Bonferroni correction. Correlation map of the original data is shown in the top image of Fig. 4 (a), with the areas corresponding to activations in the somatosensory cortex (SC) and somatosensory thalamic nuclei (STN) encircled. The middle image in Fig. 4 (a) is the correlation map of the reconstructed fMRI data without filtering the feature projections. It was found that more activated voxels were

[1] http://www.kyb.tuebingen.mpg.de/bs/people/spider



(a) (b)

Fig. 4. Correlation (a) and CS (b) maps of the original, reconstructed fMRI data without and with the proposed filtering, are shown from top to bottom. The encircled areas in the top-left image indicate the activation in the SC and STN, respectively. Correlation analysis was performed using a significance level of 1% and the Bonferroni correction. CS maps show voxels with normalized CS values (between 0 and 1) above 0.5.

detected with an increased number of mis-detections, which might be due to the incomplete reconstruction. Most mis-detections are isolated and can be easily removed by a morphological operation. The bottom image of Fig. 4 (a) shows the correlation map of the reconstructed data after filtering the feature projections. More voxels are correlated with the paradigm compared with the top and middle images of Fig. 4 (a), indicating that filtering can attenuate the baseline drift and physiological noise, and increase the sensitivity of activation detection. Table 1 lists the number of activated voxels in the SC and STN regions detected by correlation analysis. There are 10 more activated voxels in the SC and 3 more in the STN after processing the original data using the proposed method.

Table 1. The number of activated voxels (NA) in the SC and STN, and skewness, kurtosis of CS values before and after the proposed processing.

	NA		Skewness		Kurtosis	
	SC	STN	Mean	Std	Mean	Std
Before	26	6	0.518	0.27	5.19	1.11
After	36	9	0.522	0.15	4.40	0.60

CS values were also calculated and normalized between 0 and 1. Fig. 4 (b) from top to bottom shows activated voxels (with CS values above 0.5) in the original, reconstructed fMRI data without, and with the filtering of feature projections. The skewness and kurtosis of the distribution of CS values were computed before and after KPCA decomposition and filtering. The mean and standard deviation (Std) values of skewness and kurtosis are listed in Table 1. After the processing, the mean value of skewness is increased, and that of kurtosis is decreased. The Std values of both measurements are decreased. These observations are consistent with our expectation.

5. CONCLUSIONS

We presented a method using KPCA and FIR filter to attenuate baseline drift and physiological fluctuations in the fMRI data. In order to maintain the detailed anatomic structure of brain, none of the KPCs are removed, and only the projections to those components containing baseline drift and physiological noise are filtered. This approach differs from the previous discriminant analysis-based denoising methods that remove insignificant components or components corresponding to noise before the reconstruction. Experimental results show that the proposed method can increase the BOLD contrast sensitivity and consequently the detection sensitivity of activated voxels.

6. REFERENCES

[1] X. Hu, T. Le, T. Parrish, and P. Erhard, "Retrospective estimation and correction of physiological fluctuation in functional MRI," *Magn. Reson. Med.*, vol. 34, pp. 201–212, 1995.

[2] W. Backfriender, R. Baumgartner, M. Samal, E. Moser, and H. Bergmann, "Quantification of intensity variations in functional MR images using rotated principal components," *Physics in Medicine and Biology*, vol. 41, no. 8, pp. 1425–1438, 1996.

[3] M. J. McKeown, S. Makeig, G. G. Brown, T. P. Jung, S. S. Kindermann, A. J. Bell, and T. J. Sejnowski, "Analysis of fMRI data by blind separation into independent spatial components," *Human Brain Mapping*, vol. 6, pp. 160–188, 1998.

[4] P. Gruber, F. Theis, K. Stadlthanner, E. lang, A. Tom*é*, and A. Teixeira, "Denoising using local ICA and kernel-PCA," in *proc. IEEE Int. Joint Conf. on Neural Networks*, July 2004, vol. 3, pp. 2071–2076.

[5] C. Huang, M. Liou, and P. Cheng, "Baseline correction of functional MR time courses with PCA," in *proc. the 9th IEEE Int. Joint Conf. on Neural Information Processing*, Nov. 2002, vol. 1, pp. 433–435.

[6] C. Thomas, R. Harshman, and R. Menon, "Noise reduction in bold-based fMRI using component analysis," *NeuroImage*, vol. 17, pp. 1521–1537, 2002.

[7] R. Liao, J. Krolik, and M. McKeown, "An information-theoretic criterion for intrasubject alignment of fMRI time series: Motion corrected independent component analysis," *IEEE Trans. Medical Imaging*, vol. 24, no. 1, pp. 29–44, 2005.

[8] B. Sch*ö*lkopf, A. Smola, and K. M*ü*ller, "Nonlinear component analysis as a kernel eigenvalue problem," *Neural Comput.*, vol. 10, pp. 1299–1319, 1998.

[9] J. Kwok and I. Tsang, "The pre-image problem in kernel methods," *IEEE Trans. Neural Networks*, vol. 15, no. 6, pp. 1517–1525, 2004.

[10] R. Menon, C. Thomas, and J. Gati, "Investigation of BOLD contrast in fMRI using multi-shot EPI," *NMR Biomed.*, vol. 10, pp. 197–182, 1997.

[11] B. Thirion and O. Faugeras, "Dynamical component analysis of fMRI data through kernel PCA," *NeuroImage*, vol. 20, pp. 34–49, 2003.