NOISE SUPPRESSION OF FMRI TIME-SERIES IN WAVELET DOMAIN

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ABSTRACT
Because of poor signal-to-noise ratio (SNR) of the fMRI time series and confounding effects, the results of fMRI analysis are often unsatisfactory. Existence of significant noise and artifacts in fMRI time-series as well as their unknown structure, complicates the problem of activation detection in the time domain. This makes the fMRI noise suppression a challenging problem. Based on some assumptions, different parametric denoising methods such as wavelet based denoising methods have been introduced in the literature. But these assumptions may not necessarily hold for the fMRI data. To remedy this problem, using randomization analysis, we propose a novel wavelet-based denoising method for fMRI analysis. The proposed denoising method is employed to build a feature space for fMRI cluster analysis and its efficiency is shown using simulated and experimental datasets.

KEY WORDS
fMRI, fuzzy clustering, randomization, wavelets, denoising.

1. Introduction

A variety of analysis methods have been developed for detecting brain activations in fMRI [1]-[4]. However, due to poor signal-to-noise ratio (SNR) of fMRI time series and existence of significant noise and confounding effects, fMRI time series often need preprocessing. Denoising, is an important preprocessing step which is usually done via Gaussian smoothing. But smoothing changes the intensity variation of the underlying image. This suppresses, or even removes, detailed features of the original image. Wavelet-based denoising has the advantage over low-pass filtering that relevant detail information is retained, while small details, due to noise, are discarded [5]. The problem in using these denoising methods for fMRI data is that these general denoising methods are based on assumptions such as Gaussian noise, which may not necessarily hold for the fMRI data because the structure of fMRI noise in unknown and still is an open problem [6]. To remedy this problem, we introduce a non-parametric wavelet-based denoising method. Making no specific assumptions, using randomization analysis, we estimate the distribution of the wavelet coefficients under the null hypothesis (no activation) and eliminate the coefficients corresponding to noise. The efficiency of the proposed denoising method is examined in this feature space by analyzing the simulated and experimental fMRI datasets.

2. Materials

2.1 Finger Tapping fMRI Data

Functional images were acquired from 6 normal volunteers using a T_2^*-weighted gradient echo single-shot EPI sequence (TR=3 sec, TE=50 ms, FOV=250×250×100 mm^3, matrix size=64×64×20) on a 1.5 Tesla Siemens Vision MRI scanner. The subjects performed a finger to thumb opposition task. The task consisted of 4 periods of 84 seconds, where each period contained 30 seconds of left hand finger opposition, 12 seconds of rest, followed by 30 seconds of right hand finger opposition, and another 12 seconds of rest. A 3D high-resolution anatomical image volume was also acquired from each subject.

2.2 Simulated fMRI Data

For a realistic simulation of fMRI data, computer generated "activation" time-series were added to the measured time-series of a single slice from a resting state experimental fMRI data. The "activated" areas have different sizes (3, 6, 8, and 12 pixels) and different contrasts (1%, 1.5%, 2%, and 2.5%). The simulated activation time-series consisted of 252 points obtained by convolving a stimulation pattern with the hemodynamic response function (HRF) modeled by Gamma function and then adjusting its amplitude to the desired contrast.

3. Methods

Existence of significant noise and artifacts in the fMRI signal complicates the problem of activation detection in the time domain. We use a wavelet decomposition of the signal followed by a denoising procedure to decrease the influence of these interfering components. To suppress the noise effect in a non-parametric manner, we use the randomization analysis to estimate the distribution of the wavelet coefficients under null hypothesis. This step is explained in Section 3.1. After eliminating the noisy coefficients, we combine the remaining coefficient to build the desired feature space (described in Section 3.2). Then we used the method proposed by Jahanian *et al.*[7] to find the activation map.

3.1 Noise Suppression

Assume d is an arbitrary wavelet coefficient. By comparing d of each time series with a threshold d_a, one tests the null hypothesis H_0: contains no activation and rejects H_0 if $d>d_a$. To eliminate the coefficients with a level of confidence α, a threshold d_a must be found such that $prob(d>d_a \mid H_0) = \alpha$. This requires the probability density function (pdf) $f_u(d|H_0)$, which is difficult to derive theoretically. The resampling procedure of Bullmore *et al.* [6], permutates the wavelet coefficients of the fMRI time series in order to make surrogate data under the null hypothesis. The wavelet coefficients of the fMRI time series are permutated at different levels of resolution, and then an inverse wavelet transform is applied on them to generate various realizations of the data under the null hypothesis. Wavelet transform is then applied on each set of randomized data. These wavelet coefficients construct an empirical histogram which estimates the required pdf $f_d(d|H_0)$. Using this histogram we find a set of thresholds corresponding to the desired α. Then wavelet coefficients of each time series are compared to their corresponding thresholds and those smaller than the corresponding threshold are set to zero.

3.2 Feature Extraction

To obtain the desired feature, C_i, for each time series, X_i, we combine the wavelet coefficients of each time series, DX_i, according to Eqs. (1)-(2) where DR is the wavelet coefficients of R (the reference signal computed by convolving the time pattern of the stimulation and HRF)

$$C_i = \frac{< DX_i, DR_e >}{\sqrt{< DX_i, DX_i >}} \tag{1}$$

$$DR_e = \frac{DR - Mean(DR)}{\| DR - Mean(DR) \|} \tag{2}$$

4. Results

To choose the optimal wavelet basis, we examined different wavelets on a simulated dataset with various false alarm rates. The db4 wavelet revealed the best detection accuracy among all wavelets that have been examined.

To see the effect of noise suppression procedure, we compared the wavelet feature space without noise suppression with the proposed feature space.

The results show that the proposed noise suppression method increases the detection sensitivity at high levels of confidence (see Fig. 1). We also applied these feature spaces to 6 finger-tapping fMRI datasets. We found that the proposed method for noise suppression help the proposed wavelet feature space with detecting more activated voxels in the expected regions (Supplementary Motor Area (SMA), SensoriMotor Cortex (SMC), and Cerebellum) (see Fig. 2).

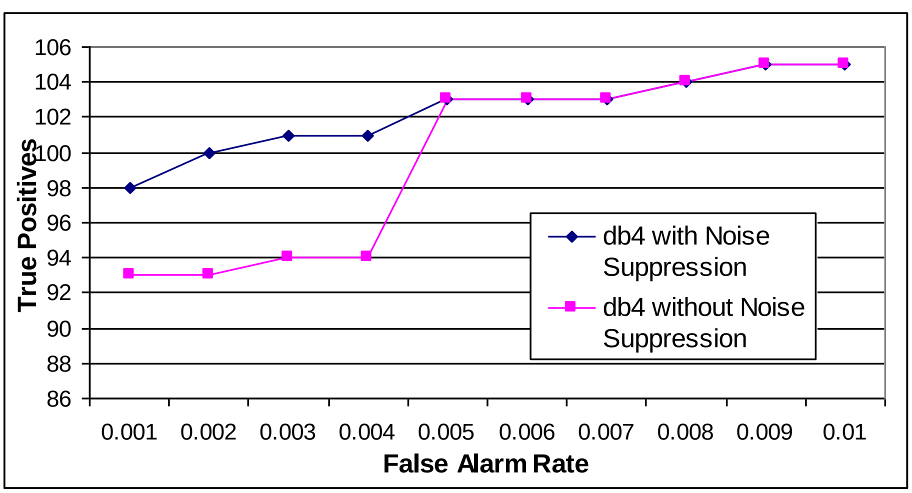

Fig. 1. Number of true positives in analyzing simulated dataset at different false alarm rates for db4 wavelet feature space with and without noise suppression.

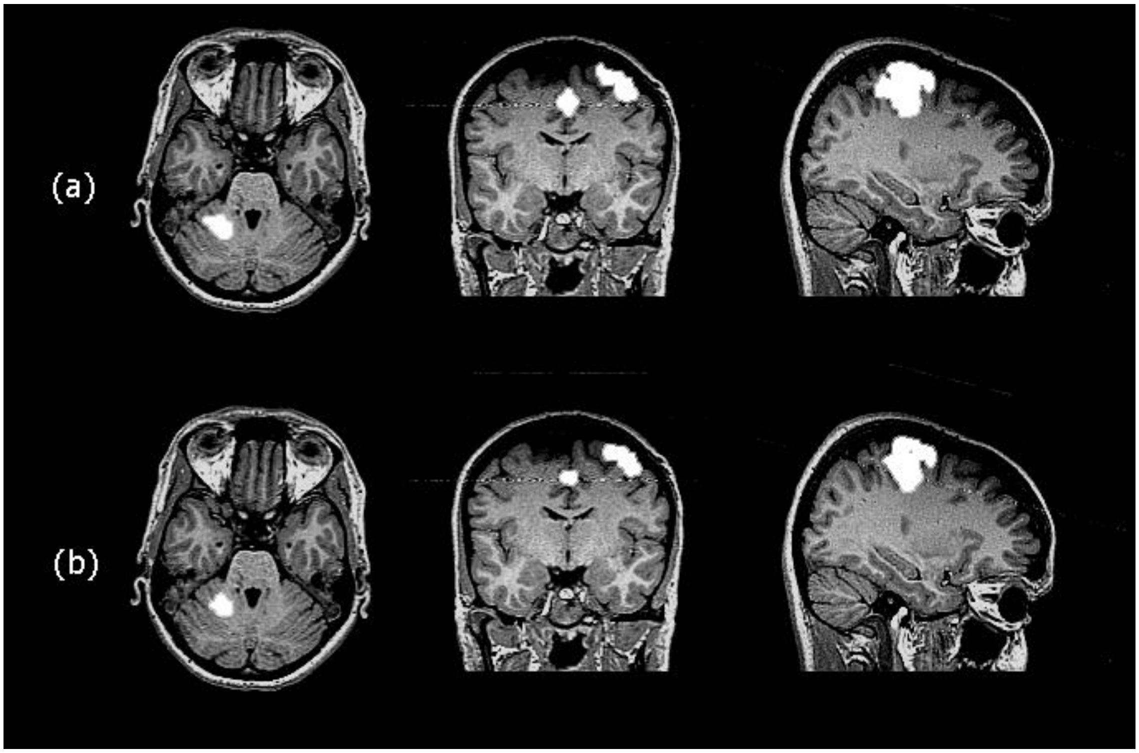

Fig. 2. Detected activation regions using (a) The proposed feature pace with noise suppression at α=0.003, (b) The proposed feature space without noise suppression.

5. Discussion and Conclusion

A novel model-free method for denoising fMRI time series is introduced and its benefit is shown using fuzzy cluster analysis of simulated and experimental fMRI datasets. The proposed method increased the detection sensitivity, especially, at low false alarm rates. This behavior is expected because sensitive detection methods usually manifest their ability at small false alarm rates. Detecting more activated voxels in the same expected regions (SMA, SMC, and Cellebrum) at the same false alarm rates when analyzing finger-tapping fMRI dataset shows superior detection sensitivity of the proposed method compared to the previous method. This reveals efficiency of the proposed method in eliminating noise and detecting activated regions in real fMRI data. This superiority stems from non-parametric estimation of the noise distribution for a particular dataset which is obtained at the expense of computational complexity of the randomization analysis.

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