An adaptive wavelet approach for joint EEG-fMRI data

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AbstractIn recent years, the combination of electroencephalography (EEG) with functional magnetic resonance imaging (fMRI) has become a hot spot in the research of cognitive neuroscience, which can provide a complement between time and space in terms of the cerebral activity research. However, as an extraordinarily feeble neurophysiological signal, the EEG data that is jointly collected in MR scanner may be very vulnerable to the magnetic-field interference, resulting in a relatively low signal to noise ratio (SNR). Therefore, the research on how to extract the EEG feature efficiently under the MR environment appears to be particularly important. In the current study, we introduced an adaptive wavelet transform approach to extract magnitude of evoked EEG signals simultaneously recorded with fMRI data. First, we selected quadratic bi-orthogonal B-Splines wavelet basis. Then we utilized a soft threshold method of unbiased risk estimate to determine the threshold of wavelet parameters. In addition, we utilized the modulus maximum to determine layer number. Simulated data was constructed by including ERP components with the real EEG signals as noise under different SNR to testify the proposed approach. The results showed that the approach yielded higher accuracy of P300 magnitude and increased SNR of EEG. Finally, the proposed approach was applied to the simultaneous EEG/fMRI data of N-back working memory task. The results showed there were significant differences of P300 magnitudes under different loads, which was in line with the previous studies. These results suggested the adaptive wavelet transform approach could extract the EEG feature efficiently.

Keywords: EEG-fMRI, wavelet, P300, soft threshold, modulus maxima

1 Introduction

In recent years, the combination of electroencephalography (EEG) with functional magnetic resonance imaging (fMRI) has become a hot spot in the research of cognitive neuroscience, which can provide a complement between time and space in terms of the cerebral activity research. However, as an extraordinarily feeble neurophysiological signal, the EEG data that is jointly collected in MR scanner may be very vulnerable to the magnetic-field interference, resulting in a relatively low signal to noise ratio (SNR). Therefore, the research on how to extract the EEG feature efficiently under the MR environment appears to be particularly important.

The amplitude of event related potentials (ERP) is a kind of EEG feature induced by similar repetitive stimulation under specific cognitive tasks, which has time-locked to experimental stimulation with relatively stable waveform. However, under the influence of noise of gradient magnetic field and ECG interference in nuclear magnetic (NM) environment, the waveform of a single trial ERP is seriously disturbed, thus increasing the difficulty of extracting the amplitude of the single trial ERP. There are already several methods of extracting ERP amplitude under the NM environment, such as average superposition [1] and Independent Component Analysis (ICA) [2], etc. However, all the EEG data of these methods need to be collected completely and analyzed off-line, which could not satisfy the demand of extracting the single trial ERP feature. In previous studies, the wavelet transform has been applied on extracting ERP features including under the NM environment. Quian Quiroga et al. choose the quadratic bi-orthogonal B-Splines wavelet basis to extract P300 feature [3]. However, the layer number and de-noising threshold of these methods are set according to experience, which are lacking of objectivity and are not dependent on the data itself.

In this paper, we introduced an adaptive wavelet transform approach to extract magnitude of evoked EEG signals simultaneously recorded with fMRI data by selecting a wavelet basis, threshold and layer number respectively. First, we selected quadratic bi-orthogonal B-Splines wavelet basis due to their similarity with the event-related potentials (ERPs), thus having a good localization of the ERPs in the wavelet domain. Then we utilized a soft threshold method of unbiased risk estimate to determine the threshold of wavelet parameters. In addition, considering the feature of evoked and spontaneous potential of EEG signal, we utilized the modulus maximum to determine layer number. Simulated data was constructed by including ERP components with the real EEG signals as noise under different SNR to testify the proposed approach. Finally, the proposed approach was applied to the simultaneous EEG/fMRI data of N-back working memory task.

2 Methods and Materials

Adaptive Threshold

Adaptive threshold wavelet transform is mainly achieved by selecting an appropriate threshold to truncate the wavelet coefficient, that is, the coefficient whose absolute value is smaller than the threshold value is set to zero, otherwise, it is retained or shrunk. Besides, through a threshold function mapping, the wavelet coefficient estimation is obtained and reconstructed to obtain the denoised signal finally. In this paper, we utilize the soft threshold method of unbiased risk estimate [4]. Such a method can set different thresholds according to the characteristics of varying signals. Each element in the signal $s(i)$ is taken the absolute value, sorted by ascending counts and then squared. Therefore, we obtain a new signal sequence, as is shown in formula (1):

$$\boldsymbol{f}(\boldsymbol{k}) = (\boldsymbol{sort}\left|\boldsymbol{s}(\boldsymbol{i})\right|)^2, \qquad \boldsymbol{k} = 0,1,\ldots \boldsymbol{N}-1 \tag{1}$$

The risk generated by threshold is as follows:

$$\boldsymbol{Risk}(\boldsymbol{k}) = \left[\boldsymbol{N} - 2\boldsymbol{k} + \sum_{\boldsymbol{j}-1}^{\boldsymbol{k}} \boldsymbol{f}(\boldsymbol{j}) + (\boldsymbol{N}-\boldsymbol{k})\boldsymbol{f}(\boldsymbol{N}-\boldsymbol{k})\right] / \boldsymbol{N} \tag{2}$$

Where, the minimum risk point corresponds to the value of $k_{\min}$, the threshold is as follows:

$$\lambda_{\boldsymbol{k}} = \sqrt{\boldsymbol{f}(\boldsymbol{k}_{\min})} \tag{3}$$

Adaptive Layer Number

EEG signal is basically consists of spontaneous and evoked EEG. The spontaneous potential is the electrophysiological activity generated under the resting state, which has the characteristics of continuity and rhythm, thus can be seen as white noise. As well as the evoked potential is the electrophysiological activity generated by subjects in response to external stimulation, which has the characteristic of time-locking. Considering that the maxima modulus of signal and noise have different performance in the wavelet domain [5], in this paper, we utilize the method of maxima modulus to determine the wavelet decomposition layer number.

Supposing that $s(t) \in L^2(R)$, and $s(t)$ has the Lipschitz exponent of $\alpha \le n$ ($n \in Z^+$) is the order of wavelet basis. Therefore, there exists the constant A satisfying the formula as follows:

$$\left|\boldsymbol{WT}_{\boldsymbol{s}}(\boldsymbol{a},\boldsymbol{b})\right| \le \boldsymbol{A}\boldsymbol{a}^{\alpha+0.5}\left(1 + \left|\frac{\boldsymbol{t}-\boldsymbol{t}_0}{\boldsymbol{a}}\right|^{\boldsymbol{a}}\right) \tag{4}$$

Where, $|WT_s(a,t)|$ is defined as wavelet module of signal $s(t)$. If it meets the following requirement:

$$\frac{\partial \boldsymbol{WT}_{\boldsymbol{s}}(\boldsymbol{a}_0,\boldsymbol{t}_0)}{\partial \boldsymbol{t}} = 0 \tag{5}$$

(a_0,t_0) will be local extrema point of $WT_s(a,t)$. When t belongs to the left or right neighborhood of t_0, there will always be $|WT_s(a_0,t)| < |WT_s(a_0,t_0)|$, (a_0,t_0) becomes the modulus maxima point of $WT_s(a,t)$ and the $WT_s(a_0,t_0)$ is the corresponding modulus maxima.

In terms of the signal, the Lipschitz exponent is generally greater than zero, while the noise's is less than zero, the characteristics of the signal and noise are opposite at different scales of wavelet transform. With the decomposition level increasing, the amplitude of modulus maxima of noise decreases, while the signal increases [5]. Firstly, we decompose the mixed signal into n layers and obtain n+1 wavelet spaces (D_1, D_2, D_3, ..., D_n, A_n), where D_n is the n-layer of detail coefficient and A_n is the n-layer approximate coefficient. Reserving A_n and utilizing D_n to reconstruct the signal, we obtain the new signal. If the modulus maxima of such new signal satisfies following formula:

$$\|\boldsymbol{wpeak}(1)\|_2 \leq \|\boldsymbol{wpeak}(2)\|_2 \leq \ldots \leq \|\boldsymbol{wpeak}(\boldsymbol{j})\|_2 \qquad (6)$$

The decomposition layer number is n-1, otherwise, continuing to decompose until the modulus maxima of the signal satisfies the formula (4), where *wpeak* is the modulus maxima sequence.

Construction of simulated data

The simulated data constructed by including the components of P100, P200, N200 and P300, whose peak amplitudes were 0.5, 0.6, -0.8 and 1 respectively with latency of 100, 200, 200 and randomly from 250-450 ms. The noise was the real spontaneous EEG data chosen from the non-simulated response signal after removing gradient and ballistocardiogram artifacts. The selected SNR was totally four grades of 0.9, 1.0, 1.1 and 1.2, and each of them was constructed 100 trails.

Joint EEG-fMRI data

Thirteen healthy right-handed subjects took part in the experiment. Brain images were acquired with a 3T Siemens scanner at the MRI Center of Beijing Normal University using a standard echo-planar image sequence (EPI, TR=2s, TE = 30ms, matrix = 64×64, In-plane resolution = 3.12×3.13mm^2, slice = 33, slice thickness = 3.5mm, slice gap = 0.6mm, flip angle = 90°). Simultaneous EEG data was recorded at 5-kHz sampling frequency with a 64-channel MR-compatible amplifier (Brain Product) referenced to FCz.

A classical digital N-back paradigm using event-related design was adopted in this study. The whole experimental procedure consisted of six runs of which the digital 1-back run and the digital 3-back run were arranged in an interleaved manner. During each run, 90 figures ranging from 0 to 9 were presented in a pseudo-randomized order with a random inter-stimulus interval (ISI) of 4s or 6s. In the 1-back run, subjects were required to make a quick key-press with right index finger if the number they saw was identical to the previous one or press the key with right middle finger if not. In the 3-back run, the subjects were required to judge whether the current number was the same as the third one backward and response in the same way as in the 1-back run. Subjects were instructed to rest for 5 to 10 minutes after each run.

3 Results

Simulations

The adaptive wavelet transform approach was applied to the simulated data, focusing on the signal's mean square error (MSE) and P300 amplitude error. The standard ERP was the constructed ERP without any noise. The MSE was calculated by comparing the standard ERP with the simulated data before or after wavelet analysis (Figure 1). The results showed that the proposed approach significantly reduced the MSE (paired *t*-test, $p<0.05$) as well as the P300 magnitude error ($p<0.05$), suggesting that the proposed approach of combining the adaptive thresholding and layer number can efficiently extract ERP amplitudes under lower SNR.

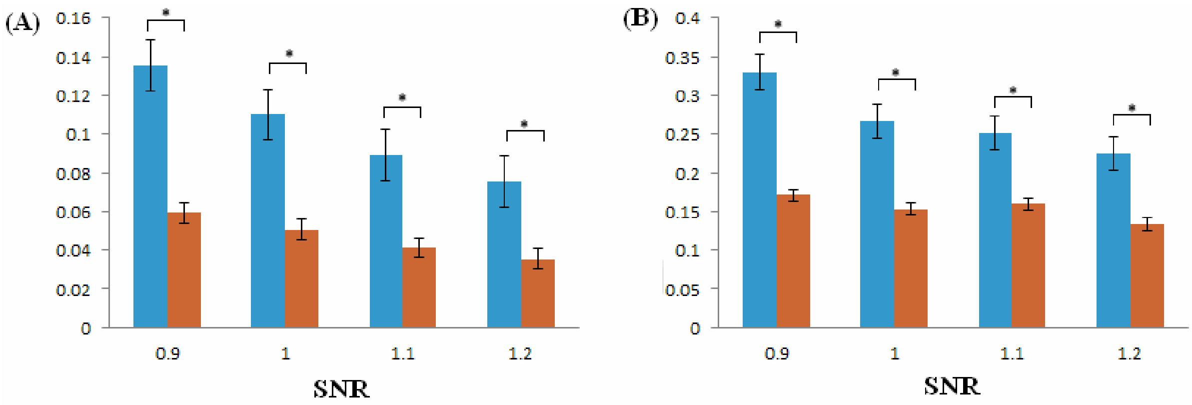

Figure 1. The adaptive wavelet transform of simulated data. (A) The MSE of signal. (B) The P300 magnitude error. Blue bar: before wavelet analysis, red bar: after wavelet analysis.

Real data

After preprocessing of gradient artifact correction, bardioballistic artifacts correction, segmentation and baseline correction to EEG data, we applied the proposed wavelet approach to the preprocessed EEG data and then made average across trials to obtain the average ERP (Figure 2). The results showed that both 1-back and 3-back tasks evoked a relatively obvious P300 component which lasted from 250ms to 450 ms post stimulus and maximized at the P4 electrode. The statistical analysis indicated that with the increasing of the task load, the P300 amplitudes decreased correspondingly, which was in line with the previous studies.

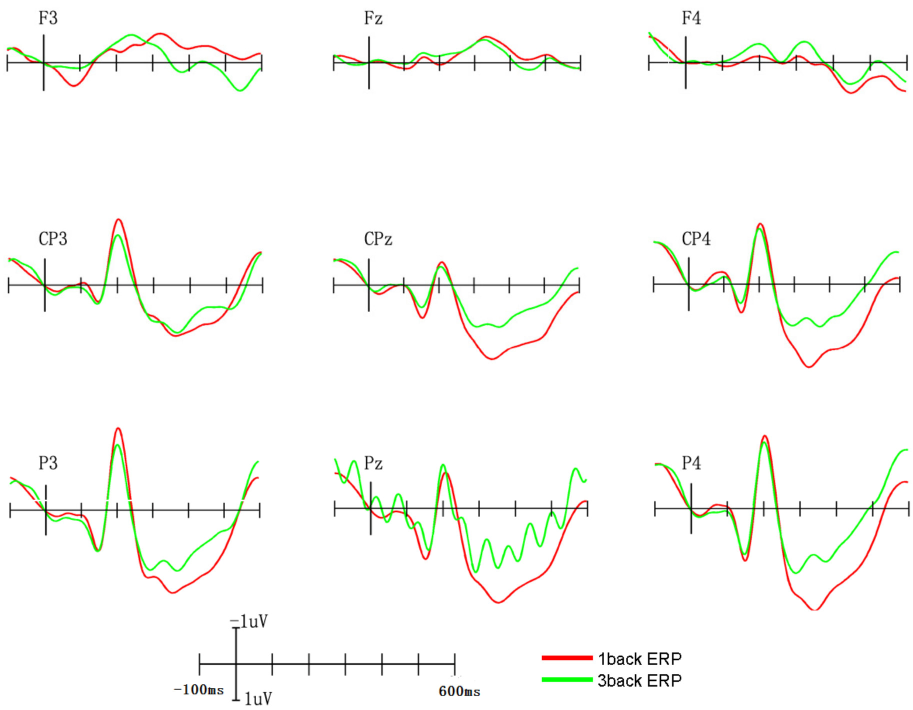

Figure 2. Grand average ERPs at representative electrodes under different loads. Significant decreasesof the mean P300 amplitudesin a 80ms window after the peak were found in3-back condition thanthat in1-back condition(p=0.047).

4 Conclusion

In this paper, we introduced an adaptive wavelet approach in joint EEG-fMRI data to get amplitude of ERP component. The results demonstrated that the approach yielded higher accuracy of P300 magnitude in simulated data and yielded significant differences of P300 magnitudes under different loads, which was in line with the previous studies. These results suggested the adaptive wavelet transform approach could extract the EEG feature efficiently.

Acknowledgments

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