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Depression discrimination using fMRI and DTI data by wavelet based fusion scheme

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Abstract: Both functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) can provide different information of the human brain, so using the wavelet transform method can achieve a fusion of these two types of image data and can effectively improve the depression recognition accuracy. Multi-resolution wavelet decomposition is used to transform each type of images to the frequency domain in order to obtain the frequency components of the images. To each subject, decomposition components of two images are then added up separately according to their frequencies. The inverse discrete wavelet transform is used to reconstruct the fused images. After that, principal component analysis (PCA) is applied to reduce the dimension and obtain the features of the fusion data before classification. Based on the features of the fused images, an accuracy rate of 80.95% for depression recognition is achieved using a leave-one-out cross-validation test. It can be concluded that this wavelet fusion scheme has the ability to improve the current diagnosis of depression.

Key words: classification; functional magnetic resonance imaging (fMRI); diffusion tensor imaging (DTI); medical image fusion; depression

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Depression is one of the most commonly diagnosed mental diseases currently. During recent years, medical imaging techniques have developed greatly, and thus have been widely used in clinical diagnosis of mental diseases. At the same time, there are still not any effective methods that can combine two or more different types of medical images together for depression reorganization. Given the limitation of using image information, more measures that can effectively join different images together are strongly required.

Structural and functional MRI has been widely applied to recognize some mental diseases. Event-related fMRI paradigm was used to classify depression subjects and healthy controls by Fu et al[1]. Structural MRI data were used in autistic spectrum disorder by Ecker et al[2]. In Ref. [3], DTI features were employed to achieve accurate identification of MCI patients. There are also methods using different types of imaging data in one research. In Ref. [4], bipolar disorder and schizophrenia were clarified by combining fMRI and fractional anisotropy (FA) data. In Refs. [5 – 6], electroencephalography (EEG) and fMRI data were combined together.

We try to apply the wavelet method to fuse two different types of imaging data together. The wavelet frame forms new images that contain information of two images. As there will be more information that describe the state of the brain in one image after the fusion, we expect that there will be a sharp discrimination between depression subjects and healthy controls with our method.

1 Material

Eleven patients were recruited from in-patient facilities. Eligibility screening procedures included structured clinical interview for the DSM-Ⅳ (SCID), 24-item HDRS and common clinical laboratory tests. Patients with other psychiatric illness and a history of electroconvulsive therapy were excluded. Ten healthy comparison subjects, matched by gender, age, education level and no history of any psychiatric disorder, were recruited. The study was approved by the Research Ethics Review Board. Imaging data were acquired using a GE Signa 1. 5 T MRI scanner. Sad and neural emotional faces were made by young students from the Academy of Art of Nanjing University of the Arts. When scanned, the subjects were asked to identify whether the stimuli were sad or not.

Diffusion-weighted images of each participant were acquired axially parallel to the anterior and posterior commissures (AC-PC) line with twenty-five-direction diffusion-weighted whole-brain volumes using diffusion weighting values. b is equal to 0 and 1 000 s/mm^2; the flip angle is 90°; the repetition time is 1 000 ms and the echo time is 81. 2 ms. The imaging matrix is 128 × 128 with a rectangular FOV of 240 mm × 240 mm.

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2 Method

2.1 Data preprocessing

Data are analyzed using the statistical parametric mapping (SPM2) software. Images are realigned, spatially normalized, and smoothed with a Gaussian kernel of 6 mm full width at a half maximum. The BOLD response is modeled by an event-related wave convolved with the canonical hemodynamic response function (HRF) and its temporal derivative. High and low pass filters (session cutoff period 78 s and the HRF, respectively) are applied to the BOLD response data.

DTI data are preprocessed using the DTI toolbox of DtiStudio. After correcting for susceptibility artifacts, from the 12 gradient directions and the unweighted scan, we estimate the diffusion tensor to extract eigenvalues and eigenvectors in order to determine fractional anisotropy (FA) maps.

2.2 Wavelet transform

We apply wavelet transform[7-8] to carry out the fusion. To guarantee that its wavelet transform is stably invertible, the mother wavelet must meet several conditions shown as below:

$$\int |\psi(x)|^2 \mathrm{d}x = 0 \tag{1}$$

$$\int |\psi(x)| \mathrm{d}x < \infty \tag{2}$$

$$\int \psi(x) \mathrm{d}x = 0 \tag{3}$$

A daughter wavelet $\psi_{a,b}(x)$ is defined as

$$\psi_{a,b}(x) = a^{-1/2}\psi\left(\frac{x-b}{a}\right) \tag{4}$$

where a, $b \in \mathbf{R}$ and $a \neq 0$; a is called the scaling or dilation factor and b is called the translation factor.

In discrete wavelet transforms, a scaling function is required to cover the low frequencies. In mathematical terms, $\varphi(x)$ is chosen so that the set $\{\varphi(x-k),\ k \in \mathbf{Z}\}$ forms an orthonormal basis for the reference space V_0. Since the father wavelet is in V_0, it can be expressed as linear combinations of the basis functions for V_1 and $\varphi_{1,k}(x)$.

$$\phi(x) = \sum_k l_k \varphi_{l,k}(x) \tag{5}$$

$$\Psi(x) = \sum_k h_k \varphi_{l,k}(x) \tag{6}$$

Wavelet transforms provide a framework in which a signal is decomposed, with each level corresponding to a coarser resolution, or lower frequency band.

For a particular dilation a and translation b, the wavelet coefficient $W_f(a, b)$ for a signal f can be calculated as

$$W_f(a, b) = \langle f, \psi_{a,b} \rangle = \int f(x)\psi_{a,b}(x)\,\mathrm{d}x \tag{7}$$

The original signal can be reconstructed by applying the inverse transform:

$$f(x) = \frac{1}{C_{\mathrm{w}}}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} W_f(a, b)\psi_{a,b}(x)\,\mathrm{d}b\,\frac{\mathrm{d}a}{a^2} \tag{8}$$

where C_{w} is the normalization factor of the mother wavelet.

Because the signal and the wavelet function must have closed forms, which makes it difficult or impractical to apply, we use a discrete wavelet here.

Discrete transforms are more widely used. At a given scale J, a finite number of translations are used in applying multi-resolution analysis to obtain a finite number of scaling and wavelet coefficients. The signal can be represented in terms of these coefficients as

$$f(x) = \sum_k c_{Jk}\phi_{Jk}(x) + \sum_{j=1}^{J}\sum_k d_{jk}\psi_{jk}(x) \tag{9}$$

At each level of decomposition, the signal is split into high frequency and low frequency components. The low frequency components can be further decomposed until the desired resolution is reached.

As we know, if we can introduce separable 2-D scaling and wavelet functions as the tensor products of their 1-D complements, then the 1-D multi-resolution wavelet decomposition will be extended to two dimensions successfully.

The 2-D wavelet analysis operation consists of filtering and down-sampling horizontally using the 1-D low pass filter and high pass filter on each row in the image. Four images at the lower resolution are produced, one approximation image and three wavelet detailed images.

2.3 Fusion scheme

The aim of image fusion is to obtain a single image that coveres most of useful information of the fused images. In general, the problem that image fusion tries to solve is to combine information from several images taken from the same subject in order to achieve a new fused image, which contains the best information coming from the original images. Hence, the fused image covers more information of one subject than any of the original images.

In this research, we use event-related data and FA as input images. Fig. 1 shows how our fusion frame works.

In the fusion step, each type of data of one subject is transformed to four features with different frequencies. Then the low frequency features of the fMRI image and the DTI image are added together. And so are the high frequency features. After that, the added-up images of four features are transformed back to time domain to form new images.

After image fusion with the proposed method, we apply PCA (principal component analysis) to reduce the dimension of the data. PCA attempts to find linear combinations of the original features that explain most of the variances in these features using just a few components, which is exactly suitable for our fused image data. And this method has been proved effective in neuroimaging dimension reduction[1, 9-10].

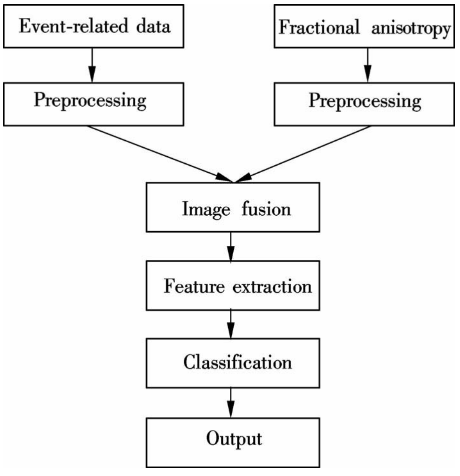

Fig. 1 Fusion scheme

3 Results

There are 21 subjects totally in our experiment, comprised of 10 depression patients and 11 healthy controls. We evaluate the performance of the classifier using a leave-one-out cross-validation test.

We also employ each type of image data to classify subjects respectively in order to make comparisons with our fusion results. As summarized in Tab. 1, the performances of the classifier are not satisfying when only one type of the data is used. And when the fused data are used, the discriminative performance is enhanced with a generalization rate of 80. 95%.

Tab. 1 Classification performance using FDA and LDA based on three types of features %

Classification feature	Classifier	Sensitivity	Specificity	Generalization rate
Event-related data	FDA	54. 55	60	57. 14
	LDA	72. 73	30	52. 53
Fractional anisotropy	FDA	45. 45	60	52. 38
	LDA	81. 82	60	71. 43
Event-related data + fractional anisotropy	FDA	72. 73	90	80. 95
	LDA	90. 91	60	76. 19

Besides, a linear discrimination analysis (LDA) classifier is also employed for a comparison with the Fisher discrimination analysis (FDA) classifier which is widely used in the related field. The LDA performs better than the FDA in classifying the depression patients. And for the healthy controls, the FDA is better. With FA data, the LDA has a generally better performance than the FDA. When using fused data, we obtain a better performance in classifying depression people with the LDA and in classifying healthy controls with the FDA.

4 Conclusion

At present, depression is mainly diagnosed by clinical doctors according to signs and symptoms. We develop a method which tends to determine whether a subject is depressive or not by using both fMRI data and DTI data. In our research, the two types of images are joined together in our fusion frame to form new images. The classification performance of the fused data is obviously better than those using individual types of data. We find that the LDA does a better job in classifying patients than the FDA, and in classifying healthy people, the FDA works better. In other words, the FDA has a more stable performance than the LDA. Generally speaking, we successfully achieve a significant way to decide whether one is a depression patient or not.

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基于 fMRI 和 DTI 小波融合信号的抑郁症识别

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摘要:功能核磁共振和弥散张量这 2 种成像方式能够反应人类大脑不同方面的信息,采用小波变换的方法来对这 2 种医学图像进行融合可以有效改善抑郁症的识别准确率. 首先,利用多尺度小波分解方法把每种类型的图像都转换到频域,以得到各频率的成分参数. 其次,对于每个被试,将 2 种图像的分解参数根据频率各自相加,并且通过小波逆变换重建出融合图像. 然后,使用主成分分析方法对融合的数据进行降维并得到图像特征. 基于融合后图像的特征,采用留一检验方法最终得到了 80.95% 的抑郁症识别率. 可以看出,该小波融合方法能够对当前抑郁症的诊断识别进行有效的改进.

关键词:分类;功能核磁共振成像;弥散张量成像;医学图像融合;抑郁症

中图分类号:Q64; TP310.4