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P300 Detection Algorithm Based on Fisher Distance

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Abstract: **With the aim to improve the divisibility of the features extracted by wavelet transformation in P300 detection, we researched the P300 frequency domain of event related potentials and the influence of mother wavelet selection towards the divisibility of extracted features, and then a novel P300 feature extraction method based on wavelet transform and Fisher distance. This can select features dynamically for a particular subject and thereby overcome the drawbacks of no systematic feature selection method during traditional P300 feature extraction based on wavelet transform. In this paper, both the BCI Competition 2003 and the BCI Competition 2005 data sets of P300 were used for validation, the experiment results showed that the proposed method can increase the divisibility by 121.8% of the features extracted by wavelet transformation, and the classification results showed that the proposed method can increase the classification accuracy by 1.2% while reduce 73.5% of the classification time. At the same time, integration of multi-domain algorithm is proposed based on the research of EEG feature extraction algorithm, and can be utilized in EEG preprocessing and feature extraction, even classification.**

Index Terms—BCI; wavelet transform; P300; Fisher distance; Feature extraction

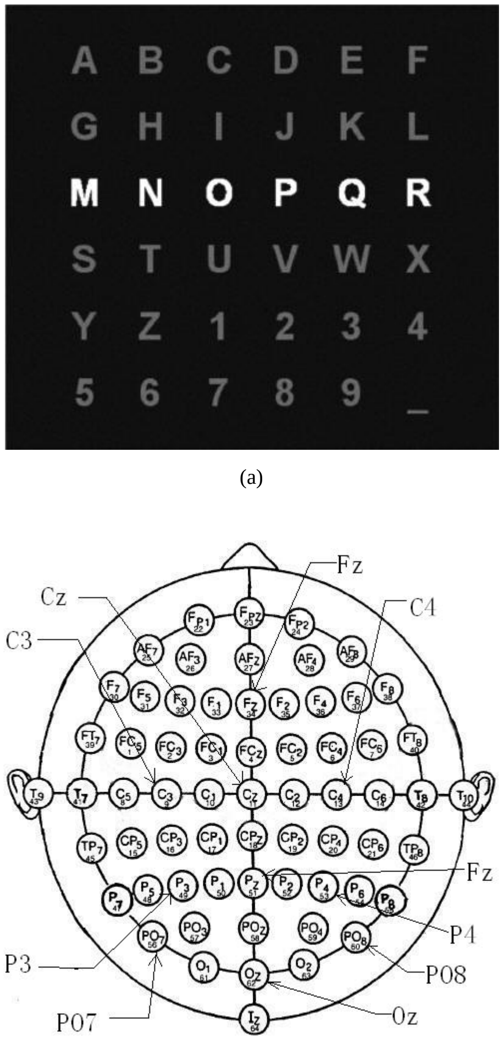
INTRODUCTION

A brain-computer interface (BCI) is a device that uses brain signals to provide a non-muscular communication channel between human beings and computers, or peripheral electronic equipment[1]. The original propose of BCI is to provide individuals with severe neuromuscular disabilities a new communication tool[2]. At present, a great many kinds of EEG(electroencephalography) signals are utilized successfully in the field of BCI, such as motor imagery brain signals and P300[3-4]. Among these different kinds of EEG signals, P300 is drawing more and more attentions of the researchers because of its excellent characteristics, such as needless types of training[5].

The P300 is a psycho-physiological correlates of neuro-cognitive functioning that reflect the response of the brain to events in the external or internal environment of the organism, which is classified as event related potentials of the brain, and it is named so due to the positive deflection of the EEG at the central electrodes around 300ms post stimulus[6].

Recently, researchers have proposed lots of feature extraction algorithms in order to extract the characteristics precisely, such as wavelet transform[7], independent component analysis[8] and adaptive filtering[9]. Wavelet transform has been proved to be perfect for processing non-stationary random signals like EEG due to its multi-resolution[10]. Traditionally, EEG signals are decomposed by wavelet, and then the time-frequency features between 0 Hz and 30 Hz are extracted and classified simply, such as literature[11]. These similar algorithms are fast, but cause low divisibility of the extracted features, and much more powerful classifier like support vector machines (SVM) should be used in order to get satisfied classification accuracy [11].

With the aim to improve the divisibility of the features extracted by wavelet transformation in P300 detection, we research the P300 frequency domain of event related potentials, and then integration of multi-domain algorithm are proposed in this paper, which can describe EEG from different aspects in order to avoid the drawbacks brought by unilateral features. Although describing EEG from different facets will increase the running time of BCI, integration of multi-domain algorithm will perform better in EEG classification if a tradeoff can be found between system running time and classification accuracy. Then based on integration of multi-domain, a new P300 feature extraction method, based on wavelet transformation, and Fisher distance is proposed, which overcomes the drawbacks of no systematic feature selection method during traditional P300 feature extraction based on wavelet transform. We also research the influence of mother wavelet selection towards the divisibility of extracted features, and then we take the feature extraction algorithm in literature [11] for comparison due to the deficiency of literatures related to P300 feature extraction by wavelet transform directly. Then we improve the P300 detection algorithm of literature [11] through proper electrode selection and more reasonable wavelet decomposition layer.



(a)

(b)

Fig.1 Experimental set-up. (a) Example of a 6 × 6 user display in P300 Speller.; (b) Channel location and assignment numbers used for EEG acquisition

1. Experiment design and data source

The datasets we used are from P300 Speller Paradigm supplied by BCI Competition II Data set IIb and BCI Competition III data set II. The P300 Speller was proposed by Farwel and Donchin in 1988, which was based on add-ball experiment paradigm, refer to Fig.1 [12].

A 6×6 matrix that includes all the alphabet letters as well as other useful symbols which are presented to the user on a computer screen, refer to Fig. 1(a). The rows and columns of the matrix are intensified successively in randomly. At any given moment, the user selects one of the letters or symbols that he wishes to communicate, and maintain a mental count of the number of times the row and the column of the chosen symbol are intensified. In response to this mental counting, a potential is elicited in the brain. This procedure is called one trail, which is repeated 15 times for each selected letter or symbol. The EEG signal is acquired from 64 electrodes, whose locations are showed in Fig.1(b), and the sampling rate is 240Hz. Related literatures demonstrate that electrode Fz, Cz, Pz, Oz, C3, C4, P3, P4, PO7 and PO8 have much more influences to P300 detection[13-14], so we choose the data from this 10 electrodes in our experiment, and extract 600ms' data after 12 rows/columns being intensified for each trail. In this case, one selected letter or symbol has 12×15 groups EEG data, each group has 144 samples, and 2×15 groups contain P300, 10×15 do not[6,12].

2. Feature extraction and divisibility judging

In order to make the experiment results more reasonable, two classes of EEG signals should be balanced before feature extraction. We randomly choose 1000 groups of EEG signals with P300, and 1000 groups without, and name them target dataset and non-target dataset respectively. The following procedures are based on these two datasets. The P300 classification experiment's procedure including the proposed P300 feature selection algorithm based on Fisher Distance and wavelet transform as described as below:

First, preprocess is deployed to the original EEG signals. Second, wavelet transform is used to decompose original EEG signals, and extract approximate coefficients as features. Third, we use Fisher distance to analyze the divisibility of the extracted features in order to select optimal features, and this method can replace the traditional methods that select optimal features through the final classification accuracy. At last, neural network is utilized as the classifier to classify the selected features. The features from the same electrode are treated as one feature vector to calculate the Fisher Distance in this paper, so feature selection is equal to the electrode selection here, but the combination of features is not limited to one electrode when using the proposed algorithm in practice. In this case, the proposed algorithm selects features, not electrodes.

2.1 Wavelet transform

Wavelet transformation is potentially one of the most powerful signal processing techniques, because of its ability to adjust to signal components and its multi-resolution. Wavelet transformations can provide a low time resolution and a high frequency resolution in low frequency band while provide a high time resolution and a low frequency resolution in high frequency band. It provides a time-frequency decomposition that is proved to be very suitable for non-stationary random signals analysis, so it is broadly used to analyze EEG signals in recent years[13] .

The wavelet transform and inverse wavelet transform are defined below[13]:

$$d_{j,k}=2^{-j/2}\sum_{n=-\infty}^{\infty}f(x)\bar{\phi}(2^{-j}x-k),\ j,k\in Z \qquad (1)$$

$$f(x)=\sum_{j=-\infty}^{\infty}\sum_{k=\infty}^{\infty}d_{j,k}\phi_{j,k}(x),\ j,k\in Z \qquad (2)$$

In eq.(1)(2), f(x) is the EEG signal, and $d_{j,k}$ is the wavelet coefficient，and $\phi_{j,k}(x)=2^{-j/2}\phi(2^{-j}x-k)$ is the mother wavelet. Integer j and k means decomposition scale and time shifts respectively. Mallat algorithm is usually applied to calculate the coefficients of wavelet transform in practice[14], which decomposes the original signal into two parts that is called appropriate coefficient and detail coefficient respectively, and then continue to decompose the low frequency part till obtaining the target frequency band.

For example, S means a signal, and then the whole Mallat algorithm is finished within $\log_2 N$ steps, refer to Fig.2[14].

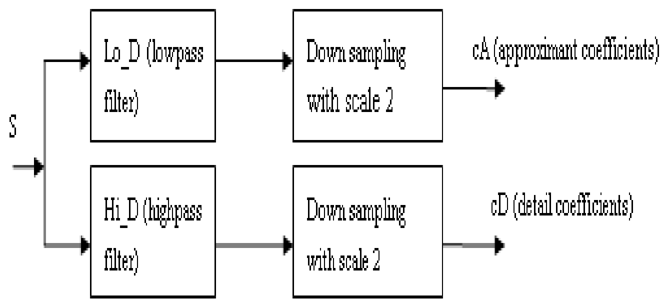


Fig. 2 one-step of the Mallat algorithm

If *f* is the sampling rate of signal *S*, then *cA* and *cD* represent S's characteristic within band *0* to f/(2x2), and band f/(2x2) to 2/f respectively. Mallat is to repeat the step in Fig.2 until the satisfied resolution, which results multi-resolution of wavelet transform.

2.2 Fisher distance

Fisher distance is an efficient criterion of divisibility between two classes, which is broadly used in pattern recognition, and it computes the ratio of between-class scatter degree and within-class scatter degree between two classes. Larger ratio means larger divisibility of the two classes. So Fisher distance can be used as the criterion to choose optimal features. Fisher distance is defined as below[15]:

$$FisherDis = \frac{S_B}{S_W} \qquad (3)$$

In eq.(3), S_B and S_W represents between-class matrix and within-class matrix respectively. Assume we have n samples, $x_1,...,x_n$, divided into c classes, then between-class matrix and within-class matrix are defined as below:

$$S_B = \sum_{i=1}^{c} n_i (m_i - m)(m_i - m)^T \qquad (4)$$

$$m = \frac{1}{n}\sum_{k=1}^{n} x_k \qquad (5)$$

$$m_i = \frac{1}{n_i}\sum_{i=1}^{n_i} x_i \qquad (6)$$

$$S_W = \sum_{i=1}^{c} S_i \qquad (7)$$

$$S_i = \sum_{j=1}^{n_i} (x_j - m_i)(x_j - m_i)^T \qquad (8)$$

Among eq.(4) to eq.(8), m means the average value of all the samples, m_i, n_i and S_i represents the average value , sample number and within-class matrix of class i respectively.

Based on the above excellent characteristics of Fisher distance, it is chosen in this paper to be the criterion of feature divisibility.

3. Experiment procedures and results analysis

Firstly, we extract the data from the 10 electrodes mentioned in section 1 from dataset target and non-target, and in order to compare with literature [11], we also choose haar[11] as mother wavelet, and then decompose the EEG signals from each electrode into layer 3 to layer 6, and extract the approximate coefficients as features after decomposition. After that, we compute the Fisher distance of EEG signals with P300 and EEG signals without P300 from each electrode, the results are showed in Table 1. In Table 1, “Total” column means the Fisher distance of the combination of the features from all 10 electrodes mentioned in section 1.

Literature [11] used 3 layer wavelet transformations, and extracted approximate coefficients as the features. From Table 1, we can see that the feature divisibility increases after the decomposition layer of wavelet is increased to 4 and 5. The definition of wavelet transform in section 2 shows that the number of the extracted features will decrease as the decomposition layer increases, and the number of features is a key factor to the running time of classification system, so reducing the feature number will definitely speed up the classification system, and contribute to the online request of BCI.

The EEG sampling rate is 240Hz refer to section 1, then the corresponding band of approximate coefficients from different wavelet decomposition layer is computed according to the definition of wavelet transform, as showed in Table 2.

Some existing literatures demonstrate that P300 appears between 0 Hz to 10 Hz, even a lower band[16]. Table 1 and Table 2 demonstrate that feature divisibility is largest between 0 Hz to 7.5 Hz as approximate coefficients being chosen to be the features, and feature divisibility declines when the feature band decreases, so the phenomenon of P300 is the most obvious in band 0-7.5Hz. The two tables also show that choosing the appropriate frequency band can improve the divisibility of the extracted features.

The common method to select EEG signal features is to put the candidates into classifier, and select the optimal features according to the final classification accuracy. In this paper, we propose a feature selection

TABLE 1 THE FISHER DISTANCE OF TWO KINDS OF EEG SIGNALS UNDER DIFFERENT LAYERS

Elec / layer	Fz	Cz	Pz	Oz	C3	C4	P3	P4	PO7	PO8	Total
3	0.0156	0.0171	0.0098	0.0025	0.0162	0.0134	0.0070	0.0037	0.0073	0.0096	0.0101
4	0.0185	0.0195	0.0114	0.0027	0.0200	0.0156	0.0081	0.0041	0.0083	0.0102	0.0115
5	0.0200	0.0204	0.0114	0.0029	0.0224	0.0159	0.0086	0.0041	0.0085	0.0114	0.0117
6	0.0081	0.0113	0.0091	0.0015	0.0124	0.0113	0.0080	0.0034	0.0031	0.0010	0.0066

TABLE 2 THE CORRESPONDING FREQUENCY OF APPROXIMATE COEFFICIENTS UNDER DIFFERENT WAVELET DECOMPOSITION LAYER

Wavelet decomposition layer	Band/Hz
3	0-30
4	0-15
5	0-7.5
6	0-3.75

algorithm based on wavelet transformation and Fisher distance, which provides a systematic features selection method before final classification.

Fisher distance algorithm is simple and fast, while classification has two main parts, training and testing. These will take a long time, so the designing lifecycle of EEG signal processing algorithm will be dramatically decreased and the algorithm efficiency will be improved after replacing the former feature selection criterion by Fisher distance.

The last column from Table 1 shows that feature divisibility isn’t improved when combining features from 10 electrodes as one feature vector. Although some literatures indicates that these 10 electrodes have larger influence to P300 detection, and literature [11] also extracted features from these 10 electrodes. P300 has low Signal Noise Ratio (SNR) and it is random and non-stationary, which is different from one person to another, and even to the same person[17]. So it is unreasonable to extract features only from these 10 electrodes for every subject, features should be selected from different electrodes according to different subjects, and choosing electrodes can be taken as a kind of feature selection. Based on above analysis, a feature selection method based on wavelet transformation and Fisher distance is proposed, which can solve this issue to some extent:

(1) Signals from all electrodes are decomposed by wavelet, and then extract features from all electrodes and compute their Fisher distance, and select the features from one electrode which has the biggest Fisher distance as the initial feature vector;

(2) Select features from one of the other electrodes, and then combine them with the initial feature vector and compute the Fisher distance. If the new distance is smaller than the initial one, discard this new selected electrode; if the new distance is bigger than the initial one, take this new feature vector as initial feature vector, and turn to step (2) until all the electrodes have been selected. The final “initial feature vector” is the optimal features related to specific subjects. Different optimal features will be selected related to different subjects.

Using the above proposed method to select optimal features from the 10 electrodes, and the results show that feature divisibility reaches its maximum value when only C3 is selected. The maximum value is 0.0224, which is increased by 121.8% compared with 0.0101, obtained from literature [11]. Using BP (Back Propagation)[18] neural network as classifier to classify the features extracted both by the proposed algorithm and the traditional algorithm form literature [11] respectively, and the classification accuracy and time is showed in Table 3. Whether the structure of the classifier is optimal isn't our consideration, we just care about the classification accuracy under the same classifier.

The classification results in Table 3 show that the proposed algorithm can increase the classification accuracy by 1.2% while decrease the running time of the whole EEG classification algorithm by 73.5% through reducing the number of the extracted features.

TABLE 3 THE PERFORMANCE COMPARISON BETWEEN THE PROPOSED ALGORITHM AND TRADITIONAL ALGORITHM

	The number of features	Feature extraction time/ms	Classification time/ms	Classification accuracy/%
Literature [11]	360	4.6	15.0	83.8
The proposed method	14	4.7	0.5	85.0

For now, we select haar wavelet to be the mother wavelet when decomposing the original EEG signal for comparison with literature [11], but haar wavelet is the simplest wavelet and isn't suitable to non-stationary random signals such as EEG, so after the following research of the influence caused by wavelet selection, a more proper and reasonable wavelet is selected, which can perform better during the EEG classification.

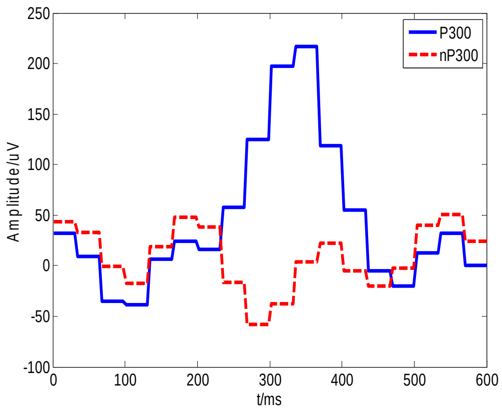
Some related literatures demonstrate that P300 is the most obvious in Cz electrode, which is located in vertex, and it is inconsistent with our results that is happened to prove that P300 is extremely unstable and different from one to another. In order to research on the influence of mother wavelet selection towards feature extraction with wavelet transform and compare the results with existing literatures, we select EEG signals from electrode Cz, which has a higher divisibility according to Table 1, from dataset target and non-target, and decompose the signals with different layer by wavelet transformation and reconstruct them with their approximate coefficients, the results are showed in Fig.3. For simple comparison, we just select EEG waves from some typical decomposing layers.

In figure 3(a), the EEG signals are reconstructed by the method in literature [11], in order to comparing, we select 3 layer and 5 layer reconstructed signals by Daubechies4[7] mother wavelet, see Fig.3(b)(c). The comparison of Fig.3(a) and Fig.3(b) demonstrates that Choosing haar as the mother wavelet to extract P300 features has some drawbacks, because the reconstructed signals are not smooth enough, and the difference between EEG signals with P300 and EEG signals without P300 is less obvious than the difference when choosing Daubechies4 as the mother wavelet. So the selection of mother wavelet is very important when deploy wavelet transform into the field of EEG feature extraction.

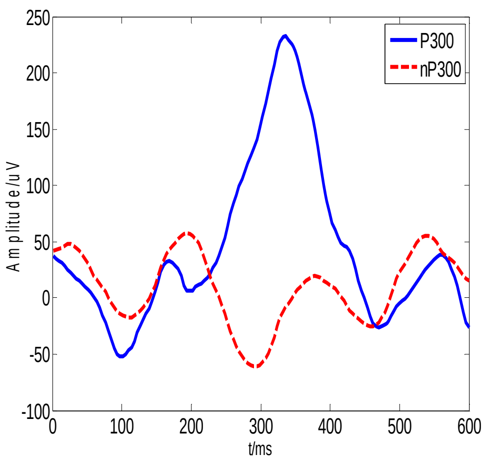
The comparison of Fig.3(b) and Fig.3(c) indicates that 5 layer wavelet decomposition has more obvious P300 phenomenon compared with 3 layer decomposition, and this result also verifies the conclusion that P300 phenomenon of band 0 -7.5Hz is the most obvious.

CONCLUSION

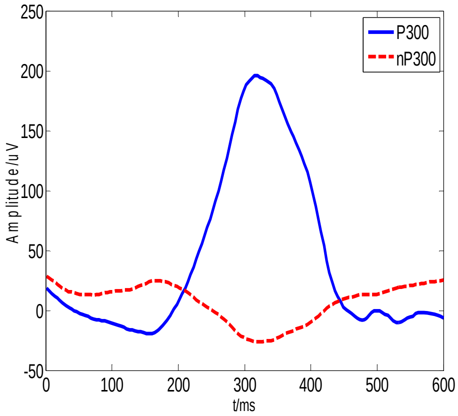
The P300 is a psycho-physiological correlates of neuro-recognitive functioning that reflect the response of the brain to changes or events in the external or internal environment of the organism. Due to its excellent characteristics, such as needless of training, P300 is drawing more and more attentions of the researchers around the world. But P300 has low Signal Noise Ratio



(a)



(b)



(c)

Fig.3 The wavelet reconstructed signal. (a)There layers wavelet reconstructed signal, haar; (b) There layers wavelet reconstructed signal,db4; (c) Five layers wavelet reconstructed signal, db4.

and it is random and non-stationary, which is different from one person to another, and even to the same person, so traditional signal processing algorithm can not extract its features precisely. Wavelet transformation is perfect for processing non-stationary random signals like EEG due to its multi-resolution, which is broadly used in the field of P300 detection. But the features extracted by wavelet transform have a low divisibility, and need to be classified before selecting proper features. It takes lots of time on training and testing of classifier, and raises the time of the whole signal processing algorithm.

In order to solve the above issues in P300 detection, we research the P300 frequency domain of event related potentials and the traditional P300 detection algorithms, and then integration of multi-domain algorithm is proposed in this paper, which can describe EEG from different aspects in order to avoid the drawbacks brought by unilateral features, but this will increase the running time of the whole P300 detection algorithm. If tradeoff can be found between system running time and classification accuracy, integration of multi-domain still can contribute to the P300 detection algorithm. So a novel P300 feature selection method based on wavelet transform and Fisher distance is proposed, which can select optimal features according to the analysis of the feature divisibility before final classification and overcome the drawbacks of no systematic feature selection method during traditional P300 feature extraction based on wavelet transformation. Firstly, the original EEG signals are decomposed by wavelet transformation, and extract wavelet coefficients from related band; secondly, Fisher distance of different electrode combinations is deployed to select optimal features; finally, the optimal features are sent to the classifier. We also research the influence of mother wavelet selection towards the divisibility of extracted features, and then we improve the P300 detection algorithm of literature [11] through proper electrode selection and wavelet decomposition layer. The experiment results show that the proposed method can increase the divisibility by 121.8% of the features extracted by wavelet transform, and also increase 1.2% of the final classification accuracy while decrease the running time of the whole P300 classification algorithm by 73.5%.

REFERENCE

[1] D.J. Krusienski, E.W. Sellers, T.M. Vaughan. Common Spatio-Temporal Patterns for the P300 Speller[A]. In: Proceedings of the 3rd international IEEE EMBS Conference on Neural Engineering[C]. Hawaii, USA. 2007. 421-424.

[2] Schalk G, Dennis J, Thilo H，*et a1*. BCl2000：A general-purpose brain-computer interface(BCI) system[J]. IEEE Transactions on Biomedical Engineering，2004，5l(6)：1034-1043.

[3] Alexander Lenhardt, Matthias Kaper, Helge J. Ritter. An Adaptive P300-Based Online Brain–Computer Interface[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2008, 16(2): 121-130.

[4] Tomonari Yamaguchi, Mitsuhiko Fujio, Katsuhiro Inoue, *et al*. Wavelet Analysis of EEG Singnals During Motor Imagery [A]. In: Proceedings of the 2008 International Conference on Wavelet Analysis and Pattern Recognition [C]. Hong Kong: 2008. 454-459.

[5] Kana Omori, Tomonari Yamaguchi, Katsuhiro Inoue. Feature Extraction from EEG Signals in P300 Spelling System[A]. In: ICROS-SICE International Joint Conference 2009[C]. Fukuoka International Congress Center, Japan. 2009. 849-852.

[6] Mathew Salvaris, Francisco Sepulveda. Wavelet and Ensemble of FLDs for P300 Classification[A]. In: Proceedings of the 4th international IEEE EMBS Conference on Neural Engineering[C]. Antalya, Turkay. 2009. 339-342.

[7] YANG Bang Hua, YAN Guo Zheng, YAN Bo. Extracting EEG Feature in Brain-computer Interface Based on Discrete Wavelet Transform [J]. Chinese Journal of Biomedical Engineering, 2006, 25(5): 518-522

[8] WU Xiao Pei, YE Zhong Fu, GUO Xiao Jing, *et al*. Dynamic Independent Component Analysis and its Application to EEG of Motor Imagination[J]. Chinese Journal of Biomedical Engineering, 2007, 26(6): 818-824.

[9] Chan F, Lam F, POoh P, *et al*. Detection of brainstem auditory evoked potential by adaptive filtering[J]. Med Biol Eng Comput, 1995, 33(2): 69-75.

[10] Seyedehmina Ayoubian Markazi, Lampros.S.Stergioulas, Anusha Ramchurn, *et al*. Wavelet Filtering of the P300 Component in Event-Related Potentials[A]. In: Proceeding of the 28th IEEE EMBS Annual International Conference[C]. New York, USA. 2006. 1719-1722.

[11] YANG Li Cai, LI Jin Liang, YAO Yu Cui, *et al*. P300 Detection Algorithm Based on Wavelet Decomposition and Support Vector Machines[J]. Chinese Journal of Biomedical Engineering, 2007,26(6): 804-809.

[12] Hilit Serby, Elad Yom-Tov, Gideon F. Inbar. An Improved P300-Based Brain-Computer Interface[J]. IEEE Trans on Neural System and Rehabilitation Engineering, 2005,13(1): 89-98.

[13] WANG Da Kui, PENG Jin Ye. Wavelet Analysis and Application in Signal Processing [M]. Beijing: Publishing House of Electronics Industry, 2006.1.

[14] DONG Chang Hong. Principle and Application of Matlab wavelet analysis toolbox[M]. Being: National Defense Industry Press, 2004.1.

[15] D. Huang, C. Xiang, S.S. Ge. Recursive Fisher Linear Discriminant for BCI Applications [A]. In: ISSNIP 2007 3rd International Conference [C]. Melbourne, Australia: 2007. 383-388.

[16] Ozair Idris Khan, Sang-Hyuk Kim, Adil Khan, *et al*. Extraction of P300 Using Constrained Independent Component Analysis[A]. In: 31st Annual International Conference of the IEEE EMBS[C]. Minnesota, USA. 2009. 4031-4034.

[17] Abeer E. Selim, Manal Abdel Wahed, Yasser M. Kadah. Machine Learning Methodologies in P300 Speller Brain-Computer Interface Systems[A]. In: 26rd National Radio Science Conference[C]. Future Univ, Egypt. 2009. 1-8.

[18] A. Bashashati, M. Fatourechi, R. K Ward, et al. A Survey of signal processing algorithms in brain-computer interfaces based on electrical brain signals [J]. J. Neural Eng, 2007, 32-57.

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