DOI:10.21276/sjbr.2017.2.1.2

Saudi Journal of Biomedical Research
Scholars Middle East Publishers
Dubai, United Arab Emirates
Website: http://scholarsmepub.com/

ISSN 2518-3214 (Print)
ISSN 2518-3222 (Online)

Original Research Article

Application of Wavelet Packet Transformation in EEG Signal Processing

Juan Tian*, Haitao Du
College of Medical Information and Engineering, Taishan Medical University, Taian 271000, China

***Corresponding Author:**
Juan Tian
Email: tianjuan0001@163.com

Abstract: In this paper, the feature extraction method based on the WPT (wavelet packet transformation) is proposed according to ERD/ERS phenomenon in the motor imagery EEG signals. The method takes the data of the 2005 brain-computer interface competition as the process object. Firstly, EEG signals are preprocessed. Then the average energy difference of wavelet coefficients in the specific frequency bands between C3 and C4 channels extracted with WPT is taken as feature vector. Finally, BP neural network is adopted to classify motor imagery EEG signals of right and left hands.

Keywords: Brain-computer interface, Wavelet packet transformation, Feature extraction, BP neural network.

INTRODUCTION

BCI, short for Brain-Computer Interface, is a system to achieve the direct communication between brain and computer, does not rely on the normal physiological pathway comprised of peripheral nerves and muscles but is a brand new communication and control method to reflect people's consciousness through EEG signals [1]. As an interdisciplinary science, BCI involves informatics, neurosciences, psychology and cognitive science, biomedical engineering and other fields. With continuous improvement of computer science and signal processing technology, BCI technology developed rapidly in the last decade and has significant application value in man-machine control, rehabilitation engineering and military, etc., increasingly attracting concerns and attentions from scientists and researchers all over the world [2].

EEG signals of BCI system have rhythmicity. According to the frequency, it could be divided into δ rhythm (2-4Hz), θ rhythm (4-8Hz), μ rhythm (8-13Hz), β rhythm (13-30Hz) and γ rhythm (above 30Hz) [3]. The research from Graz Research Center in Austria indicates that Motor sensory cortex could be activated by unilateral limb movement or imagery movement; ERD (event-related desynchronization) is generated from contralateral of brain and ERS (event- related synchronization) is generated from ipsilateral of brain. ERD refers to amplitude reduction presented by periodic activity of specific frequency when a certain cortical area is activated; ERS refers to amplitude increase presented by periodic activity of specific frequency when the related cortical area is not activated obviously in certain moment and activity. It further shows that, the obvious ERD/ERS phenomenon mainly exists in μ rhythm and β rhythm of corresponding sensorimotor cortex in brain during imagery movement [4-6].

SIGNAL PROCESSING OF MOTOR IMAGERY EEG

A complete BCI system mainly consists of EEG signal acquisition, processing, control peripherals and other parts, of which the core part is signal processing. It also involves the following three parts, namely the preprocessing, feature extraction and classification. The main contents of this paper are based on ERD / ERS phenomenon. According to its characteristics, WPT is used for feature extraction of the right and left hand motor imagery EEG signals and BP neural network is used to classify features.

EEG data sources

The EEG data used in this paper are the bipolar EEG recordings from Dataset IIIb of the BCI Competition III, and the collected EEG signals are from three healthy experimenters. Data sets are divided into two categories and correspond to two different conceptual works respectively. These data were recorded by the two-stage lead of C3, C4, and CZ electrodes. The sampling frequency was 125Hz and filtered through 0.5-30Hz. All electrodes are distributed in the scalp surface in accordance with the international standard 10-20, as shown in Figure 1.

Each experiment lasts for 8s, as shown in Fig-2.

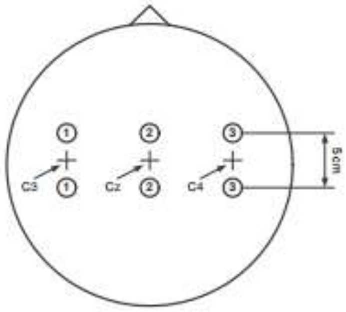


Fig-1: Electrode Position Diagram

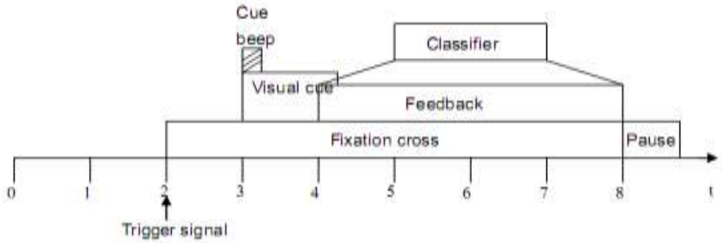


Fig-2: Experiment Process of Left and Right Hands Motor Imagery

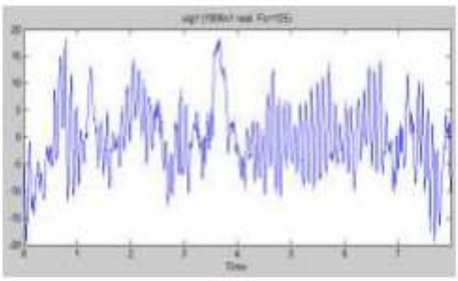
The experimental process is: rest time is 0-2s; there is a trigger signal at 2s, suggesting that the experiment is about to start. A warning tone will appear at 3s to remind the experimenter to notice the movement of cursor (right or left) on the screen; Meanwhile, it requires the experimenter to imagine the left hand or right hand movement according to the moving direction of the cursor, and the movement of cursor (right or left) will continue until the completion of experiment. 4-8s is the information feedback stage. In the feedback stage, BCI system will classify the two types of motor imagery tasks and give the feedback results to the experimenter. The experimenter could see a virtual scene after conducting electrode through wearing special electrode cap, and the classifier will make feedback to the experimenter through this view of virtual scene and tilt direction, and then record the feedback information. Data specifications are shown in Table 1.

Table 1: Data specifications table

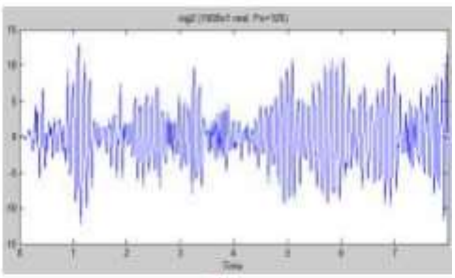
	Feedback	Feedback presentation	Channels	#of Trials	Classes
O3	Virtual reality	4-8s	C3,C4	640	Left-Right
S4	Basket, adaptive classifier	4-7s	C3,C4	1080	Left-Right
X11	Basket, adaptive classifier	4-7s	C3,C4	1080	Left-Right

Preprocessing of EEG signals

The preprocessing of EEG signals is the process of removing the noise signal which is not related to the EEG signal. It is the basis of realizing the good performance of BCI system. Before the feature extraction, this paper describes using the elliptic filter to carry out an 8-30Hz digital band-pass filtering to the original EEG data. The passband cut-off frequency is 8-30Hz, the stop-band cut-off frequency is 5Hz and 35Hz, the passband attenuation is 0.5dB, the stop-band attenuation is 50dB, and take the 8s data with one trigger from the total data. EEG wave form of C3 channel filtering before and after filtering EEG waveform is shown in Figure 3.



(a)



(b)

Fig-3: Figure of EEG wave forms before and after filtering (a) Signal before filtering (b) Signal after filtering

Feature extraction of EEG signals

At present, there are many methods of feature extraction of motor imagery EEG signals based on ERD/ERS, such as power spectrum analysis, parameter model method, wavelet transformation and independent component analysis, etc. Wavelet transformation, because of its ability to characterize the local characteristics of the signal in both the time and frequency domains and to conduct multi-resolution analysis, is a well-known “mathematical microscope” and is well appropriate for analyzing non-stationary and nonlinear EEG signals. However, the characteristics of unevenness band allocation of wavelet transformation may reduce the analytical precision of motor imagery EEG signal. WPT can further decompose the low-frequency part and high-frequency part, and the time-frequency resolution can also get improved. Therefore, in this paper, the WTP is used to conduct an analysis and feature extraction of the EEG signal. [7-9]

Fundamental principles of wavelet packet

Assume that the wavelet basis function is $\varphi(t)$, and the scaling function is $\phi(t)$. According to the concept of multi-resolution analysis, $\phi(t)$ and $\varphi(t)$ is the standard orthogonal basis function of scale space V_0 and wavelet space W_0 respectively. From this, the two-scale equation will be obtained

$$\phi(t)=\sqrt{2}\sum_n h_0(n)\phi(2t-n) \qquad (1)$$

$$\varphi(t)=\sqrt{2}\sum_n h_1(n)\phi(2t-n) \qquad (2)$$

The two-scale relationship also occurs between random adjacent scales $j, j-1$, therefore, the equations (1) and (2) are transformed into:

$$\phi_{j,0}(t)=\sum_n h_0(n)\phi_{j-1,n}(t) \qquad (3)$$

$$\varphi_{j,0}(t)=\sum_n h_1(n)\phi_{j-1,n}(t) \qquad (4)$$

where, $h_0(n)$ and $h_1(n)$ represent the filter coefficients.

According to Mallat fast decomposition algorithm, for arbitrary function $f(t)\in V_j$, it will be

$$f(t)=\sum_k c_{j,k}2^{-j/2}\phi(2^{-j}t-k)+\sum_k d_{j,k}2^{-j/2}\varphi(2^{-j}t-k) \qquad (5)$$

where, $c_{j,k}=\sum_m h_0(m-2k)c_{j-1,m}$ is the coefficient of scale; $d_{j,k}=\sum_m h_1(m-2k)c_{j-1,m}$ is the wavelet coefficient. Decomposition course is shown in Figure 4.

<table>
<tr><td colspan="8">$U_0^0(V_0)$</td></tr>
<tr><td colspan="4">$U_1^0(V_1)$</td><td colspan="4">$U_1^1(W_1)$</td></tr>
<tr><td colspan="2">$U_2^0(V_2)$</td><td colspan="2">$U_2^1(W_2)$</td><td colspan="2">U_2^2</td><td colspan="2">U_2^3</td></tr>
<tr><td>$U_3^0(V_3)$</td><td>$U_3^1(W_3)$</td><td>U_3^2</td><td>U_3^3</td><td>U_3^4</td><td>U_3^5</td><td>U_3^6</td><td>U_3^7</td></tr>
</table>

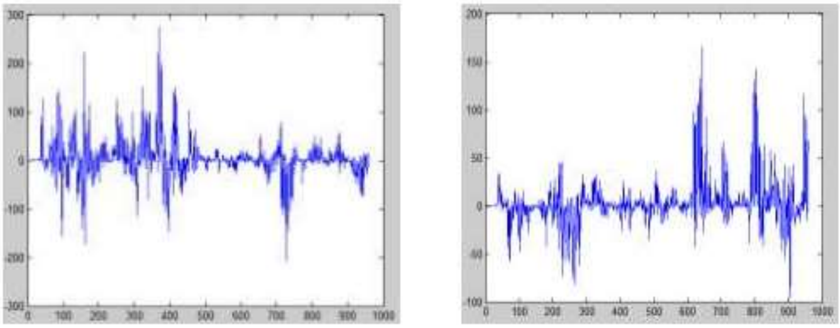
Fig-4: Three-level wavelet packet decomposition of signals

It is supposed that the collection of initiative EEG signals is from C channels (C=1, 2, 3…C), and the data length of each channel is 2^N, with the sampling rate is f_s; An average energy of wavelet coefficient in specific frequency band is shown in equation (6):

$$E=\frac{1}{N}\sum_{j=1}^{N}\left|d_{j,k}\right|^2 \qquad (6)$$

Result analysis

Different transform results could be obtained if different wavelet basis functions are selected, so db4 wavelet is selected in this paper as the wavelet basis function to decompose wavelet packet at the second level with preprocessed EEG signal based on the requirements of features such as orthogonality, regularity and symmetry of wavelet basis function, and the scope of the four frequency bands obtained as follows: 8-13.5H$_Z$, 13.5-19H$_Z$, 19-24.5H$_Z$, 24.5-30Hz. Difference of motor imagery of right and left hands could be well reflected by energy difference between C3 and C4 channels in the motor imagery, namely, average energy of μ rhythm in C3 channel is obviously larger than average energy of μ rhythm in C4 channel in the motor imagery of left hand, which is opposite with the right hand. Combine equation (6), extract the energy difference of wavelet coefficients between C3 and C4 channels as the feature value of motor imagery, as shown in Figure 5.



(a) (b)

Fig-5: Energy difference figure. (a) left hand (b) right hand

SORTING ALGORITHMS OF EEG SIGNALS

EEG signals are characterized by strong randomness, weak amplitude and low signal-to-noise ratio, while artificial neural network is a kind of information processing system which imitates the way of human brain work, in which the error back propagation (BP) neural network is a kind of multi-layer mapping artificial neural network that can correct errors and has got widely used in BCI system. Therefore, this paper chooses BP neural network to classify motor imaginary EEG signals of left and right hands [10, 11].

BP neural network is consisted of input layer, hidden layer and output layer, and learning process includes forward-propagation and back-propagation. When an input mode is given, the input signal from the input layer to the output layer is a forward transmission process. If the actual output signal and the desired output signal are different, that means there exist errors. Then it turns into the error back propagation process, and then the weights of each layer should be adjusted according to the size of each layer.

Assume the input added into network $x_i(i=0,1,\cdots N-1)$, output of network hidden layer $h_j(j=0,1,\cdots L-1)$, and actual output of network $y_k(k=0,1,\cdots M-1)$, desired output of network $d_k(k=0,1,\cdots M-1)$, weight from input layer to hidden layer is recorded as V_{ij}, weight from hidden layer to output layer is recorded as W_{jk}, then

The output of hidden layer is

$$h_j = f(\sum_{i=0}^{N-1} V_{ij}x_i - \phi_j) \tag{7}$$

The output of output layer is

$$y_k = f(\sum_{j=0}^{L-1} W_{jk}h_j - \theta_k) \tag{8}$$

where, ϕ_j and θ_k represent thresholds of input layer and hidden layer respectively, and S-type function is selected by action function normally, namely $f(x)=\dfrac{1}{1+e^{-x}}$.

Assume the error function is

$$E = \frac{1}{2}\sum_{k=0}^{M-1}(d_k - y_k)^2 \tag{9}$$

Based on gradient descent [12],the weight formulas are adjusted as

$$W_{jk}(n+1) = W_{jk}(n) + \Delta W_{jk}(n) + \mu\Delta W_{jk}(n-1) \tag{10}$$

$$V_{ij}(n+1) = V_{ij}(n) + \Delta V_{ij}(n) + \mu\Delta V_{ij}(n-1) \tag{11}$$

where,

$$\Delta W_{jk}(n) = \eta\delta_k h_j = \eta(d_k - y_k)y_k(1-y_k)h_j \tag{12}$$

$$\Delta V_{ij}(n) = \eta\delta_j^{\,*}x_i = \eta h_j(1-h_j)x_i\sum_{k=0}^{M-1}\delta_k W_{jk} \tag{13}$$

η is the constant of learning rate

The training process is described as follows: select a training data to initialize the weights and thresholds, and calculate the output of the hidden layer and the actual output of the network respectively, compare the actual output with the desired output, calculate the square of the error, and then calculate the weight adjustment amount to adjust the weight until the stability of weight and minimum error get achieved. When the training task is completed and the current weight is fixed, the BP neural network will constitute a pattern classifier. The test data is added to the network and the respective output quantities are calculated to determine the category to which the pattern belongs.

In this paper, a three-layer BP neural network model with a hidden layer is used, the energy difference between the wavelet coefficients in the frequency band 8-13HZ from C3 and C4 channels is selected as the feature vector, the implicit nodes are selecting 5, the output layer is the one-dimensional binary vector, corresponding to the category to which the sample belongs, "0" representing the left hand motor imagery, "1" represents the right hand motor imagery. A total of 200 sets of data were selected as the training samples and 100 sets of data as the test samples. The corresponding program is programmed by Matlab, and the classification of left-right hand motor imagery pattern is realized.

CONCLUSIONS

BCI research involves many disciplines with a large number of complex issues to be resolved, among which feature extraction and classification are the core issues. Calculation of feature extraction with WPT is proposed in this paper through the verification of 2005 BCI contest Data Set IIIb data. This method firstly uses the WPT to conduct level 2 decomposition of the 2-way motor imaginary EEG signals collected by C3 and C4 channels, extract the average energy of the wavelet coefficients of the rhythm of interest, take the energy difference between the two channels as the feature vector, and use the BP neural network to classify the motor imaginary EEG signals. Research results prove that this method is simple and effective, and could be programmed easily. It could provide a new way of thinking for BCI to research the mode identification of EEG signals.

ACKNOWLEDGMENTS

The work is supported by Project of Shandong Province Higher Educational Science and Technology Program, China(Grant No. J13LN04)

REFERENCES

1. Wolpaw, J. R., Birbaumer, N. N., & Heetderks, N. (2000). Brain-computer interface technology: a review of the first international meeting. *IEEE Trans. Rehab.Eng.*, *8*(2), 164-173.
2. MullerPutz, G. R., & Pfurtscheller, G. (2008). Control of an electrical prosthesis with an SSVEP-based BCI. *IEEE Trans Biomed Eng*., *55*(1), 361-364.
3. Dennis, J. M., Dean, J. K., & Jonathan, R. W. (2006). Brain–computer interface signal processing at the Wadsworth Center: mu and sensorimotor beta rhythms. *Progress in Brain Research*, *159*(6), 411-419.
4. Houdayer, E., Labyt, E., & Cassim, J. (2006). Relationship between event-related beta synchronization and afferent inputs: analysis of finger movement and peripheral nerve stimulation. *Clinical Neurophysiology, l17,* 628-636.
5. Pfurtscheller, G., Muller, G. R., & Pfurtscheller, J. (2003). Thought-control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neuroscience Letters*, *351*, 33-36.
6. Pfurtscheller, G., Neuper, C., & Muller, G. R. (2003). Graz-BCI: state of the art and clinical applications. *IEEE Trans.on Neural System and Rehab,Eng.*, *11*(2), 177-180.
7. McFarland, D. J., & Wolpaw, J. R. (2008). Sensorimotor rhythm-based brain-computer interface(BCI):model order selection for autoregressive spectral analysis. *Journal of Neural Engineering*, *5*(2), 155-162.
8. Kevric, J., & Subasi, A. (2016). Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system. *Biomedical Signal Processing & Control*, *31,* 398-406.
9. Ebrahimpour, R., Babakhani, K., & Mohammad-Noori, M. (2012). EEG-based motor imagery classification using wavelet coefficients and ensemble classifiers. *Csi International Symposium on Artificial Intellience & Signal Processing,* 458-463.
10. Nawroj, A., & Wang, S. (2012). An event classifier using EEG signals: An artificial neural network approach. *Bioengineering Conference*, 386-387.
11. Nikola, M., & Tomasevic. (2012). Artificial Neural Network Based Approach To Eeg Signal Simulation. *International Journal of Neural Systems*, *22*(3), 1250008-1250008.
12. Wu, W., & Wang, J. (2011). Convergence analysis of online gradient method for BP neural networks. *Neural Networks the Official Journal of the International Neural Network Society*, *24*(1), 91-98.