Research on motor imagery EEG signal processing algorithm

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Abstract. To address the difficulty of extracting features from motor imagery EEG signals and the low classification accuracy, a method for feature extraction and classification of multiple types of motor imaging EEG signals based on wavelet and support vector machine (SVM) is proposed. This work first calculated the power of motor imagery EEG data and selected the scale of wavelet packet by theoretical analysis. Then, wavelet packet decomposition on power was discussed, wavelet packet entropy (WPE) of power was calculated, and wavelet packet entropy interpolation of leads C3, C4 was extracted, which composed the feature vector. Finally, this work fed the feature vector as the classifier input into a support vector machine to achieve classification. From Graz’s EEG data from the international BCI competition in 2003, the highest accuracy rate of classification was 97.56%. The feature vectors of this algorithm are low in dimension, are small in data size, and have high classification accuracy, which provides a reference method for the task of EEG feature extraction and classification.

1. Introduction
Brain-computer interface (BCI) is a technology that establishes a connection between the brain and a computer or other device. This connection does not need to pass through the usual brain output pathways (peripheral nerves and muscle tissue of the brain) [1-3]. A typical brain-computer interface system is composed of an EEG signal extraction and acquisition module, an EEG signal processing module, an EEG signal output module, and an EEG signal feedback module. The EEG signal processing algorithm in the EEG signal output module is the research focus of the brain-computer interface [4]. In the actual application of the brain-computer interface, the benefits and limitations of the algorithm affect the final result, which directly reflects the performance of the brain-computer interface system.

In recent years, the brain-computer interface has been used in military target searches [5], in flight simulator controls [6], for car driving [7], in education [8] and to help people who are disabled with sports or sensory problems to restore information and communication functions. [9] Great breakthroughs and progress have been made, and brain-computer interfaces have received widespread attention in fields such as bioengineering, computer science, and automation. Brain-computer interfaces based on motor imagination are an important part of many brain-computer interface paradigms. At present, the brain-computer interface based on motor imagination still has problems of low signal-to-noise ratio, low control rate, and few online analysis and processing methods. The key to solving these kinds of problems is the EEG signal classification method, and the EEG signal feature extraction is the prerequisite for the correct classification of EEG signals. Therefore, many EEG signal feature extraction algorithms have appeared. At present, commonly used EEG signal feature extraction
methods include Fourier transform (FT), surface-Laplacian, autoregressive model, and power spectrum estimation. In the process of feature extraction of EEG signal with nonlinear, stochastic, nonstationary and strong noise, the use of Fourier transform and surface Laplace method is limited, and the autoregressive model and power spectrum estimation cannot well characterize the time-domain characteristics of EEG signals. The above methods cannot guarantee higher resolution in the time and frequency domains at the same time, and the extracted feature vectors cannot effectively characterize the characteristics of the EEG signals, which raise the requirements of subsequent EEG signal classification methods, resulting in a lower classification accuracy rate. The wavelet transform algorithm selected in this paper has strong adaptability to high and low frequency signals in both time and frequency resolutions and can better extract the characteristics of EEG signals. Then, a support vector machine is used for classification. The support vector machine method is widely used in EEG signal classification. It has strong adaptability and high classification accuracy in the processing of small sample sizes and nonlinear pattern recognition problems[10].

2. Experimental data selection

The experimental data were taken from the standard data in the 2003 International BCI Competition Data Group, which were provided by the Medical Information Department and Biomedical Engineering Institute of Graz University of Technology, Austria. The task of this experiment is to control the movement of a feedback bar by imagining left and right hand movements according to the arrow prompts. The electrode placement is shown in Figure 1. In this article, only leads C3 and C4 are used. The time sequence of the collected EEG data experiment process is shown in Figure 2.

Each experiment lasts 9 seconds. The first 2 seconds are the preparation time, which requires the subject to remain still. After two seconds, a buzzer sounds to indicate that the experiment started, and a cross ‘+’ symbol appears on the screen for 1 second. In the third second, an arrow indicating left or right appears; at the same time, the subject is asked to move the feedback bar on the screen through motion imaging in the direction indicated by the arrow.

The experimental flow chart is shown in Figure 3. There were 7 groups in this experiment; each group was run 40 times, for a total of 280 times, and the data were collected once for each experiment. The 280 experimental data were collected and divided into training data and test data, with 140 data in each set; in each set, 70 data were for left-hand movement imagination, and 70 data were for right-
hand movement imagination. The sampling frequency of the EEG signal is 128 Hz, and 0.5-30 Hz bandpass filtering is performed.

Start

The buzzer sounds and the '+' symbol appears on the screen

Imagine to moving the feedback bar

Whether 7 data collections have been completed

Whether 40 experiments have been completed

A prompt arrow appears on the screen

Yes

No

Yes

No

Figure 3. Experimental flow chart

3. EEG signal feature extraction

3.1. EEG signal power calculation

When performing motor imaging of unilateral limbs, the event-related desynchronization potential (ERD) phenomenon appears on the side of the cerebral motor cortex, μ and β, with reduced energy, and the event-related synchronization potential (ERS) phenomenon occurs on the side with increased energy.

According to equation (1), to calculate the average power of lead C3, imagine the left hand, lead C3 imagine the right hand, lead C4 imagine the left hand, and lead C4 imagine the right-hand EEG signal. Among them, $V$ is the average power of the motor imaging EEG signals, $V_0$ is the original EEG data, $V_i$ is the average power of leads C3 and C4, and $n$ is the number of events.

$$V = V_i + \frac{V_0}{n}$$

The average power of the left-hand and right-hand EEG signals in leads C3 and C4 is shown in Figures 4 and 5.

Figure 4. The average power of the left-hand EEG signals in leads C3 and C4

Figure 5. The average power of the right-hand EEG signals in leads C3 and C4
As shown in Figures 4 and 5, the power of lead C3 is higher than that of lead C4 when the left-handed movement is imagined; when imagining right-hand movement, the power of lead C3 is lower than that of lead C4. Therefore, selecting the signal power as the input signal of the subsequent wavelet packet processing can perform better feature extraction.

3.2. Wavelet packet type and scale selection

Many studies have shown that the signal frequency of event-related synchronization potential and event-related desynchronization potential is 8~13 Hz. In this paper, the wavelet basis functions of Daubechies wavelet system, Biorthogonal wavelet system, Coiflet wavelet system and symletsA wavelet system were analyzed and tested. These wavelet systems are widely used in EEG signal processing, and the specific effects vary with different EEG signals. The Daubechies function is a tightly supported standard orthogonal wavelet, which is the basis of discrete wavelet analysis. Biorthogonal function has the characteristics of linear phase. The Coiflet function has better symmetry than the Daubechies function. Symlet function is an improvement of Daubechies function[11]. According to the sampling frequency of the data, the frequency range of the EEG signal is 1 - 64 Hz[12-13]. The abovementioned wavelet is used to perform 4-layer wavelet packet decomposition on the average power signal of leads C3 and C4.

Let \( U^j \) be the wavelet packet family, \( g_j^x(t) \in U^j \), then,

\[
g_j^x(t) = \sum_j d_j^x U_j(2^j t - l)
\]

Principle of wavelet packet decomposition: available from \( \left\{ d_j^{j+1,n} \right\} \),

\[
\begin{align*}
d_j^{j,2n} &= \sum_k a_{k-2j} d_k^{j+1,n} \\
d_j^{j,2n+1} &= \sum_k b_{k-2j} d_k^{j+1,n}
\end{align*}
\]

Principle of wavelet packet reconstruction: available from \( \left\{ d_j^{j,2n} \right\} \) and \( \left\{ d_j^{j,2n+1} \right\} \),

\[
d_j^{j+1,n} = \sum_k [h_{k-2j} d_k^{j,2n} + g_{k-2j} d_k^{j,2n+1}]
\]

The frequency range of some nodes in the fourth wavelet packet after decomposition is shown in Table 1. The frequency interval we need is exactly the node (4,3), so we reconstruct the node (4,3).

Table 1. Layer 4 wavelet packet decomposition partial node frequency range.

| Wavelet packet node | Frequency range/Hz | Wavelet packet node | Frequency range/Hz |
|---------------------|--------------------|---------------------|--------------------|
| (4,1)               | 0-4                | (4,5)               | 16-20              |
| (4,2)               | 4-8                | (4,6)               | 20-24              |
| (4,3)               | 8-12               | (4,7)               | 24-28              |
| (4,4)               | 12-16              | (4,8)               | 28-32              |

3.3. Wavelet packet entropy calculation

The node energy after wavelet packet decomposition and reconstruction can be regarded as signal energy, and the energy of the signal is defined as equation (5),

\[
E_f = \int_{-\infty}^{\infty} f^2(t) dt
\]

The signal \( f(t) \) is decomposed into \( j \) layers by the wavelet packet, then \( 2^j \) wavelet packet nodes are generated, and the energy of the wavelet packet node \( f_j^j(t) \) is

\[
E_{f_j^j} = \int_{-\infty}^{\infty} f_j^j(t)^2 dt
\]

The total energy of the signal is the sum of the energy of each wavelet packet node,
$$E_{all} = \sum_{i=1}^{2^j} E_{ij}$$  \hspace{1cm} (7)$$

If the wavelet packet node energy is $E_j$, the normalized wavelet packet energy is

$$p_i = \frac{E_j}{E_{all}}$$  \hspace{1cm} (8)$$

$p_i$ can reflect the distribution of wavelet packet energy.

Shannon entropy can reflect the uncertainty of the signal, defined as

$$WPE = -\sum p_i \ln(p_i)$$  \hspace{1cm} (9)$$

It is known that the time required for one experiment is 9 s, the EEG signal is 128 Hz according to the sampling frequency, and the number of sampling points for one experiment is 1152. A time window with a length of 64 points is used to analyze the movement of the signal, which is a total of 18 times. After each movement, the 4-layer wavelet packet decomposition is performed on the signal in the time window; then, the (4,3) node is reconstructed, and the wavelet packet entropy of the reconstructed signal is calculated according to equation (2.9). Finally, the wavelet packet entropy obtained from 70 experiments is superimposed and averaged. Taking bior2.8 wavelet as an example, the changing trend of wavelet packet entropy is shown in Figures 6 and 7.

![Figure 6](image_url)

**Figure 6.** The left-handed average wavelet packet entropy of leads C3 and C4 based on bior2.8 wavelet

![Figure 7](image_url)

**Figure 7.** The right-handed average wavelet packet entropy of leads C3 and C4 based on bior2.8 wavelet

As shown in Figure 6, when imagining left-handed motion, the average wavelet packet entropy of lead C3 increases, the average wavelet packet entropy of lead C4 decreases, and the average wavelet packet entropy amplitude of lead C3 is higher than that of lead C4. According to Figure 7, when imagining right-hand movement, the average wavelet packet entropy of lead C3 decreases, the average wavelet packet entropy amplitude of lead C4 increases, and the average wavelet packet entropy amplitude of lead C3 is lower than that of lead C4 in 4-9 seconds. These findings are consistent with the trend of event-related synchronization potential and event-related desynchronization potential. According to the data from leads C3 and C4, the difference between the average wavelet packet entropy data of leads C3 and C4 can be obtained to determine the difference $WPE(C3 - C4)$ of the wavelet packet entropy. The changing trend of $WPE(C3 - C4)$ is shown in Figure 8.
According to Figure 8, the average wavelet packet entropy interpolation of the left-hand motor imagination increases within 4-9 seconds, the average wavelet packet entropy interpolation of the right-hand motor imagination decreases within 4-9 seconds, and the amplitude of the average wavelet packet entropy of the left hand is greater than that of the right hand. The difference in wavelet packet entropy is good for separating the features of the left- and right-hand EEG signals. Therefore, it can be regarded as the feature vector of the EEG signal of the motion imagination. The feature vector has one dimension and 18 data points. Compared with the original 2D data with 1152 data points, this feature vector has reduced data and dimension, which greatly simplifies the calculation amount and time.

4. EEG signal classification

In a classification simulation, 100 data were randomly selected from 280 experimental data as training data, and the WPE (C3-C4) of the training data was obtained according to the above algorithm. WPE (C3-C4) was input as the classification feature vector, and the support vector machine was trained. The rest of the experimental data are used as test data to determine the classification accuracy of the trained support vector machine. Each wavelet basis function performs 10 classifications and finds its average classification accuracy. The support vector machine kernel function used in this paper is the Radial Basis Function (RBF):

\[
H(x, x') = \exp(-\gamma \|x - x'\|^2)
\]

(10)

According to the simulation experiment flow, the algorithm is simulated in MATLAB R2014a, and the classification accuracy of different wavelet basis functions is obtained. The results are shown in Table 2.

**Table 2.** The average classification correct rate of each wavelet basis function.

| Wavelet name | Average classification correct rate | Wavelet name | Average classification correct rate | Wavelet name | Average classification correct rate | Wavelet name | Average classification correct rate |
|--------------|-------------------------------------|--------------|-------------------------------------|--------------|-------------------------------------|--------------|-------------------------------------|
| db1          | 83.29%                              | bior1.1      | 81.13%                              | bior4.4      | 81.13%                              | Sym2        | 86.61%                              |
| db2          | 91.12%                              | bior2.2      | 92.78%                              | bior5.5      | 92.78%                              | Sym3        | 84.78%                              |
| db3          | 83.32%                              | bior2.4      | 93.96%                              | bior6.8      | 93.96%                              | Sym4        | 81.15%                              |
| db4          | 90.11%                              | bior2.6      | 96.01%                              | bior4.4      | 81.13%                              | Sym5        | 81.63%                              |
| db5          | 81.45%                              | bior2.8      | 87.29%                              | coif1        | 84.23%                              | Sym6        | 90.27%                              |
| db6          | 81.36%                              | bior3.1      | 93.26%                              | coif2        | 82.26%                              | Sym7        | 84.86%                              |
| db7          | 83.96%                              | bior3.3      | 84.27%                              | coif3        | 83.74%                              | Sym8        | 84.25%                              |
After sorting the above simulation results, the last 9 scales of the Biorthogonal function have obvious advantages over the classification accuracy of other wavelet basis functions in terms of classification accuracy. The first four scales of the Coiflet wavelet system and the SymletsA wavelet system have a slightly lower classification accuracy rate in the processing of these data, while the classification accuracy rates of the remaining wavelet systems are more average. Among them, the average classification rate obtained by bior3.3 wavelet basis function ranks first among the four types of wavelet basis functions. In the 10 classification simulations, the highest single classification rate reached 97.56%. Regardless of which wavelet basis function is chosen, the classification accuracy of the algorithm remains above 80%. The method used in this paper has higher classification accuracy than those of other methods. The comparison results are shown in Table 3.

| Method               | Classification accuracy |
|----------------------|-------------------------|
| The method of this article | 97.56%       |
| The method of Reference [2] | 92.80%       |
| The method of Reference [13] | 85.70%      |
| The method of Reference [12] | 85.70%      |

5. Conclusion
In this paper, the power of the EEG signal is used as the input of the EEG signal processing module for the rhythm energy changes of the event-related synchronization potential (ERS) and desynchronization potential (ERD) phenomena. Using wavelet packet decomposition and wavelet packet entropy to reflect the speed of energy distribution changes in different frequency bands of EEG signals, the left-hand and right-hand EEG signal features are better separated, and the obtained EEG signal feature vectors are correctly classified by support vector machines. Compared with other methods, the highest classification accuracy can reach 97.56%. Therefore, the feature extraction and classification of motor imaging EEG signals can be effectively performed. The method used in this paper requires a small amount of data and low dimensionality for the motion imaging EEG signal classification feature vectors, which greatly reduces both the data processing time and the data storage space. Additionally, this method can provide research ideas for the study of real-time online brain-computer interface systems.

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