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The Improvement of Motor Imagery Based on Spectral Feature and Transformation on Multivariate Empirical Mode Decomposition

Jingtao Guan[a] and Feng Duan[*, b]

[*]Jinnan District, Nankai University, Tianjin, China

Email: [a]guanjingtao1@126.com; [b]duanf@nankai.edu.cn

Abstract. Brain computer interface (BCI) allows persons to express their wishes, emotions. It is essential to connect the brain signals and computers. Through the BCI system, the multi-channel Electroencephalogram (EEG) classification of Motor Imagery (MI) based on Common Spatial Pattern (CSP) can get a good result. However, when it comes to less channels, the classification's result is not so practical. This paper focuses on the improvement of less channels' accuracy. Through the methods of spectral feature and transformation based on Multivariate Empirical Mode Decomposition (MEMD), the accuracy can improve 15.5% on average. As a result, the methods are effective on this issue.

1. Introduction

BCI is a system that can transfer the brain signals to control commands without the normal ways of peripheral muscles and nerves [1]. It is a bridge that connect people and computer through a new way. BCI helps people communicate with the external environment and enrich the ways of communication [2]. Besides, the BCI system can also meet with the severe motor disabilities' requirements. The aim of BCI system is to enable people, especially the paralyzed to express their wishes to other persons or machines, like caregivers, robots, etc.

Over the past several years, the BCI system has developed fast. From the point of collecting, the BCI contains 2 types: noninvasive and invasive ways. Invasive BCI can get more precise result, but it does harm to subjects. Compared with invasive BCI, the noninvasive BCI can obtain the signals without hurting subjects by deriving from neuronal action potentials or local field potentials, and the result can be good to some degree [3, 4]. From another perspective, the BCI system studies the Motor Imagery (MI), Steady State Visual Evoked Potential (SSVEP), P300 and so on. MI is a research based on imaging movement and SSVEP, P300 depend on the stimuli flicking which can stimulate subjects to produce corresponding EEG signals. As a result, we adopt the noninvasive BCI to study MI in this paper.

The EEG signals are collected from the scalp of a head as brain signals and corresponding to the imagination of movements. To enhance the contact with scalp and electrodes, it is essential to use the gel or liquid. This way can get away of bad contact. We can also get subjects' intentions by analysing EEG signals from different bands of frequency, such as μ (8-13Hz), β (13-25Hz) and so on.

For the multi-channel EEG signals, there are many methods to process the data. One of the best methods is CSP. This method does a large amount of contribution on EEG signal classification and fit in with multiple channels [5]. CSP method is a spatial filtering algorithm that extracts spatial features

from multi-channel EEG signals [6]. And it is used to extract features from two types of EEG signals. Nevertheless, compared with brilliant performance on multi-channel EEG signals, the CSP performance is not so good on less channels.

In this paper, we propose a new method which can improve the accuracy of three channels' EEG signals. It combines spectral feature and a transformation on MEMD. This new method can acquire a better result of classification.

2. BCI Structure

In this experiment, the subjects imagine 2 actions: lefthand and righthand movements. The data last 4 seconds. 96 groups of data are for training and 24 groups are for testing.
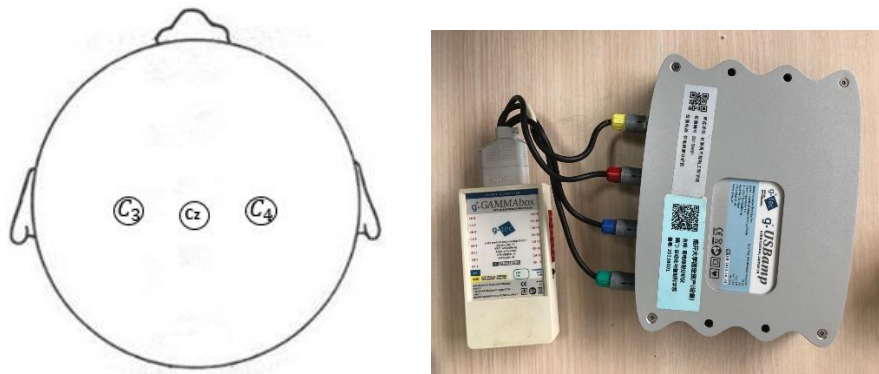

Figure 1. EEG electrodes' location and g-tec device

As shown in Figure 1, the channels used to collect EEG signals are C_3, C_4, Cz. C_3 and C_4 is the symmetrical channels on the head. For quickly and easily collecting EEG signals, we collect 16 seconds' data at one time. Collect data time for 15 times and separate every data into 4 seconds, then we get 60 groups of data at last. This method of collecting EEG signals saves a lot of time. In addition, the sampling frequency is 256 Hz.

Besides, we collect EEG signals by a collecting system, which contains electrodes, g-tec and g.USBamp devices. The g-tec device is used to obtain the EEG signals through electrodes and g.USBamp device works as an amplifier.
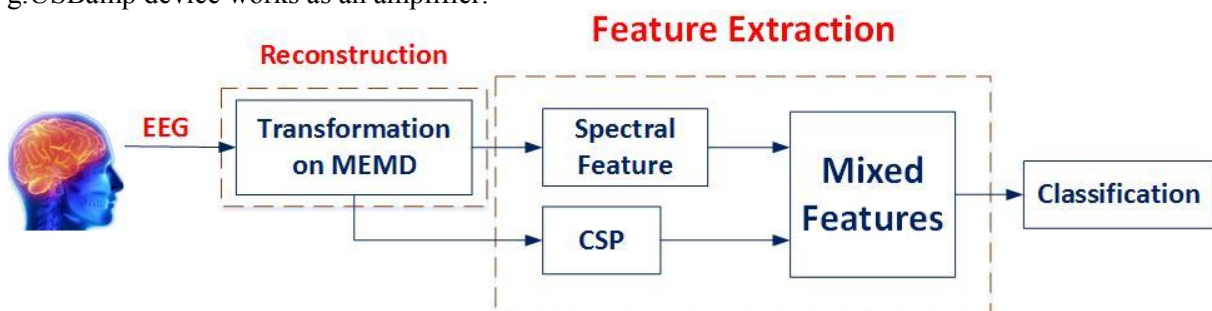
Figure 2. BCI structure

The Figure 2 shows the structure of the experiment. First, collect EEG data by a collecting system, then filter the data between 8 and 30 Hz. After that, through a new method which is a transformation on MEMD. We get 3 lists of Intrinsic Mode Functions (IMFs) from the 3 channels (C3, C4, Cz), and these three lists are separated as IMF_x, IMF_y and IMF_z. Because the first IMF carries the most oscillating component, we take the first IMF in each IMF_x, IMF_y, IMF_z and reconstruct the IMFs into a new data source.

After getting the new data source, extract spatial features by the CSP algorithm and spectral feature from frequency spectrum. The mixed features combine the spatial and spectral features. Finally, the mixed features are classified by Support Vector Machine (SVM).

3. Transformation on MEMD

3.1. EMD

Empirical Mode Decomposition (EMD) is a method that decompose a signal into several oscillating modes and a residue [7]. It is used for nonlinear, nonstable time domain data. When a signal decomposes to finite IMFs, the IMFs should obey the rules, which are that the number of extrema and zero-crossings differ at most by 1; the mean value of the envelope defined by the local maxima and minima is 0 [8, 9].

We define $m_1(t)$ as the mean value of upper and lower envelope. The difference between the data and $m_1(t)$ is the first component $h_1(t)$:

$$x(t) - m_1(t) = h_1(t) \tag{1}$$

If the $h_1(t)$ is not satisfy the two standards, then continue to sift until the $h_1(t)$ meets the standards. Completing the procedures above, we find the first IMF $c_1(t)$ and the first IMF carries the most information than other IMFs.

Repeat the procedures to find other IMFs and stop to find when there is no more IMFs can be extracted. There can be a residue $r(t)$ at last which is a monotonic function. The $x(t)$ finally decomposes to several IMFs and a residue:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{2}$$

By the EMD method, a group of righthand EEG signal is decomposed in the Figure 3.
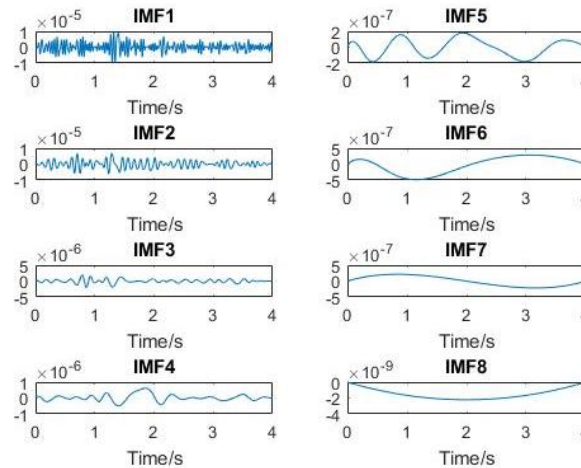
Figure 3. IMFs and a residue decomposed by an EEG signal

The EEG signal is decomposed into seven IMFs and a residue. The residue is a monotonic function. The IMFs' oscillating level and the information they carry decline from first IMF to the last IMF. When there cannot be a more IMF, the residue comes as a monotonic function.

Besides, EMD can decompose a signal according to the time scale itself. This can make the local signal smoother without any basic function predefined. This feature can make process a signal easier and more practical.

3.2. MEMD and transformation

MEMD process a list of multivariable signals while EMD deal with only 1 dimensional signal. MEMD is more complicated than EMD [10]. The envelopes of MEMD are produced by the projection of different directions in n-variate spaces. The local mean of MEMD can be regarded as approximation of the all directions' envelopes under the n-dimensional spaces [11]. The n-variate signal $X(t)$ can be decomposed by MEMD in this function:

$$X(t) = \sum_{i=1}^{n} C_i(t) + R(t) \tag{3}$$

Besides, the direction vectors based on the projections of signals are formed as a circle for Bivariate Empirical Mode Decomposition (BEMD), a 3-dimensional sphere for trivariate Empirical Mode Decomposition (TEMD) and a multidimensional sphere for MEMD.

In this paper, we collect EEG signals from C_3, C_4, Cz. The direction vectors are showed as a 3-dimensional sphere. The transformation of MEMD is used to change the uniform direction vectors to nonuniform direction vectors which can fit in with the EEG signals.

The procedures of transformation based on MEMD are shown as follows: the input 3 channels' signals $X(t)$ and the covariance matrix C.

$$C = V \Lambda V^T \tag{4}$$

V is the eigenvector matrix and Λ is the eigenvalue matrix. The eigenvector v_1 corresponds to the first eigenvalue λ_1 which contains the most information than any eigenvalue. And design another eigenvector v_o which satisfied with the function $v_o = -v_1$. By the help of Hammerseley sequence, uniformly sample a sphere to generate 3 direction vectors $\{X^{\theta_k}\}_{k=1}^{3}$, whose values are between 0 and 1. Then, get the Euclidean distance from each vectors to v_1. At last, relocate the half of all the uniform projection vectors which are nearest to v_1. The relocating function is:

$$\overset{\Lambda}{X}{}^{\theta_k}_{v_1} = \frac{X^{\theta_k}_{v_1} + \alpha v_1}{\left| X^{\theta_k}_{v_1} + \alpha v_1 \right|} \tag{5}$$

It is the same as the opposite eigenvector v_o. And the parameter α is 0.3. Finally, the $\overset{\Lambda}{X}{}^{\theta_k}_{v_1}$ and $\overset{\Lambda}{X}{}^{\theta_k}_{v_o}$ replace the uniform direction vectors and apply them into traditional MEMD algorithm.

4. CSP method

CSP method is a spatial filter feature extraction algorithm under the two types' classification. This algorithm can extract the spatial contribution from multi-channel EEG data [12]. It does well in multiple channels but perform a little bad in less channels, especially 3 channels.

The principle of CSP method is that by the diagonalization of matrixes, find a group of optimal spatial filter, get the projection to maximize the differences between the variances of two types' signals, and then acquire the eigenvectors with high degree of discrimination [13].

X_L is the EEG signal of lefthand movement imagination and X_R is about the righthand. The covariance matrixes R_L and R_R are:

$$R_L = \frac{X_L X_L^T}{trace(X_L X_L^T)} \tag{6}$$

$$R_R = \frac{X_R X_R{}^T}{trace(X_R X_R{}^T)} \tag{7}$$

The mixed covariance matrix R is shown in the function. Sort the eigenvalues Λ in a descending way, and then obtain the whitening matrix P:

$$R = R_L + R_R = U_0 \Lambda U_0{}^T \tag{8}$$

$$P = \sqrt{\Lambda^{-1}} U_0{}^T \tag{9}$$

Whiten covariance matrixes R_L, R_R and there must be a common feature matrix U between S_L and S_R. Besides, Λ_L plus Λ_R is an identity matrix :

$$S_L = PR_L P^T \qquad S_R = PR_R P^T \tag{10}$$

$$S_L = U \Lambda_L U^T \qquad S_R = U \Lambda_R U^T \tag{11}$$

At last, we acquire the projection matrix W and the features from EEG signal X :

$$W = U^T P \tag{12}$$

$$Z = WX \tag{13}$$

5. Spectral feature

5.1. Spectral feature and other features

Before confirming which feature is the most important, it is essential to compare with those features' contributions on classification. In addition, different people's spectral powers are different [14]. As for this subject, the most active spectral power is among 14 to 27 Hz. Therefore, in this experiment, we choose some features illustrated in Table 1 as follows.

Table 1. Features

Domain	Feature list
Frequency	Spectral power**s** from 14 to 18 Hz, 17 to 21 Hz, 20 to 24 Hz, 23 to 27 Hz Peak frequency of spectrum Spectral edge frequency 80%, 90%, 95% Normalized power from 14 to 18 Hz, 17 to 21 Hz, 20 to 24 Hz, 23 to 27 Hz
Time	Number of maxima and minma Autoregressive modelling error Root mean squared amplitude Skewness Kurtosis Variance

The Random Forest is an algorithm which combines many trees by Ensemble Learning method. The basic unit of Random Forest is Decision Tree. The Random Forest is skilled in calculating different features' contribution on the original data. Besides, its advantages are obvious. It is more accurate, efficient and can process multiple dimensional data without variable deletion [15].

By the Random Forest, we can obtain the importance of each feature. The contribution of features are listed in Figure 4.
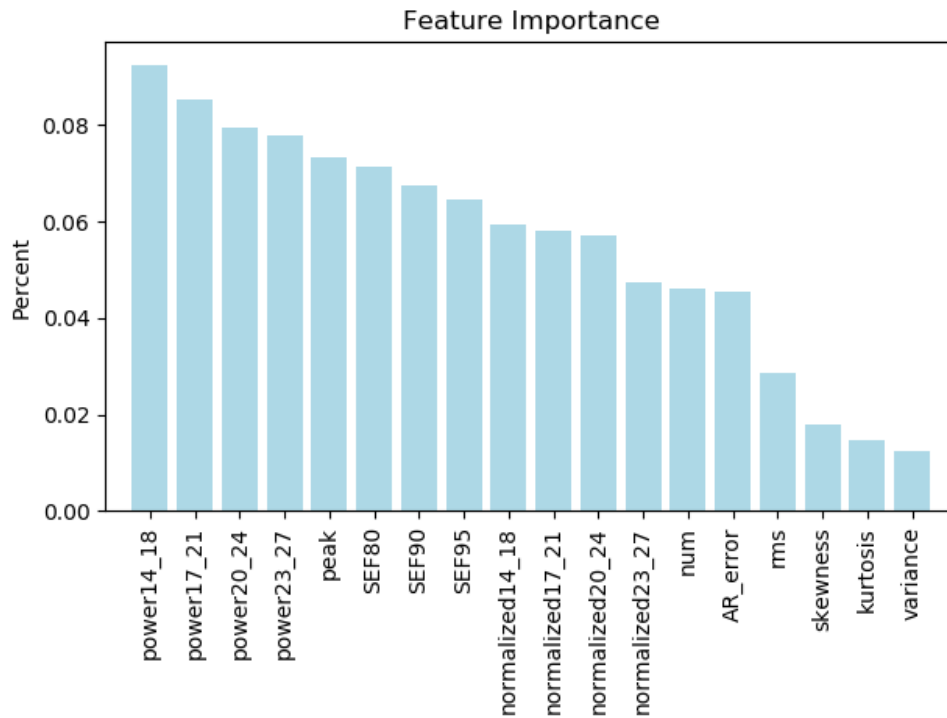
Figure 4. Different contributions from features

The features' contributions are sorted in a descending order from spectral power to variance. We can get the most significant feature, spectral power. This feature does the most contribution to the EEG signals than others. As a result, we will extract the spectral features from EEG signals.

5.2. Spectral feature extraction

According to random forest, we decide to extract spectral features. The Fast Fourier Transformation (FFT) method is used to transfer the EEG signals into spectrum. FFT is a quick calculating algorithm based on Discrete Fourier Transform (DFT) and Inverse Discrete Fourier Transform (IDFT). FFT's complexity is $O(n \log n)$ which is better than $O(n)$ in multiplication of polynomials [16].
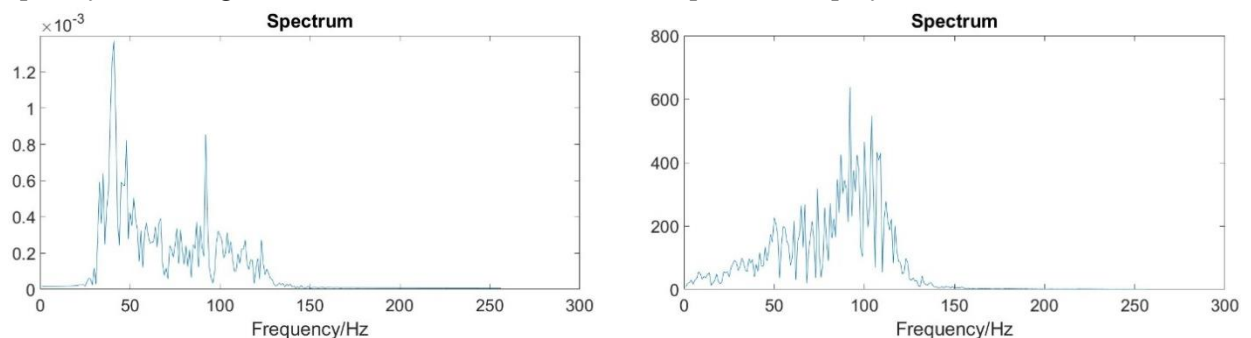

Figure 5. The spectrums of two EEG signals

It is easy to acquire the peak of the spectrum. And take the spectral power of some frequencies near the peak as the feature. For an example, if the peak is at 50Hz, we may take spectral power from 40 to 60 Hz or 50 to 70 Hz. The peaks of different subjects are different. When this method applies in the right figure in Figure 5, it can work. However, it does not fit in with the left figure in Figure 5. The peak of this figure is at the edge of the useful period of spectrum.

Therefore, a new method is designed to solve this problem.

a. Obtain the upper envelop of the spectrum which is processed by FFT algorithm
b. Find the local maxima above a threshold which is defined differently for each persons and calculate the average value of these maxima
c. Take the spectral power from average frequency to the frequency which equals to 20 plus the frequency itself.

6. Result

When we get the EEG signals, reconstruct by the transformation on MEMD, then the new data are processed by the CSP algorithm. Meanwhile, extract the spectral feature from the new data. Combine the two features as the mixed feature. At last, we propose the Support Vector Machine (SVM) method to classify the mixed feature. Besides, we compare the features extracted from original EEG signals by CSP with the mixed features.

Besides, we compare the features extracted from original EEG signals by CSP with the mixed features. Both features are classified by SVM. The train data are 96 groups and the test are 24 groups. The result is shown in the Table 2:

Table 2. The result of classification

	CSP Feature	Mixed feature	improvement
Subject1	70.1%	91.7%	21.6%
Subject2	58.3%	75%	16.7%
Subject3	75%	83.3%	8.3%
Average	67.8%	83.3%	15.5%

The result confirms the methods in this paper. The accuracy of mixed features from reconstructed EEG signals is more precise than the CSP features from original EEG signals. Moreover, the accuracy improves by 15.5%.

The subjects are different from each other, so the improvements of mixed features are also different. We can see the methods proposed in this paper are practical.

7. Conclusion

This paper proposes the methods to improve the accuracy of features extracted by CSP. CSP algorithm is efficient at multi-channel EEG signals. But it does not work well in less channels, especially the three channels, C_3, C_4, C_Z in this experiment. To solve this question, the mixed feature from the new data reconstructed replace the feature extracted by CSP from original EEG signals. For the spectral power feature, we apply a new method to solve the problem that the peak of spectrum is not in the centre of useful period. In addition, collect the EEG signals for 16 seconds at a time, and then separate 16 seconds' data into 4 signals. Each of the 4 signals lasts 4 seconds. This method reduces the time wasted at the interval of experiments. Because of the time reduced, the subjects may not be tired and the EEG signals may be better.

In a nutshell, the result is clear that the accuracy of classification has improved by 15.5% on average. The methods are practical and functional for the 3 channels' EEG signals.

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