# Feature extraction of EEG signal based on EMD in OVR-CSP

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## Abstract

**Common Spatial Pattern(CSP) depends highly on operational frequency band. To solve this problem, this article applies a new method—EMD-OVR-CSP algorithm—to the feature extraction of four types of motion imaginary EEG signals. In light of the good performance of Empirical Mode Decomposition(EMD) in band selection, this algorithm uses EMD to decompose EEG signals into intrinsic mode functions for accurate band selection. In this way, the typical two-class algorithm CSP is extended to OVR-CSP algorithm, which transforms the four-class problem into that of the two-class with four one-class to three-class, and four spatial filters are constructed. Experiments prove that the feature extraction algorithm of OVR-CSP based on EMD can extract the features of four types of MI-EEG signals efficiently and the accuracy is much higher than other CSP algorithm.**

## Keywords

**EEG, empirical mode decomposition, Common Spatial Pattern, Brain Computer Interface.**

## 1. Introduction

Brain Computer Interface (BCI) is an advanced communication system established between external devices such as the human brain and the computer. It does not depend on the human brain's peripheral nerves and muscles, and It makes our brain thinking activities directly on the external devices[1]. BCI mainly includes the human brain to the equipment and equipment to the human brain two parts, There is a constant exchange of information between them.the external devices in this paper generally refers to intelligent wheelchairs, mobile phones and PC and other intelligent devices, people through the brain electrode cap, with brain waves to the device to convey the intention, while the device also through the sound or visual means to provide feedback.

At present, The study o f BCI for EEG signals focuses on motion imagination of EEG signals Wavelet transform[2], AR model [3], HHT[4],linear discriminant analysis (LDA)[5], artificial neural network (ANN) [6]and so on are widely used. However, these algorithms still have limitations, such as the wavelet transform does not have the adaptability and its phase nonlinearity, HHT has modal aliasing and endpoint effects, LDA only in the classification signal linear separable case has a better classification effect , ANN implicit layers and the number of units is difficult to determine, easy to fall into the local optimal and generalization ability difference. The CSP algorithm is based on CSSD a feature extraction algorithm, Which has a good spatial filtering performance. In recent years, the use of CSP extract EEG signal characteristics have achieved very good recognition effect, And it is the classical algorithm for analyzing two types of EEG signals[7,8],Based on the empirical mode decomposition, this paper proposes an OVR-CSP algorithm to extend the CSP algorithm to the recognition of four types of EEG signals.

Experiments show that the feature extraction algorithm of OVR-CSP based on empirical modal decomposition is more efficient and robust to the four sets of EEG samples. The validity of the proposed algorithm is verified..

## 2. Band Selection

### 2.1 Empirical Mode Decomposition

EMD is a signal decomposition method based on signal local feature time scale. Its essence is to recognize the inherent oscillation mode in the signal, to smooth the signal, and to have good adaptive characteristics [9-11]. The EMD method is based on three assumptions: the existence of the maximum minimum point of not less than 1, The interval between adjacent extremes is the time scale and The signal without the extreme point is subjected to constant differential processing until the extreme point is obtained. Based on these three assumptions, the EMD will gradually decompose the fluctuates or trends of the scale without getting a series of IMFs, and these IMFs must satisfy:

(1) The difference between the zero point and the extreme point is 1 or equal.

(2) the IMF's two envelopes on the time pumping symmetry.

While the two conditions to meet the IMF was effective.

Set the original EEG signal as, the EMD decomposition process is:

(1) All local extreme points determined according to the three assumptions.

(2) Based on the principle of the three spline interpolation, the fitting of the maximum point is carried out to obtain the upper envelope , and the fitting of the minimum point is obtained to get the lower envelope , and then the upper and lower envelope mean curve  is calculated:

$$m(t)=\frac{1}{2}(\mu(t)+\nu(t)) \tag{1}$$

(3) The residual function is:

$$h_1(t)=X(t)-m(t) \tag{2}$$

(4) According to the IMF conditions, to determine whether the residual function $h_1(t)$ satisfies the conditions for full, $h_1(t)$ is the first IMF component, if not satisfied, while the $h_1(t)$ of the remaining steps, then the function to determine the conditions, and so on, until the K times, a new residual function satisfied $h_{1k}(k)$ condition the first is that the IMF component is the original EEG signals, which will be recorded as:

$$c_1(t)=h_{1k}(t) \tag{3}$$

According to the principle of EMD decomposition, the earliest isolated IMF frequency is the highest, and the frequency of separation later decreases,so $c_1(t)$ is the highest frequency component of the IMF component.

(5) and then $X(t)$ subtracted $c_1(t)$, it will get a new residual signal $r_1(t)$.

(6) $r_1(t)$ replace the original $X(t)$ repeat steps 1-5, when the resulting residual signal becomes a monotonic function or constant to stop the decomposition.

After the above decomposition, the original signal is decomposed into a series of IMF and the final part $r_n(t)$, the original EEG signal can be expressed as:

$$X(t)=\sum_{i=1}^{n}c_i(t)+r_n(t) \tag{4}$$

$c_i(t)$ for the $i$ decomposition of the IMF component, which is the EEG signal obtained by the EMD from high frequency to low frequency band components.

Through the above steps to the original EEG signal local subtle features step by step "screening" out. In order to ensure that the resulting components have practical physical meaning, rather than the infinite screening, resulting in the final IMF component is only a constant amplitude FM signal without the original physical meaning of the signal. So, EMD decomposition has a stop condition. This article uses the conditions proposed by Huang et al., When the (5) SD is between 0.2 and 0.3.

$$SD = \frac{\sum_{t=0}^{T} \left| h_{1k}(t) - h_{1(k-1)}(t) \right|^2}{\sum_{t=0}^{T} \left| h_{1(k-1)}(t) \right|^2} \tag{5}$$

## 2.2 Signal Decomposition.

When people are in motion imagination, EEG signal will have a significant $\alpha$ wave (8 ~ 12Hz) and $\beta$ wave (13 ~ 30Hz).In this paper, the EEG signal of each channel of Emotiv EEG acquisition instrument is selected to select the EEG signals of FC5 and FC6 to simulate the left and right hand, foot and tongue EEG signals. According to EMD principle, EMD decomposition of these four kinds of MI-EEG signals is obtained, and a series of IMF components are obtained.The FC5 channel imagery-EEG EMD right hand movement decomposition process is shown in Figure 1.

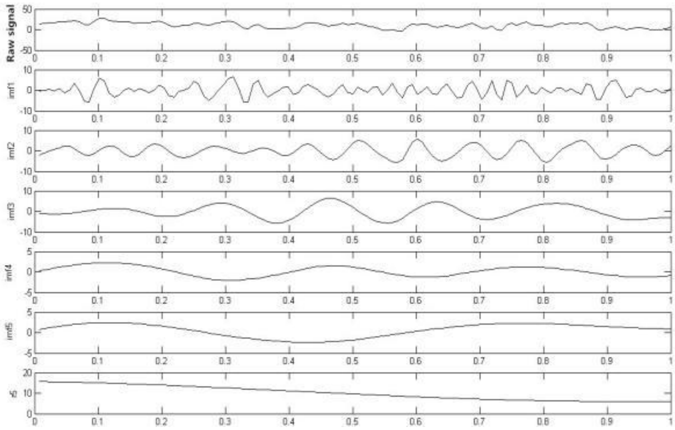

Fig. 1 EMD decomposition of the various IMF

As can be seen from the above figure, with the decomposition of the IMF order increases, the separation of the IMF component frequency is getting lower and lower, the first separation is the high frequency part, and low frequency finally separated. For different EEG signals, the IMF component that is separated may be different, and its base function does not need to be pre-designed to isolate the EEG signal local information well. According to the IMF components and the original brain electrical signal correlation degree, the following effective IMF selection, that is, the band selection.

According to the judgment of the degree of correlation between each IMF component and the original EEG signal in [12], this paper also introduces the correlation coefficient $r$, which is calculated as follows:

$$r = \frac{\sum_{i=1}^{n} (c_i - \bar{c})(x_i - \bar{x})}{\sqrt{\sum_{i=1}^{n} (c_i - \bar{c})^2 \sum_{i=1}^{n} (x_i - \bar{x})^2}} \tag{6}$$

$r$ is the degree of correlation between an IMF and the original EEG signal, $c_i$ is the i-th IMF component data, $\bar{c}_i$ is the corresponding IMF component mean, $x_i$ is the $i$ -th original EEG signal data, and $\bar{x}_i$ is its corresponding mean.If $r_i$ is used to represent the correlation coefficient of the i-th IMF component, then the choice for a valid IMF is $|r_i| \geq \lambda$ .

Where $\lambda$ is a constant with an absolute value less than 1.

If the calculated $|r| < 0.4$, then the IMF for the low correlation, if $0.4 \leq |r| \leq 0.7$ , then the IMF significantly first off.if $0.7 \leq |r| \leq 1$, then said a high degree of correlation. Each group of experimental samples obtained 4s of EEG data, so the greater the correlation coefficient IMF and the original EEG signal correlation degree is higher, the more conducive to follow-up EEG signal feature extraction. The correlation coefficients between the IMF components and the original EEG data of the EEG signal are shown in Table 1 below.

Table 1 The correlation coefficients between the IMF and the original signal

| IMF Component | IMF 1 | IMF 2 | IMF 3 | IMF 4 | IMF 5 |
|---|---|---|---|---|---|
| Coefficient $r$ | 0.2 | 0.8 | 0.4 | 0.1 | 0.1 |

In this paper, the IMF component of $|r|>0.4$ is chosen as the effective feature component. From Table 1, the IMF2 was highly correlated, IMF3 was significantly correlated, so the IMF2 and IMF3 were selected for the effective IMF set, and the remaining low correlation was excluded from the IMF. Different channels EEG signal decomposition of the effective IMF set may be different for other channels of the IMF is also the same selection.

# 3. Feature Extraction

## 3.1 CSP Algorithm

As a widely used spatial filtering algorithm, CSP algorithm can not only improve the signal-to-noise ratio of signal, but also extract the multidimensional feature information of the signal, and apply it to the feature extraction of EEG signal, which has a good effect. It is calculated by calculating the covariance matrix of the signal, diagonalization of the signal, the need to sort the signal for effective projection, making the difference between the two types of signal variance widened. A class of the largest and the other is the smallest, so to clearly distinguish between two types of signals [13].

CSP algorithm for EEG feature extraction, the process is as follows:

1. Calculate the covariance matrix $C_i$ of the original EEG signal. Let $X_i$ be a single MI-EEG signal, its size is $N \times n$, $N$ is the number of EEG signal acquisition channel, $n$ is a single imagination task collected under the EEG points, then:

$$C_i = \frac{X_i X_i^T}{trace(X_i X_i^T)} \tag{8}$$

Where $X_i^T$ is the transpose of $X_i$, and $trace(X_i X_i^T)$ is the sum of the diagonal elements of $X_i X_i^T$.

2. Calculate the average covariance of EEG sample matrices under two types of tasks. With 1 and 2, respectively, said two types of signal sample matrix, C1 and C2, respectively, said the average covariance, then:

$$C_1 = \frac{1}{r}\sum_{i=1}^{l} C_i^1, C_2 = \frac{1}{l}\sum_{i=1}^{r} C_i^2 \tag{9}$$

Where $r$ and $l$ respectively represent the number of sample data for the corresponding category.

3. Synthesize spatial covariance matrix. Expressed in $C$, then:

$$C = C_1 + C_2 \tag{10}$$

4. Decompose matrix $C$ .According to matrix theory, then:

$$C = B\lambda B^T \tag{11}$$

$\lambda$ is a diagonal matrix and the eigenvalues are nonzero, and $B$ is a $N$-dimensional eigenvector matrix.

5. whitening transformation. The whitening matrix $P$ for calculating the covariance matrices $C_1$ and $C_2$ is:

$$P = \lambda^{-\frac{1}{2}} B^T \text{,} \quad S_1 = PC_1P^T \text{,} \quad S_2 = PC_2P^T \tag{12}$$

6. Principal component decomposition. In the formula (12), the principal component is decomposed into:

$$S_1 = D\lambda_1 D^T \text{,} \quad S_2 = D\lambda_2 D^T \text{,} \quad \lambda_1 + \lambda_1 = I \tag{13}$$

Where $D$ is the eigenvector matrix and $I$ is a unit matrix. When the eigenvalue of $S_2$ is the smallest, the eigenvalues of the same set of eigenvectors in $S_1$ are the largest, and vice versa.

7. Space filter construction. According to the conclusion that the two types of eigenvalues of the same set of eigenvectors in step 6 are the largest and the other is the smallest, the eigenvalues in $\lambda_1$ and $\lambda_2$ can be used to construct the spatial filter.

$$W=[W_1+W_2]=D_1^T P+D_2^T P \tag{14}$$

Finally, the EEG signal processed by the filter becomes $Z_i=WX_i$.

### 3.2 OVR-CSP Algorithm

CSP is a typical two-class algorithm, for the multi-classification problem, we need to study its extended method OVR-CSP algorithm. The main process of the OVR-CSP algorithm is still in accordance with the CSP, but only the multi-classification problem into a number of two classification issues for processing. As the study of the four types of MI-EEG signal (tongue, foot, left hand and right hand) classification, in accordance with the OVR-CSP algorithm principle, first of all need to choose one of the four types of signals, the other three types of signals As a class, and then is a two classification problem, according to the CSP algorithm for the construction of spatial filters to feature extraction. This paper is a class of four categories on the two categories of classification, it is necessary to construct four spatial filters. The specific process is as follows:

The i-th experimental sample data with the EEG signal class $d$ is set to $X_i^d$, (T, F, L and R, respectively, $d\in\{T,F,L,R\}$ that the motion imagination tongue, foot, left hand and right hand EEG signal),then $X_i^d$ is a dimension matrix, $N$ indicates the number of channels collected by EEG, $n$ indicates the number of EEG signal samples of these channels.

Calculate the spatial covariance matrix of the four MI-EEG signals:

$$C_i^d=\frac{(X_i^d)(X_i^d)^T}{trace((X_i^d)(X_i^d)^T)} \tag{15}$$

$(X_i^d)^T$ represents the transpose of $X_i^d$, $trace((X_i^d)(X_i^d)^T)$ is the sum of the main diagonal elements of $(X_i^d)(X_i^d)^T$.

Calculate the average covariance matrix $C_T$, $C_F$, $C_L$ C and $C_R$ of the four EEG signal samples according to Eq. (9).

Calculate the synthetic spatial covariance matrix for the four EEG signals:

$$\mathrm{C}=C_T+C_F+C_L+C_R \tag{16}$$

4. The eigenvalue decomposition of the synthetic spatial covariance matrix is carried out:

$$C=U\lambda U^T \tag{17}$$

Where $\lambda$ is a diagonal matrix with diagonal eigenvalues in descending order and nonzero values. $U$ denotes its corresponding dimension vector matrix.

Define the whitening matrix.

$$P=\lambda^{-\frac{1}{2}}U^T \tag{18}$$

And then T as a class of signals, the rest as another category, there are:

$$\mathrm{C}_T^{'}=C_F+C_L+C_R \tag{19}$$

$$\mathrm{S_T}=P_T C_T P_T^T, \mathrm{S}_T^{'}=P_T C_T^{'} P_T^T \tag{20}$$

Perform two principal components of the signal decomposition:

$$\mathrm{S}_T=U_T\lambda_T U_T^T, \mathrm{S}_T^{'}=U_T\lambda_T^{'} U_T^T \tag{21}$$

$\mathrm{U}_T$ is the eigenvector matrix $\lambda_{\mathrm{T}}+\lambda_T^{'}=I$, $I$ is a unit matrix.

Perform a T-class spatial filter $\mathrm{W}_T$ construct. The eigenvalues corresponding to the largest $m$ eigenvalues in $\lambda_{\mathrm{T}}$ are constructed. The EEG signal is filtered by $\mathrm{W}_T$ as:

$$Z_T = W_T X_i^d \tag{22}$$

The spatial filter $W_F$ of the F-class, the spatial filter $W_L$ of the L-class, and the R-class spatial filter $W_R$ are constructed in the same manner as described above. Fig 2 shows the flow chart of the OVR-CSP algorithm, where T VS (F, L, R) refers to the combination of T-class and F, L, and R as the two inputs of the CSP, and after the three input combinations with this reason.

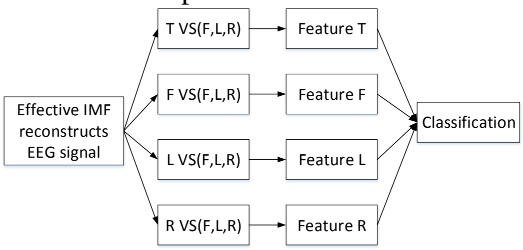


Fig 2. Algorithm flowchart

### 3.3 Four Types of MI-EEG Signal Feature Extraction

As the motion imagination of the left and right hand, feet and tongue EEG signal difference is mainly reflected in the α and β wave, therefore, we use EMD to obtain the effective IMF sets of four kinds of MI-EEG signals, and then select EEG signal reconstruction for EEG band. Then we reconstruct the EEG signal by OVR-CSP algorithm to extract the left and right hand, foot and tongue.

First define the motion to imagine the left and right hand, foot and tongue EEG signal characteristics.

Set the effective band EEG signal reconstruction of the imagination of the tongue movement, imagine the foot movement, imagine the left hand movement, imagine the right hand movement of the EEG signal of one of the $X$ ,The $X$ through $W_T$ , $W_F$ , $W_L$ , $W_R$ four spatial filters, the four types of MI-EEG signal characteristics can be defined as:

$$f_T = \lg\left(\frac{\operatorname{var}(Z_T)}{\operatorname{var}(Z_T)+\operatorname{var}(Z_F)+\operatorname{var}(Z_L)+\operatorname{var}(Z_R)}\right) \tag{23}$$

$$f_F = \lg\left(\frac{\operatorname{var}(Z_F)}{\operatorname{var}(Z_T)+\operatorname{var}(Z_F)+\operatorname{var}(Z_L)+\operatorname{var}(Z_R)}\right) \tag{24}$$

$$f_L = \lg\left(\frac{\operatorname{var}(Z_L)}{\operatorname{var}(Z_T)+\operatorname{var}(Z_F)+\operatorname{var}(Z_L)+\operatorname{var}(Z_R)}\right) \tag{25}$$

$$f_R = \lg\left(\frac{\operatorname{var}(Z_R)}{\operatorname{var}(Z_T)+\operatorname{var}(Z_F)+\operatorname{var}(Z_L)+\operatorname{var}(Z_R)}\right) \tag{26}$$

Where var denotes the variance of the vector.

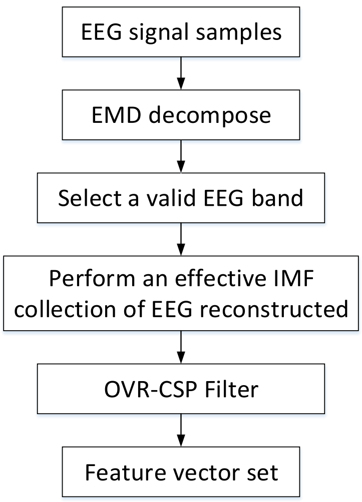


Fig 3. The EEG Signal Feature Extraction Process Based on EMD - OVR - CSP

In this paper, the EEG signals of AF3, AF4, F3, F4, FC5, FC6, T7, T8, O1 and O2 channels are selected to extract the four MI-EEG signal characteristics. The flow is as follows:

(1) EEG effective frequency band selection. In order to solve the problem of frequency band selection in CSP algorithm, EMD is selected for the four MI-EEG signals, and the effective signal frequency band is selected to remove the EEG signal independent of the custom experiment task.

(2) Calculate the correlation between each IMF component and the original EEG signal according to (16), then select the effective IMF component and reconstruct the EEG signal.

(3) The channel EEG signals reconstructed in the above steps are input to four OVR-CSP spatial filter filters, and then the extracted EEG signal characteristics are calculated according to Eqs. (23), (24), (25) and (26) , And form a 4-dimensional feature vector set $f = [f_T, f_F, f_L, f_R]$.

The EEG signal feature extraction process is shown in Fig 3.

## 4. Experiments

### 4.1 Experimental Data

The experiment was conducted using BCI Competition 2008 Graz data set A. The experimental data collected 22 electrodes, the electrode position shown in Figure 4.

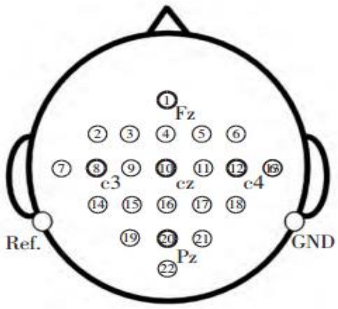


Fig 4. The EEG Signal Feature Extraction Process Based on EMD - OVR - CSP

The experiment, a total of nine subjects, including four kinds of sports imagination (left, right, Feet, tongue). Each set of data includes training data and test data, each containing four samples of 72 different samples, 288 training samples, 288 test samples. The sampling frequency of the data set is 250 Hz, after 0.5 Hz to 100 Hz Broadband filtering.

Before the start of the experiment, the subjects relaxed sitting in a comfortable chair and a black cross on the screen, with a short sound, suggesting that subjects ready to start the test, after 2 s, it will appear on the screen one arrow pointing to the left and right upper and lower one (corresponding to imagine movement left right hand, foot and tongue), arrow duration is 1.25 s, the arrow indicates the emergence of the subjects of motor imagery until the restore screen black, the end of the experiment.

### 4.2 .Experimental Analysis

If the reconstructed class is $p$ (T, F, L, and R, $p \in \{T, F, L, R\}$ respectively, the motion of the tongue, the foot, the left hand and the right

hand of the EEG signal) of the i-th experimental sample is set to $X_i^p$ , then an $N \times n$ dimensional matrix; Indicates the number of selected channels, that is, N = 10; M represents the number of points per channel,that is, n = 512. Figure 5 shows the left-hand MI-EEG signal data samples after EMD extract valid IMF, the reconstruction of the 10-channel EEG signal waveform.

The average covariance matrix is calculated based on the reconstructed new EEG signal:

$$\mathrm{C}_T = \frac{1}{260}\sum_{i=1}^{260} C_i^T, \mathrm{C}_F = \frac{1}{260}\sum_{i=1}^{260} C_i^F \tag{27}$$

$$\mathrm{C}_L = \frac{1}{260}\sum_{i=1}^{260} C_i^L, \mathrm{C}_R = \frac{1}{260}\sum_{i=1}^{260} C_i^R \tag{28}$$

In equation (27), A, B, C, and D denote the average covariance matrix of the EEG signal of the imagination tongue, the foot and the left and right hand, respectively. E, F, G and H are given by Eq. (25).

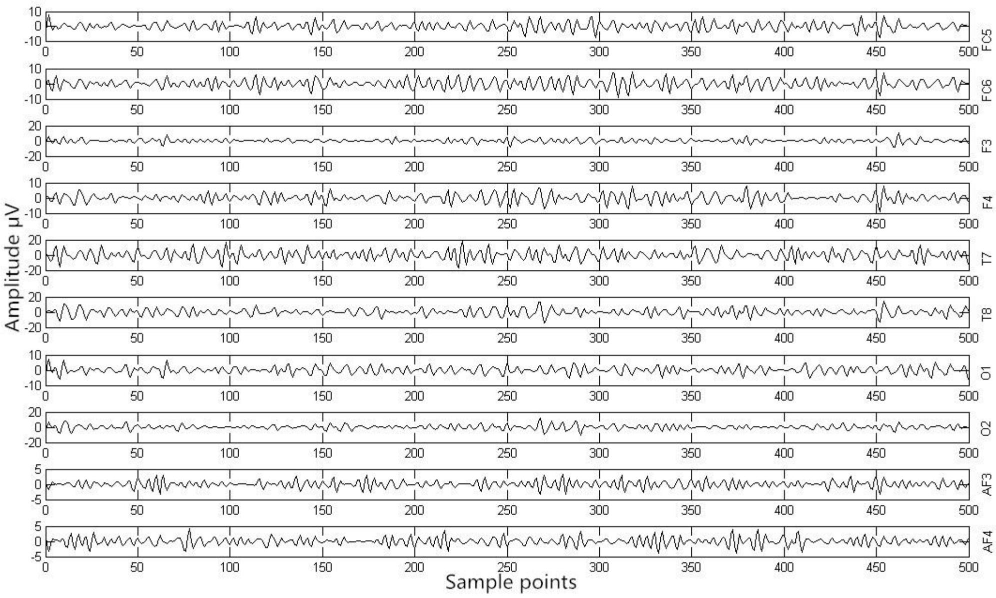


Fig 5. Reconstruction of effective IMF sets for each channel of motor imaginary left hand EEG

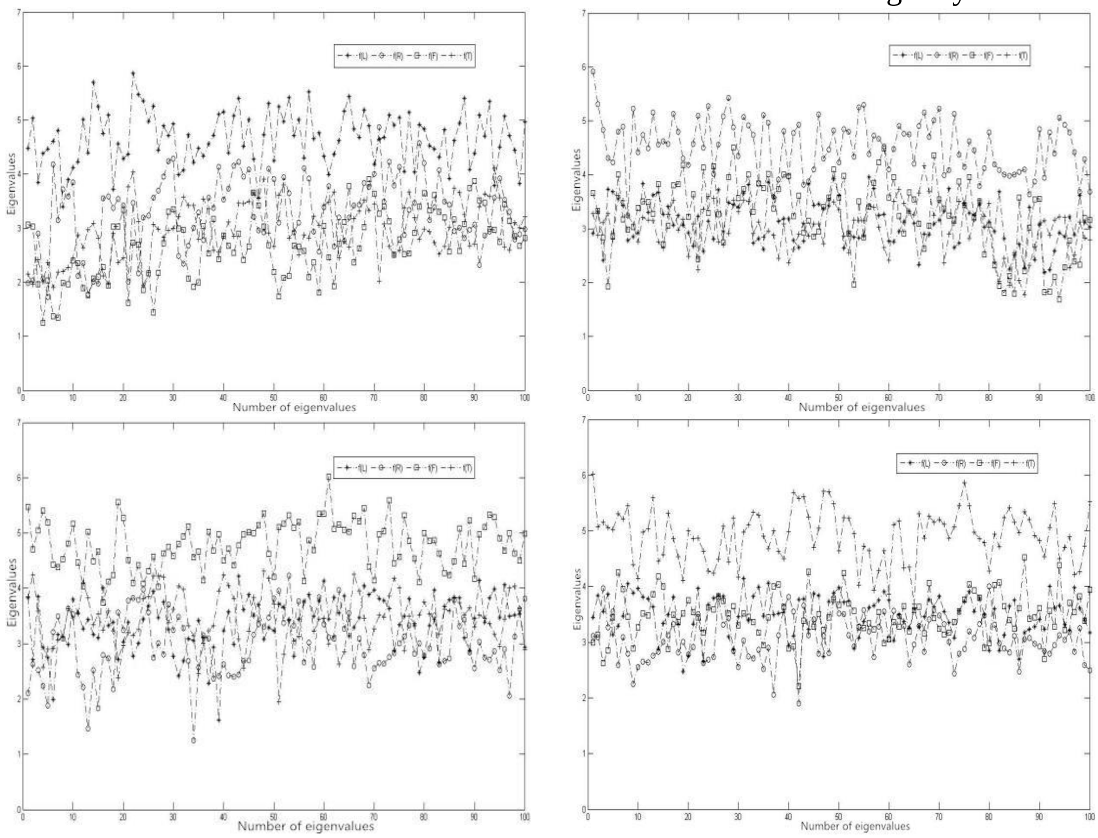


Fig 6. The Eigenvalue Distribution of the, Effective IMF Components of Four EEG Signals After $W_L$ , $W_R$ , $W_F$ and $W_T$

Four types of EEG signals effectively IMF component by $W_L$ , $W_R$ , $W_F$ , $W_T$ after the value distribution, and then CSP filter according to the eigenvalues and the corresponding eigenvectors are constructed of four kinds of MI-EEG signal. The four MI-EEG signal through the filter $W_L$ , $W_R$ , $W_F$ , $W_T$ after the feature value distribution as shown in fig 6. Among them, $f(L)$ , $f(R)$ , $f(F)$ , $f(T)$ said the movement as left hand movement imagination respectively, right hand, foot and tongue image features of motor imagery movement.

It can be seen from Figure 6, four types of MI-EEG signal through the $W_L$ after the movement of the imaginary left hand feature was significantly higher than the other three types of signal characteristics;

Figure 6 shows that the four types of MI-EEG signal through the $W_R$ after the movement of imaginary right-hand features Which is obviously higher than that of the other three types of signals. It can be seen from Fig. 6 that the four types of MI-EEG signals are obviously higher than those of the other three types of signals after $W_F$ . From Fig.6, four types of MI-EEG The signal obtained by the $W_T$ has been significantly higher than that of the other three types of signals. This indicates that the proposed EMD-OVR-CSP algorithm is effective in extracting the four types of MI-EEG signals.

In order to verify the superiority of the proposed method, the EMD-OVR-CSP algorithm and the traditional CSP feature extraction method are used for the BCI Competition 2008 Graz data set A data set. The results are shown in the table. EMD-OVR-CSP algorithm is used to recognize the four types of EEG signals, and the robustness is better.

Table 2. Classification Accuracies ± Standard Deviation (%) of 4 classes (left, right, tongue and foot) MI EEG

| Subjects | Four classes MI EEG | |
|---|---|---|
| | OVR-CSP/% | CSP/% |
| S1 | 86.16±0.65 | 80.53±0.84 |
| S2 | 93.04±0.53 | 95.81±0.70 |
| S3 | 81.08±0.85 | 75.56±1.00 |
| S4 | 87.56±0.35 | 84.74±0.68 |
| S5 | 83.61±0.50 | 78.06±0.53 |
| S6 | 90.56±0.48 | 87.78±0.75 |
| S7 | 87.50±0.50 | 84.72±0.81 |
| S8 | 96.06±0.76 | 93.83±1.00 |
| S9 | 87.56±1.00 | 85.42±1.26 |

## 5. Conclusion

In this paper, an EMD-OVR-CSP algorithm for four types of MI-EEG signal feature extraction is proposed. The four classification problems are transformed into four categories of two categories of two classification problems, and in BCI Competition 2008 data set A to verify its effectiveness. Experiments show that the ECD signal feature extraction algorithm based on empirical mode decomposition can effectively extract the four kinds of MI-EEG signals, and the final recognition rate is higher than the ordinary CSP algorithm. Indicating that the superiority of the algorithm, BCI system provides a new way of thinking.

## Acknowledgements

Technology Commission of Chongqing Municipality (Grant No. cstc2015jcyjBX0066).

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