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Feature Extraction of Motor Imagery EEG Signals Based on PSD and CSP Fusion

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Abstract. Aiming at the current problems of single feature extraction of motor imagery EEG signals and low accuracy of classification and recognition, a feature extraction method of motor imagery EEG signals based on the fusion of PSD and CSP (PSD-CSP) is proposed. Firstly, the FastICA algorithm is employed for artifact signal removal from the raw EEG data. Subsequently, features are extracted from the Power Spectral Density (PSD) and Common Spatial Pattern (CSP), followed by their serial fusion. Finally, a Support Vector Machine (SVM) classifier is used for classification. In binary motor imagery classification experiments on the BCI Competition IV Dataset I, the average classification accuracy reaches 91.43%, and comparative analysis with other methods demonstrates the feasibility of the proposed fusion algorithm.

Keywords. EEG signals; Feature extraction; Power spectral density; Common spatial pattern

1. Introduction

Brain Computer Interface (BCI) technology is a neural interface that enables users to interact directly with external systems by capturing and interpreting the electrical activities of the brain. Currently, the primary challenge in BCI technology lies in improving the accuracy of EEG signal recognition. Therefore, optimizing EEG signal feature extraction algorithms is a focal point of current BCI research, particularly in the field of motor imagery EEG signals.

Because of its weak and nonlinear, nonsmooth, and time-varying sensitivity, time-frequency domain analysis and spatial filtering are widely used in the feature extraction process of EEG signals [1]. Time-frequency domain analysis mainly includes Short-term Fourier Transform (STFT) [2], Wavelet Transform (WT) [3], and Wavelet PackageTransform (WPT) [4], and spatial filtering is mainly common. Spatial Pattern (CSP) algorithm [5].

In recent years, since a single feature can only characterize specific EEG information, multi-feature fusion has become one of the research hotspots in multi-categorical feature extraction for motor imagery because it can contain valid EEG information of different dimensions. Representative ones include: Li Mingai et al [6] proposed a feature extraction algorithm based on the Hilbert-Huang transform (HHT) and co-space subspace decomposition algorithm (CSSD), extracted the Hilbert instantaneous energy spectrum and marginal energy spectrum as the time-frequency features and extracted the spatial features, and the fused features were classified by using

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vectorized neural network classifier for classification. Yang Mohan et al [7] proposed a multi-feature extraction method combining EEMD and approximate entropy. Aiming at the problem that a single feature extraction method cannot represent EEG signal features in multiple aspects, this paper proposes a feature extraction method for motor imagery EEG signals based on the fusion of PSD and CSP (PSD-CSP). The multidimensional features are utilized for weighted fusion, and finally, the fused features are input to the SVM classifier to obtain higher classification accuracy.

2. EEG Signal Preprocessing

2.1 Description Of The Data Set

The dataset was derived from the "BCI Competition IV Dataset 1", which recorded 59 channels of EEG data from 7 subjects. Each subject was asked to perform two types of motor imagery with either the right or left hand or both feet 100 times each, and the first 6s of each trial would first display a fixed cross in the center of the computer screen. A fixation cross was displayed, an arrow pointing left, right, or down was displayed at t=2s, and participants were asked to perform the corresponding MI task (left/right hand and foot), and then the screen appeared black at 6s~8s, and participants were asked to take a break for 2s. The raw signals were band-pass filtered between 0.05 Hz and 200 Hz and later downsampled to 100 Hz.

2.2 FastICA denoising

The experiments were conducted on the MATLAB2018b software platform for Windows 10.0 system, and the EEGLAB toolkit was utilized for the analysis of EEG signals. The raw EEG signals have noise and artifacts, and in order to prevent their influence on feature extraction, the data need to be preprocessed first. In this paper, a fifth-order Butterworth bandpass filter with a range of [0.5-60Hz] is used to remove the interference from the useless frequency bands and the industrial frequency and to obtain the frequency band region of interest of the motor imagery EEG signal shown in Figure 1. Since other artifacts are also mixed in, it is also necessary to decompose the data using the FastICA algorithm [8] based on the EEGLAB toolkit and remove the data such as ocular artifacts, so as to obtain the EEG signals that satisfy the requirements of the experiments and can effectively improve the accuracy of the experiments.

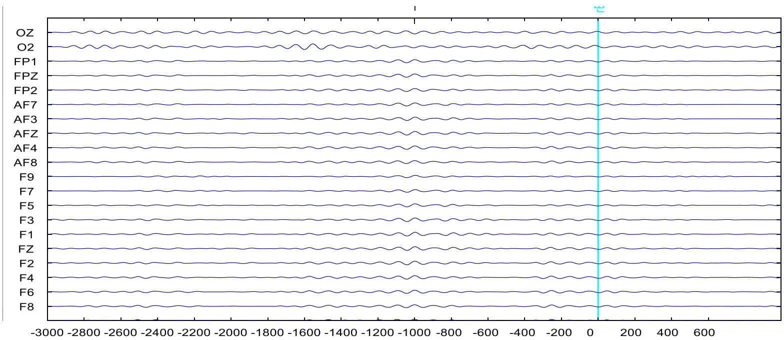

Figure 1. A segment of EEG signal after preprocessing

3. The Proposed PSD-CSP Method

3.1 Algorithmic Process

The specific implementation steps of the feature extraction method for motor imagery EEG signals based on the fusion of PSD and CSP are as follows: (1) Input the EEG signals and use the CSP algorithm to transform the original motor imagery EEG signals into a new feature space; (2) Segment the signals into segments in the new feature space and compute the power spectral density of each segment; (3) Perform the feature vectors of PSD and CSP for feature selection, selecting the subset of features with the most discriminative ability; (4) assigning weights to the feature vectors of PSD and CSP, respectively; (5) linearly weighting the weighted feature vectors of PSD and CSP according to the weights to obtain the fused feature vectors.

3.2 Power Spectral Density

Power Spectral Density (PSD) [9] describes the distribution of the power of a random signal at different frequencies as a measure of the average power per unit frequency and uses the density to characterize the distribution of the signal at frequency points. The calculation steps are as follows:

$x(n)$ is an infinite-length random sequence and the intercepted length N becomes a finite-length sequence called $x_N(n)$.

Calculate $x_N(n)$ the autocorrelation function $Rx(m)$ at a point $(2m-1)$.

$$Rx(m) = \frac{1}{N}\sum_{n=0}^{N-1} x(n)x(n+m) \tag{1}$$

In which $m = -(M-1), \cdots -1, 0, 1, \cdots M-1, M \le N$.

Find the Fourier transform of the correlation function to obtain the power spectrum:

$$\hat{S}_x(e^{j\omega}) = \sum_{m=-(M-1)}^{M-1} \hat{R}x(m)e^{-j\omega m} \tag{2}$$

3.3 Common Spatial Pattern

The Common Spatial Pattern (CSP) [10] algorithm is a classical spatial filtering method for the two-class task, which is able to extract the spatial distribution pattern of each class of signals from the multichannel EEG data, and its basic principle is to construct a spatial filter by matrix diagonal algorithm to project the multichannel EEG data into a low-dimensional subspace and to maximize the difference of covariance matrices of the two classes of samples. The basic principle is to construct a spatial filter through the matrix diagonal algorithm to project the multichannel EEG data into a low-dimensional subspace and maximize the difference between the two types of samples. The specific steps of the algorithm are:

Step 1: Normalize X to obtain the associated covariance matrices:

$$R_H = \frac{X_H X_H^T}{\mathrm{trace}(X_H X_H^T)} \qquad R_F = \frac{X_F X_F^T}{\mathrm{trace}(X_F X_F^T)} \tag{3}$$

Where X^T represents the transpose matrix of X and $\mathrm{trace}(X)$ represents the sum of all elements on the diagonal of X.

Step 2: Decompose the synthesized covariance matrix:

$$R = U_0 \sum U_0^T \tag{4}$$

Where is the eigenvector of R, the diagonal matrix formed by the eigenvalues of the mixed covariance matrix R

Step 3: Construct the whitening matrix P:

$$P = \sum^{-\frac{1}{2}} U_0^T \tag{5}$$

Step 4: The whitening transformation:

$$S_H = P\overline{R_H}P^T \qquad S_F = P\overline{R_F}P^T \tag{6}$$

Step 5: Main Component Breakdown:

$$S_H = U_H \sum{}_H U_R{}^T \qquad S_F = U_F \sum{}_F U_F{}^T \tag{7}$$

Step 6: Find the spatial filter of the CSP SF:

$$SF_H = U_H{}^T P \qquad SF_F = U_F{}^T P \tag{8}$$

4. Experimental Results And Analysis

The experiments were conducted on the Jupyter Notebook software platform for Windows 10.0 system, and the MNE toolkit was utilized for the analysis of EEG signals. The whole system is divided into training mode and test mode: in the training mode, the data are first intercepted using downsampling, and then the PSD power spectral density is applied for frequency filtering and the CSP co-space mode is applied for null-domain filtering; finally, the SVM classifier is used to train and classify the data. In the test mode, the filters and classifiers obtained in the training mode are directly utilized to classify and identify the test samples, so as to verify the effectiveness and practicality of the algorithm.

Import the preprocessed EEG signals, perform 8-15Hz filtering, demonstrate the epoch features by feature engineering, and plot the C3, Cz, and C4 channel features as in Figure 2.

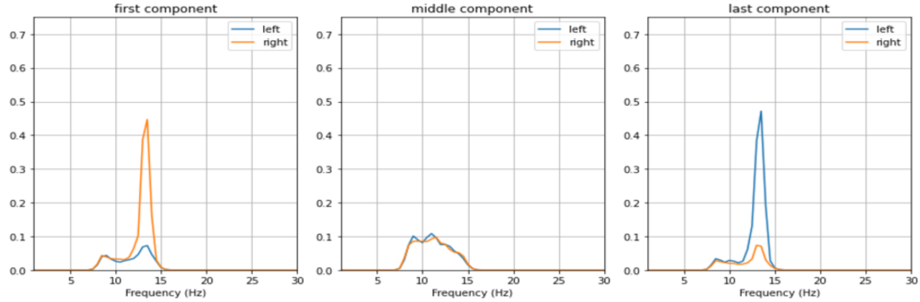

Figure 2. C3, Cz, C4 left and right hand channel characteristics

Subsequently, the logarithmic variables of the 59 channels are depicted, as illustrated in Figure 3. Following the CSP spatial filtering process, the resulting representation is visualized in Figure 4.

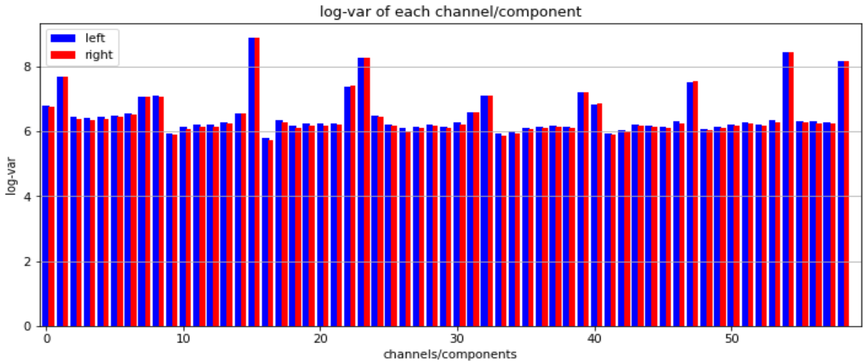

Figure 3. Plot of logarithmic variables before CSP treatment

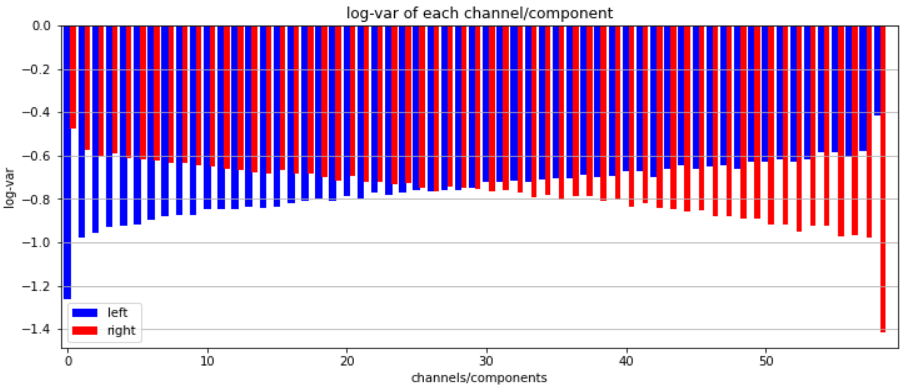

Figure 4. Plot of logarithmic variables after CSP treatment

Finally, the feature vectors were used to train the SVM classifier for classification. Three algorithms, PSD, CSP, and PSD-CSP fusion, were used to extract features from EEG signals imagining left and right hand movements, and the extracted feature vectors were transformed into energy entropy ratios, whose magnitude reflects the complexity of the movement imagery, and normalized by Newton's method of logistic regression, and transformed into a two-dimensional feature-point map. The comparison chart of the feature extraction results is as follows Figure 5, Figure 6 and Figure 7. It can be seen that for the two types of left- and right-handed motion imagery signals, after PSD-CSP fusion feature extraction, the distinction between left- and right-handed tasks is significantly better than that of the feature extraction algorithm using PSD and CSP alone.

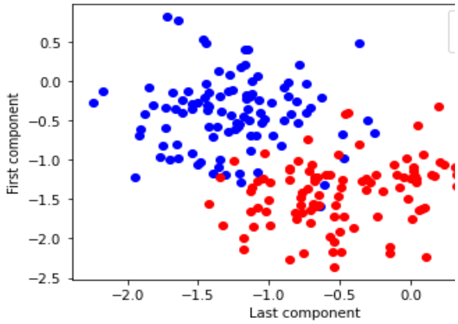

Figure 5. PSD feature extraction

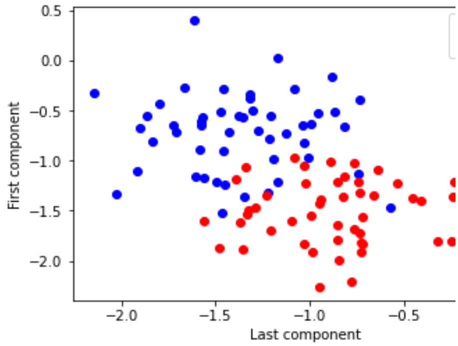

Figure 6. CSP feature extraction

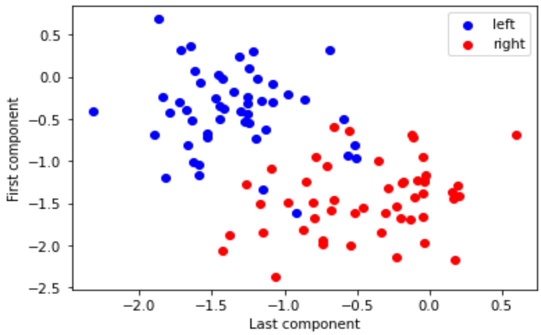

Figure 7. PSD-CSP fusion feature extraction

The classification algorithms for extracting motor imagery EEG features from other literature in recent years are compared with the experimental results in the paper, as shown in Table 1. As can be seen from Table 1, the PSD-CSP fusion feature extraction can effectively make the difference between the two types of vectors increase, which improves the classification accuracy. Overall, the accuracy of the algorithm in the paper is significantly higher than the classification accuracy of the remaining four groups.

Table 1. Comparison of classification accuracy with other feature extraction algorithms.

Serial number	Arithmetic	Classifier	Accuracy/%
1	LMD + fuzzy entropy[11]	SVM	85.35
2	HCHT[12]	SVM	89.14
3	BS-CSP[13]	SVM	90.21
4	AR+WPE+CSP[14]	SVM	91.07
5	PSD-CSP	SVM	91.43

5. Conclusion

Since the traditional common spatial pattern is suitable for multi-channel data analysis and the frequency domain information is lacking. Therefore, this paper proposes a feature extraction method for motor imagery EEG signals based on the fusion of PSD and CSP (PSD-CSP). The EEG signal is first preprocessed, the original signal is filtered and denoised, and then the power spectral density of the processed signal is computed as a feature of CSP filtering, and finally classified using SVM. The experimental results show that the average classification accuracy of this algorithm is as high as 91.43%, which is advantageous in improving the accuracy of multiclassification motion imagery recognition.

References

[1] Duan L, Zhang Q, Yang Z, et al. Research on Heuristic Feature Extraction and Classification of EEG Signal Based on BCI Data Set[J]. Research Journal of Applied Sciences, Engineering and Technology, 2013, 5(3):1008-1014.

[2] Wang Z, Cao L, Zhang Z, et al. Short time Fourier transformation and deep neural networks for motor imagery brain computer interface recognition[J]. Concurrency and Computation: Practice and Experience, 2018, 30(23): e4413.1-e4413.9.

[3] Murugappan M, Nagarajan R, Yaacob S Combining Spatial Filtering and Wavelet Transform for Classifying Human Emotions Using EEG Signals[J]. Journal of Medical & Biological Engineering, 2011, 31(1):45-51.

[4] Ting W, Guozheng Y, Banghua Y. EEG feature extraction in brain computer interface based on wavelet packet decomposition[J]. Chinese Journal of Scientific Instrument, 2007, 28(12):2230-2234.

[5] Sang-Hoon,Park,David,et al.Motor Imagery EEG Classification Using Filter Bank Regularized Common Spatio-Spectral Pattern[J].The Journal of Korean Institute of Information Technology, 2017, 15(10):127-134.

[6] LI Mingai, CUI Yan, YANG Jinfu,et al.Multi-domain fusion adaptive EEG feature extraction method based on HHT and CSSD[J]. Journal of Electronics, 2013, 41(012):2479-2486.

[7] YANG Mohan,CHEN Wanzhong, LI Mingyang. Research on motor imagery EEG recognition method based on overall empirical modal decomposition with multi-class features[J]. Journal of Automation, 2017, 43(5):10.

[8] Jin-Hui S, Gang Z, University B U, A Novel GA Based Blind Signal Separation of Multi-Channel EEG[J]. Chinese Journal of Medical Physics, 2013, 30(6):4547-4552.

[9] Wang R, Wang J, Yu H, et al. Power spectral density and coherence analysis of Alzheimer's EEG[J]. Cognitive Neurodynamics, 2015, 9(3):291-304.

[10] Shu Chen, Qing Zhou. A multi-domain fusion EEG signal classification method based on LMD and CSP[J]. Computer Applications and Software, 2023, 40(3):130-136.

[11] ZHU Xiaojun, FAN Liujuan, LV Shiqin, et al. Application Research of LMD Method in EEG Signal Processing LMD Method in EEG Signal Processing[J]. Computer Science, 2012, 39(2):273-275.

[12] Luo Fei, Liu Pengfei, Luo Yuan, et al. Multi-feature fusion for motor imagery EEG feature extraction[J]. Computer Applications, 2020, 40(2):5.

[13] Yang, Jinfu, Li, et al. A novel EEG feature extraction method based on OEMD and CSP algorithm[J]. Journal of intelligent & fuzzy systems: Applications in Engineering and Technology, 2016, 30(5):2971-2983.

[14] LONG Jiawei, ZHENG Wei, LIU Yan, et al. EEG signal feature extraction based on alignment entropy and CSP fusion[J]. Computer Technology and Development, 2022, 32(3):157-162.