A Stepwise Discriminant Analysis and FBCSP Feature Selection Strategy for EEG MI Recognition

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***Abstract*—Accurate decoding of brain intentions is a pivotal technology within Brain-Computer Interface (BCI) systems that rely on Motor Imagery (MI). The effective extraction of information features plays a critical role in the precise decoding of these brain intentions. However, there exists significant individual and environmental variability in signals, and the sensitivity of EEG signals from different subjects also varies, imposing higher demands on both feature exploration and accurate decoding. To address these challenges, we employ adaptive sliding time windows and a stepwise discriminant analysis strategy to selectively extract features obtained through the Filter Bank Common Spatial Pattern (FBCSP). This entails the identification of an optimal feature combination tailored to specific patients, thereby mitigating individual differences and environmental variations. Initially, adaptive sliding time windows are applied to segment electroencephalogram (EEG) data for different subjects, followed by FBCSP for feature extraction. Subsequently, a stepwise discriminant analysis (SDA) incorporating prior knowledge is employed for optimal feature selection, effectively and adaptively identifying the best feature combination for specific subjects. The proposed method is evaluated using two publicly available datasets, the EEG recognition accuracy for Dataset A is 98.47%, and for Dataset B, it is 95.2%. In comparison to current publicly reported research results (utilizing Power Spectral Density (PSD) + Support Vector Machine (SVM) methods) for Dataset A, the proposed method improves MI recognition accuracy by 25.37%. For Dataset B, compared to current publicly reported results (FBCNet method), the proposed method improves MI recognition accuracy by 26.4%. The experimental results underscore the method's broad applicability, scalability, and substantial value for promotion and application.**

Keywords—Stepwise discriminant analysis; electroenceph alogram; motor imagery; sliding time window; filter bank common spatial pattern

I. Introduction

Brain-computer interface (BCI) technology has witnessed rapid development, injecting new vitality into the fields of neuroscience and engineering [1, 2]. Among various BCI applications, the interpretation of electroencephalogram (EEG) signals through Motor Imagery (MI) has emerged as a notable research focus [3-12]. MI-EEG technology enables individuals to control external devices through brain activity, holding tremendous promise in neuroscience, medical rehabilitation, and intelligent assistive devices. It offers a potential pathway for individuals who have lost motor capabilities due to illness or injury [13-16]. This technology finds widespread application in neurorehabilitation, particularly for patients recovering from conditions such as stroke [17] and spinal cord injuries [18]. Through MI-EEG, patients can control external devices by imagining movements, promoting the re-adaptation and repair of damaged neural systems. Additionally, MI-EEG plays a crucial role in controlling smart assistive devices, providing a more flexible and independent lifestyle for individuals with disabilities [19 -22].

Internationally and domestically, research teams have made substantial progress in EEG signal studies, delving into BCI systems' five processes: signal acquisition, signal preprocessing, feature extraction, feature classification, and external device control [23-25]. Feature extraction is a critical aspect of MI recognition, and common methods in MI-BCI include Common Spatial Pattern (CSP) [26], Power Spectral Density (PSD) [27], and wavelet feature extraction algorithms [28]. Wu et al. [29] proposed a PSD-based frequency band pre-determination method to effectively extract EEG signal features related to motion imagery when wearing exoskeletons. The CSP was then applied to extract features from the EEG's highest energy frequency band. Zheng et al. [30] introduced a new Regularized Common Spatial Patterns (RCSP) algorithm based on traditional CSP to handle small-sample EEG data. RCSP adjusts the values of two regularization parameters, introducing a certain degree of correlation among experimental data to reduce errors caused by individual differences. Results from testing on public datasets showed that RCSP algorithm classification outperformed traditional CSP by approximately 8%. Wei et al. [31] used the Filter Bank Common Spatial Pattern (FBCSP) with a one-to-one multi-class extension to classify four classes of MI-EEG (BCI Competition IV Datasets 2a). A majority voting strategy was applied to the selected individual classifiers, yielding a considerable classification accuracy of 68.52%. Siviero et al. [32] combined multi-channel empirical wavelet transform representation with Scattering Convolutional Networks (SCN) to effectively decode brain activity and extract MI-based BCI's relevant wave patterns. The highest average accuracy in the classification of tongue and left-hand MI tasks reached 82.05%. Jiang et al. [33] redefined regularized spatial or temporal filters through a reweighting technique, iterating them as CSP problems. Experimental validation on two sets of BCI competition motor imagery EEG data demonstrated the algorithm's effectiveness, achieving an average accuracy of 85%. These studies primarily focus on feature extraction, highlighting the crucial role of this process in final result performance. Among various feature extraction methods, Filter Bank Common Spatial Pattern (FBCSP) stands out due to its comprehensive consideration of signal frequency information compared to traditional CSP and RCSP methods. This method exhibits superior performance in handling complex tasks and has gained wide usage in the BCI field, especially in applications demanding high levels of personalization and accuracy. Consequently, the FBCSP algorithm was selected as the EEG feature extraction method in this study.

Due to factors such as individual differences in reaction time, physical state, and environment, EEG data exhibit variability in terms of duration, space, frequency bands, etc. In recent years, researchers have proposed various sliding window techniques to improve classification accuracy. Gaur et al. [34] introduced two sliding window techniques, one calculating the longest continuous repetition of all sliding window prediction sequences, and the other computing patterns in all sliding window prediction sequences. CSP was used for feature extraction, and linear discriminant analysis was employed for classification in each time window, resulting in an overall classification accuracy of approximately 80%. Phunruangsakao et al. [35] presented two mutual information-based adaptive algorithms: the sliding window adaptive algorithm and the genetic algorithm adaptive algorithm. Both algorithms continuously adjust the starting point and length of the time window using optimized reference signals and mutual information analysis. The algorithms optimize reference signals based on mutual information analysis and performance evaluation. Finally, feature extraction and classification algorithms were applied to assess the performance of the sliding window adaptive algorithm and genetic algorithm adaptive algorithm. The results demonstrated that these adaptive algorithms improved traditional methods, enhancing classification accuracy by 6.00% and 6.37%, respectively. Shin et al. [36] performed feature extraction on the temporal process of EEG signals using a moving time window. Linear discriminant analysis (LDA) was used for classification, achieving a classification accuracy of 65.6% for MI-EEG. To enhance classification accuracy, P. Saideepthi et al. [37] introduced a post-processing step based on the longest continuous repetition of sliding windows using EEGNet as a decoding basis. The average classification accuracy reached 77%. However, individual differences in brain signals and susceptibility to environmental influences pose challenges. Moreover, different components extracted from features contribute differently to MI recognition for different subjects. The use of generic feature extraction algorithms may not effectively select high-quality feature components. The challenge is how to adaptively extract common features with significant contributions from specific subjects in effective data, enhancing the generalization of BCI systems.

Q. Dong et al. [38] utilized an electrode selection algorithm based on Independent Component Analysis (ICA). Time-domain features of the selected P300 electrode were extracted, and stepwise linear discriminant analysis was applied for classification, achieving the best recognition rate of 80.2% and an average recognition rate of 74.4% for nine participants. This validated the feasibility of spatial auditory-evoked P300 experiments and the effectiveness of the algorithm. Numerous studies on stepwise discriminant analysis suggest its feasibility in feature selection. However, the MI recognition accuracy of the proposed algorithm remains relatively low. Pane et al. [39] proposed a channel selection method for emotion recognition in EEG signals based on Stepwise discriminant analysis (SDA). SDA is an extension of discriminant analysis statistical tools, incorporating stepwise techniques. In their study, data were obtained from a public emotional EEG dataset using EEG devices with 62 channels targeting three target emotions (positive, negative, and neutral). To handle high-dimensional data in EEG signals, differential entropy features were extracted from five frequency bands: δ, θ, α, β, and γ. SDA's selection criterion was based on Wilks Lambda scores to obtain the best channels. To measure the performance of the selected channels, EEG signal feature vectors were fed into an LDA classifier. In experiments, several scenarios with different numbers of selected channels, such as 3, 4, 7, and 15 channels, were considered. In the case of 15 channels, the highest accuracy of 99.85% was achieved across all frequency band combinations.

To overcome the impact of individual differences in EEG data in terms of time, space, and frequency bands caused by factors such as subjects' reaction time, physical state, and environment, this study employed an optimized sliding time window algorithm combined with a stepwise discriminant feature selection algorithm. This algorithm not only expands the data volume and improves accuracy but also enables optimal feature selection for specific patients. To optimize the results of stepwise discriminant feature selection, this study introduced a method of incorporating prior knowledge, allowing the algorithm to adaptively select the optimal features applicable to specific individuals. For the FBCSP features of EEG signals, we adopted an adaptive feature selection method, and the experiments demonstrated that this method exhibits robust adaptability in handling EEG data features while maintaining strong generalization capabilities. The structure of the article is arranged as follows: Section II provides a detailed introduction to the data and methods, including the dataset used, the overall framework of the algorithm, and the feature extraction method. Section III presents the experimental results, while Section IV conducts an in-depth discussion of the proposed method. Section V draws the final conclusion.

II. Data and Methods

A. Dataset Introduction

1) Dataset A: Dataset A [36] consists of EEG data from 29 healthy participants, including 28 right-handed individuals and 1 left-handed individual, with a gender distribution of 14 males and 15 females. The average age was 28.5 ± 3.7 years (mean ± standard deviation). EEG data were recorded using a BrainAmp EEG amplifier with 30 active electrodes, connected to mastoid reference, and sampled at 1000 Hz. Fourteen sources and sixteen detectors generated 36 physiological channels, placed in frontal areas (9 channels around Fp1, Fp2, and Fpz), motor areas (12 channels around C3 and C4), and visual areas (3 channels around Oz). The inter-electrode distance was 30 mm.

The EEG dataset includes both Motor Imagery (MI) and Mental Arithmetic (MA) tasks. This paper focuses on the MI dataset, which comprises three sessions of left and right-hand motor imagery tasks. Each session consists of 20 trials for each condition, resulting in a total of 60 trials per participant across the three sessions. Each session begins with a one-minute pre-experiment resting period, followed by 20 repetitions of the given task, and concludes with a one-minute post-experiment resting period. Each task involves a two-second visual cue (indicating right or left-hand movement), a 10-second task period, and a 15-17-second rest period. The participants are instructed to imagine grasping movements of their left or right hand at a rate of 1 Hz. Further details about the dataset can be found in the reference [36].

2) Dataset B: Dataset B [40] involves experiments with 25 healthy participants without prior Motor Imagery (MI)-based Brain-Computer Interface (BCI) experience, aged between 20 and 24 years, with 12 females. The experiment used a 32-channel solid electrode cap with Ag/AgCl, ensuring high current density, good anti-interference, and low impedance. The amplifier supported wireless transmission and real-time impedance monitoring, maintaining electrode impedance below 20 KΩ throughout the 250 Hz sampling. Data were stored in microvolts (uV). Bad segments were removed before preprocessing and automatically flagged by EEGLAB for amplitude exceeding 100 uV. Additional manual inspection by two experienced researchers determined the presence of bad segments. The four-second EEG data for MI tasks were saved for further processing. The sampling frequency was 250 Hz, providing a total time sample of 1000 for each trial. Baseline removal and bandpass filtering between 0.5-40 Hz using Finite Impulse Response (FIR) filters were applied. Some trials were lost due to the removal of bad segments in certain sessions.

Before the experiment, participants received detailed explanations of the experimental methods and procedures, ensuring a thorough understanding. Experiment supervisors oversaw the process to guarantee reliability. The experiment took place in a spacious enclosed laboratory, where participants sat in a chair one meter away from a 15-inch LCD monitor. Each trial started with a fixed crosshair in the center of the monitor, signaling the upcoming task to the participant. When a left or right-hand movement was displayed on the monitor, participants were prompted to imagine the next movement. Trials consisted of 100 repetitions, with four interruption periods during the experiment. Participants imagined movements based on visual and auditory cues, maintaining rest and stillness to preserve physical and mental states and ensure high signal quality. The dataset is available for free download on Figshare 17 and is organized according to EEG-BIDS 28, an extension of the EEG Brain Imaging Data Structure. Various access methods, such as IEEE P273129, FAIR 30, and EEG-BIDS, are provided. IEEE P2731 defines a complete storage system, including decoding algorithms, preprocessing, feature extraction, and classification. This system comprehensively describes the generation, processing, and utilization of EEG datasets.

Datasets A and B are representative EEG data in the field of brain computer interfaces, which have been validated by a large number of researchers and have higher reference value.

B. Algorithm Framework

This study conducts analysis and validation on two EEG datasets, and the algorithm framework is depicted in Fig. 1. The algorithm consists of four modules:

1) Raw data input and preprocessing: For EEG data from Dataset A, it undergoes downsampling to 200 Hz. Filtering is applied with a passband of 0.5 - 50 Hz using a fourth-order Chebyshev II filter. Baseline correction is performed by subtracting the average value between -3 seconds and 0 seconds from the segmented windows in the range of -10 seconds to 25 seconds. EEG data from Dataset B, having undergone preprocessing in the original data, is not detailed in this section.

2) Sliding time windows: For EEG data from Dataset A, after obtaining the necessary data, a sliding time window (window size: 3 s, step size: 1 s) is applied, dividing the data into 33 windows. Each window undergoes individual feature extraction. EEG data from Dataset B, after obtaining the necessary data, is subjected to a sliding time window (window size: 3 s, step size: 2 s), resulting in 49 windows. Similar to Dataset A, each window undergoes individual feature extraction.

3) Feature extraction: For EEG data from both Dataset A and Dataset B, three methods are employed for feature extraction: Common Spatial Patterns (CSP), Regularized Common Spatial Patterns (RCSP), and Filter Bank Common Spatial Patterns (FBCSP). Through experimentation, CSP demonstrates superior performance on Dataset A, while FBCSP outperforms other methods on Dataset B. In general, FBCSP, considering signal frequency information comprehensively, exhibits better performance in handling complex tasks. Given its widespread use in brain-computer interface applications, especially in scenarios requiring high personalization and accuracy, FBCSP is ultimately selected as the EEG feature extraction method.

4) Optimal feature selection and result prediction: For each window of EEG data from Dataset A and Dataset B after feature extraction, the features are split into training (70%) and testing (30%) sets. The training set undergoes normalization and stepwise discrimination to obtain an optimized new feature set, used to train a Linear Discriminant Analysis (LDA) classifier. During online testing, the optimal feature sequence index obtained through cross-validation based on the Stepwise discriminant analysis (SDA) algorithm is used to select feature components for testing data. The testing data is filtered based on the data index obtained from SDA in the training set and serves as the source signal. The LDA classifier calculates the classification accuracy.

C. Feature Selection Strategies Based on FBCSP and SDA

In brain-computer interface motor imagery tasks, significant variations exist in individuals' reaction speeds and response times. These differences lead to inconsistent timing when subjects receive commands and perform corresponding actions, impacting the data and potentially introducing errors in data processing. To address this issue, the sliding time window method is employed to effectively mitigate prediction result biases arising from inconsistent reaction times, thereby enhancing the dataset's volume and accuracy [41]. For Dataset A, EEG samples for each subject are sampled from -10 to 25 seconds with a sliding window of 3 seconds and a step size of 1 second, resulting in 33 windows. For Dataset B, a sliding window of three seconds with a step size of two seconds is applied, yielding 49 windows.

For the EEG signals of the two datasets, this study experimented with three feature extraction methods: Common Spatial Patterns (CSP), Regularized Common Spatial Patterns (RCSP), and Filter Bank Common Spatial Patterns (FBCSP). CSP is a feature extraction method designed for EEG or other biological signals to find projection directions that maximize the difference between two classes while minimizing the variance within the same class. By identifying the optimal projection direction in different spatial filters, CSP enhances differences between different classes and effectively increases the classification accuracy of task-related information in brain signals.

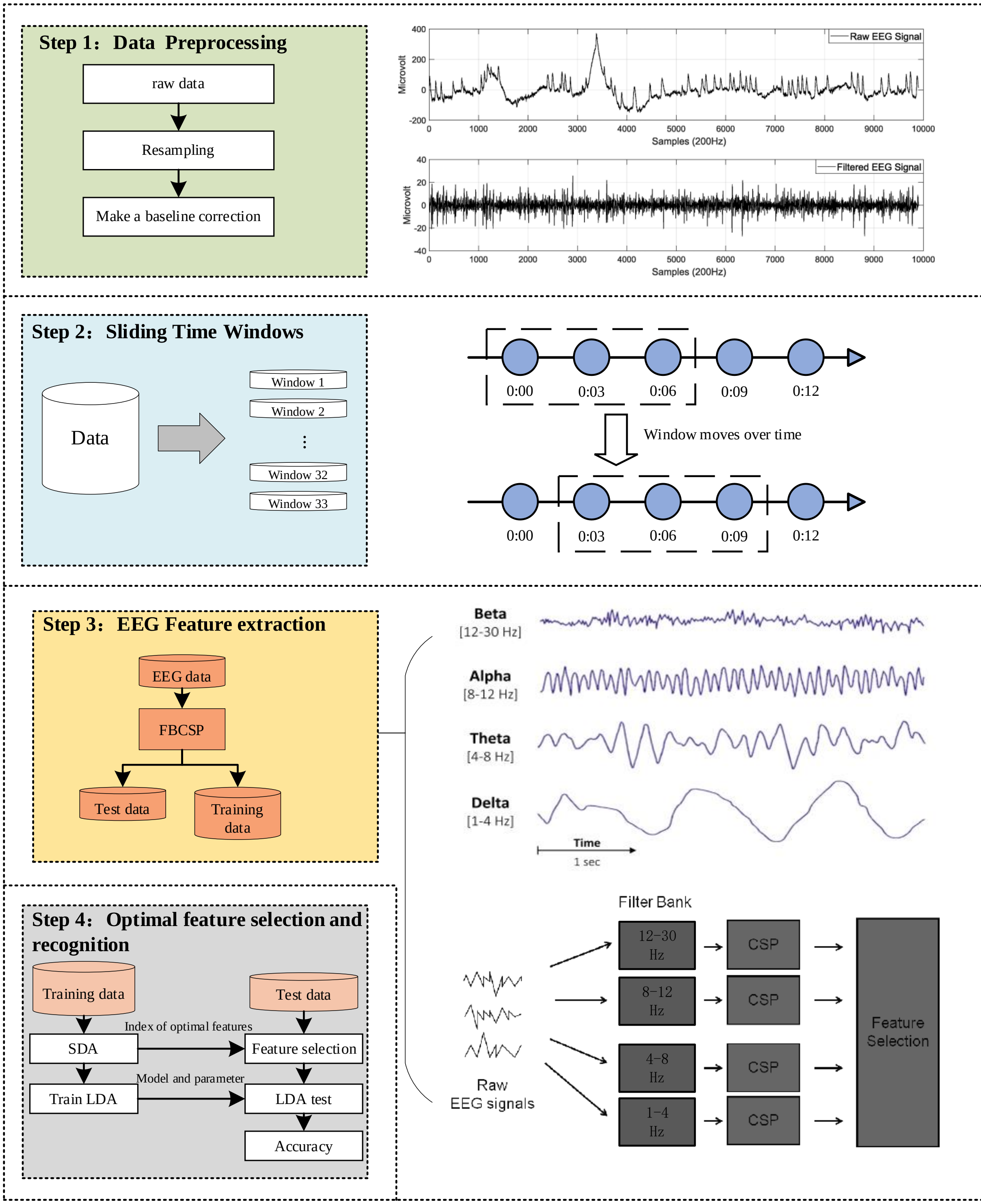


Fig. 1. Algorithm framework diagram.

The objectives of CSP are to find a projection matrix W, such that the covariance of the projected signals is diagonalized in the new coordinate system. This can be achieved by solving the following generalized eigenvalue problem:

$$S = W^T R_1 W = Q_1 \tag{1}$$

$$S = W^T R_2 W = Q_2 \tag{2}$$

Here, S is the total covariance matrix, Q1 and Q2 are diagonal matrices containing generalized eigenvalues. By solving this problem, the obtained projection matrix W can be used to project EEG signals into the new coordinate system.

RCSP is an improvement upon CSP, introducing a regularization term to enhance the model's generalization performance and reduce overfitting. RCSP is commonly used for handling high-dimensional data, mitigating the overfitting issue associated with limited samples. By incorporating regularization, RCSP can better adapt to new data, thereby improving the model's robustness. Formulas (3) and (4) are provided below, where I is the regularization parameter, and α is the identity matrix. Regularization contributes to enhancing the model's generalization performance.

$$S = W^T (R_1 + \alpha I) W = Q_1 \tag{3}$$

$$S = W^T (R_2 + \alpha I) W = Q_2 \tag{4}$$

FBCSP decomposes the signal into multiple frequency bands and applies CSP to each band individually. Finally, it consolidates the features extracted from different frequency bands for the ultimate classification. FBCSP takes into account the frequency information of the signal, allowing for a more comprehensive capture of features in brain signals, especially effective in complex BCI applications involving various movements or tasks. Formulas (5) and (6) are presented below, where W_i represents the corresponding CSP projection matrix. Thus, the objective function for FBCSP can be expressed as follows, where R_1i and R_2i are the covariance matrices for the two classes within its frequency band:

$$S_i = W_i^T R_{1i} W_i = Q_{1i} \tag{5}$$

$$S_i = W_i^T R_{2i} W_i = Q_{2i} \tag{6}$$

The three feature extraction methods produce different effects on different datasets. RCSP is an extension of CSP, introducing regularization to address the issue of small sample data and improve the algorithm's generalization ability. FBCSP introduces frequency domain decomposition, breaking down the signal using a filter bank to better handle information in different frequency bands. RCSP focuses primarily on regularization for scenarios with limited samples, while FBCSP concentrates on frequency domain decomposition to enhance performance through operations in the frequency domain. Eventually, these three methods were chosen as feature extraction techniques. In summary, FBCSP, compared to traditional CSP and RCSP methods, comprehensively considers the frequency information of signals, exhibiting better performance in handling complex tasks. This method is widely used in the field of brain-computer interfaces, particularly in scenarios requiring high personalization and accuracy. In this paper, the FBCSP algorithm is selected as the EEG feature extraction method.

Through multiple experiments, it was observed that different feature variables exhibit varying sensitivity, with different dimensions, units, and ranges, leading to the neglect of certain indicators. This affects the performance of subsequent stepwise discriminant analysis. To address this issue, the feature set underwent normalization. Since min-max normalization enables data from different ranges to be calculated within the same range, it facilitates easier processing and comparison, enhancing computational efficiency. Additionally, normalization helps avoid proportional relationships between attribute values, reducing the impact of attribute value magnitudes on the final result and mitigating algorithm bias. Therefore, max-min normalization was selected based on the feature set.

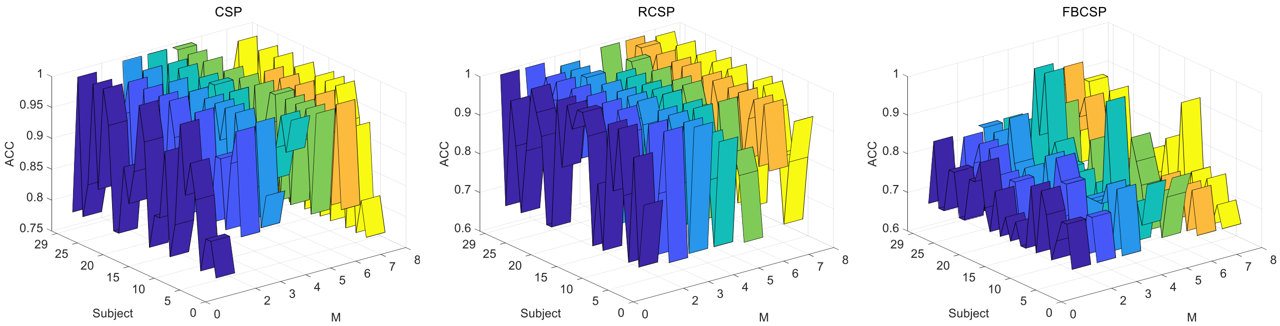
After normalization, the feature data is within the same order of magnitude, significantly improving comparability among indicators. Despite being in the same order of magnitude, there are still significant differences in the statistical significance of features. To resolve this, the optimal feature subset containing all relevant features was determined, and irrelevant features were removed. The stepwise discriminant analysis (SDA) algorithm was employed to further process the feature data. SDA is a comprehensive method that combines forward introduction and backward elimination. It reduces multicollinearity by removing unimportant variables highly correlated with other variables [42, 43]. During the experiment, the SDA [44] algorithm introduced variables into the model one by one. After introducing each explanatory variable, an F-test was conducted, and the already selected explanatory variables were individually subjected to t-tests. If an originally introduced explanatory variable became insignificant due to the subsequent introduction of other explanatory variables, it was removed to ensure that the regression equation contained only significant variables before each new variable introduction. This process was repeated until there were no significant explanatory variables to include in the regression equation and no insignificant explanatory variables to remove, ensuring that the final set of explanatory variables obtained was optimal. Selecting the optimal set of variables enhances the accuracy of the results. Formula (7) is as follows, where Y is the target variable, Xi is the added independent variable, and βi is the corresponding regression coefficient.

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i + \cdots + \beta_k X_k + \epsilon \tag{7}$$

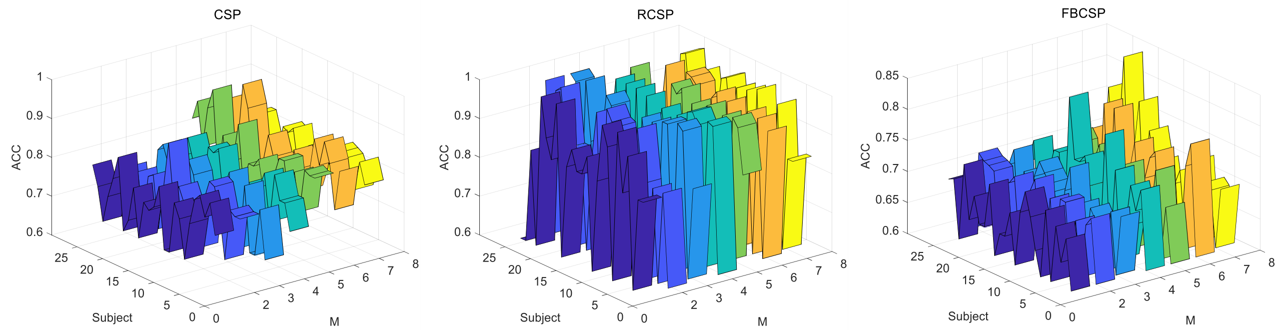
III. Experimental Results

A. Comparison of Different Feature Extraction Methods for Specific Subjects

CSP and its variants, such as FBCSP and RCSP, exhibit distinct effects in feature extraction, and this variability is notable across individual EEG datasets. To select the optimal spatial feature extraction algorithm, experiments, and parameter selections were conducted on two publicly available datasets, evaluating CSP, RCSP and FBCSP. The datasets were initially segmented using sliding time windows, followed by feature extraction using CSP, RCSP, and FBCSP. Finally, the prediction accuracy of 30% of the blind source signals was assessed using an LDA classifier. To investigate the optimal feature extraction results, the experiments were conducted with different feature dimensions, m=2~8. The experimental results are illustrated in Fig. 2.



(a)



(b)

Fig. 2. (a) and (b) are 3D plots of ACC with varying feature dimensions M for specific subjects in datasets A and B.

As shown in Fig. 2, the plots correspond to the accuracy of each subject as the feature dimension varies from 2 to 8. For dataset A, using the three methods, CSP exhibits stable performance when the feature dimension is 6, with an optimal average accuracy of 92.72% among the 25 subjects. RCSP achieves its optimal average accuracy of 76.63% when the feature dimension is 5. FBCSP reaches its optimal average accuracy of 91.57% when the feature dimension is 7. For dataset B, using the three methods, CSP achieves its optimal average accuracy of 77.35% when the feature dimension is 5. RCSP reaches its optimal average accuracy of 69.41% when the feature dimension is 5. FBCSP attains its optimal average accuracy of 83.32% when the feature dimension is 4. From the results of these two datasets, it can be observed that among these three feature extraction methods, FBCSP performs more outstandingly.

B. *Feature Selection Strategy of FBCSP and SDA for Specific Subjects*

Due to the presence of feature redundancy in the results of feature extraction, coupled with the individual differences in features among different subjects, further efforts are made to select the optimal feature combination from the extracted features. This aims to make the features more adaptive to specific subjects. In this section, we propose the additional use of the SDA method for adaptive feature selection. Initially, a sliding time window is applied for segmentation. Subsequently, CSP, RCSP, and FBCSP are employed for feature extraction. Following this, SDA is utilized for feature selection. Compared to PSD and FBCNet, the additional use of SDA for feature optimization can effectively eliminate some poor feature data and improve the quality of features. Finally, an LDA classifier is employed to predict the accuracy of 30% of the blind source signals. We investigate the optimal feature extraction results, where the feature dimensions for the three feature extraction algorithms range from m=2~8. The experimental results are illustrated in Fig. 3.

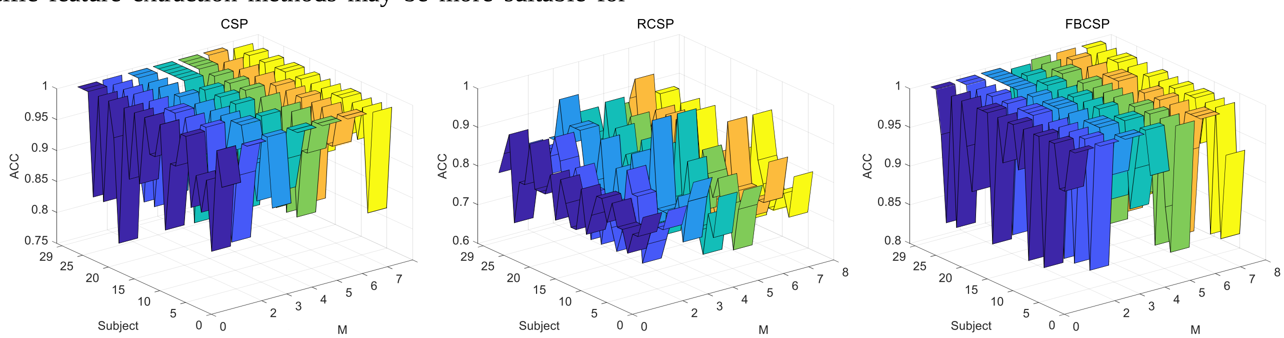
As shown in Fig. 3, the overall performance of the RCSP method is suboptimal for both datasets. It exhibits significant fluctuations and lower accuracy, ranging between 60% and 80% for each individual. Conversely, the FBCSP method yields predominantly favorable results, with accuracy consistently surpassing 80%. For Dataset A, the maximum average accuracy achieved by CSP, RCSP, and FBCSP is 96.36%, 81.23%, and 98.47%, respectively. Notably, CSP utilizes a feature count M of 5, RCSP with M of 4, and FBCSP with M of 4. In the case of Dataset B, the maximum average accuracy for CSP, RCSP, and FBCSP is 82.26%, 72.12%, and 95.2%, respectively. CSP uses M=2, RCSP uses M=3, and FBCSP employs M=2. From the experimental results, it is evident that there is significant individual variability in the accuracy distribution of different subjects in both Dataset A and Dataset B. The adoption of this adaptive feature selection strategy substantially improves the recognition accuracy of specific subjects.

To validate the effectiveness and generalization ability of the proposed sliding window-optimized stepwise regression feature selection algorithm and investigate the optimal feature selection count and corresponding recognition accuracy for different subjects, based on the experimental results, feature counts M for CSP, RCSP, and FBCSP for Dataset A and B are set to 5, 4, 4, and 2, 3, 2, respectively. Adaptive sliding time window truncation is applied to EEG data from different subjects in Datasets A and B. Various feature extraction methods are employed for feature extraction, followed by stepwise discriminant analysis for further feature selection. The optimal feature selection count and corresponding recognition accuracy for different subjects in Datasets A and B are depicted in Fig. 4 and Fig. 5.

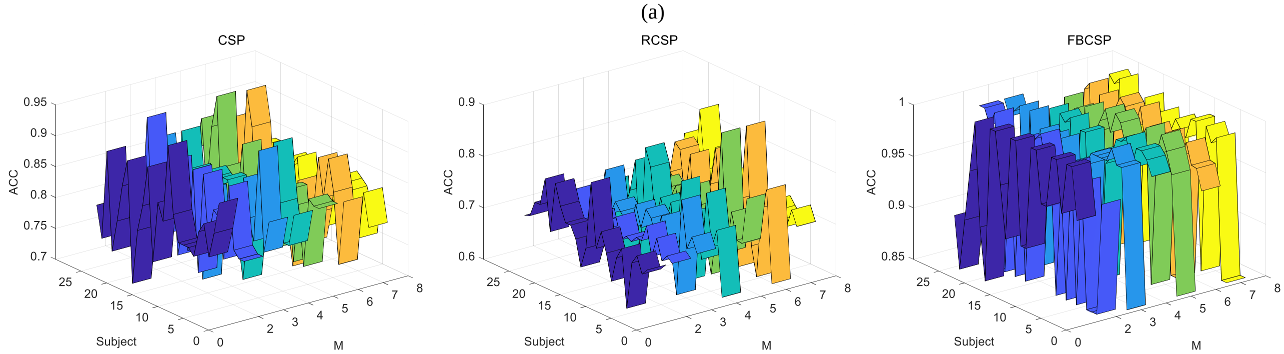
As illustrated in Fig. 4, the optimal feature count varies among the 29 subjects, with the majority selecting three features. The graph depicts the number of features selected through stepwise regression under the condition of maximum accuracy. For instance, for Subject 1, using the CSP method with an accuracy of 100%, the corresponding feature count is 6; with the RCSP method and an accuracy of 88.89%, the feature count is 5; and with the FBCSP method and an accuracy of 100%, the feature count is 2. For Dataset A, after CSP, RCSP, and FBCSP feature extraction and feature selection, the average feature selection counts are 3.41, 2.45, and 3.93, respectively. The classification accuracy obtained from each subject indicates that stepwise regression possesses strong feature selection capabilities.

The graph reveals that under different feature extraction methods, individual accuracy shows a certain trend of variation. FBCSP and CSP methods exhibit relatively high accuracy, with average accuracies reaching 98.47% and 96.36%, respectively. In contrast, RCSP shows larger fluctuations and an average accuracy of only 80.44%. On an individual level, differences in performance are observed across different subjects under various feature extraction methods. The ninth subject achieves 100% accuracy across all three feature extraction methods. The fourteenth subject demonstrates high accuracy in CSP and FBCSP feature extraction methods, while possibly showing average performance in the RCSP method. This suggests that specific feature extraction methods may be more suitable for certain individuals, and individual responses to these methods are diverse.

As depicted in Fig. 5, the optimal feature count varies among the 25 subjects, with the majority selecting 2 features. The graph illustrates the number of features selected through stepwise regression under the condition of maximum accuracy. For instance, for Subject 1, using the CSP method with an accuracy of 89.47%, the corresponding feature count is 1; with the RCSP method and an accuracy of 70.33%, the feature count is 3; and with the FBCSP method and an accuracy of 95%, the feature count is 2. After CSP, RCSP, and FBCSP feature extraction and feature selection for Dataset B, the average feature selection counts are 2.08, 1.96, and 2, respectively. The classification accuracy obtained from each subject indicates that stepwise regression possesses strong feature selection capabilities. Compared to Dataset A, the impact of the three methods on Dataset B's predictions is more distinct, with FBCSP being advantageous and RCSP at a disadvantage. RCSP exhibits relatively stable prediction results, but the average accuracy is only 72.12%; CSP shows larger fluctuations with an average accuracy of 82.26%. The overall best performance is observed in FBCSP, which maintains good stability while achieving an average accuracy of 92.5%. On an individual level, differences in performance are observed across different subjects under various feature extraction methods. The eighteenth subject achieves 70%, 71%, and 100% under the CSP, RCSP, and FBCSP methods, respectively. The nineteenth subject achieves 89.47%, 70.4%, and 85% under the CSP, RCSP, and FBCSP methods, respectively. This indicates that specific feature extraction methods may be more suitable for certain individuals, and individual responses to these methods are diverse.



(a)



(b)

Fig. 3. (a) and (b) are 3D graphs depicting the ACC variation with the feature count M for specific subjects in Datasets A and B.

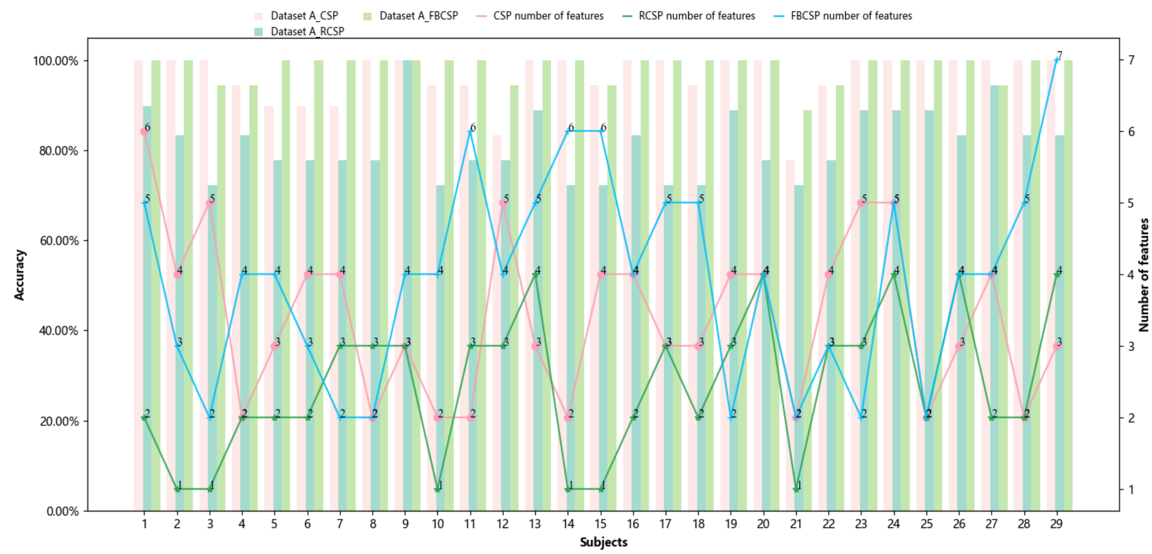


Fig. 4. Optimal feature number and corresponding recognition accuracy for different feature extraction algorithms in dataset A.

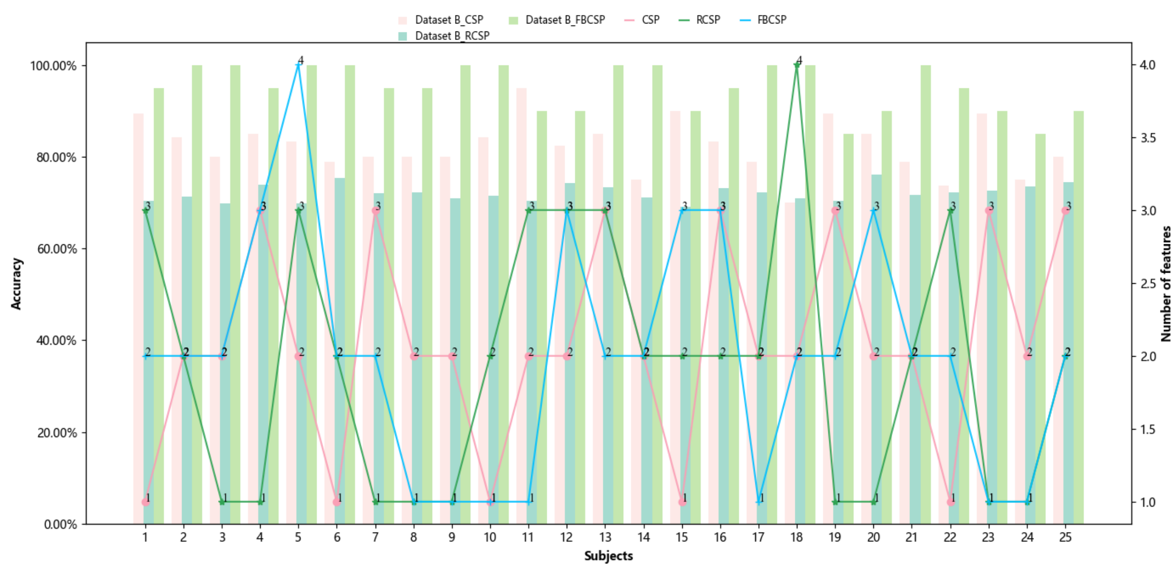
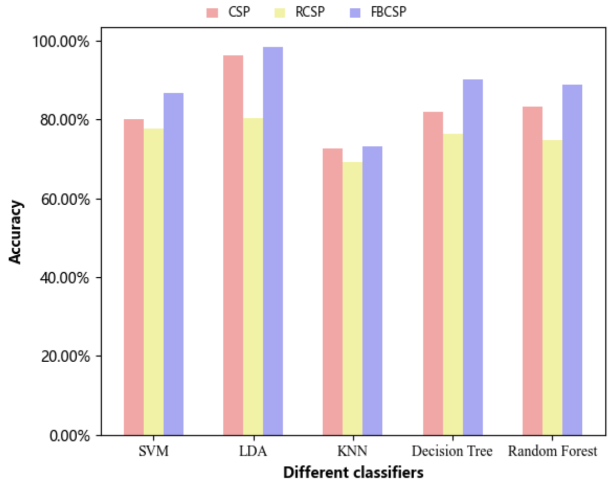


Fig. 5. Optimal feature number and corresponding recognition accuracy for different feature extraction algorithms in dataset B.

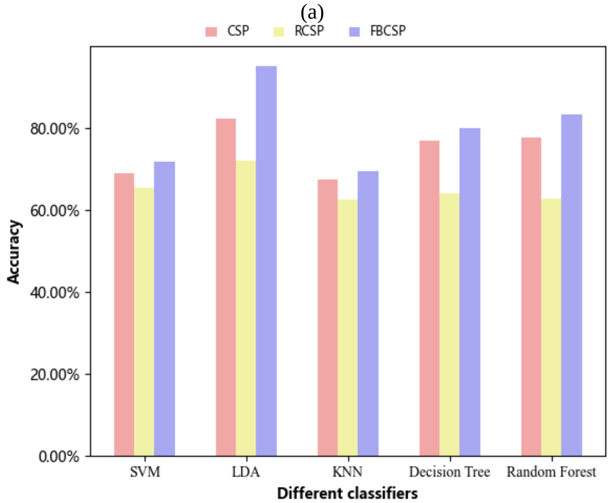
C. Recognition Results of Different Classifiers

To verify the generalization capability and robustness of the proposed method, this paper employs Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and k-nearest Neighbors (kNN) to evaluate the performance of the selected feature subset. As shown in Fig. 6, for Dataset A, three feature extraction methods and three classifiers—LDA, SVM, kNN, Decision Tree, and Random forest yield the following accuracies: CSP+LDA achieves an accuracy of 96.36%, CSP+SVM achieves 80.08%, CSP + KNN achieves 72.61%, CSP + Decision Tree achieves 81.99%, and CSP + Random Forest achieves 83.14%. Similarly, RCSP+LDA achieves an accuracy of 80.44%, RCSP+SVM achieves 77.78%, RCSP+KNN achieves 69.16%, RCSP + Decision Tree achieves 76.25%, and RCSP + Random Forest achieves 74.71%. FBCSP+LDA achieves an impressive accuracy of 98.47%, FBCSP+SVM achieves 86.8%, FBCSP+KNN achieves 73.18%, FBCSP +Decision Tree achieves 90.06%, and FBCSP + Random Forest achieves 88.72%. For Dataset B, the accuracies are as follows: CSP+LDA achieves 82.26%, CSP+SVM achieves 68.82%, CSP+KNN achieves 67.42%, CSP + Decision Tree achieves 76.88%, and CSP + Random Forest achieves 77.65%. RCSP+LDA achieves 72.12%, RCSP+SVM achieves 65.45%, RCSP+KNN achieves 62.58%, RCSP + Decision Tree achieves 64.1%, and RCSP + Random Forest achieves 62.73%. FBCSP+LDA achieves an accuracy of 95.2%, FBCSP+SVM achieves 71.65%, FBCSP +KNN achieves 69.51%, FBCSP + Decision Tree achieves 80.07%, and FBCSP + Random Forest achieves 83.4%.

From the figures, it is visually apparent that, under the same classifier, FBCSP outperforms others. Furthermore, when employing the same feature extraction algorithm, the performance of the LDA classifier is notably superior to other classifiers.



(a)



(b)

Fig. 6. The recognition results of different classifiers under datasets A and B. (a) the result of dataset A, and (b) the results of dataset B.

IV. Discussion

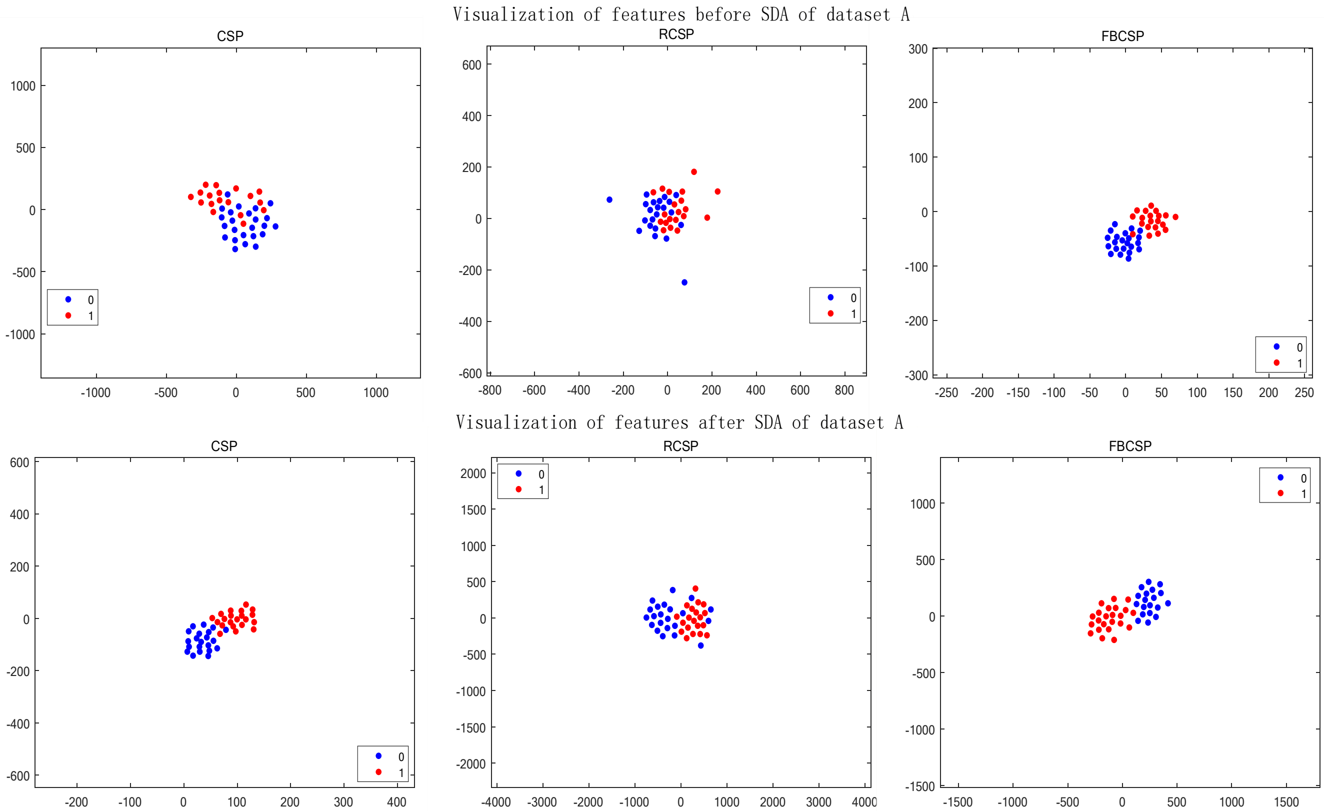
EEG feature extraction is crucial for decoding MI signals. However, due to factors such as individual variability among subjects and environmental variations during testing, spatial feature extraction methods and their improved versions, as well as the selection of feature parameters, can exhibit different effects on individuals. Experimental evidence has shown that FBCSP demonstrates superior generalization capabilities. Despite the significant redundancy in the features extracted by this spatial feature extraction method, effectively eliminating redundant information can greatly enhance EEG decoding accuracy. Therefore, this paper proposes the use of a Sliding Time Window-based Spatial Domain Adaptation (SDA) method to improve performance. To validate the effectiveness of this SDA feature selection strategy on the effects of feature extraction and generalization capabilities, we compared the distribution of features with and without the SDA feature selection strategy and performed experiments on two datasets. Fig. 7 illustrates the optimal feature visualization of EEG data from datasets A and B.

Fig. 7 presents the t-SNE [45] visualization results for binary MI classification of the 9th participant, with (a) and (b) representing the feature visualization comparisons before and after stepwise discrimination for datasets A and B, respectively. It can be seen that the separability of data features has a certain effect. The features extracted by the proposed method achieved better feature separability which will enhance the classification performance of the model. Therefore, the visualized feature maps demonstrate that the latent features extracted by our method can more significantly represent the MI tasks, resulting in outstanding classification performance. This also indicates that our method can indeed uncover valuable information. Moreover, the strong generalization capability of the method is evident from the figure, highlighting its applicability to various modalities of data.

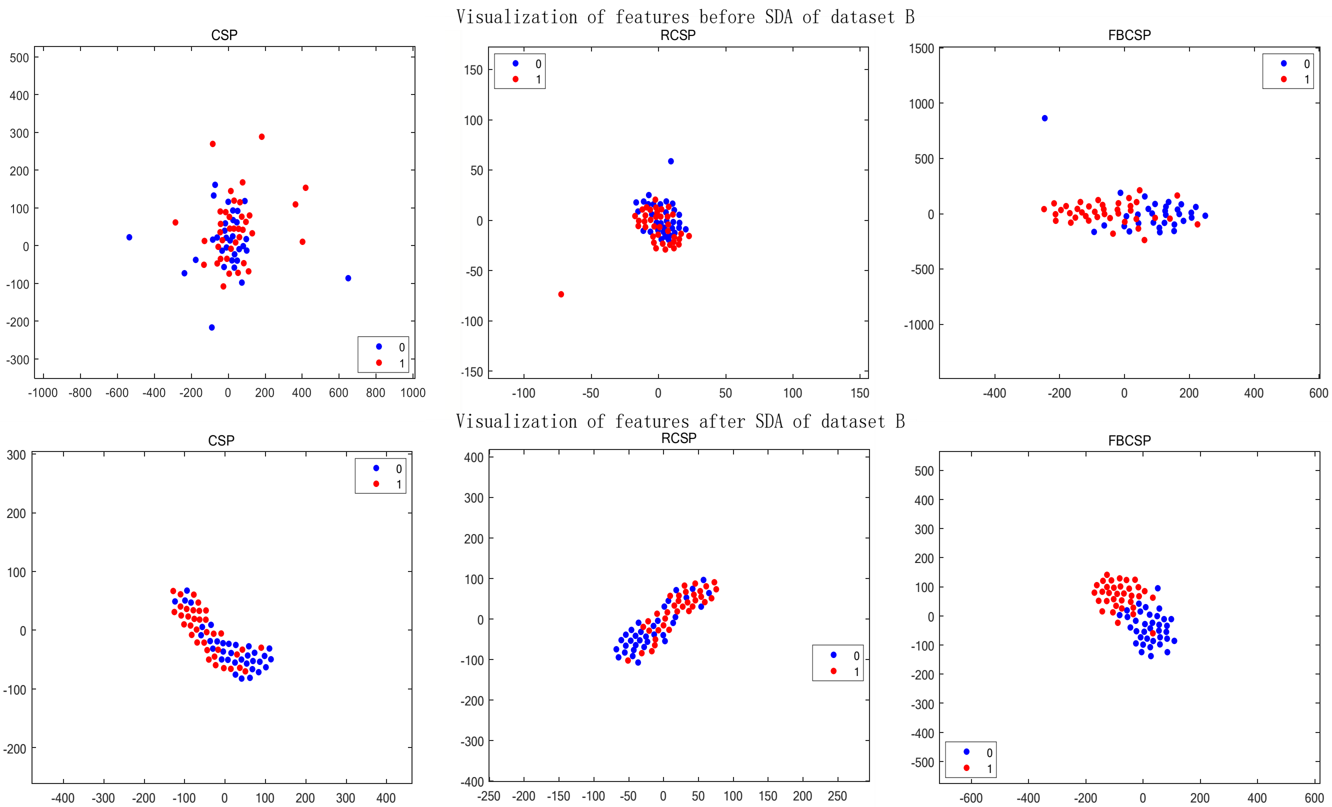
To further evaluate the results of our work, we compared the performance of our method with studies using the same benchmarks, as shown in the Table I. The Table I presents the classification accuracy of different methods. From the Table I, it is evident that our method improves the classification accuracy and generalization performance of the model. The work by Shin et al. [36] utilized a comprehensive feature extraction and classification approach for BCI tasks. They extracted features from the logarithmic variances of the first three and last three CSP components of EEG signals and employed a regularized LDA classifier for classification. The average accuracy on the MI dataset was 65.5%. Ergun et al.'s [34] notable contribution lies in employing diverse feature extraction methods, including Katz fractal dimension and Hilbert transform. They used a k-nearest neighbors classifier, a simple yet effective method suitable for various data types. Jiang et al. [33] proposed the use of Independent Decision Path Fusion (IDPF), incorporating multiple decision paths, each using different features and machine learning methods for classification. They achieved outstanding accuracy of 78.56% on the dataset using power spectral features and CSP features with SVM and LDA.

As dataset B is newly publicly available, there are limited research results for dataset B. In the literature [40], Ma et al. data from dataset B was divided into training, validation, and test sets in an 8:1:1 ratio. The average accuracy of 10-fold cross-validation results reached 68.8%. In contrast, our proposed method achieved an accuracy of 95.2%. As there are limited publicly available results for dataset B, our comparison is based on the existing literature.

Currently, individual variability, training speed of decoding algorithms, and online recognition speed are key challenges in motor imagery recognition. This paper focuses on addressing individual variability and improving online testing efficiency and training learning time. In comparison to current deep learning algorithms, our method is more efficient and addresses issues related to individual time and feature variability. Among publicly available literature using this dataset, our proposed method achieves the highest classification accuracy compared to traditional efficient machine learning algorithms. Our research not only achieves an accuracy of 98.47% in terms of classification accuracy but also performs exceptionally well in response time. In practical applications, our method can rapidly and accurately classify users' intentions, implying that our research has significant potential in the practical application of BCI technology, providing users with faster and more reliable feedback and control experiences.



(a)



(b)

Fig. 7. Comparison of t-SNE projection maps for feature extraction (a) the t-SNE visualization results of the features before and after stepwise discrimination for dataset A， and (b) the t-SNE visualization results of the features before and after stepwise discrimination for dataset B.

TABLE I. COMPARISON OF CLASSIFICATION ACCURACY OF DIFFERENT METHODS FOR DATASET A

Method	Algorithm	Classification Accuracy (%)
Shin et al	CSP+Shrinkage LDA	65.5
Ergun et al	Power-Spectrum+SVM	73.1
	CSP+LDA	63.39
Jıang et al	Independent Decision Path Fusion	78.56
Our method	CSP + Sliding time window optimized SDA +LDA	96.39
	RCSP + Sliding time window optimized SDA +LDA	80.44
	FBCSP + Sliding time window optimized SDA+LDA	98.47

Our research method holds important advantages in the BCI field. Firstly, we successfully address individual differences and environmental variations, a longstanding major challenge for BCI systems. Different individuals' neural activity patterns may vary significantly, and changes in environmental conditions can also have a crucial impact on signal quality. By using a sliding time window approach, our system can flexibly adapt to different situations, thereby enhancing system adaptability and robustness. This means that our method is not only applicable to laboratory environments but can also operate effectively in the diversity and complexity of the real world. Secondly, our method tackles the feature selection problem effectively through stepwise discriminant feature extraction, combining prior knowledge. Feature extraction is crucial in BCI systems as it directly influences system performance. Our method can more accurately select neural signal features related to motor imagery, thereby improving recognition accuracy. This not only helps optimize system performance but also reduces unnecessary computational burden. Therefore, our method provides an innovative solution to the feature extraction problem.

In the future, our research method will have vast application prospects and development potential. Firstly, we can further optimize the method, such as adjusting the parameters of the sliding time window or improving feature extraction algorithms, to further enhance system performance. Additionally, we can consider introducing more data modalities, such as physiological data or brain imaging data, to enrich information sources and improve recognition accuracy and diversity. In practical applications, our method can be widely used in various fields. In the medical field, it can assist people with disabilities in regaining limb function, improving their quality of life. In virtual reality and gaming, our method can provide a more natural and faster user experience, enhancing interactivity. In the military and security fields, it can be used for operation control, improving response speed and decision accuracy.

In conclusion, our research method not only provides an effective approach to addressing individual differences and environmental variations in BCI systems but also has extensive application prospects. Future research can further explore and expand this method to promote the application and development of BCI technology in various fields.

V. CONCLUSION

In our work, we combined an optimized sliding time window algorithm with a stepwise discriminative feature selection algorithm. Firstly, we adopted an adaptive sliding time window method that successfully addressed the challenges of individual differences and environmental changes. Secondly, our method integrates prior knowledge, utilizes SDA for feature extraction to improve recognition accuracy, and effectively adapts to finding the optimal feature combination for specific participants. It effectively solves the problem of feature selection. The experimental results show that this method improves the accuracy of motion image recognition. Specifically, for dataset A, use CSP The accuracy of EEG data using RCSP and FBCSP methods was 96.36%, 80.44%, and 98.47%, respectively. For dataset B, use CSP The accuracy of RCSP and FBCSP methods is 82.26%, 72.12%, and 95.2%, respectively. Compared with the currently published research results, this method significantly improves the recognition accuracy of MI. This indicates that the method has wide applicability, scalability, and high promotion and practical value. In this study, the dataset used for this method is unimodal data. Taking this article as a reference, this method can be extended to the study of multimodal datasets in future work. Moreover, this method is not limited to the field of motion imagination, but also has practical applications in emotion recognition, SSVEP, Many fields such as human-computer interaction have certain reference value.

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REFERENCES

[1] Padfield, N., Ren, J., Qing, C. et al. Multi-segment Majority Voting Decision Fusion for MI EEG Brain-Computer Interfacing. Cogn Comput 13, 1484–1495 (2021). https://doi.org/10.1007/s12559-021-09953-3.

[2] N. Kobayashi, T. Nemoto, and T. Morooka, "High Accuracy Silent Speech BCI Using Compact Deep Learning Model for Edge Computing," 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea, Republic of, 2023, pp. 1-6.

[3] Roy, G., Bhaumik, S. Classification of MI EEG Signal Using Minimum Set of Channels to Control a Lower Limb Assistive Device. J. Inst. Eng. India Ser. B (2022). https://doi.org/10.1007/s40031-022-00783-x.

[4] L. Zheng et al., "A Power Spectrum Pattern Difference-Based Time-Frequency Sub-Band Selection Method for MI-EEG Classification," in IEEE Sensors Journal, vol. 22, no. 12, pp. 11928-11939, 15 June 15.

[5] Z. Wang et al., "Incorporating EEG and fNIRS Patterns to Evaluate Cortical Excitability and MI-BCI Performance During Motor Training," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 2872-2882, 202.

[6] M. M. Wankhade and S. S. Chorage, "Eye-Blink Artifact Detection and Removal Approaches for BCI using EEG," 2021 International Conference on Recent Trends on Electronics, Information, Communication & Technology (RTEICT), Bangalore, India, 2021, pp. 718-721.

[7] J. H. Jeong, D. -J. Kim and H. Kim, "Hybrid Zero-Training BCI based on Convolutional Neural Network for Lower-limb Motor-Imagery," 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2021, pp. 1-4.

[8] P. Li et al., "Granger Causal Inference Based on Dual Laplacian Distribution and Its Application to MI-BCI Classification," in IEEE Transactions on Neural Networks and Learning Systems.

[9] P. Deny and K. W. Choi, "Hierarchical Transformer for Brain-Computer Interface," 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea, Republic of, 2023, pp. 1-5.

[10] Y. Yao, B. Yang, X. Xia, Z. Peng, S. Gao, and X. Meng, "Design of Upper Limb Rehabilitation Training System Combining BCI and AR Technology," 2021 40th Chinese Control Conference (CCC), Shanghai, China, 2021, pp. 7131-7134.

[11] Y. Shin, J. Kwon, J. S. Kim, and C. Kee Chung, "Introduction of Beat Oscillation to Improve the Performance of Music BCI Decoder," 2022 10th International Winter Conference on Brain-Computer Interface (BCI), Gangwon-do, Korea, Republic of, 2022, pp. 1-5.

[12] A. Mehtiyev, A. Al-Najjar, H. Sadreazami, and M. Amini, "DeepEnsemble: A Novel Brain Wave Classification in MI-BCI using Ensemble of Deep Learners," 2023 IEEE International Conference on Consumer Electronics (ICCE), Las Vegas, NV, USA, 2023, pp. 1-5.

[13] S. K. Mandal and M. N. B. Naskar, "Algorithmic Analysis on Automated Channel Selection Framework for Motor Imagery BCI," 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2021, pp. 32-39.

[14] J. Alfred, H. S and J. S. R. Alex, "BCI based Robotic Arm Control using MI-EEG and Spiking Neural Network," 2022 13th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2022, pp. 1-6.

[15] H. Nam, J. -M. Kim and T. -E. Kam, "Feature Selection Based on Layer-Wise Relevance Propagation for EEG-based MI classification," 2023 11th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea, Republic of, 2023, pp. 1-3.

[16] K. Parashar, "Analyzing The Efficiency of Mutual Information (MI) and A Genetic Algorithm (GA) For Selecting Spectral Entropy Features From An EEG Signal," 2023 1st International Conference on Innovations in High-Speed Communication and Signal Processing (IHCSP), BHOPAL, India, 2023, pp. 194-198.

[17] Ling, P., Xi, K., Chen, P., Yu, X., Li, K. (2023). The Effect of Channel Ordering Based on the Entropy Weight Graph on the MI-EEG Classification. In: Yang, H., et al. Intelligent Robotics and Applications. ICIRA 2023. Lecture Notes in Computer Science(), vol 14272. Springer, Singapore. https://doi.org/10.1007/978-981-99-6480-2_43.

[18] J.R. Wolpaw, N. Birbaumer, D.J. McFarland, G. Pfurtscheller, T.M. Vaughan, Brain–computer interfaces for communication and control, Clin. Neurophysiol.113 (2002) 767–791.

[19] H. Kwon, C. Hwang, and S. Jo, "Vision Combined with MI-Based BCI in Soft Robotic Glove Control," 2022 10th International Winter Conference on Brain-Computer Interface (BCI), Gangwon-do, Korea, Republic of, 2022, pp. 1-5.

[20] M. Kamandar, "Kernel-Based Embedded Feature Selection for Motor Imagery Based BCI," 2023 31st International Conference on Electrical Engineering (ICEE), Tehran, Iran, Islamic Republic of, 2023, pp. 144-148.

[21] L. K. P. Gunarathne, D. V. D. S. Welihinda, H. M. K. K. M. B. Herath and S. L. P. Yasakethu, "EEG-Assisted EMG-Controlled Wheelchair for Improved Mobility of Paresis Patients," 2023 IEEE IAS Global Conference on Emerging Technologies (GlobConET), London, United Kingdom, 2023, pp. 1-6.

[22] M. G. Shobana, S. Sajitha and S. Abirami, "Brain-Computer Interface using EEG Signal for Actuating a 3 DOF Robotic Arm," 2022 4th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India, 2022, pp. 637-640.

[23] K. P. Sahoo et al., "Alterations in Multi-channel EEG Dynamics During a Stressful Shooting Task in Virtual Reality Systems," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 6207-6210.

[24] S. Cha, J. Yang, and J. An, "Does FES Contribute to Cognitive Motor Task Discrimination?: An fNIRS study," 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2021, pp. 1-3.

[25] K. Won, M. Kwon, M. Ahn, and S. C. Jun, "Selective Subject Pooling Strategy to Achieve Subject-Independent Motor Imagery BCI," 2021 9th International Winter Conference on Brain-Computer Interface (BCI), Gangwon, Korea (South), 2021, pp. 1-4.

[26] J. Lin, S. Liu, G. Huang, Z. Zhang, and K. Huang, "The Recognition of Driving Action Based on EEG Signals Using Wavelet-CSP Algorithm," 2018 IEEE 23rd International Conference on Digital Signal Processing (DSP), Shanghai, China, 2018, pp. 1-5.

[27] M. Masitoh, S. Suprijanto, and R. S. Joko Sarwono, "Quantitative EEG Analysis Based on PSD and eLORETA-Source Localization Approach in Spatial Auditory Process," 2023 8th International Conference on Instrumentation, Control, and Automation (ICA), Jakarta, Indonesia, 2023, pp. 329-334.

[28] S. Ramya and M. Uma, "Evaluation of Wavelet Transformed Features on Detection of Epileptic Seizures using 2D Scalogram Images of EEG Signals," 2023 12th International Conference on Advanced Computing (ICoAC), Chennai, India, 2023, pp. 1-6.

[29] Y. Wu, J. Li, Z. Ren, B. Lu, C. Zhang, and P. Qi, "Feature Extraction of Motor Imagination EEG Signals for a Collaborative Exoskeleton Robot Based on PSD Analysis," 2023 42nd Chinese Control Conference (CCC), Tianjin, China, 2023, pp. 3448-3453.

[30] Y. Zheng, Y. Ma, Q. Zhang, and Q. She, "EEG feature extraction algorithm based on CSP and R-CSP," 2020 7th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS), Guangzhou, China, 2020, pp. 280-285.

[31] X. Wei, E. Dong and L. Zhu, "Multi-class MI-EEG Classification: Using FBCSP and Ensemble Learning Based on Majority Voting," 2021 China Automation Congress (CAC), Beijing, China, 2021, pp. 872-876.

[32] I. Siviero, L. Brusini, G. Menegaz, and S. F. Storti, "Motor-imagery EEG signal decoding using multichannel-empirical wavelet transform for brain-computer interfaces," 2022 IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI), Ioannina, Greece, 2022, pp. 1-4.

[33] A. Jiang, J. Shang, X. Liu, Y. Tang, H. K. Kwan, and Y. Zhu, "Efficient CSP Algorithm With Spatio-Temporal Filtering for Motor Imagery Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 28, no. 4, pp. 1006-1016, April 2020.

[34] P. Gaur, H. Gupta, A. Chowdhury, K. McCreadie, R. B. Pachori and H. Wang, "A Sliding Window Common Spatial Pattern for Enhancing Motor Imagery Classification in EEG-BCI," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-9, 2021, Art no. 4002709.

[35] C. Phunruangsakao, D. Achanccaray and M. Hayashibe, "Mutual Information-Based Time Window Adaptation for Improving Motor Imagery-Based BCI," 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Melbourne, Australia, 2021, pp. 2942-2947.

[36] J. Shin et al., "Open Access Dataset for EEG+FNIRS Single-Trial Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 10, pp. 1735-1745, Oct. 2017.

[37] P. Saideepthi, A. Chowdhury, P. Gaur, and R. B. Pachori, "Sliding Window Along With EEGNet-Based Prediction of EEG Motor Imagery," in IEEE Sensors Journal, vol. 23, no. 15, pp. 17703-17713, 1 Aug.1, 2023.

[38] Q. Dong, L. Wang, and X. Hu, "Recognition and Classification of Spatial Auditory Evoked P300 EEG Signal," 2018 11th International Symposium on Computational Intelligence and Design (ISCID), Hangzhou, China, 2018, pp. 383-387.

[39] E. S. Pane, A. D. Wibawa and M. H. Pumomo, "Channel Selection of EEG Emotion Recognition using Stepwise Discriminant Analysis," 2018 International Conference on Computer Engineering, Network and Intelligent Multimedia (CENIM), Surabaya, Indonesia, 2018, pp. 14-19.

[40] Ma, J., Yang, B., Qiu, W., et al. A large EEG dataset for studying cross-session variability in motor imagery brain-computer interface. Sci Data 9, 531 (2022).

[41] Y. He and F. Yang, "The effect of time window length on dynamic brain network analysis under various emotional conditions," 2022 IEEE 6th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Beijing, China, 2022, pp. 569-573.

[42] W. Liu, J. Song, Z. Wang, and H. Cheng, "Comparison of Performance of EEG-Based Depression classification," 2022 2nd International Conference on Frontiers of Electronics, Information and Computation Technologies (ICFEICT), Wuhan, China, 2022, pp. 125-130.

[43] R. Zhang et al., "Motor Imagery EEG Classification with Self-attention-based Convolutional Neural Network," 2022 7th International Conference on Intelligent Informatics and Biomedical Science (ICIIBMS), Nara, Japan, 2022, pp. 195-199.

[44] A. Y. Timofeeva and M. S. Murtazina, "Feature Selection for EEG Data Based on Logistic Regression," 2021 XV International Scientific-Technical Conference on Actual Problems Of Electronic Instrument Engineering (APEIE), Novosibirsk, Russian Federation, 2021, pp. 604-609.

[45] Laurens V D M, Hinton G. Visualizing Data using t-SNE[J]. Journal of Machine Learning Research, 2008, 9(2605): 2579-2605.