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EEG Signal Classification for Multitasking Motor Imagery Using Multi-Layer Time-Varying Functional Brain Network Features

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Abstract: Existing research methods for recognizing EEG (Electroencephalogram) signals in motor imagery (MI) often overlook the dynamic changes of brain networks over time, resulting in insufficient classification accuracy for MI tasks. This article addresses the recognition problem of dynamic changes in brain networks during MI tasks and applies an EEG signal classification method based on multi-layer time-varying functional brain networks. This article uses the BCI (Brain-Computer Interface) Competition IV 2a dataset to preprocess the raw EEG signals through bandpass filtering and CSP (Common Spatial Pattern) algorithm. The EEG signals of the MI task are divided into 7 1-second time windows with a step size of 0.5 seconds. Within each time window, Pearson correlation coefficients between EEG channels can be calculated to generate corresponding brain networks, and multiple time-varying functional brain networks can be constructed by stacking the brain networks from multiple time windows. The network topology features, node degree, clustering coefficient, network efficiency, and multi-layer network features of each window can be extracted, including Multiplex Clustering Coefficient (MCC), Multiplex Participation Coefficient (MPC), and inter layer correlation coefficient. By dividing the dataset through 10 fold cross validation, the random forest algorithm can be used to classify and recognize four types of motion imagination tasks. The experimental results show that the average recognition rate of the article's method in four types of MI tasks reached 89.19%. This method can improve the classification accuracy of MI tasks and enhance a comprehensive understanding of the dynamic changes in brain networks during the process of MI.

1. Introduction

Understanding the dynamic characteristics of brain networks is crucial for grasping temporal changes in brain function. However, current research often overlooks the time-varying nature of EEG signals during MI, limiting insights into brain network dynamics [1-2]. This gap is particularly significant in multi-class MI tasks [3-4], where capturing these temporal dynamics is key to enhancing classification accuracy.

This study innovatively divides EEG signals during the process of MI into multiple time windows. By setting the window length to 1 second and the step size to 0.5 seconds, 7 consecutive time windows are obtained in each MI paradigm. This segmentation method enables the capture of the time-varying characteristics of EEG signals and the generation of multiple brain networks through Pearson correlation coefficients, thereby constructing multi-layer time-varying functional brain networks. In this process, by comparing the brain network topologies of different windows, the window brain network with the most obvious differences is selected as the core brain network, and the rationality of the core brain network is further verified by extracting core brain network features and interlayer brain network features. MCC and MPC were extracted in the study to describe the dynamic changes and separation integration features of brain networks. After combining these features with the core brain network features, a multi-layer time-varying functional brain network feature vector is formed, and precise classification of four types of MI tasks is achieved through the random forest algorithm. The BCI Competition IV 2a dataset used in this article consists of 22 EEG channels and data from 9 participants. These subjects were required to perform four different MI tasks of left hand, right hand, feet, and tongue during the experiment. Through the analysis method of multi-layer time-varying functional brain networks, this article not only understands the dynamic changes of brain networks in the process of MI at a more detailed spatiotemporal scale, but also provides new ideas and technical support for future classification methods of MI EEG signals.

2. Related Works

The MI task has received widespread attention in the field of brain computer interfaces, as it does not rely on external stimuli and can be non invasively recorded through EEG signals, making it one of the core tasks in brain computer interface research. A large amount of research aims to improve the classification accuracy of MI tasks and explore their potential clinical application value. Significant progress has been made in the accuracy of motion imagery classification [5] by introducing advanced feature extraction methods and machine learning algorithms. Common methods include time-frequency analysis, co spatial patterns [6], and multivariate autoregressive models, which can effectively extract EEG features related to MI and improve classification performance. In recent years, the application of deep learning techniques, such as convolutional neural networks and recurrent neural networks, has further promoted the research on MI EEG signal classification [7-8], and some studies have achieved satisfactory classification accuracy. However, although these methods perform well on specific tasks and individuals, they still face problems such as insufficient cross individual generalization ability and complex feature extraction processes. Traditional classification methods for MI tasks are mostly based on the activity of local brain regions, such as signals from the motor cortex. More and more studies have shown that MI tasks [9] not only involve the activity of local brain regions, but also rely on the synergistic effects between different brain regions and complex connections across the entire brain. Relying solely on local brain region features for classification cannot fully capture the whole brain dynamic activity during MI, thereby limiting further improvement in classification accuracy. Although previous studies have attempted to incorporate whole brain EEG signals into classification models, the accuracy of MI classification still needs to be further improved due to the difficulty in comprehensively analyzing connections and interactions across the entire brain.

The study of functional brain networks provides a new perspective for understanding brain function, especially in the application of MI tasks, which has attracted widespread attention. The functional brain network [10] quantifies the functional connections between different brain regions, revealing the coordinated activity patterns of the brain under different cognitive tasks. In the study of MI tasks, functional brain network features [11] have been widely applied in the analysis and classification of EEG signals. The functional connectivity patterns of different brain regions during MI can reflect neural mechanisms related to specific movements. Classification methods based on such functional connectivity features, such as synchronicity analysis, phase synchronicity, and graph theory-based network feature extraction methods, have been proven to effectively improve classification performance. Although functional brain network features have shown significant advantages in classifying MI tasks, current research mostly focuses on static functional brain network analysis, ignoring the dynamic changes of brain networks over time. In the process of MI [12], the functional connectivity patterns of the brain are dynamically changing, and the separation and integration processes between different brain regions are crucial for task completion. The static functional brain network features cannot fully reflect the complex neural mechanisms involved in MI, leading to insufficient understanding of the dynamic changes in the brain network. The existing functional brain network feature extraction methods mainly focus on local network features, node degrees, clustering coefficients, etc., but fail to effectively describe the overall dynamic changes of the brain network and separate and integrate features, which to some extent limits the improvement of classification performance in MI tasks. There is an urgent need for an analysis method that can describe the dynamic changes and separation integration features of brain networks for the study of MI tasks, in order to further improve the accuracy and stability of classification.

3. Methods

3.1 Dataset Selection and Preprocessing

This article uses the BCI Competition IV 2a dataset [13-14], which includes 9 participants. Each participant is required to complete four different MI tasks during the experiment, including left hand (category 1), right hand (category 2), feet (category 3), and tongue (category 4) MI. These tasks aim to activate activity in different regions of the brain, generating EEG signals related to specific MI.

Open eyes for two minutes: The subjects are asked to open their eyes and gaze at the gaze cross on the screen, during which potential EEG artifacts caused by eye orientation are mainly recorded.

Close the eyes for one minute: The subjects are asked to close their eyes and record the changes in eye tracking artifacts caused by closing their eyes. The EEG signals in the open eye state are compared to identify and reduce the impact of eye tracking artifacts.

Eye Movement for One Minute: Participants are required to perform specific eye movements, such as moving their eyes left, right, up, and down, and record the artifact signals caused by these movements to provide reference for subsequent data preprocessing.

The structure of the dataset is shown in Figure 1.

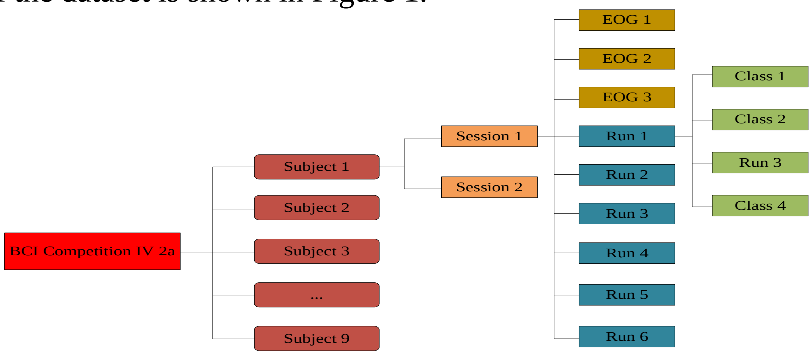

Figure 1: Dataset Structure

Each session consists of 6 sets of tests, each set containing 48 exercise imagination tasks. The paradigm of MI is shown in Figure 2.

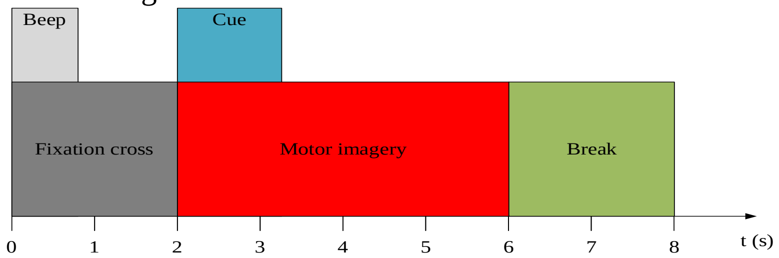

Figure 2: Paradigm of MI

In each test, participants face a computer screen. At the beginning of the test (t=0s), a fixed cross can appear on the black screen accompanied by a brief sound prompt. After two seconds (t=2s), an arrow pointing to left, right, down, and up (corresponding to left hand movement, right hand movement, foot movement, and tongue movement, respectively) can appear on the screen for approximately 1.25 seconds. It can prompt participants to imagine the corresponding motion to the image, and each participant needs to complete this imagination task until the cross on the screen disappears (t=6s). After each trial, participants have a 2-second rest period during which there are no specific task requirements. The time for exercise imagination is 2s-6s, a total of 4 seconds.

Data preprocessing is crucial in the analysis of MI EEG signals to improve signal quality and the effectiveness of subsequent feature extraction. Bandpass filtering can be applied to the original EEG signal, selecting a frequency range of 8-30Hz. This frequency band contains μ rhythms and β rhythms highly correlated with MI tasks, effectively removing low-frequency noise and high-frequency artifacts from EEG signals. The CSP algorithm is used for spatial filtering to maximize the variance between two motor imagery tasks. It enhances task-related features while suppressing background noise and artifacts unrelated to the task.

3.2 Time Window Division and Brain Network Construction

In a 4-second MI task, the EEG signals are segmented into 1-second time windows with a 0.5-second step, resulting in 0.5-second overlaps between adjacent windows. This produces 7 consecutive windows: [2,3], [2.5,3.5], [3,4], [3.5,4.5], [4,5], [4.5,5.5], and [5,6] seconds. Each time window can cover EEG signals at different time points during the process of MI, capturing subtle changes in EEG signals over time.

By dividing the time window, high temporal resolution data is provided throughout the entire time range of the MI task, and multiple time windows are analyzed to capture changes in brain functional connectivity patterns during the process of MI. Corresponding brain networks can be constructed based on functional connections between EEG channels within each time window. The nodes of a functional brain network represent EEG channels, while the edges between nodes represent functional connections between EEG channels. Functional connectivity can be quantified by calculating Pearson correlation coefficients between EEG channels.

For two EEG channels i and j within a given time window, the Pearson correlation coefficient is expressed as:

$$r_{ij} = \frac{\sum_{t=1}^{N}(X_i(t)-\overline{X}_i)(X_j(t)-\overline{X}_j)}{\sqrt{\sum_{t=1}^{N}(X_i(t)-\overline{X}_i)^2}\sqrt{\sum_{t=1}^{N}(X_j(t)-\overline{X}_j)^2}} \tag{1}$$

$\overline{X}_i$ and $\overline{X}_j$ are the mean values of the corresponding channel signals, and N represents the number of sampling points within the time window.

3.3 Construction and Feature Extraction of Multi-layer Time Varying Functional Brain Networks

The research framework of multi-layer time-varying functional brain networks is shown in Figure 3.

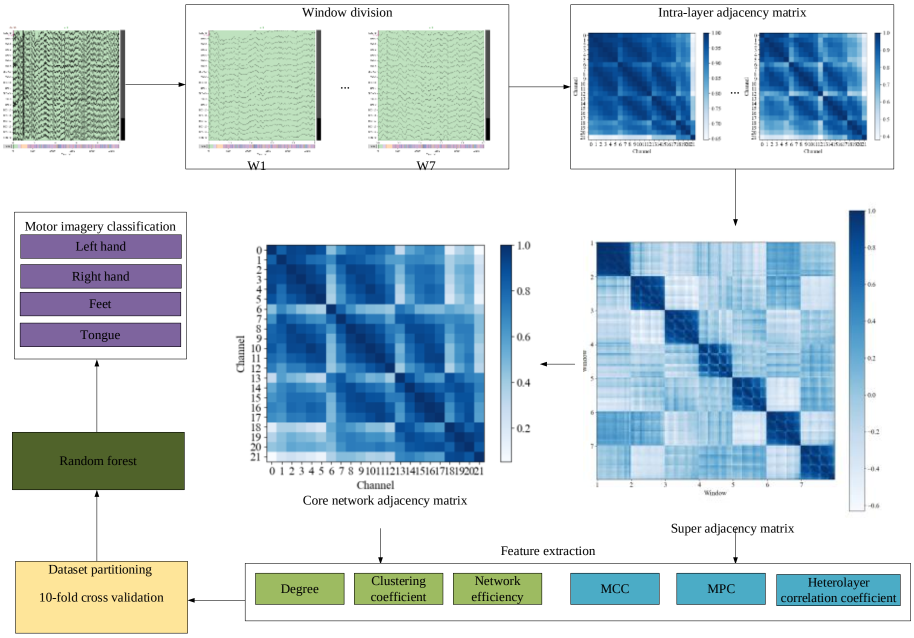

Figure 3: Research framework of multi-layer time-varying functional brain network

Multiple brain networks within continuous time windows divided in MI tasks can be stacked together to construct a multi-layer time-varying functional brain network. Each layer corresponds to a time window, and the connections between layers reflect the changes in functional connections between different time points, capturing the dynamic changes of EEG signals over time. Traditional network features like node degree and clustering coefficient describe brain network structure at each time point. For the multi-layer time-varying network, features such as MCC, MPC, and inter-layer correlation capture dynamic changes. The most distinctive window network is selected as the core, and its features are combined with those from the multi-layer network to create a comprehensive feature vector. This vector is used with a random forest algorithm and 10-fold cross-validation to accurately classify motor imagery tasks.

For node i in an undirected graph, the formula for node degree k_i is:

$$k_i = \sum_{j \in V} A_{ij} \tag{2}$$

A_{ij} is the element of the adjacency matrix, and V is the set of all nodes.

The formula for clustering coefficient is:

$$C_i = \frac{2T_i}{k_i(k_i - 1)} \tag{3}$$

The global network efficiency E is calculated by taking the average of the reciprocal of the shortest path lengths between all node pairs

$$E = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{4}$$

The formula for the MCC of node i is:

$$C_{i,1} = \frac{\sum_{\mu} \sum_{k \neq \mu} \sum_{i \neq j, m \neq i} a_{ij} a_{jm} a_{mi}}{(M-1) \sum_{\mu} k_i^{\mu} (k_i^{\mu} - 1)} \tag{5}$$

The average MCC of all nodes is represented as:

$$MCC = \frac{1}{N} \sum_i^N C_{i,1} \tag{6}$$

The formula for MPC of node i is:

$$p_i = \frac{M}{M-1} [1 - \sum_{L=1}^{M} (\frac{k_i^L}{o_i})^2] \tag{7}$$

The formula for the average MPC is:

$$MPC = \frac{1}{N} \sum_i^N p_i \tag{8}$$

The cross layer correlation coefficient is used to measure the correlation of node degrees between different layers, and it can reveal the structural similarity between different layers. CP (Conditional Probability) reveals the impact of node degrees in one layer on the corresponding node degree distribution in another layer. The formula is:

$$CP = \sum_{ij} a_{ij}^{\alpha} a_{ij}^{\beta} / \sum_{ij} a_{ij}^{\beta} \tag{9}$$

a^{β} represents the adjacency matrix within β.

The random forest algorithm can be used to classify the extracted multi-layer time-varying functional brain network features. Random forest constructs multiple decision trees and takes their majority voting results. In the classification of four types of MI tasks, the model outputs four classification results, effectively distinguishing the MI of the left hand, right hand, tongue, and leg. To ensure the robustness of the model, 10 fold cross validation can be used to divide the dataset into training and testing sets. The training set is used for training the random forest model, ensuring that the model can fully learn the features of the motion imagination task. After the model training is completed, its performance can be evaluated on the test set, and the classification results can be quantified using metrics such as accuracy. To verify the effectiveness and superiority of the proposed method, the results were compared with benchmark methods to evaluate its performance in different tasks. The efficiency and accuracy of the random forest algorithm in classifying motion imagery tasks can be ensured through a systematic model training and evaluation process.

4. Results and Discussion

4.1 Network Topology and Network Feature Analysis Results

The network topology structure is shown in Figure 4.

In MI tasks, the connectivity density of brain network nodes shows significant dynamic changes at different time windows. In the left hand movement imagination, the network node connections of

W1-W3 windows are relatively dense, indicating strong functional connections in the brain at this time. In the W4 window, the connections of network nodes become relatively sparse, and then in the W5-W7 window, the network density increases again, showing a re-enhancement of connections. This density change reflects the specific processing of the brain during left-handed MI. In right-handed MI, the network nodes in the W4 window are most densely connected, indicating a significant increase in functional connectivity of the brain in processing right-handed MI tasks at this time. In the imagination of foot movement, the network node connections of W1, W2, and W6 windows are relatively dense, while the connections of W3, W4, W5, and W7 windows are relatively sparse. This indicates that the brain has different functional connection patterns when processing foot movement imagination, which may be related to the complexity of motion control. For tongue movement imagination, the network density within the W1-W3 window gradually becomes sparse from initially dense, but from W4 onwards, the network density increases significantly, indicating dynamic changes in functional connectivity of the brain in processing tongue movement imagination tasks. Therefore, the W4 window exhibits unique network topology changes in four types of motion imagination tasks, at a critical moment of interlayer changes, indicating that the W4 window may be a key time point for functional network reorganization and optimization in different motion imagination tasks.

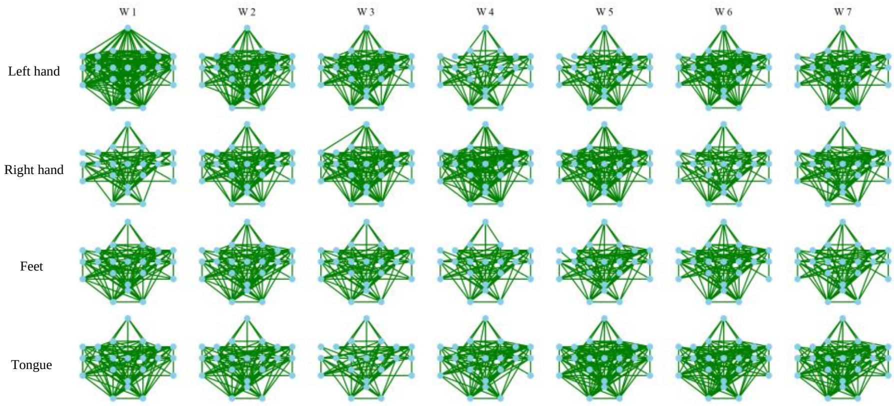

Figure 4: Network topology structure

The average feature parameter results of single-layer and multi-layer networks under W4 window are shown in Figure 5.

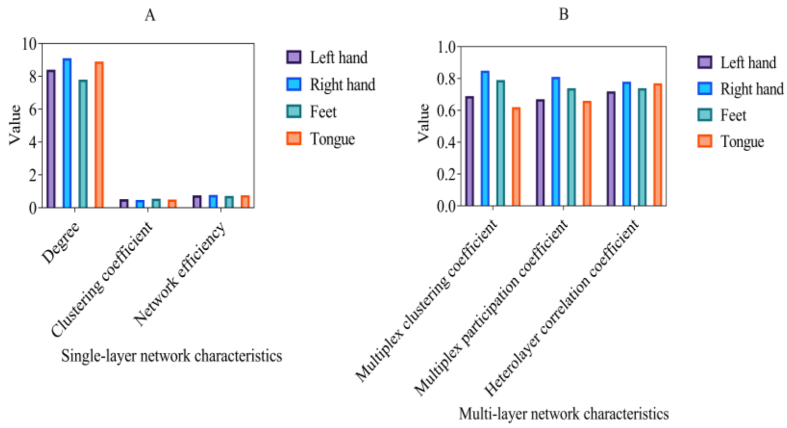

Figure 5A Single layer network features Figure 5B Multi-layer network features

Figure 5: Single layer and multi-layer network feature parameter results under W4 window

Each feature parameter has a certain degree of discrimination. Among the single-layer network features, the node degree of the right-handed motion imagination task is the highest, at 9.1, indicating that the network connections under this task are the most dense; The node degree of the bipedal task is the lowest, at 7.8, reflecting relatively few functional connections. In terms of clustering coefficient, the coefficient of the two foot task is the highest, at 0.55, indicating stronger local connectivity between nodes, while the clustering coefficient of the right-hand task is the lowest, at 0.48, showing weaker local clustering effect. In terms of network efficiency, the right-handed task once again showed an advantage with an efficiency value of 0.78, indicating fast information transmission speed and excellent network performance; The efficiency of the bipedal task is the lowest, at 0.72, indicating that the network's ability to transmit global information is relatively weak. In the characteristics of multi-layer networks, right-handed tasks exhibit the highest values in MCC, MPC, and inter layer correlation coefficients, with values of 0.85, 0.81, and 0.78, respectively, demonstrating significant advantages in multi-layer networks. This indicates that they have the highest connectivity and participation within multiple time windows, and have good stability in functional connections across layers. The MCC and MPC of the tongue task are relatively low, at 0.62 and 0.66, respectively, indicating weak clustering effects and node participation in multi-layer networks. However, the inter layer correlation coefficient is 0.77, indicating that its cross layer connections have a certain degree of stability. There are significant differences in the distribution of single-layer and multi-layer network feature parameters between various types of motor imagination tasks under the W4 window, especially the advantage of right-handed motor imagination tasks in multi-layer network features is more prominent. The functional connectivity features of W4 window in different tasks have obvious task dependencies and can distinguish various types of MI tasks.

4.2 Recognition Results of Four Types of MI Tasks

The comparison of the recognition results of motion imagination tasks for core network features, multi-layer network features, and network features combining the two is shown in Table 1.

Table 1: Recognition results of different features

Category	Core network characteristics (%)	multi-layer network features (%)	Combination features (%)
Left hand	83.12±0.89	87.77±0.78	89.12±0.88
Right hand	82.89±0.92	87.12±0.91	89.14±0.44
Feet	83.99±0.89	86.98±0.83	89.29±0.76
Tongue	82.56±0.56	87.56±0.94	89.22±1.21

When using core network features alone for recognition, the recognition accuracy of various tasks is relatively low, but it still has certain discriminative ability. The recognition rate of the foot movement imagination task is the highest, at 83.99 ± 0.89%. The use of multi-layer network features significantly improves recognition, achieving over 86% accuracy. The left-hand motor imagery task shows the highest accuracy at 87.77±0.78%. When core and multi-layer network features are combined, accuracy further improves to nearly 89%, with the foot task reaching 89.29±0.76% and the tongue task at 89.22±1.21%. This combination captures dynamic brain network changes more comprehensively, enhancing classification performance in motor imagery tasks.

4.3 Comparison of Average Recognition Rates of Different Feature Extraction Methods

The comparison results of the average recognition rates of different feature extraction methods are shown in Table 2.

Table 2: Average recognition rates of different feature extraction methods

Method	Left hand (%)	Right hand (%)	Feet (%)	Tongue (%)	Average (%)
The method in this article	89.12	89.14	89.29	89.22	89.19
Double complex wavelet transform [15]	88.06	89.11	88.02	87.89	88.27
Multi-model fuses temporal-spatial features [16]	89.21	89.07	88.78	89.06	89.03
Transformer for spatio-temporal feature learning [17]	84.56	84.32	83.82	83.94	84.16

The proposed method achieves the highest recognition rates across all motor imagery tasks, with 89.12% for the left hand, 89.14% for the right hand, 89.29% for the foot, and 89.22% for the tongue, averaging 89.19%, as shown in Table 2. This indicates that the method proposed in this article can more effectively capture the dynamic changes and spatiotemporal features of brain networks when extracting features for motion imagination tasks. In contrast, the average recognition rate of the dual complex wavelet transform method is 88.27%, which is close to but still lower than the method proposed in this article, indicating a slight deficiency in capturing features. The average recognition rate of the multi-model fusion spatiotemporal feature method is 89.03%, which is close to but slightly inferior to the method proposed in this article. The Transformer-based spatiotemporal feature learning method has the lowest recognition rate among all tasks, with an average recognition rate of only 84.16%, indicating that it may have limitations in complex spatiotemporal feature extraction.

5. Conclusions

This article proposes a motion imagination task recognition method that combines core network features and multi-layer network features by constructing a multi-layer time-varying functional brain network. Experimental results show that this method has better recognition rates than existing feature extraction methods in four types of motion imagination tasks, especially in capturing the dynamic changes of brain networks and separating and integrating features. This study not only provides new ideas for the classification of MI tasks in the field of brain computer interfaces, but also promotes a deeper understanding of the dynamic characteristics of brain networks, which has important practical application value. However, this study still faces certain challenges in practical applications, including the diversity of datasets and the computational complexity of algorithms. In addition, due to the limited spatial resolution of current methods, more subtle spatiotemporal features of brain networks have not been fully revealed. In future research, the article can further explore how to combine more dimensions of brain signal data to improve the generalization ability and recognition accuracy of the model. At the same time, the article can develop more personalized and robust methods for recognizing MI based on the characteristics of different individuals' brain networks, ultimately achieving a more efficient brain computer interface system.

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