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Enhanced classification of motor imagery EEG signals using spatio-temporal representations

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Abstract:

Deep learning has shown promising results in motor imagery brain-computer interfaces. However, most existing methods fail to account for the topological relationships between electrodes and the nonlinear features of electroencephalogram (EEG) signals. To address this, we propose a model combining Gramian Angular Fields (GAF) and Phase-Locking Value (PLV) with a parallel convolutional neural network (CNN). GAF captures time-domain nonlinear features, while PLV represents spatial features based on electrode topology. Comparative experiments between the end-to-end parallel CNN model and the model with spatiotemporal feature representation demonstrate that considering both time-domain correlations and electrode topology significantly enhances model performance. Furthermore, when separately evaluating the temporal and spatial features of EEG signals, the results confirm that jointly considering spatiotemporal features leads to a substantial improvement. On the Physionet dataset, our model achieves an accuracy of 99.73% in binary classification tasks and reaches 83.37% accuracy in four-class classification tasks, outperforming other models and proving its effectiveness.

Keywords: Brain-computer interface; Motor Imagery; Gramian Angular Field; Phase Locking Value; Spatio-temporal features; Convolutional neural networks

1. Introduction

The brain-computer interface system, as a direct channel for the interaction between the brain and the external environment, can realize the exchange and communication between the human brain and external devices [1]. As a new type of human-computer interaction, the brain-computer interface has attracted much attention from researchers in recent years. BCI system was first applied in the field of medical rehabilitation, which can help stroke and paralyzed patients to realize communication with the outside world and assist patients with impaired limb function to use wheelchairs, prostheses, robotic arms, etc[2–5] Currently, with the continuous development of brain science and signal processing technology, BCI is also widely used in robot control, smart home, the military, education, entertainment, and other fields[6,7].

Neuroimaging techniques commonly used in brain-computer interface (BCI) systems include functional magnetic resonance imaging (fMRI), cortical electroencephalography (EcoG), magnetoencephalography (MEG), and electroencephalography [8]. As a non-invasive acquisition modality, EEG records the electrical activity of the brain through electrodes placed on the surface of the scalp, making it a prominent focus in BCI research [9]. EEG is typically acquired using a head-mounted EEG cap, which offers high temporal resolution and portability [10]. EEG-based brain-computer interface systems can be further divided into P300 BCIs, steady-state visual evoked potentials (SSVEP), and motor imagery (MI) [11]. Motor imagery brain-computer interfaces usually do not require additional stimuli to induce EEG potential activity and do not require additional assistive devices, making them easier to use and more promising for users and researchers [12]. However, due to the non-stationary and low signal-to-noise ratio characteristics of EEG signals, how to improve the classification recognition accuracy of motor imagery brain-computer interface systems is a challenging problem [13].

In recent years, more and more researchers have decoded EEG signals from the spatio-temporal features of EEG signals, usually using LSTM to extract the temporal features of EEG signals and CNN to extract the spatial features of EEG signals [14–19]. However, due to the non-stationarity and low signal-to-noise ratio characteristics of EEG signals, methods such as CNN and LSTM cannot fully take into account the nonlinear features of EEG signals, and most of the current models use a serial structure that makes it difficult to comprehensively consider the spatio-temporal features of EEG signals. Even if some of the methods use parallel structure, the nonlinear features of the EEG signal are ignored and the classification performance needs to be improved. While the Gramian Angular Field, as an algorithm for processing time series, can fully take into account the time series correlation [20], the brain functional connectivity matrix can estimate the instantaneous phase relationship between two neuroelectric or biomagnetic signals, which is also known as the topological relationship between the electrode channels of EEG signals [21,22]. Inspired by GAF and brain function connectivity matrix as well as a convolutional neural network, we adopt the methods of GAF and PLV to represent the spatio-temporal features of EEG signals, respectively, and use the parallel CNN structure for classification and recognition, which fully considers the nonlinear features of EEG signals and also improves the classification and recognition performance of the motor imagery brain-computer interface.

In summary, this paper makes the following contributions:

(1) To fully account for the nonlinear characteristics of EEG signals, we employed GAF to represent the temporal correlations of the signals. By calculating the Spearman correlation coefficient for each GAF matrix, we simplified the model while also exploring, to some extent, the information transfer and coordination between different brain regions.

(2) To thoroughly capture the intrinsic relationships between EEG electrodes, we utilized PLV to construct a brain functional connectivity matrix, further exploring the working mechanisms and intrinsic connections between brain regions through brain network analysis.

(3) A targeted GAF-PLV-Parallel CNN model was designed, capable of effectively extracting temporal and spatial features and classifying different motor imagery tasks. Experimental

results demonstrate that the model significantly improves classification performance by simultaneously considering both temporal and spatial features, validating the effectiveness of this spatiotemporal feature representation method.

(4) Compared to traditional end-to-end spatiotemporal decoding models, the proposed method more efficiently integrates the spatiotemporal information of EEG signals.

The rest of the work in this paper is organized as follows: the second part briefly introduces the related work in this field. The third part introduces the experimental methodology and provides a preliminary understanding of GAF and PLV as well as Convolutional Neural Networks. The fourth part is the spatio-temporal characterization of EEG signals of vinyl class in combination with GAF and PLV and demonstrates the classification performance of the model designed in this paper. The fifth part is the summary.

2. Related work

The motor imagery classification task can usually be categorized into traditional machine learning methods and deep learning methods based on feature extraction algorithms. The motor imagery classification methods based on traditional machine learning mainly have the steps of preprocessing, feature extraction, and classification and recognition[23]. First, the EEG signal is preprocessed, which mainly contains operations such as filtering and removing artifacts. Secondly, the pre-processed data are subjected to feature extraction, and the methods mainly include wavelet transform based on time-frequency features and common spatial pattern algorithm based on spatial domain features, among which CSP and the improved algorithm of CSP are widely used. Finally, traditional machine learning algorithms such as LDA, KNN, SVM, and RF are used for classification and recognition [24–27]. However. Traditional machine learning methods often require preprocessing, which is time-consuming and also requires personal experience as well as a priori knowledge. Relying only on personal experience as well as a priori knowledge is difficult to apply with various scenarios and is less robust, which ultimately leads to lower accuracy of MI signal recognition [28].

With the development of deep learning, an increasing number of researchers are integrating deep learning models into the processing of electroencephalogram signals. Currently, the classification of motor imagery based on deep learning can be roughly divided into two types: end-to-end approaches and approaches combining feature representation algorithms with deep learning models. In the end-to-end approach, deep learning models directly process raw EEG signals, automatically extracting features for classification. This approach eliminates the manual preprocessing and feature extraction steps, saving time and improving classification accuracy compared to traditional methods. For example, Schirrmeister et al.[29] proposed three convolutional neural network models (Shallow ConvNet, Deep ConvNet, and Hybrid ConvNet) for motor imagery classification. Experimental results showed a 1.9% improvement in accuracy compared to the traditional FCSP method. Although the improvement is not substantial, it demonstrates that deep learning methods can achieve comparable results to traditional methods. Dose et al. [30]proposed an end-to-end shallow convolutional neural network model for motor imagery classification. This model utilizes two convolutional layers for spatiotemporal convolution. Experimental results showed that the model achieved a maximum accuracy of 86.13% in binary classification, significantly outperforming other traditional machine learning algorithms in terms of classification performance. Yang et al. [31] proposed a motion imagination classification and recognition algorithm that combines CNN, discrete wavelet transform, and LSTM. This algorithm considers both temporal and spatial features of EEG signals and achieves relatively good accuracy. Jia et al. [32]addressed inter-subject variability by proposing a multi-branch, multi-scale convolutional neural network (MMCNN), which utilizes multiple branches with different convolutional kernels for feature extraction and integrates multiple features for MI-EEG classification tasks. Li et al.[14] introduced a neural network feature fusion algorithm that utilizes parallel CNN and LSTM to extract spatial and temporal correlations, achieving an average accuracy of 87.68%. However, due to the poor interpretability of end-to-end models, an increasing number of researchers are combining different feature representation algorithms with deep learning models. This not only improves the interpretability of the models but also enhances their classification performance. For example, Lun et al. [33]employed the SSD algorithm to extract time-frequency features of EEG signals and combined it with a CNN equipped with an SE block for MI-EEG experiment classification. Experimental results demonstrate that this method exhibits high classification accuracy and robustness across subjects. Wei et al. [34] transformed one-dimensional EEG signals into two-dimensional time-frequency maps using continuous wavelet transform and combined them with convolutional neural networks to achieve a classification accuracy of 96.43%. Wang et al.[35] proposed a motion imagination classification model that combines Shannon entropy complex wavelet transform and an improved ResNet network structure, achieving relatively remarkable accuracy.

Although end-to-end deep learning models have achieved relatively impressive accuracy in the field of medical rehabilitation, their "black box" nature limits their interpretability, which poses a serious obstacle to the development of the field. Most end-to-end models use a serial structure for spatio-temporal feature extraction, which tends to lose some of the nonlinear information in the

EEG signal. Even though some studies have adopted the serial structure, the problem of nonlinear feature loss still exists. Although some studies are devoted to improving the interpretability of the model and combining feature extraction with deep learning, the current studies mainly focus on the time-frequency domain and relatively few studies on the spatial domain. Current time-frequency representations mainly include techniques such as wavelet transforms and time-frequency maps, however, these methods may lead to the loss of nonlinear information in the EEG signals, which may affect the classification performance. Therefore, although deep learning models have achieved relatively impressive results in the field of motor imagery brain-computer interfaces, further research is still needed to overcome their limitations in terms of interpretability and feature capture.

Currently, some researchers combine the GAF approach to decode EEG signals by calculating the temporal correlation of each channel through GAF and combining it with convolutional neural networks for feature extraction and classification recognition. For example, Kucukler et al.[36] extracted a model using a combination of GAF and CNN-LSTM for decoding different emotions, which showed very impressive accuracy on specific channels. Ko et al. [37] converted EEG signals into images using recurrence plots (RPs) and GAF and utilized a VGGNet-based model for the converted EEG signal images Learning was performed, and the results showed that the combination of GAF and CNN models can effectively improve the objectivity and efficiency of diagnosing various mental disorders including schizophrenia. Some researchers have also considered the intrinsic connection between electrodes to describe the connectivity between various brain regions of the brain when performing motor imagery tasks through different functional brain networks. For example, Cao et al. [38] proposed a model combining brain functional connectivity matrix and machine learning for analyzing the connections and differences between brain regions of different epileptic patients. Shamsi et al.[39] constructed dynamic brain functional connectivity by calculating its functional connectivity network from the motor imagery EEG data of each period and then combined it with LSTM to perform feature extraction and classification for identification with an average accuracy of 85.32%. Huang et al. [40] used PLV and PLV to construct a brain functional connectivity matrix and fused it into 3D features, then combined the model of 3DCNN-LSTM for use in motor imagery classification and recognition, and the highest accuracy reached 85.88%. Hou et al. [41]proposed a graph convolutional neural network-based deep learning framework to solve the problem of not being able to adequately consider the correlation between electrodes. Neural network-based deep learning framework to improve the decoding performance of different motor imagery tasks while synergizing the functional topology of electrodes. The above literature demonstrated the feasibility of GAF in decoding the temporal correlation of EEG signals and the feasibility of utilizing the brain functional connectivity matrix to decode the intrinsic connection between electrodes. However, they did not simultaneously consider the nonlinear features of EEG signals, temporal correlations, and intrinsic connections between electrodes. If the nonlinear characteristics and temporal correlation of EEG signals are considered, the intrinsic connection between electrodes may be neglected. If the intrinsic connection between the electrodes is emphasized, the nonlinear characteristics and temporal correlation of the EEG signals may be neglected.

In summary, the use of the GAF method to represent the temporal correlation of EEG signals compensates for the problem of ignoring some nonlinear features in convolutional neural networks. Since the electrode positions and functional connections do not remain consistent, the working mechanism and intrinsic connection between brain regions can be explored by calculating the brain functional connection matrix and performing brain network analysis. Therefore, to fully consider the nonlinear features of EEG signals, temporal correlation, and intrinsic relationship between electrodes, as well as to comprehensively understand the dynamic characteristics and spatial distribution of EEG signals, this study designed a combination of GAF and PLV brain functional connectivity matrices as well as a parallel CNN model to accomplish the classification and recognition of motor imagery tasks on the Physionet public dataset. Experimental results show that the algorithm proposed in this study outperforms other motor imagery EEG signal recognition methods.

3. Methodology

To fully consider the nonlinear characteristics of EEG signals, temporal correlation, and the intrinsic connection between electrodes, this paper proposes a method of motor imagery behavior recognition with GAF, PLV, and parallel convolutional neural network, and its technical route is shown in Fig. 1.

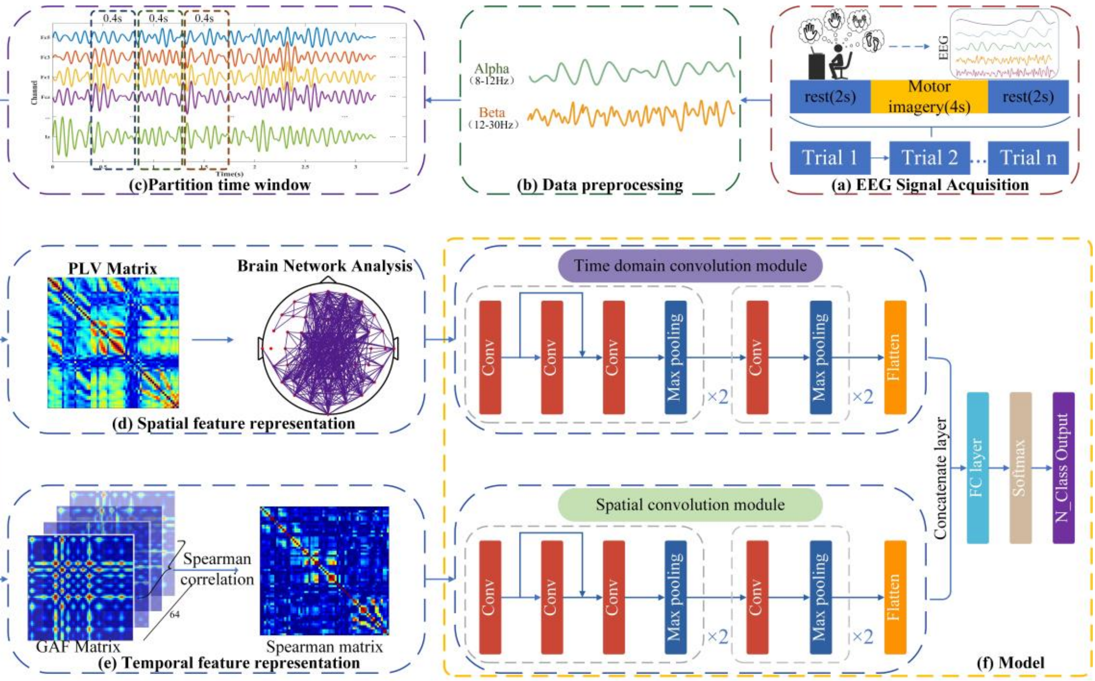

Fig. 1 Technology Roadmap. (a): motor imagery EEG signals from subjects were acquired using a 64-lead device with a sampling rate of 160 Hz. (b): Preprocessing of EEG signals, including filtering, removal of ocular and other

artifacts, etc.(c): Time window selection with 0.4s time window. (d): Spatial features were calculated for different motor imagery tasks, and the corresponding brain networks were analyzed. (e): Calculating temporal correlations for different motor imagery tasks. (f): Spatio-temporal feature extraction of EEG signals using parallel CNN models.

3.1 Temporal Feature Representation

EEG signals are characterized by low signal-to-noise ratios, weak signal amplitudes, and nonlinearities, which make it challenging to accurately analyze and understand them. To fully take into account the nonlinear characteristics of EEG signals and to efficiently compute their temporal correlation, we use the GAF to represent and analyze them. The GAF algorithm is an effective method for analyzing nonlinear time series data. It is based on the GAF matrix and obtains the relationship between data points by calculating the inner product of the data, thus revealing its temporal correlation. For motor imagery EEG signals, we can utilize the GAF method to capture the dynamic associations between different time points, to better understand the mechanism of EEG signal generation and the information transfer process. With the GAF method, the EEG signals can be converted into points in a high-dimensional vector space and their relationships can be described by calculating the angles between them. This method can effectively reduce the effect of noise while preserving the nonlinear characteristics of the signal and extracting meaningful time-dependent information. Given an EEG signal of a certain channel $X = \{x_1, x_2, x_3, ...x_n\}$, the GAF is calculated as follows:

(1) Standardization:

First, the interval to which the n values X are scaled:

$$x_i' = \frac{2(x_i - \min(x))}{\max(X) - \min(X)} - 1 \tag{1}$$

(2) Time series recording:

Then, map the standardized x_i' to the polar coordinate system.

$$\begin{cases} \theta = \arccos(x_i'), -1 \le x_i' \le 1, x_i' \in \tilde{X} \\ r = \dfrac{t_i}{N}, t_i \in \mathbb{N} \end{cases} \tag{2}$$

Where θ is the encoded angle, r is the distance from the localization point to the polar origin, t_i is the timestamp corresponding to x_i', and N denotes the total length of the time series

(3) Time correlation calculations:

After transforming the time series into a polar coordinate system, the temporal correlation between each point is represented by calculating the cosine of the sum of the polar angles of each time series point.

$$GAF_{(i,j)} = \begin{bmatrix} \cos(\theta_1+\theta_1) & \cos(\theta_1+\theta_2) & \cdots & \cos(\theta_1+\theta_j) \\ \cos(\theta_2+\theta_1) & \cos(\theta_2+\theta_2) & \cdots & \cos(\theta_2+\theta_j) \\ \vdots & \vdots & \ddots & \vdots \\ \cos(\theta_i+\theta_1) & \cos(\theta_i+\theta_2) & \cdots & \cos(\theta_i+\theta_j) \end{bmatrix} \tag{3}$$

Where θ_i, θ_j denotes the angle values at different timing points.

Since GAF is used to calculate the temporal correlation of each channel's signal, a 64-channel EEG signal generates 64 GAF matrices within a time window. However, to reduce the amount of data while better capturing the dynamic connections and synergistic activities between different brain regions, further processing of this information is required. To this end, Spearman correlation coefficients were used to assess the nonlinear relationships between the GAF matrices of each channel, thereby summarizing the 64 matrices into one. By calculating the Spearman correlation coefficients, it is possible to quantify the correlations between different channels and extract from them the dynamic connections and synergistic activities between different brain regions. This helps us to be able to better understand the mechanism of EEG signal generation and the process of information transfer.

3.2 Spatial Feature Representation

To comprehensively understand the connectivity relationship between various brain regions during motion perception and execution, and accurately characterize spatial features, we adopted the phase locking value based on phase synchronization indicators. This metric accurately measures the phase relationship between two electrodes and is used for analyzing functional connectivity in the brain. Given the EEG signals corresponding to electrode X and Y as $x(t)$ and $y(t)$ respectively, with a phase difference $\theta(t)$ between $x(t)$ and $y(t)$, the PLV is defined as：

$$PLV = \frac{1}{N}\left|\sum_{n=1}^{N} e^{j(\theta(t_n))}\right| \tag{4}$$

Where N is the length of $\theta(t)$, the range of PLV matrix values is from 0 to 1, where 0 indicates complete independence between the two signals and 1 indicates complete synchronization.

3.3 Decoding of Spatio-temporal features

In recent years, with the advancement of deep learning in the fields of computer vision and language recognition, the feature learning method of CNN models has been widely applied. CNNs demonstrate excellent performance in feature learning by stacking low-complexity features layer by layer to construct high-complexity features. This hierarchical learning approach is considered more effective than directly learning high-complexity features. Through consecutive convolution and pooling operations, CNNs can gradually extract abstract features from image or text data, ranging from basic features like edges and textures to more abstract semantic information, thus achieving multi-level representations of input data. In the field of brain-computer interfaces, CNN models can effectively extract and classify features from EEG signals. Firstly, CNNs can gradually extract rich spatial and temporal features from EEG signals, including frequency-domain features, time-domain features, etc., which can reflect different activation patterns of various motor imagination activities in the brain. Secondly, the hierarchical learning approach of CNNs can effectively capture the complex relationships between these features, thereby better distinguishing between different types of motor imagination. Therefore, we adopt parallel CNN models to decode the spatiotemporal features obtained from GAF, Spearman correlation coefficient, and PLV.

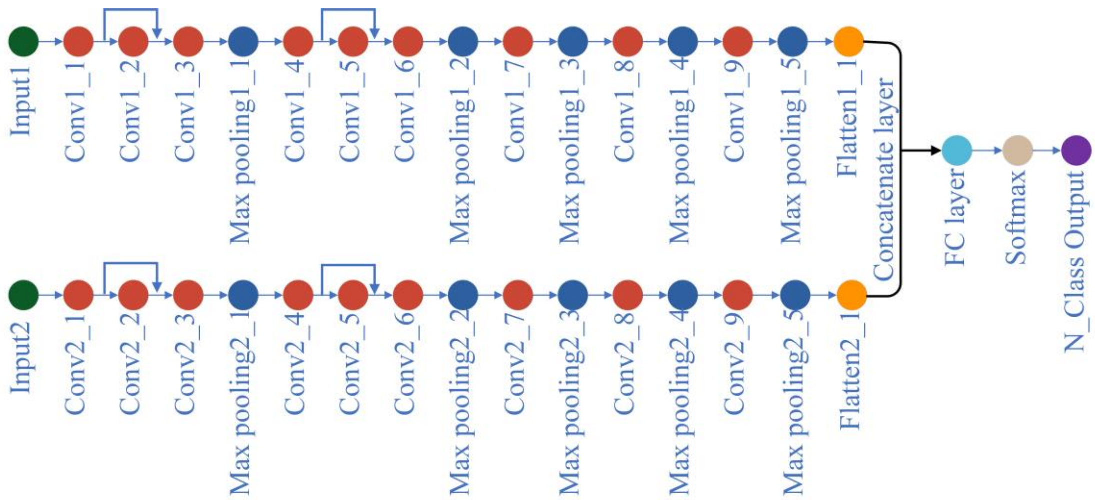

Fig. 2 Parallel CNN modeling framework based on spatio-temporal features.

Based on the spatiotemporal features, the parallel CNN model is illustrated in Figure 2. This model integrates two parallel CNN branches, each dedicated to processing different types of features to effectively capture diverse information within EEG signals. Firstly, a CNN branch is employed to extract temporal features, i.e., the features obtained from the GAF and Spearman correlation coefficient. This branch consists of nine convolutional layers, five pooling layers, and a flattened layer to capture the signal variations over time. To prevent feature loss and retain the original signals, two Concatenation layers are also utilized. Through this branch, temporal correlations and spatial distributions within EEG signals can be identified. Secondly, another branch is employed to extract spatial features, i.e., the PLV matrix obtained from electrode correlations. Similar to the temporal features branch, this branch adopts the same structure, including multiple convolutional and pooling layers, and likewise employs two Concatenation layers. This branch enables the capture of spatial correlation information within EEG signals, further enriching the model's feature extraction capability. Finally, feature fusion and transformation are performed using fully connected layers, followed by classification using the Softmax function in the output layer. L2 regularization and batch normalization are incorporated into the model to reduce overfitting, with 50% Dropout applied to the convolutional layers. The ReLU function is utilized as the activation function to alleviate the vanishing gradient problem. Training is conducted using the Adam optimizer with a learning rate of 0.0001. Table 1 provides additional details about the model. Since the structures of the parallel CNN spatiotemporal feature extraction branches are identical, only the details of one branch are described here.

Table 1 Parallel CNN model-specific details

	Layers	Kernel	Filter	Activation	Stride	Padding	Output
Spatio-temporal feature learning	Input	-	-	-	-	-	256*256*3
	Conv1_1	(3, 3)	32	ReLU	1	same	256*256*32
	Conv1_2	(3, 3)	32	ReLU	1	same	256*256*32
	Conv1_3	(3, 3)	64	ReLU	1	same	256*256*64
	MaxPooling1_1	(2, 2)	-	-	2	-	128*128*64
	Conv1_4	(3, 3)	64	ReLU	1	same	128*128*64
	Conv1_5	(3, 3)	64	ReLU	1	same	128*128*64
	Conv1_6	(3, 3)	128	ReLU	1	same	128*128*128
	MaxPooling1_2	(2, 2)	-	-	2	-	64*64*128
	Conv1_7	(3, 3)	256	ReLU	1	same	64*64*256
	MaxPooling1_3	(2, 2)	-	-	2	-	32*32*256
	Conv1_8	(3, 3)	256	ReLU	1	same	32*32*256
	MaxPooling1_4	(2, 2)	-	-	2	-	16*16*256
	Conv1_9	(3, 3)	256	ReLU	1	same	16*16*256
	MaxPooling1_5	(2, 2)	-	-	2	-	8*8*256
	Flatten	-	-	-	-	-	16384
	Dropout	-	-	-	-	-	-
	Batch normalization	-	-	-	-	-	-
Feature fusion	Concatenate	-	-	-	-	-	32768
	Fully connected	-	-	-	-	-	1024
	Dropout	-	-	-	-	-	-
	Softmax	-	-	-	-	-	N_Class

4. Experimental results and analysis

4.1 Data Acquisition

In this study, we used the PhysioNet public dataset [42], which uses a 64-lead device to collect EEG signals containing real movement and motor imagery from 109 subjects, with a sampling rate of 160 Hz. Given that the focus of our study was on the motor imagery task, only the experimental data related to the motor imagery task were selected. We selected 10 and 30 subjects for experimental validation. During the experimentation of this dataset, subjects were required to perform 14 experiments with 2 baseline sections and 3 experimental sections (each containing 4 tasks). The experimental paradigm is shown in Figure 3, and the 4 tasks were left fist, right fist, both fists, and both feet motor imagery as follows:

Task 1: The task target appears on the left side of the screen. The subject imagines opening and closing their left fist until the target disappears, and then the subject rests.

Task 2: The task target appears on the right side of the screen. The subject imagines opening and closing their right fist until the target disappears, and then the subject rests.

Task 3: The task target appears at the top of the screen. The subject imagines opening and closing both fists until the target disappears, and then the subject rests.

Task 4: The task target appears at the bottom of the screen. The subject imagines opening and closing both feet until the target disappears, and then the subject rests.

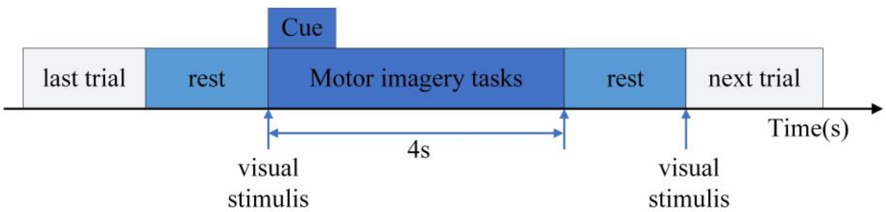

Fig. 3 Experimental Paradigms. The subject is cued to execute the real execution or MI task for four seconds while the cue appears, then rest until the next trial starts.

4.2 Data preprocessing

To obtain high-quality EEG data, we used a method similar to other EEG signal processing processes. Under the premise of preserving the original information as much as possible, we processed the data using a fourth-order zero-phase Butterworth bandpass filter to obtain the EEG frequency bands that are most relevant to the perceptual-motor rhythms, which mainly include the alpha wave (8-12 Hz) and the beta wave (13-30 Hz). For the filtered 8-30hz band we sliced each MI-EEG data segment in 0.4s sliding windows and 0.4s steps. Our preprocessing process is done based on EEGLAB and Python toolkits. Next, we built the CNN model using the TensorFlow framework.

Given that the PhysioNet public dataset includes 109 subjects, we opted to utilize 10 subjects (S1-S10) and 30 subjects (S1-S30) for our experiments to enhance computational efficiency. We formulated the following 2-class and 4-class subsets, respectively.

2-class: left and right-hand motor imagery task (L/R).

4-class: left and right hand, double fist, and double foot motor imagery tasks (L/R/B/F).

The preprocessed data were partitioned into training and validation sets at a ratio of 9:1. All network models were trained and tested on a server equipped with Nvidia 4090 GPUs.

4.3 Time-domain feature analysis

To gain deeper insights into the generation mechanism and information transmission process of electroencephalogram signals, we conducted a time-domain feature analysis. Firstly, using preprocessed EEG signals from each time slice, we computed the Gramian Angular Field matrix, which helps capture dynamic relationships between different time points. Since the dataset contains 64 EEG channels and has a sampling rate of 160Hz, each time slice yields a 64-channel GAF matrix of size 64*64. This matrix illustrates the evolution of EEG signals over time, with the darkness of colors reflecting the strength and degree of temporal correlations.

Then, to reduce the amount of data processed by the model while retaining important information, the Spearman correlation coefficients of the GAF matrices between each channel within each time slice were further calculated. In this way, a 64*64 Spearman matrix was computed for each time slice. It reflects the strength of temporal correlations between different brain regions, helping us understand the relationships of signal evolution over time. Subsequently, to better utilize these features for subsequent parallel CNN network model learning, these Spearman matrices were mapped into RGB images of size 256*256. To visualize these matrices better, as shown in Figure 4, GAF matrices for four different motor imagery tasks and the integrated Spearman matrix generated from the data of Subject 1 were used.

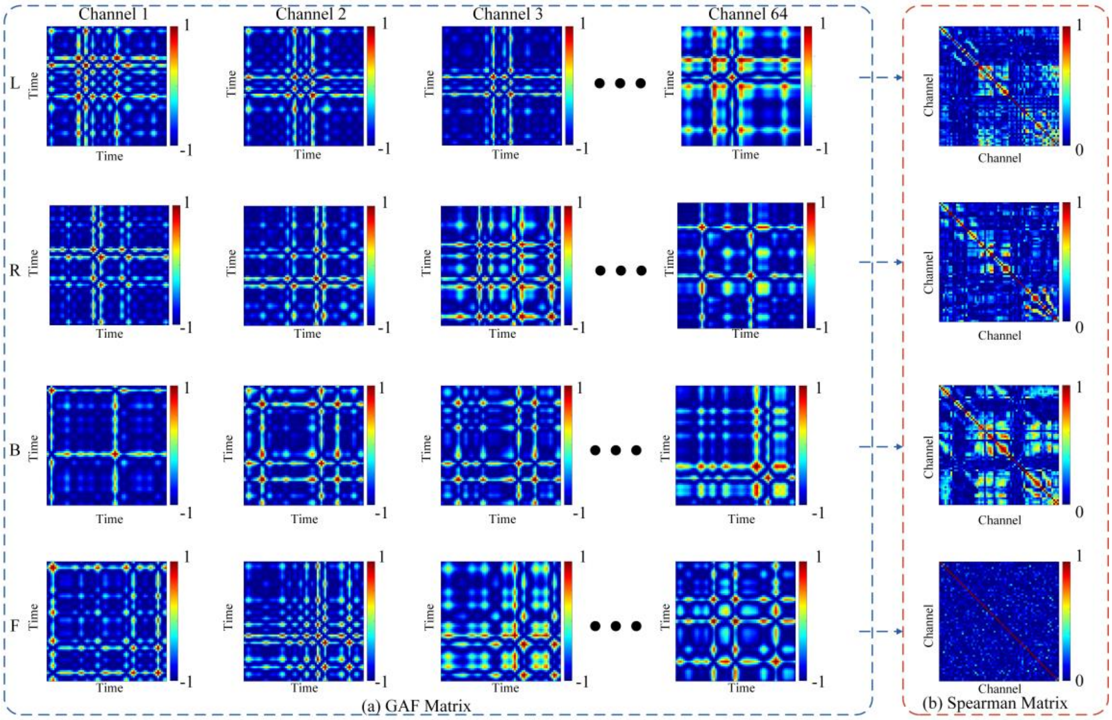

Fig. 4 GAF matrices for Subject 1 while performing four different motor imagery tasks (L, R, B, and F) and the corresponding Spearman matrices. (a): GAF matrix corresponding to each electrode channel for four types of motor imagery tasks. (b): Integrated Spearman correlation matrix.

4.4 Spatial features analysis

By calculating the phase coherence-based PLV matrices of the EEG signals, we can gain insight into the spatial features of the EEG signals, i.e., the topological relationships between the electrodes.

By calculating the PLV matrices for each time slice, subsequently, to better utilize these features for subsequent parallel CNN network model learning, this also maps these PLV matrices into RGB images of 256*256 size just as the Pierce matrices in the time domain feature analysis.

To further analyze the prior connectivity of brain regions for different motor imagery tasks, functional brain networks corresponding to different motor imagery tasks were mapped. However, since the amplitude of EEG signals is usually very weak, a large number of weak connections are generated, many of which may be caused by noise. These weak connections do not accurately reflect the true connectivity relationships between brain regions. Therefore, when constructing functional brain networks, it is crucial to choose an appropriate threshold to filter the connection weights. For this purpose, connection weights will be extracted from the computed brain functional connectivity matrix, and then these weights will be composed into a weight vector. We binarized the brain functional connectivity matrix using the upper quartile of the weight vector as the final threshold.

As shown in Figure 5, the PLV matrix and the binarized PLV matrix and their corresponding functional brain networks for subject 1 while performing different motor imagery tasks are shown. The increased connectivity between different brain regions while performing the upper limb motor imagery task (L/R/B) was mainly between the frontal, parietal, occipital, and temporal lobes. These brain regions correspond to the primary motor layer, premotor area, motor accessory area, somatosensory cortex, and visual cortex in the cerebral cortex, respectively. In lower limb motor imagery, although the overall network of electrode channels was weakly connected, there was connectivity across the whole brain, which was mainly because lower limb motor imagery required more neurons to be invoked to control the execution of the motor task synergistically compared with upper limb motor imagery.

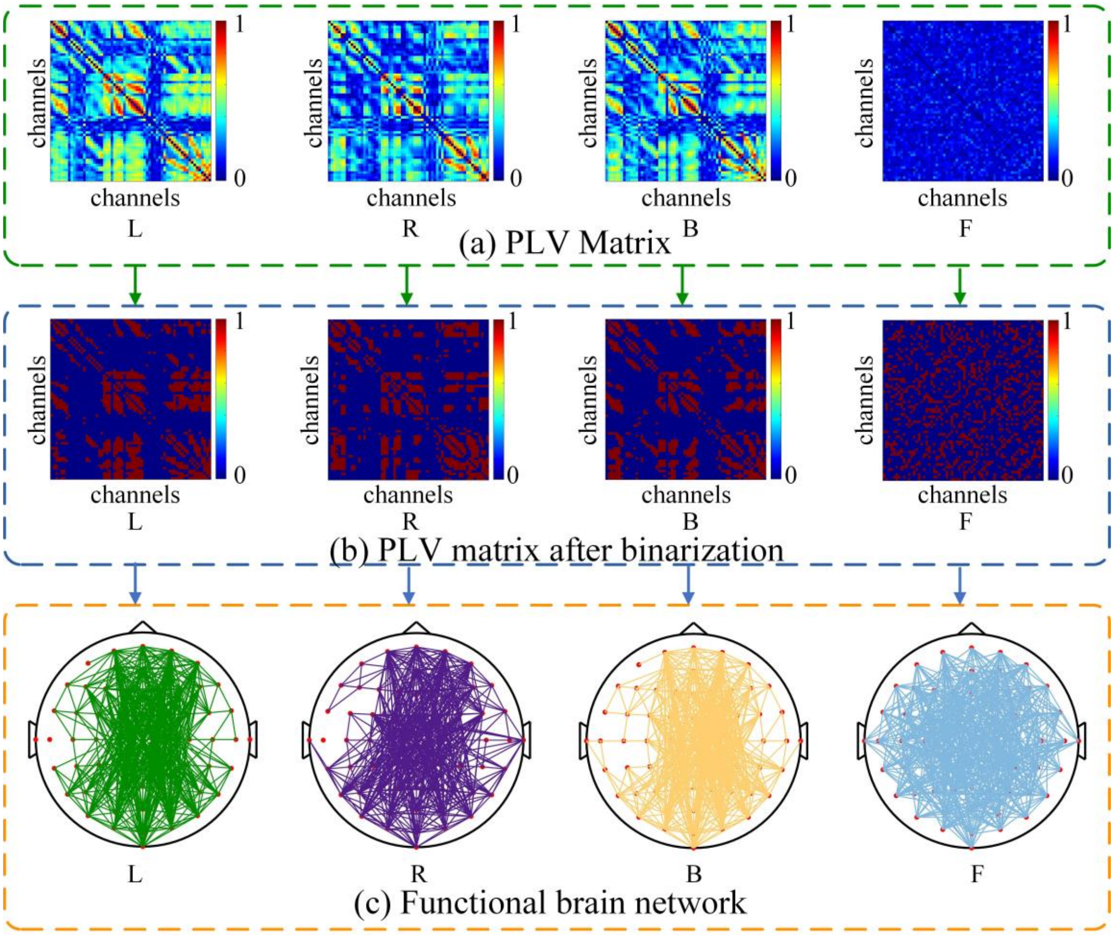

Fig. 5 Functional brain network analysis during four motor imagery tasks (L, R, B, and F) performed by Subject 1. (a): PLV matrices for Subject 1 when performing the four motor imagery tasks (L, R, B, and F). (b): Binarize the PLV matrix. (c): brain network analysis.

4.5 Spatio-temporal feature decoding

To verify the effectiveness of our proposed parallel CNN model based on GAF and PLV spatio-temporal representations, we designed an end-to-end parallel convolutional neural network model as shown in Fig. 6 for comparison experiments. In this end-to-end model, we used two parallel branches for extracting spatio-temporal features respectively. The specific model details are shown in Table 2. The model takes the raw data of the 0.4-second time window as input, and the two branches are used to extract the time-domain features and spatial features of the EEG signal, respectively. One branch uses a 1*2 convolutional kernel to extract the time-domain features of the

EEG signal, while the other branch uses a 2*1 convolutional kernel to extract the spatial features of the EEG signal. To reduce the complexity of the model, only one layer of Concatenation structure is used for the end-to-end model.

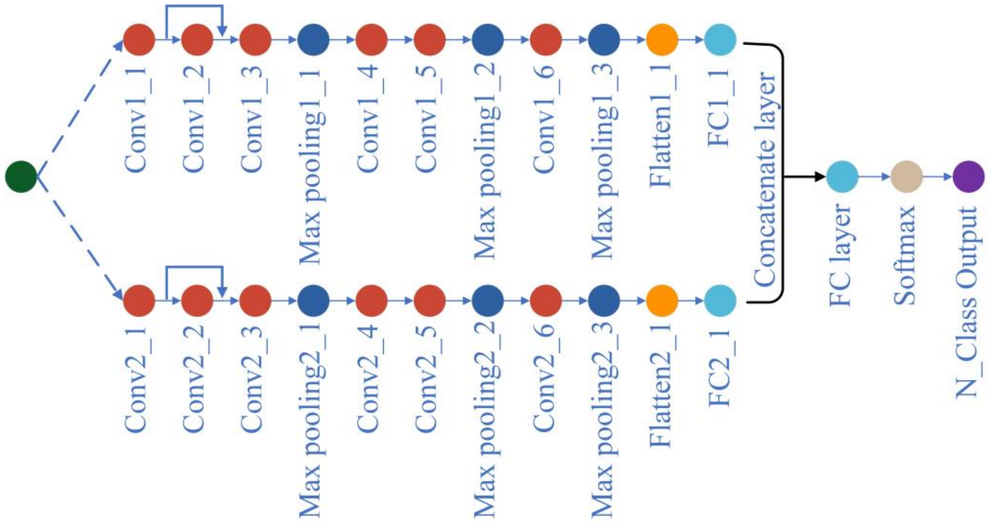

Fig. 6 End-to-end parallel CNN modeling

Table 2 End-to-end parallel CNN model details

	Layers	Kernel	Filter	Activation	Stride	Padding	Output
	Input	-	-	-	-	-	64*64
	Conv1_1	(1, 2)	32	ReLU	1	same	64*64*32
	Conv1_2	(1, 2)	32	ReLU	1	same	64*64*32
	Conv1_3	(1, 2)	64	ReLU	1	same	64*64*64
	MaxPooling1_1	(2, 2)	-	-	2	-	32*32*64
temporal feature learning	Conv1_4	(3, 3)	128	ReLU	1	valid	30*30*128
	Conv1_5	(3, 3)	256	ReLU	1	valid	28*28*256
	MaxPooling1_2	(2, 2)	-	-	2	-	14*14*256
	Conv1_6	(3, 3)	256	ReLU	1	valid	12*12*256
	MaxPooling1_3	(2, 2)	-	-	2	-	6*6*256
	Flatten1_1						9216
	FC1_1						1024
	Input	-	-	-	-	-	64*64
	Conv2_1	(2, 1)	32	ReLU	1	same	64*64*32
	Conv2_2	(2, 1)	32	ReLU	1	same	64*64*32
	Conv2_3	(2, 1)	64	ReLU	1	same	64*64*64
spatial feature learning	MaxPooling2_1	(2, 2)	-	-	2	-	32*32*64
	Conv2_4	(3, 3)	128	ReLU	1	valid	30*30*128
	Conv2_5	(3, 3)	256	ReLU	1	valid	28*28*256
	MaxPooling2_2	(2, 2)	-	-	2	-	14*14*256
	Conv2_6	(3, 3)	256	ReLU	1	valid	12*12*256

	MaxPooling2_3	(2, 2)	-	-	2	-	6*6*256
	Flatten2_1						9216
	FC2_1						1024
feature fusion	Concatenate	-	-	-	-	-	2048
	Fully connected	-	-	-	-	-	512
	Softmax	-	-	-	-	-	N_Class

Here, we conducted an experimental comparison between the end-to-end model and the model based on spatio-temporal feature representation with the same number of subjects. According to the results, as shown in Fig. 7, there is a significant difference in the performance of these two approaches on the dichotomous and quaternary classification tasks with 10 subjects and 30 subjects. Specifically, the model based on the spatio-temporal feature representation shows a substantial performance improvement, which is up to 20% in the dichotomous and quadruple classification tasks. This also illustrates the effectiveness of our proposed spatiotemporal feature representation in EEG signal analysis, as well as the superiority of our proposed parallel CNN model structure combined with the spatiotemporal feature representation. The combination of temporal and spatial features through the spatio-temporal feature representation and the modeled spatial domain of the parallel CNN can capture the spatio-temporal information in the EEG signals more comprehensively, and thus characterize the brain activities more accurately. In contrast, an end-to-end approach may not be able to fully utilize the spatiotemporal information in the EEG signal, leading to significant performance differences. The existence of such differences provides important insights and directions for further research and improvement of EEG signal analysis models.

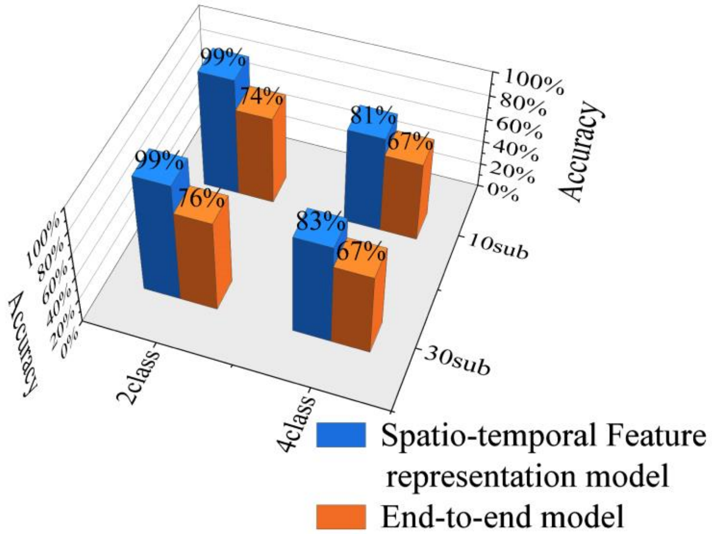

Fig. 7 Comparison of 2-classification and 4-classification accuracies of the model based on spatio-temporal feature representations with the end-to-end model in the 10-subject and 30-subject cases

To verify the effectiveness of our proposed spatio-temporal feature representation combined with parallel CNNs even further, we considered the temporal and spatial domains separately for EEG signal decoding. The experimental results are shown in Fig. 8, where it can be seen that with the same number of subjects when performing the four classification tasks, the accuracy of considering the temporal domain features alone reaches 79.31%, while the accuracy of considering the spatial domain features alone is only 56.02%. However, when both spatial and temporal features were considered, the accuracy could reach up to 83.37%. When performing the binary classification task, the accuracy of considering the time domain features alone was 87.76%, while the accuracy of considering the spatial features alone was only 54.04%. When temporal and spatial features are considered simultaneously, the accuracy can reach up to 99.18%. These results clearly show that the single-view method cannot comprehensively extract the complex spatio-temporal dynamic features in EEG signals, and the single consideration of spatio-temporal features will ignore the interaction and information transfer between different spatial locations. A single consideration of the spatial domain will ignore some of the nonlinear features of the EEG signal the correlation between different time points and the evolution trend of the signal. Therefore, the methods that consider the time domain or the space domain alone often have limitations in decoding EEG signals and are unable to comprehensively analyze the global information and dynamic changes of EEG signals. In contrast, the simultaneous consideration of temporal and spatial features of EEG signals has a significant performance improvement. This shows that our model can simultaneously take into account both temporal and spatial features of EEG signals, thus providing richer features for recognizing the activity patterns of different brain regions and their changes over time when performing a motor imagery task.

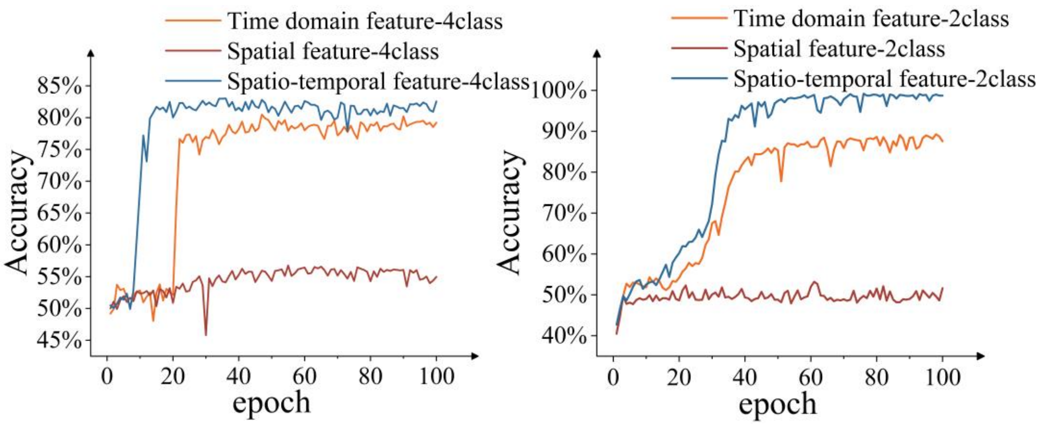

Fig. 8 Comparison of the 2-class and 4-clas accuracies of the model considering time- and space-domain features alone versus the combined time-space features

The model designed in this paper demonstrates very superior performance in the binary classification task. To illustrate the performance of the model proposed in this paper more clearly, the confusion matrices of the model in the binary classification task with 10 subjects and 30 subjects are plotted here. As shown in Fig. 9, the color shades indicate the level of accuracy, and it can be seen that the model in this paper has a very high accuracy rate for the binary classification motor imagery task, which reaches more than 99% and the highest accuracy rate can be up to 99.83%. This shows that our model can fully consider the nonlinear characteristics of EEG signals, time correlation, and the interaction between electrodes and many other factors. By taking these key features into account, the model designed in this paper can more accurately capture the temporal and spatial features embedded in the EEG signal.

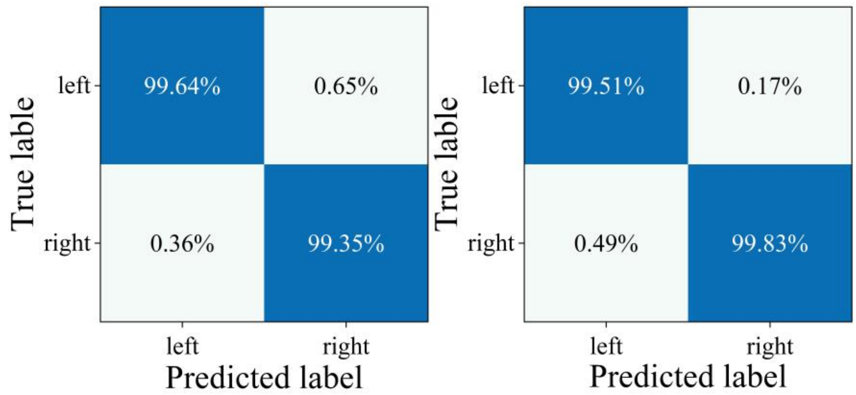

Fig. 9 Confusion matrix for 10 subjects and 30 subjects performing a left- and right-handed motor imagery task

4.6 Comparison of different methods

As shown in Table 3, to further validate the performance of the model proposed in this paper, this paper is compared with several state-of-the-art algorithms for motor imagery classification, which include both traditional and deep learning approaches: the HR-SNN [43], the MAML-CNN [44], the 3DCNN-LSTM [40], and the Mi-BMInet [45]. All these research works use the PhysioNet public dataset. The results show that the method proposed in this paper outperforms other algorithms in terms of classification performance, especially reaching 99.73% in the two-classification task and 83.37% in the four-classification task. It also proves that the use of GAF and PLV for spatio-temporal feature representation combined with parallel CNN is beneficial for the extraction of spatio-temporal features of EEG signals as well as the decoding of EEG signals. There are three reasons for this:(1): considering spatio-temporal features separately for the brain, which is a complex/dynamic system, facilitates the retention of important information about the temporal and spatial scales. (2): Deep learning is currently making a big splash in fields such as computer vision, where feature extraction and classification recognition using parallel CNN models can simultaneously take into account the temporal correlation of the EEG signal as well as the correlation between each electrode. The ability to capture the complex relationship between electrodes and the contextual information of the EEG signal helps to improve the performance of the classification task. (3): The combination of GAF and PLV and parallel CNN models can extract the deeper features of EEG signals and make them more representational and interpretable.

Table 3 Comparison results of different methods

Methods	Num. of EEG channels	Num. of subjects	Accuracy (2-class)	Accuracy (4-class)
HR-SNN	64	105	-	74.95%
MAML-CNN	17	104	80.6%	79.7%
3DCNN-LSTM	64	20	82.66%	-
Mi-BMInet	64	105	82.99%	65.62%
This work	**64**	**10**	**99.73%**	**80.66%**
	64	**30**	**99.18%**	**83.37%**

5. Conclusion

In this study, we propose a novel model for motor imagery classification that effectively considers the nonlinear characteristics of EEG signals and the interdependencies between electrodes through spatiotemporal feature representation. By constructing Gramian Angular Field (GAF) matrices to analyze temporal correlations and Phase Locking Value (PLV) matrices to examine spatial relationships among electrode channels, we enhance the understanding of EEG signal dynamics. Our experimental results indicate that this spatiotemporal feature representation method significantly outperforms an end-to-end spatiotemporal decoding parallel CNN model by better capturing critical temporal and spatial relationships. This discrepancy highlights the importance of fully utilizing spatiotemporal information, offering valuable insights for advancing EEG signal analysis. The proposed approach not only demonstrates clear advantages over traditional machine learning and other deep learning algorithms but also provides a framework for improved feature recognition in motor imagery tasks. From a practical perspective, the insights gained from spatiotemporal analysis are crucial for treating patients with motor dysfunction. For example, stroke patients can benefit from targeted treatment plans by identifying impaired brain areas through this methodology.

However, this study has limitations, particularly in not addressing frequency domain features, which are essential for comprehensive EEG analysis. Future research will incorporate these features to further enhance classification performance. Additionally, we aim to validate our method with EEG data from patients with motor dysfunction, exploring the characteristics of EEG signals across different frequency bands to improve motor imagery classification. This study provides a foundational approach for advancing EEG signal classification and has significant implications for clinical applications in rehabilitation therapies.

CRediT authorship contribution statement

Renjie Lv: Methodology, Visualization, Investigation, Original draft preparation, Writing-Reviewing, and Editing. **Wenwen Chang**: Supervision, Visualization, Methodology, Resources, Funding acquisition. **Guanghui Yan**: Supervision, Resources, Conceptualization, and Writing-Reviewing, Funding acquisition. **Muhammad Tariq Sadiq**: Supervision, Resources, Conceptualization, and Writing-Reviewing. **Wenchao Nie**: Software, Formal analysis, Investigation, Visualization. **Lei Zheng**: Data curation, Formal analysis, Writing-Reviewing, and Editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Declaration of interests

☒The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: