Dual-Branch EEG Decoding Method for Collaborative Multi-Brain Motor Imagery

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Abstract

Collaborative multi-brain motor imagery is an innovative brain-computer interface (BCI) paradigm that records and decodes brain signals from multiple individuals to collectively complete motor imagery tasks. However, existing decoding methods often rely on techniques such as averaging, concatenating, or cross-brain coupling of data or features, and lack coordination between single-brain and multi-brain decision-making in this context. To address this, we propose a dual-branch electroencephalogram (EEG) decoding method that jointly learns private and shared domain information. The method employs a Siamese network for private common spatial pattern (CSP) learning and a feature-sharing network for shared features, then combines the outputs for classification. Experiments with EEG data demonstrated a 10.27% improvement over the single-brain scenario and a 9% improvement over state-of-the-art methods. This approach effectively integrates private and shared domain learning, advancing collaborative BCI technology.

Keywords: Multi-brain motor imagery; EEG decoding; Shared and private features joint learning; CSP

Introduction

Motor imagery (MI) is one of the classic paradigms in brain computer interface (BCI) research. Unlike exogenous evoked EEG activity, MI is an endogenous spontaneous pattern that utilizes imagined motor actions rather than actual physical movements (Y. Li et al., 2021). In recent years, MI-based BCI technology has gained significant attention in fields like neural rehabilitation, assistive device control and neuroscience research. It allows users to regulate their EEG signals by simply imaging movements, enabling the system to decode their intentions and provide appropriate feedback (Singh et al., 2021). The key challenge in MI-based BCI lies in effective brain signal decoding. Electroencephalogram (EEG), konwn for its high temporal resolution and relatively low cost, is the most widely used brain signals in MI-BCI. The two main approaches to MI signal decoding are feature engineering and deep learning.

Feature engineering focuses on extracting traditional features such as power spectral density (PSD) and coherence. These features are then used for classification via methods like support vector machines (SVM) and linear discriminant analysis (LDA) (Geng et al., 2022). In contrast, deep learning methods, such as convolutional neural networks (CNNs) and Transformers, automatically learn relevant features without the need for manual feature extraction, allowing them to hanle more complex and varied signal patterns (Abibullaev et al., 2023). Despite significant progress in MI decoding, the accuracy remains limited due to the low signal-to-noise ratio (SNR) of EEG signals. Furthermore, since current systems typically rely on a single brain for decision-making, the lack of cross-validation compromises the stability and reliability of the decoding outcomes (George et al., 2021).

The emergence of hyperscanning technology offers a promising solution to address the limitations in MI signal decoding. This technology allows for the simultaneous recording of EEG signals from multiple brains, enabling the analysis of inter-brain synchrony and offering new opportunities to investigate the neural mechanisms underlying group cognition, cooperative behavior, and social interactions (Liu et al., 2018). Research has shown that synchronization between brains is enhanced in collaborative scenarios (Léné et al., 2021; Nam et al., 2020). Inspired by these hyperscanning studies, a novel multi-brain BCI paradigm has been developed, which integrates group features and decisions in collaborative tasks.

The primary challenge in multi-brain BCI is effectively integrating EEG signals from multiple brains for efficient decoding. Common approaches include EEG averaging, feature concatenation, and joint voting. For example, Yijun Wang et al. have conducted multiple studies on collaborative BCI,

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demonstrating significant performance improvements—8.2% and 14.3% with multi-brain collaboration using data averaging and feature concatenation respectively (Wang & Jung, 2011). Recently, researchers have started to focus on coupling feature learning. Song et al. proposed a framework for group detection of collaborative multi-brain dynamic visual targets through mutual information learning among brains (Song et al., 2022), while Zhu et al. introduced a multi-brain MI decoding method leveraging coupling features (Zhu et al., 2023). In summary, existing multi-brain MI-BCI research has not fully explored joint learning strategies for both private and inter-brain collaboration.

Inspired by related works, this paper proposes a dual-branch EEG decoding method for multi-brain motor imagery BCI, designed to jointly learn both private and cross-brain features. The main contributions of this paper are summarized as follows:

- A method suitable for multi-brain motor imagery decoding is proposed, which includes two branches: an intra-brain private CSP (common spatial pattern) feature learning branch and a cross-brain EEG shared feature learning branch, jointly learning private and shared features.
- A task-related measurement module is designed, wherein task-relevant features are pre-extracted when processing private features, enhancing the quality of feature processing and significantly improving decoding accuracy.
- Multiple experiments were conducted and results show that the dual-brain scenario outperforms the single-brain approach, as shared feature learning yields more discriminative representations than individual feature extraction.

Related Works

In the following section, we describe the background of related work involved in the proposed method. Specifically, these work based on MI-based EEG decoding method, hyperscanning for social interaction, and multi-brain brain-computer interface.

Motor Imagery-based EEG Decoding Method

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MI-based EEG decoding methods are widely applied in the field of Brain-Computer Interface (BCI). MI signals refer to the brain activity generated when an individual activates the motor cortex by imagining the movement of a body part, without physically performing the movement. Existing decoding methods include both feature engineering and automatic feature learning.

MI features are typically categorized into two types: spectral features and spatial features (Nguyen et al., 2020). Feature engineering focuses on capturing Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) mechanisms, including energy-based methods, spectral feature extraction, and Common Spatial Pattern (CSP) spatial filtering. For instance, Lu et al. proposed a multi-wavelet decomposition framework combining Morlet and Haar wavelets for multi-level decomposition of EEG signals, extracting energy features across various frequency bands (Lu et al., 2024). Yang et al utilized wavelet transform to decompose the EEG signals into α and β frequency bands, and combined fuzzy entropy (Fuzzy Entropy) to extract non-linear time-domain features (Yang et al., 2021). Masaki et al. introduced a multiclass CSP approach for classifying finger movements in MI, improving discrimination between different tasks (Kato et al., 2020). Among these methods, CSP is the most widely used technique for extracting features from EEG data and improving classification accuracy by maximizing signal differences between classes.

Automatic feature learning, primarily driven by deep learning, enables neural networks to autonomously extract multi-level features in an end-to-end manner, removing the need for manual feature extraction. This allows the model to capture more complex patterns. The EEG-transformer utilizes multi-head self-attention to capture global dependencies in both spectral and temporal dimensions, modeling long-range interactions in raw EEG signals for superior performance (Lee & Lee, 2022). Spatio-Temporal Graph Neural Networks (ST-GNN) model dynamic functional connectivity between brain regions through graph convolutions, addressing the non-stationary nature of MI-EEG and outperforming traditional methods by 12% on cross-subject benchmarks(Pan et al., 2023). Among deep learning models, CNNs are lightweight and particularly effective in capturing both local and global features through multi-scale convolution operations. By integrating residual connections or Inception modules, CNNs efficiently reuse features, making them ideal for MI decoding (Liang et al., 2024).

Hyper-scanning for Social Interaction and Multi-Brain Brain Computer Interface

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Hyperscanning technology simultaneously records neural synchrony and interaction across multiple brains to study social activities between individuals. In recent years, hyperscanning has demonstrated its effectiveness in brain-to-brain synchrony, emotional communication, and collaborative tasks. For example, Zhu et al. used hyperscanning to simultaneously record EEG activity of two participants during an interaction task involving positive and negative emotional stimuli, investigating the neural mechanisms of brain-to-brain synchrony and emotional perception under different emotional conditions (Zhu et al., 2018). Hu et al. investigated the impact of cooperation on interbrain synchrony during interactive decision-making. Their study found that, in highly cooperative situations, interbrain synchrony in the θ and α bands was significantly enhanced, particularly in the central frontal and central parietal regions. These enhanced synchronies were closely associated with increased cooperative choices (Hu et al., 2018).

Multi-Brain Brain-Computer Interface (BCI) aims to study the integration of brain activity from multiple brain into a

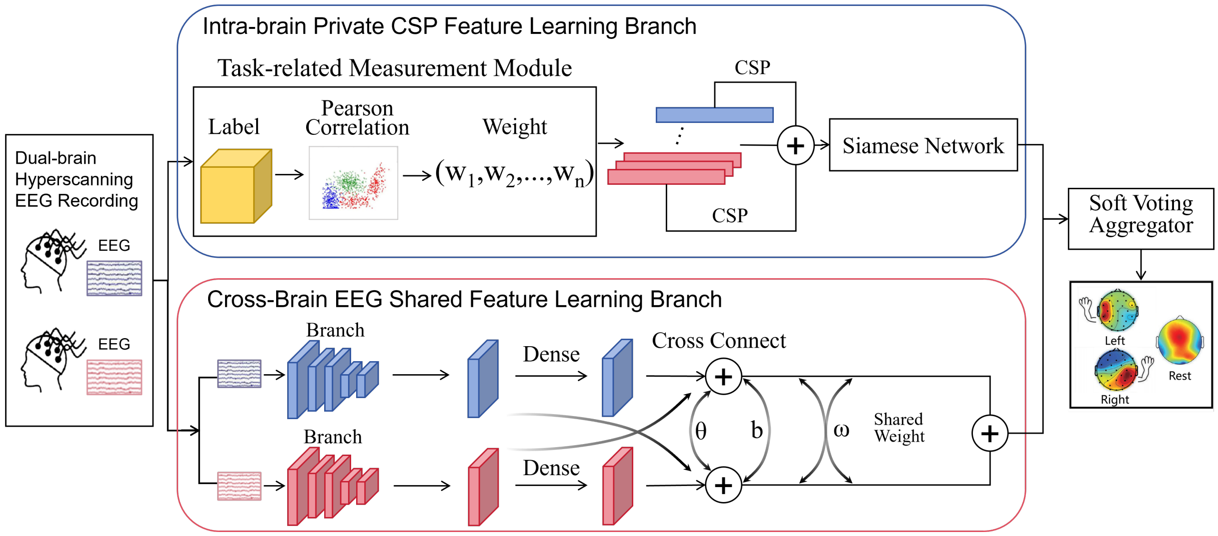

Figure 1: The overall framework of our method

single system to enable collaboration and decision-making (Nijholt, 2015). Yijun Wang et al. proposed a method involving data averaging and feature concatenation, which resulted in improvements of 8.2% and 14.3% in decoding accuracy, respectively. In recent years, research has emerged exploring joint learning of cross-brain features. Song et al. developed a framework for group detection of collaborative multi-brain dynamic visual targets by employing mutual information learning across brains. Zhu et al. proposed an EEG-based multi-brain MI decoding method, using coupled feature extraction and few-shot learning to capture the coupling relationship between multiple brains (Zhu et al., 2023).

However, most existing decoding methods still rely on data or feature averaging or concatenation, effectively treating signals as coming from a single brain and lacking coordination between individual and multi-brain decision-making. While recent studies have explored cross-brain coupling, they often overlook the joint learning of shared inter-brain features and individual-specific patterns, limiting the full utilization of available information.

Methods

This paper proposes a dual-branch EEG decoding method based on the joint learning of private and shared domain information, aimed at achieving robust multi-brain motor imagery decoding. The overall framework of the proposed method is shown in Figure 1. The intra-brain private CSP feature learning branch and the cross-brain EEG shared feature learning branch respectively learn private and shared features. The intra-brain private CSP feature learning branch primarily consists of the task-related measurement module, the CSP module, and the siamese network module, while the cross-brain shared EEG decoding branch mainly includes the shared feature module.

Dual-brain Hyperscanning EEG Recording and Preprocessing

In the experiment, as shown in Figure 2, two participants simultaneously performed a motor imagery task, which included left-hand and right-hand motor imagery as well as a resting state. A total of five sessions were conducted, with each session consisting of 75 trials. Each trial lasted 7.5 seconds, including 1.5 seconds of video cues, 4 seconds of motor imagery task, and 2 seconds of rest. Dual-brain EEG signals were recorded using two connected 64-channel Neuroscan amplifiers according to the international 10-20 system simultanously. The signal sampling rate was 1000 Hz.

A total of 8 gruops of data, namely group 1 to group8, were collected in this experiment, with all 16 participants having signed informed consent forms. After data acquisition, common average referencing was applied, bandpass fitering wai performed to retain the 1-40 Hz frequency bands. Independent component analysis (ICA) was then utilized to enhance data quality (Kaliraman et al., 2022). The sample data were extracted from the 1.5s to 5.5s duration of each trial.

Intra-brain Private CSP Feature Learning Branch

This branch aims to extract the task-relevant private features from the EEG data of two participants within the same group, and fuse these features with their CSP features. The classification result, determined by the private features, is then obtained through a Siamese network.

Task-related Measurement Module

This module measures the correlation between the EEG channels and the task labels by calculating the Pearson correlation coefficient. The Pearson correlation coefficient is a statistic that quantifies the degree of linear correlation between two variables(Šverko et al., 2022). In this module, the

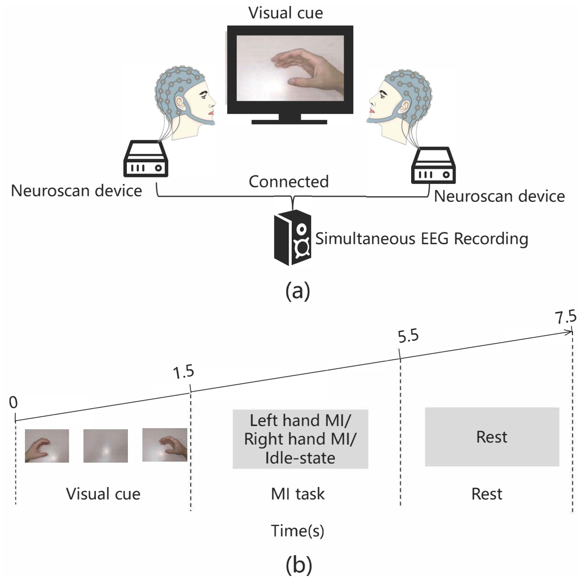

Figure 2: Multi-brain MI experimental environment and design.(a) Environment of the multi-brain MI. (b) Experiment protocol in each trial.

calculation formula is as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

Where X_i represents the value of a channel signal, and Y_i denotes the corresponding value of the task label. The signal for each channel is averaged over the temporal dimension. When the Pearson correlation coefficient approaches ±1, it indicates a strong correlation between the channel and the task. In the EEG data from both brains, there are 62 channels each, from which the top k channels most relevant to the task were selected out of the total 124 channels, and only the data from these k channels were retained.

Common Spatial Pattern (CSP) Module

Followed by task-related measurement module,is the common spatial pattern (CSP) module. It computed the CSP features of the EEG data from the top k channels.The CSP is calculated using the following formula:

$$\mathrm{CSP} = \arg\max_{W} \frac{W^T C_2 W}{W^T C_1 W} \quad (2)$$

Where C_1 and C_2 are the covariance matrices of the signals corresponding to different classes, and W represents the spatial filters that maximize the separation between the left hand, right hand, and idle state.

Siamese Network Module

A Siamese Network is a network architecture composed of two or more neural networks that share the same structure and weights, typically used to compare the similarity between the inputs. The design philosophy of this architecture is to use the same network to process both inputs in order to assess their relationship or similarity.

In this module, the output data from the CSP module is fed into a Siamese network. During the processing, the network minimizes the distance between trials of the same task and maximizes the distance between trials of different tasks. The final decoding classification result of the intra-brain private CSP feature learning branch is then obtained.

Cross-Brain EEG Shared Feature Learning Branch

This branch aims to extract shared features related to motor imagery through the interactive coupling between the EEG data of two participants within the same group. By establishing cross-connections and the interaction of parameters and weights, the shared features are learned in depth.

Backbone Network Module

The Backbone Network Module of the Cross-Brain Shared EEG Decoding Branch is a convolutional neural network (CNN) consisting of three convolutional blocks, with the number of filters increasing progressively from 64 to 256. Each convolutional layer uses kernels of varying sizes (3, 5, 3) to extract features at different dimensions. To improve training stability and mitigate overfitting, residual connections are applied after each convolution, and the dropout rate increases with each layer. Global pooling integrates the features, and the motor imagery decoding classification result is determined by the outputs of the two CNNs.

Shared Feature Module

This module facilitates feature interaction and sharing between the backbone networks, thereby achieving the coupling of cross-brain EEG data. In each epoch, after the convolutional operations of the convolutional neural networks corresponding to the two participants are completed, a cross-connection is performed. The features extracted by one participant are fused into the data of the other participant, while parameters and weights are shared between the networks. The method of cross-connections is illustrated by the following equation:

$$o = W \cdot (y + W_{\text{cross}} \cdot \tilde{y} + b_{\text{cross}}) + b \quad (3)$$

Where o is the final features of one brain, y is the original features extracted from one brain. $\tilde{y}$ is the original features extracted the other brain. W_{cross} is the weight matrix associated with the cross-connections. b_{cross} is the bias term associated with the cross-connections. W is the weight matrix for the final fully connected layer. b is the bias term for the final fully connected layer. This process effectively couples the information from both brains, enabling better extraction of shared features for multi-brain motor imagery decoding.

Soft Voting Aggregator

The final decoding result is determined by a soft voting aggregator that combines the outputs from both branches. The process of soft voting is as follows:

$$W = \operatorname{softmax}\left(\left[O_{\text{private}}, O_{\text{shared}}\right]\right)$$

$$P(C_j \mid x) = \sum_{i=1}^{K} W_i \cdot P_i(C_j \mid x) \tag{4}$$

$$C_{\text{final}} = \arg\max_{C_j} P(C_j \mid x)$$

Where O_{private} denotes the output of the intra-brain private CSP feature learning branch, and O_{shared} denotes the output of the cross-brain EEG shared feature learning branch. $P_i(C_j \mid x)$ represents the predicted probability of class C_j given input x from the i-th branch.

Model Setup

In this study, each subnetwork of the Siamese architecture comprises four convolutional layers with kernel sizes of 3, 5, 3, and 3, respectively. The number of filters doubles per layer from 32 to 256. Dropout rates of 0.3, 0.4, and 0.5 are applied to the first three layers to reduce overfitting. Each layer is followed by residual connections and L2 regularization (rate: 0.001). The cross-brain shared EEG decoding branch adopts the same parameter configuration.

Model training employs the Adam optimizer with cross-entropy loss and an initial learning rate of 0.001. A dynamic adjustment strategy halves the learning rate if loss stagnates after 10 epochs. Early stopping is triggered after 20 stagnant epochs, restoring the best-performing model. Data is class-balanced across all three tasks.

Five-fold cross-validation is used for performance evaluation, where each of five non-overlapping subsets serves as the test set once, and the remaining four as training data. Final accuracy is reported as the average across folds. The task-related measurement module uses a fixed parameter of k = 30.

Results

Comparison to the State-of-the-Art (SOTA) models

First, we compared the performance between the dual-brain MI and the single-brain MI scenario within the same model framework, as shown in Table 1. The experimental results demonstrate that the average accuracy in the dual-brain scenario reached 75.62%, along with an improvement of more than 10% compared to the single-brain scenario.

Table 1: Average Decoding Accuracy (%) Among SOTA Methods

	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Average
Ours	74.37	74.37	73.75	74.37	76.88	78.75	78.13	74.37	75.62
CNN	68.75	66.87	65.00	68.75	68.12	66.25	65.63	68.75	67.27
LSTM	68.12	60.00	67.50	63.13	68.75	64.38	62.5	68.12	65.31
EEGNet	63.75	63.75	69.38	68.12	69.38	66.87	66.25	62.5	66.25
Transformer	67.50	67.50	68.75	66.87	69.38	66.25	67.50	61.87	66.95
Single-brain	65.00	66.25	63.44	68.44	67.19	60.00	64.38	68.13	65.35
Zhu et al	67.23	70.31	70.44	72.51	66.80	67.10	66.93	66.60	68.49

Additionally, we conducted experiments comparing the proposed method with state-of-the-art (SOTA) approaches, including convolutional neural networks (CNN) which consists of sequential convolutional layers interleaved with pooling layers(Rajwal & Aggarwal, 2023), long short-term memory recurrent neural networks (LSTM) which employs recurrently connected memory cells equipped with gating mechanisms(H. Li et al., 2022), EEGNet which utilizes depthwise and separable convolutions (Deng et al., 2021) and transformer whose architecture leverages self-attention mechanisms (Zhang et al., 2023). Recent research efforts have introduced an innovative methodology that synergistically merges hybrid feature extraction methods with data-efficient learning frameworks in few-shot scenarios (Zhu et al., 2023). As shown in Figure 1, the classification accuracies of these methods in 3-class classification task were similar: CNN achieved an average accuracy of 67.27%, LSTM reached 65.31%, EEGNet reached 66.25%, transformer obtained 66.95%. In comparison, method of Zhu et al. attained the highest accuracy at 68.79%. Our model demonstrated an approximately 8% improvement over these SOTA methods.

Impacts of Frequency Bands and Length of Samples

This section reports experiments on EEG data across different frequency bands and sample lengths to identify the optimal configuration. Given that motor imagery primarily involves the α (8-12 Hz) and β (13-30 Hz) bands, three configurations were evaluated are presented in Table 2. Results show that, despite inter-group variability, the highest classification accuracy was generally achieved when the α and β frequency bands were extracted separately from the two paired participants, likely due to the complementary information captured by the two bands.

Table 2: Decoding Accuracy (%) in Terms of Different Frequency Bands

	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Average
α	73.12	71.88	71.88	70.63	71.88	73.75	69.38	73.75	72.03
β	71.25	71.25	70.63	72.50	73.12	72.50	70.73	71.88	71.72
α-β	70.63	72.19	73.44	75.32	71.57	72.81	74.38	74.07	73.05

Additionally, the classification accuracy of the EEG data was assessed for different lengths of samples. The results are presented in Table 3. Variations were observed between groups, for example the best performance for Group 1 and Group 2 are obtained from 3s and 1s length of samples. However, on average, the highest accuracy was achieved when using the 4s length of the samples.

Table 3: Decoding Accuracy (%) in Terms of Different Length of Samples

	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Average
1s	70.63	78.13	69.38	70.00	72.70	73.12	69.38	73.75	75.62
2s	75.00	70.00	71.88	75.00	72.50	73.12	73.12	71.25	72.19
3s	76.88	68.75	71.25	74.37	73.12	68.12	68.12	76.88	72.73
4s	74.37	74.37	73.75	74.37	76.88	78.75	78.13	74.37	72.11

Ablation Experiments

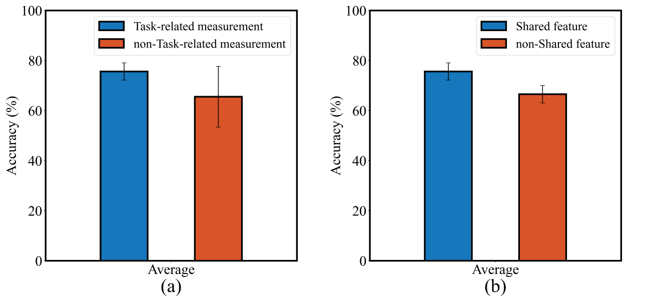

Figure 3: Investigation on the impacts of Task-related measurement module and shared feature module.

The ablation experiments were conducted to validate the effectiveness of each module in the proposed EEG decoding method. The results of the ablation experiments are displayed in Figure 3. First, the effectiveness of the task-related Measurement Module was evaluated. This module contributed to an averaged improvement of 10.07% in classification accuracy (75.62% vs. 65.55%). The module improved classification accuracy across groups, with particularly significant improvements observed in Groups 4, 5, and 6.

Furthermore, the effectiveness of the shared feature module was assessed. This module led to a substantial enhancement in motor imagery decoding accuracy, resulting in an improvement of 9.06% (75.62% vs. 66.56%). When analyzed by group, the inclusion of this module led to an accuracy increase ranging from 4.99% to 11.26%.

Discussion

The Impacts of Private and Shared Feature learning for Multi-Brain EEG Decoding

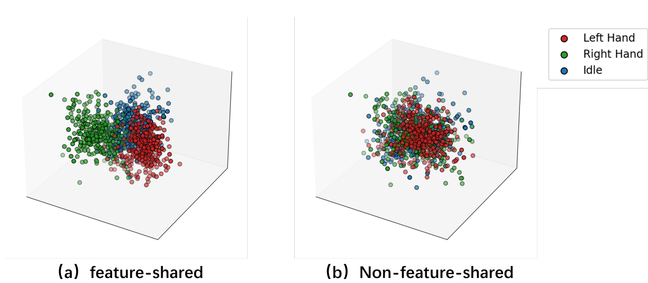

Figure 4: The impact of the Feature Shared Module on feature distribution.

According to the results of the ablation experiments , the decoding classification accuracy increased by 10.07% after applying the task-related Measurement compared to the scenario without it. Since MI is a self-initiated paradigm, it is challenging to ensure that participants are genuinely performing motor imagery during the task state. As a result, task-irrelevant features may affect decoding accuracy. The primary role of the task-related measurement module is to select the private features most relevant to the MI task. This ensures that the features involved in decoding are highly correlated with the MI task, thereby improving decoding accuracy.

After implementing feature sharing, decoding accuracy improved by 9.06% compared to without it. As shown in Figure 4, feature sharing significantly enhanced the feature distribution of the three tasks, allowing for clearer separation of features. In hyperscanning, interbrain synchrony during joint decision-making is greatly enhanced. By learning from shared features, it becomes possible to capture the synchrony between brains during task imagery, improving both feature distribution and decoding performance.

Limitations and Future Directions

In this study, the method employed in the task-related measurement module involves selecting the top k channels most relevant to the task. To further enhance the method's effectiveness, an adaptive parameter k selection algorithm is necessary. The method is also expected to generalize to cross-session, cross-device scenarios and be validated on larger-scale datasets.

Looking ahead, online multi-brain motor imagery shows great potential for neurological and psychological rehabilitation. In stroke therapy, synchronized group imagery could boost engagement and motivation, while in psychological interventions, it may promote emotional support through group interaction. The proposed framework, which jointly learns both individual-specific and shared cross-brain features, offers a novel approach to feature extraction in multi-user online BCIs

Conclusions

In this paper, we propose a dual-branch EEG decoding framework for multi-brain motor imagery, which leverages a dual-branch architecture to simultaneously extract individual (private) features and cross-brain coupled shared features. By integrating both personal and inter-brain representations, the proposed method significantly enhances the decoding performance in multi-brain MI-based brain–computer interfaces. This approach provides methodological support for the practical development of collaborative BCIs, paving the way for more effective multi-user neural interaction systems.

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