International Journal of Computer and Technology Vol 25 (2025) ISSN: 2277-3061 https://rajpub.com/index.php/ijct

DOI https://doi.org/10.24297/ijct.v25i.9793

Joint Independent Component Analysis for Enhanced Preprocessing in Collaborative Multi-Brain Motor Imagery BCIs

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Abstract: Collaborative brain–computer interfaces (cBCIs) extend single-user BCIs to multi-brain recordings, enabling the investigation of inter-brain synchrony and cooperative neural processing. Motor imagery (MI) paradigms are of particular interest but face challenges such as low signal-to-noise ratio, inter-subject variability, and artifact contamination in electroencephalography (EEG) data. Independent component analysis (ICA), though widely applied in single-user MI-BCIs, is suboptimal in cBCIs since it is performed separately for each participant, thereby overlooking shared neural dynamics and potentially distorting inter-brain coupling. To address these limitations, this work proposes a joint ICA-based preprocessing framework that jointly decomposes EEG data from paired participants to enhance artifact suppression while preserving cross-brain synchrony. The performance of joint ICA is evaluated against subject-wise ICA from two perspectives: (i) motor imagery decoding accuracy, examined using spatial filtering with subsequent linear discriminant classification and a convolutional neural network architecture, and (ii) inter-brain synchrony quantified by the phase locking value (PLV) across homologous electrode pairs. Experimental results show that joint ICA improves decoding accuracy by 4.8% and 3.67% in the respective pipelines, while also yielding significantly stronger inter-brain PLV. These findings demonstrate that joint ICA offers an effective preprocessing strategy to improve both neural fidelity and classification robustness in MI-driven cBCI systems.

Keywords collaborative brain–computer interface (cBCI); motor imagery; joint independent component analysis; EEG preprocessing; inter-brain synchrony

1 Introduction

Collaborative brain computer interfaces (cBCIs), which extend single-user BCIs to simultaneous multi-brain recordings, have emerged as a promising paradigm for investigating inter-brain synchrony and enhancing system performance in cooperative tasks. In such settings, electroencephalography (EEG) hyperscanning is widely employed due to its millisecond temporal resolution and portability. Among different paradigms, motor imagery (MI) is particularly important because it enables intentional modulation of brain rhythms without overt movement, thereby offering a non-invasive approach for both neurorehabilitation and cognitive studies (Leeuwis et al., 2021; Ma et al., 2024). Nevertheless, MI decoding in multi-brain scenarios remains challenging owing to the low signal-to-noise ratio (SNR) of EEG, strong inter-subject variability, and contamination from ocular and muscular artifacts.

Independent Component Analysis (ICA) has long been the standard preprocessing tool in single-subject MI-BCIs, as it can effectively isolate neural from non-neural sources (Cheng & Wang, 2024; Gao et al., 2025). However, applying ICA independently to each participant in collaborative experiments introduces significant drawbacks: it neglects the temporal alignment of neural processes across subjects, may inadvertently distort inter-brain coupling signals central to cBCIs (Czeszumski et al., 2020), and is prone to unstable decompositions due to the small trial sizes typical of MI datasets (Yi et al., 2024). Furthermore, independent ICA cannot exploit shared features across brains that could otherwise stabilize decomposition and enhance artifact suppression (Richard et al., 2021).

To overcome these limitations, joint ICA provides a unified decomposition of multi-subject data, extracting both shared and individual components while preserving inter-brain synchrony and improving reproducibility (Heugel et al., 2022; Luo et al., 2024). Building on this idea, we introduce a joint ICA-based preprocessing framework for MI-driven cBCIs, in which EEG signals from two participants are concatenated, jointly decomposed, cleaned of artifact-related components, and reprojected into individual channel spaces. Crucially, rather than focusing solely on downstream decoding, we evaluate the two preprocessing strategies: subject-wise ICA and joint ICA from complementary perspectives. On the one hand, their impact on MI decoding accuracy is examined using two representative pipelines: one based on common spatial pattern (CSP) feature extraction combined with linear discriminant analysis (LDA) classification, and another employing a convolutional neural network (CNN). On the other hand, we assess how well each strategy preserves cross-brain neural coupling by computing the *phase locking value* (PLV) across participants. Specifically, PLV is calculated between homologous electrode pairs to quantify inter-brain phase synchrony, which is a fundamental marker of cooperative neural processes. Experimental results demonstrate that joint ICA not only yields higher MI decoding accuracy compared to independent ICA but also maintains significantly stronger inter-brain PLV, suggesting that collaborative preprocessing provides a principled means to enhance both the fidelity of neural dynamics and the robustness of classification in cBCI systems.

2 Materials and Methods

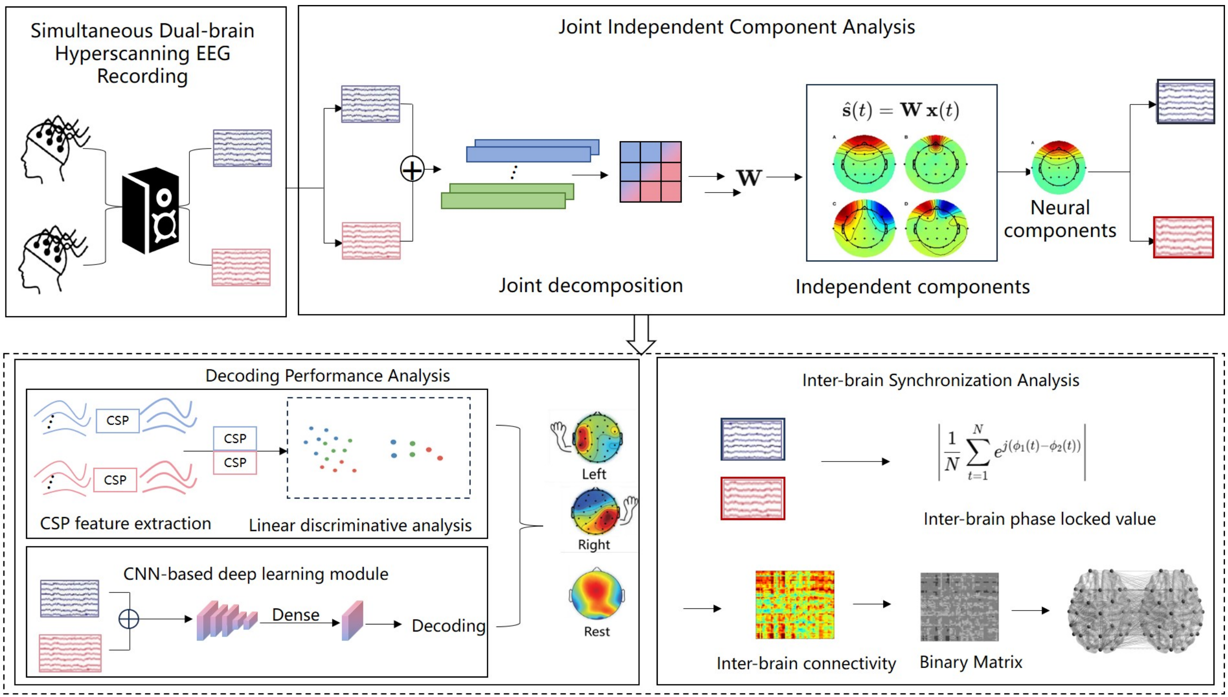

Figure 1: The overall framework of integrated pre-processing for collaborative EEG-based motor imagery

2.1 Framework of Integrated Pre-processing for Collaborative EEG-Based Motor Imagery

The proposed framework (as shown in Figure 1) begins with simultaneous dual-brain EEG hyperscanning during motor imagery tasks, followed by a joint ICA that concatenates and jointly decomposes data from paired participants to separate neural from artifact components while preserving shared dynamics. The cleaned signals are then evaluated from two complementary perspectives: decoding performance and inter-brain synchrony. For decoding, motor imagery features are extracted using spatial filtering with subsequent linear discriminant classification, as well as through a convolutional neural network–based deep learning module. For synchronization analysis, phase locking value (PLV) is computed between homologous electrode pairs to quantify inter-brain phase coupling, which is further represented as connectivity matrices. This integrated framework enables a systematic comparison between subject-wise ICA and joint ICA in terms of both motor imagery decoding accuracy and preservation of cross-brain neural synchrony.

2.2 Dataset Description

Pairs of participants simultaneously performed a MI paradigm involving left-hand MI, right-hand MI, and idle state. Each pair completed five sessions of 75 trials, with each trial lasting 6 s, consisting of a 1 s visual cue, a 4 s MI period, and a 1 s rest interval. Dual-brain EEG was recorded using two synchronized 64-channel Neuroscan amplifiers configured according to the international 10–20 system at a 1000 Hz sampling rate. A total of eight groups data, namely Group 1 to Group 8, were collected from 16 participants, all of whom provided written informed consent.

2.3 Joint Independent Component Analysis

In EEG-based motor imagery research, the recorded signals typically consist of linear, instantaneous mixtures of multiple spatially distributed neural sources and non-neural artifacts. ICA is a family of blind-source separation techniques designed to recover statistically independent source signals from multichannel observations. ICA is frequently employed to separate task-related brain activity from various contaminants, such as ocular (electrooculographic, EOG) and muscular (electromyographic, EMG) artifacts. The underlying linear mixing model can be expressed as:

$$x(t) = As(t), \quad t = 1, \ldots, T \tag{1}$$

Where $x(t) \in \mathbb{R}^n$ denotes the observed vector at time t (corresponding to multichannel EEG recordings), $s(t) \in \mathbb{R}^m$ represents the unknown independent source vector, and $A \in \mathbb{R}^{n \times m}$ is the unknown mixing matrix. The objective is to estimate an unmixing matrix $\mathbf{W}$ such that

$$\hat{\mathbf{s}}(t) = \mathbf{W}\mathbf{x}(t) \tag{2}$$

approximates the true sources $\mathbf{s}(t)$ as closely as possible. Solutions to ICA can be derived from several equivalent principles: maximization of non-Gaussianity, minimization of mutual information among components, or approaches based on maximum-likelihood estimation.

In this study, to extract the common independent components from two subjects, a channel-concatenation based joint ICA approach was employed. The channels of the paired subjects were concatenated in sequence to form a joint signal matrix $\mathbf{X}_{\text{joint}} \in \mathbb{R}^{124\times N}$, where N denotes the number of time points:

$$\mathbf{X}_{\text{joint}} = \begin{bmatrix} \mathbf{X}_A \\ \mathbf{X}_B \end{bmatrix}. \tag{3}$$

Subsequently, FastICA was fitted to $\mathbf{X}_{\text{joint}}$ to extract independent components. Artifact components were automatically identified based on the kurtosis of each component and their maximum correlation with the original channels, and were labeled as $\mathbf{I}_{\text{bad}}$. After applying ICA and removing the identified artifacts, the cleaned signal for each participant were reconstructed as

$$\hat{\mathbf{X}}_{\text{joint}} = \mathbf{W}\mathbf{X}_{\text{joint}}, \tag{4}$$

$$\mathbf{X}_A^{\text{clean}} = \hat{\mathbf{X}}_{\text{joint}}[1:62,:], \quad \mathbf{X}_B^{\text{clean}} = \hat{\mathbf{X}}_{\text{joint}}[63:124,:] \tag{5}$$

2.4 Decoding Performance Analysis

2.4.1 Common Spatial Pattern

Common Spatial Patterns (CSP) is an energy-based feature extraction technique that has been widely applied in brain–computer interfaces (BCIs). CSP learns a set of linear spatial filters that project multichannel EEG signals onto a lower-dimensional subspace, where the variance of the projected signals is maximally discriminative between different classes. This property makes CSP particularly effective for motor-imagery EEG, in which class-dependent modulations of band-limited oscillatory power lead to distinct variance patterns (Šverko et al., 2022). The CSP filters are obtained by solving the following optimization problem:

$$\text{CSP} = \arg\max_{W} \frac{W^T C_2 W}{W^T C_1 W} \tag{6}$$

Where C_1 and C_2 denote the covariance matrices of the EEG signals of different classes, and W corresponds to the spatial filters that maximize the discriminative variance.

2.4.2 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a class of deep neural networks designed to exploit local spatial structure in data. Their core operation is the convolution, in which learnable kernels (filters) are applied to the input to capture localized patterns across receptive fields. The resulting feature maps are further processed through pooling layers, nonlinear activation functions, and typically fully connected layers for classification or regression. By leveraging local connectivity and parameter sharing, CNNs achieve translation-equivariant feature learning while substantially reducing the number of trainable parameters compared to fully connected architectures. Owing to their ability to support end-to-end training and automatically learn hierarchical spatiotemporal representations from raw or minimally preprocessed signals.

2.4.3 Classifier

2.4.3.1 Linear Discriminative Analysis

Linear Discriminant Analysis (LDA) is a classical linear classification method that seeks a projection maximizing inter-class separability while minimizing intra-class variability. Equivalently, LDA identifies discriminant vectors that maximize the ratio of between-class to within-class variance. In motor imagery (MI) decoding, LDA is frequently combined with low-dimensional features extracted by CSP, as it provides robust performance with small-sample datasets and when class-discriminative structure is approximately linearly separable. For the three-class classification problem considered in this study, let the sample sets be $X_i \subset \mathbb{R}^d$, for $i = 1, 2, 3$. The within-class scatter matrix is defined as

$$S_W = \sum_{i=1}^{3} \sum_{x \in X_i} (x - \mu_i)(x - \mu_i)^T \tag{7}$$

Where μ_i denotes the mean vector of class i. And the between-class scatter matrix is defined as

$$S_B = \sum_{i=1}^{3} N_i(\mu_i - \mu)(\mu_i - \mu)^T \tag{8}$$

Where N_i is the number of samples in class i, and μ represents the overall mean of all samples. Then it seeks the projection directions by solving the generalized eigenvalue problem

$$S_B w = \lambda S_W w \tag{9}$$

where $\mathbf{S}_B$ and $\mathbf{S}_W$ are the between-class and within-class scatter matrices, respectively. The eigenvectors corresponding to the largest $C - 1 = 2$ eigenvalues form the projection matrix $\mathbf{W}$. Each sample vector $\mathbf{x}$ is then mapped into the discriminant subspace as

$$\mathbf{y} = \mathbf{W}^T \mathbf{x}, \tag{10}$$

and classification is performed based on the projected class means.

2.4.3.2 Evaluation of performance

In this study, the performance of the preprocessing procedure was evaluated based on decoding accuracy. The evaluations were conducted using two decoding perpectives: a CSP feature extraction combined with LDA, and a CNN-based architecture. Each experiment for every group was repeated ten times under identical parameter settings, with the mean accuracy across the ten repetitions reported as the final result.

2.5 Inter-brain Synchronization Analysis

Phase-Locking Value (PLV) is a classical measure of phase consistency between two time series within a specified frequency band. The fundamental concept involves representing the instantaneous phase difference of two narrow-band signals as unit vectors in the complex plane, and then computing the vector average of these unit vectors across observations (time points or trials). The modulus (length) of the resulting mean vector represents the PLV. When the phase difference remains approximately constant across observations, PLV approaches 1; when the phase difference is randomly distributed, PLV approaches 0. In collaborative Brain-Computer Interface (cBCI) studies, PLV is commonly used to quantify inter-subject phase synchronization (Hakim et al., 2023; Pili et al., 2025). In this study, the PLV between the EEG signals of two paired subjects within the same group was computed as follows:

$$\mathrm{PLV}_{ij}(t) = \left| \frac{1}{N} \sum_{n=1}^{N} \exp\left(i \left[\phi_{i,n}^{(1)}(t) - \phi_{j,n}^{(2)}(t) \right] \right) \right| \tag{11}$$

Where $\phi_{i,n}^{(A)}$ and $\phi_{j,n}^{(B)}$ denote the instantaneous phase of channel i of the one participant and channel j of the other participant in trial n, respectively.

3 Results and Discussion

3.1 Comparison to the independent component analysis in the context of CSP feature extraction combined with LDA

Within the CSP feature extraction combined with LDA framework, as shown in Table 1, applying joint ICA to paired EEG signal increased the average accuracy from 52.32% (when ICA was applied separately to each subject's EEG signal) to 57.17%, with all participants exhibiting positive gains. A paired t-test further confirmed that the difference in accuracy between the two preprocessing methods was statistically significant ($p = 0.0034$), and the corresponding effect size was large (Cohen's $d = -1.53$). These results indicate that, within the CSP+LDA framework, preprocessing with joint ICA yields a substantial and significant improvement over applying ICA individually.

Table 1: Average decoding accuracy (%) achieved by CSP feature extraction combined with LDA.

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Average
Independent Component Analysis	52.00	54.67	49.33	52.00	50.56	53.33	56.00	50.67	52.32
Joint Independent Component Analysis	56.00	64.00	56.00	54.67	52.00	62.67	58.67	53.33	57.17

3.2 Comparison to the independent component analysis in the context of CNN

Furthermore, within the CNN framework, as presented in Table 2, joint ICA also led to a significant improvement in average accuracy compared with applying ICA separately to each subject's EEG signal, increasing performance from 58.75% to 62.42%, with every participant again exhibiting positive gains. A paired t-test confirmed that the difference in accuracy between the two preprocessing strategies was highly significant ($p = 0.000109$), and the effect size was even larger (Cohen's $d = -2.7497$). These findings demonstrate that, under the CNN framework, preprocessing with joint ICA not only yields statistically greater differences than separate ICA but also produces a more substantial practical improvement in decoding performance.

Table 2: Average decoding accuracy (%) achieved by the CNN method.

	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Average
Independent Component Analysis	58.67	58	56	56	58	60.67	62.67	60	58.75
Joint Independent Component Analysis	62	62.67	59.33	59.33	60	62.67	68	65.33	62.42

3.3 Synchronization-based comparison with independent component analysis

The PLV results obtained from performing ICA separately on each subject and from joint ICA are presented in Figure 2. The experimental findings indicate that the differences between the two methods are predominantly positive for both the left-hand and right-hand tasks, whereas in the idle state, the differences are markedly smaller and include a considerable number of negative values. These results suggest that joint ICA substantially enhances inter-subject phase synchrony during motor imagery tasks (left-hand and right-hand), while providing comparatively limited improvement in the idle condition.

Examining absolute values, for the left and right hand motor imagery tasks, the inter-subject PLV was already relatively high when ICA was applied separately to each subject and was further increased following Joint ICA. By contrast, in the idle condition the inter-subject PLV was low under subject-wise ICA and did not exhibit a significant change after Joint ICA.

In terms of spatial patterns, for both left and right hand motor imagery tasks, the channels exhibiting the largest gains were concentrated over the sensorimotor (motor) cortex—consistent with the canonical motor-imagery scalp topography. By contrast, during the idle state there was no clear spatial focalization: the channel-wise differences were spatially diffuse and scattered.

3.4 The impact of joint independent component analysis on motor imagery decoding

When ICA is performed separately for each subject, a distinct mixing matrix is estimated per subject, and the resulting components are therefore susceptible to bias from subject-specific noise. By contrast, joint ICA concatenates the signal along the channel dimension so that both subjects share a single mixing matrix and the datasets are treated as joint observations of the same underlying physical sources. In this joint formulation, noise components—being uncorrelated across the two views—are attenuated by averaging, whereas genuine neural sources that are temporally consistent across views are reinforced. The net effect is an improved signal-to-noise ratio in the processed signals and, consequently, enhanced decoding accuracy.

Moreover, motor-imagery decoding typically operates in a small-sample regime, making ICA performed separately for each subject susceptible to overfitting. joint ICA effectively increases the effective sample size by pooling EEG siganl across subjects; the shared mixing matrix thus imposes a regularizing constraint analogous to shrinking subject-specific parameters toward the group mean. This regularization reduces the variance of the estimates and consequently improves the stability and generalizability of downstream decoding.

Because the recordings from the two subjects are intrinsically time-synchronized, joint ICA can treat common, phase-synchronous (i.e., phase-locked across subjects) oscillatory sources as a single, stable component during decomposition. This yields a cleaner separation of shared neural sources and attenuates nonshared noise, thereby increasing the signal-to-noise ratio of extracted sensorimotor rhythm components and reducing erroneous component assignments. Consequently, CSP applied to joint-ICA–preprocessed signal is more likely to capture task-related spatial patterns.

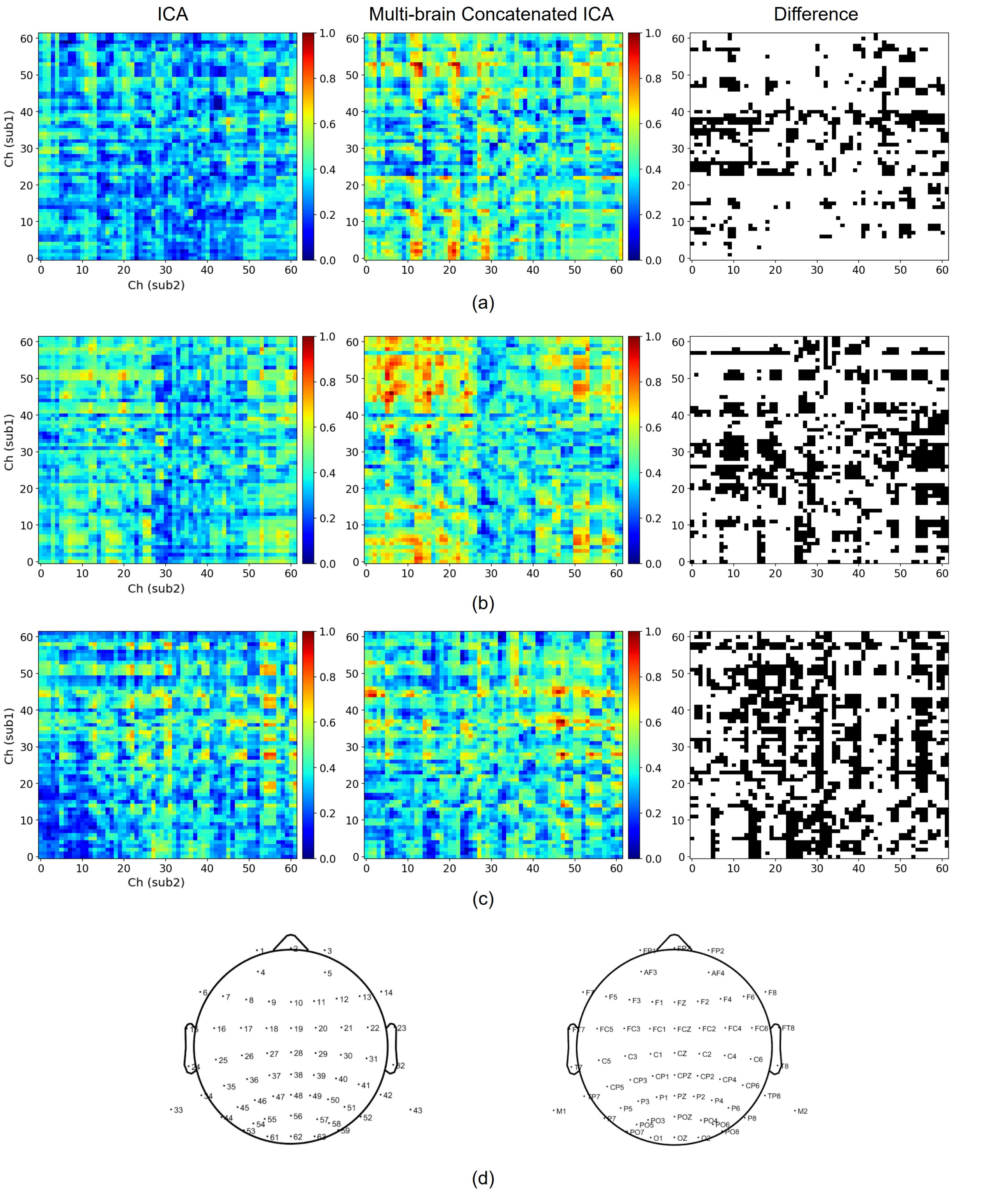

Figure 2: PLV results between paired subjects: (a) left-hand task, (b) right-hand task, and (c) idle state. (d)Correspondence between channel names and channel indice

3.5 The impact of joint independent component analysis on inter-subject synchrony

When joint ICA is performed, cross-subject common sources are explicitly incorporated into the optimization objective, thereby preserving or even amplifying task-related shared phase structures and retaining a greater number of coupled channel pairs across participants. In contrast, ICA applied separately to each subject focuses solely on achieving independence within individual recordings, which inevitably disrupts many connectivity patterns. Consequently, compared to subject-specific ICA, EEG signals processed with joint ICA exhibit stronger inter-subject synchrony within the same group.

3.6 Limitations and Future Directions

In this study, the thresholds used during joint independent component analysis were chosen according to conventional, empirically established values. To further optimize the preprocessing pipeline, the development of data-driven or adaptive threshold-selection algorithms is warranted. In addition, the effects of joint ICA on motor imagery decoding merit further investigation across different frequency bands and under a broader range of decoding approaches.

Looking ahead, multi-brain motor imagery holds considerable promise for neurological and psychological rehabilitation. For example, in post-stroke therapy, synchronized group imagery may increase patient engagement and motivation, while in clinical psychology it could facilitate emotional support via interpersonal interaction. The framework proposed here—Enhancing Collaborative EEG-Based Motor Imagery through Integrated Preprocessing with joint independent component analysis—provides a novel preprocessing strategy for multi-user BCIs that may improve the quality of shared neural signals and thereby strengthen collaborative rehabilitation paradigms.

4 Conclusions

In this paper, we propose an integrated preprocessing approach to enhance collaborative EEG-based motor imagery, in which the EEG signal from two subjects are concatenated along the channel dimension and subjected to joint independent component analysis. Experimental results demonstrate that, within both machine learning (CSP feature extraction combined with LDA) and deep learning (CNN) frameworks, EEG signal processed with joint ICA achieve significantly higher decoding accuracy compared to ICA applied separately to each participant. Moreover, relative to individual ICA, joint ICA also yields more pronounced inter-subject phase synchrony during motor imagery tasks. This method offers methodological support for the practical advancement of collaborative BCIs and paves the way for more effective multi-user neural interaction systems.

Data Availability (excluding Review articles)

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Conflicts of Interest

Authors must declare all relevant interests that could be perceived as conflicting. Authors should explain why each interest may represent a conflict. If no conflicts exist, the authors should state this. Submitting authors are responsible for co-authors declaring their interests.

Funding Statement

Authors should state how the research described in their article was funded, including grant numbers if applicable

Acknowledgments

All acknowledgments (if any) should be included at the very end of the manuscript before the references. Anyone who made a contribution to the research or manuscript, but who is not a listed author, should be acknowledged (with their permission).

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