Distributed EEG Motor Imagery Classification using Federated Common Spatial Patterns

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Abstract—**Electroencephalography (EEG)-based motor imagery decoding is a key component of brain–computer interface (BCI) applications. However, building robust models across multiple users is challenging because raw EEG recordings are sensitive and are often difficult to share or centralize. Federated learning addresses this issue by allowing multiple clients to train a shared model while keeping neural data stored locally. Despite this advantage, subject-dependent EEG variations can still affect training stability and limit classification performance. This challenge is particularly important in EEG-based BCI, where signal distributions vary across individuals, recording sessions, and physiological conditions. Therefore, an effective federated EEG framework should not only preserve privacy but also reduce feature-level variability before collaborative model optimization. In this study, we present a lightweight federated framework for EEG motor imagery classification by integrating Filter Bank Common Spatial Pattern features with a classifier trained using Federated Averaging. Each participant is modeled as an individual federated client, so local EEG data remain on the client side throughout training. The use of FBCSP enables discriminative spatial information to be extracted from multiple frequency bands before local classifier training. The proposed framework was evaluated on the PhysioNet EEG Motor Movement/Imagery dataset using recordings from 100 subjects performing left- and right-hand motor imagery tasks. Our experimental results show that the proposed federated FBCSP approach reaches approximately 89.3% classification accuracy, whereas the baseline federated model converges at only about 81–82%. The proposed method also obtains an average accuracy of 88.83%, compared with 80.95% for the baseline. Across 50 communication rounds, its accuracy increases from about 79.9% to 89.3%, indicating stable convergence during distributed training. As a result, applying task-specific spatial filtering before federated optimization helps reduce cross-subject variability and improves the reliability of EEG classification. Our proposed framework shows that combining conventional EEG feature extraction with federated learning can support privacy-preserving and scalable BCI model development without centralized access to sensitive neural recordings.**

Index Terms— **Brain–Computer Interface, Electroencephalography Signal, Filter Bank Common Spatial Pattern, Motor Imagery Classification, Privacy-Preserving Machine Learning**

I. Introduction

Brain–Computer Interfaces (BCIs) convert neural activity into control signals that can be used to operate computers or assistive devices [1]. Electroencephalography (EEG) is frequently selected for BCI development because it offers a practical balance of non-invasive recording, low implementation cost, and millisecond-level temporal resolution [2]. Within this field, motor imagery (MI) decoding has received considerable attention due to its relevance to neurorehabilitation, assistive robotic control, and human–machine interaction [3]. In MI-based BCI, users mentally rehearse specific movements, and computational models learn to distinguish the EEG patterns associated with each imagined action [4]. Recent machine learning methods have further strengthened EEG decoding by improving the recognition of MI-related neural patterns [5].

However, developing models that generalize well across users usually depends on EEG recordings collected from a broad and diverse subject group, since neural responses differ considerably between individuals [6]. Although EEG decoding techniques have advanced rapidly, reliable BCI model development remains difficult because EEG signals are highly user-dependent [7]. Conventional centralized learning often addresses this issue by pooling EEG data from many users into a single training repository [8]. Such data aggregation is problematic because EEG recordings may contain private information related to neurological health [9]. As a result, storing raw EEG data in a central location introduces privacy risks and may conflict with data protection requirements in healthcare contexts. Federated learning offers an alternative training strategy by enabling distributed model optimization while limiting direct access to sensitive user data [10].

In federated learning, model training is performed collaboratively across multiple clients without sharing raw data with a central server. Instead, each client computes local model updates using its own data and sends only updated parameters or gradients to server for aggregation. Applying federated learning to EEG-based BCI is still difficult because EEG data differ greatly across users [11]. First, subject-level EEG recordings usually follow non-independent and non-identically distributed patterns, which creates strong client heterogeneity. Second, deep models used in federated settings may converge inconsistently when each client has only limited and variable EEG samples. Therefore, federated EEG classifiers can perform worse than models trained separately for individual subjects.

To overcome these limitations, established EEG signal processing approaches can still play an important role in strengthening feature representation before model training. Common Spatial Pattern (CSP) is a widely used technique for motor imagery classification, as it learns spatial projections that highlight variance contrasts between different mental task classes. Its extended version, Filter Bank Common Spatial Pattern (FBCSP), enhances this process by separating EEG signals into several frequency sub-bands and deriving class-relevant spatial features within each band [12]. Because of its efficiency and stable performance, FBCSP has been frequently applied in conventional BCI classification pipelines.

We propose a privacy-preserving EEG decoding framework that integrates Filter Bank Common Spatial Pattern (FBCSP) feature extraction with federated learning. In the proposed system, each EEG subject is treated as an independent federated client, enabling collaborative training without sharing raw neural signals. A global FBCSP feature representation is constructed to capture discriminative spatial patterns across subjects, and a lightweight classifier is trained using the Federated Averaging algorithm. This approach combines the robustness of classical EEG feature extraction with the privacy advantages of distributed learning. To evaluate the proposed framework, we conduct experiments on a large-scale dataset containing 100 EEG subjects and analyze the impact of cross-subject variability on federated EEG learning. The results demonstrate that integrating spatial filtering techniques with federated optimization improves the stability and performance of distributed EEG classification. These findings highlight the effectiveness of combining classical signal processing techniques with modern distributed learning frameworks for EEG-based BCI systems.

The remainder of this paper is organized as follows. Section II describes the proposed federated FBCSP framework and the distributed training procedure. Section III presents the experimental setup and evaluation results on the EEG motor imagery dataset. Finally, Section IV concludes the paper and discusses future research directions.

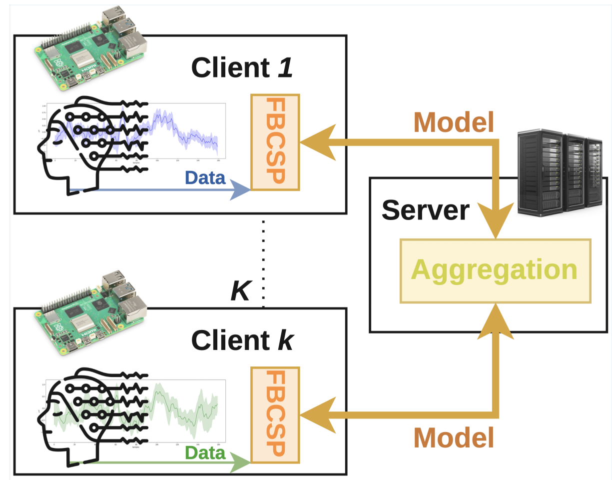

Fig. 1. Overview of the proposed federated framework

II. Methodology

This section describes the proposed federated EEG classification framework that integrates Filter Bank Common Spatial Pattern (FBCSP) feature extraction with distributed model training. The overall pipeline consists of three main stages: EEG preprocessing, spatial feature extraction using FBCSP, and federated classifier training. Each EEG subject is treated as an independent client that participates in collaborative model training without sharing raw neural signals.

A. System Overview

The proposed system is designed to support multi-subject EEG model training without requiring the collection of raw neural recordings in a centralized repository, as illustrated in Fig. 1. In this architecture, each participant acts as a separate federated client and retains local control over their EEG data. Rather than uploading raw signals, clients perform feature extraction and local classifier training on their own data, and only the resulting model updates are sent to the server for aggregation. The processing pipeline starts by filtering the EEG recordings and segmenting them into motor-imagery epochs. The segmented signals are then transformed into compact spatial feature vectors using the FBCSP procedure. These subject-level features are used to update a local classifier, after which the learned parameters are combined at the server through the FedAvg mechanism to form a new global model.

Let K represent the number of participating EEG clients. The local data stored by client k are denoted as $\mathcal{D}_k = \{(x_i, y_i)\}_{i=1}^{n_k}$, where x_i is the FBCSP-derived feature vector and y_i is the corresponding motor imagery class label. Because EEG responses vary noticeably among individuals, the client datasets are not expected to follow the same distribution. This non-IID condition makes federated optimization more difficult, since each local classifier may emphasize subject-specific signal patterns rather than globally consistent representations.

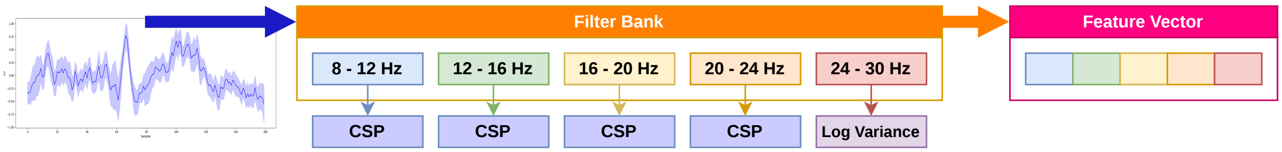

Fig. 2. Filter Bank Common Spatial Pattern (FBCSP) feature extraction process

At the beginning of each communication round, the server sends the current global parameters to the selected clients. Each client initializes its classifier with these parameters and updates the model using its local FBCSP features. Once local training is completed, the client returns only the updated parameters to the server, while the EEG recordings and extracted samples remain private. The server then computes an aggregated update from the received client models and redistributes the revised global model in next round. This iterative process continues until the training accuracy becomes stable or the predefined number of communication rounds is reached.

This design allows the model to benefit from EEG data distributed across many subjects while avoiding direct data sharing. In addition, placing FBCSP before federated optimization helps reduce the complexity of the learning problem by converting raw EEG epochs into informative spatial features. As a result, the local updates become more consistent across heterogeneous clients, which improves the stability of global model aggregation for motor imagery classification.

B. EEG Preprocessing

The raw EEG recordings are processed before feature extraction to reduce irrelevant signal components and retain the portions related to motor imagery activity. Since motor imagery responses are commonly observed within the sensorimotor μ and β rhythms, the analysis focuses on the frequency range of approximately 8–30 Hz [13]. Accordingly, each continuous EEG signal $X(t)$ is passed through a band-pass filter to attenuate slow baseline drift and high-frequency artifacts:

$$X_f(t) = \mathcal{F}(X(t), f_l, f_h) \tag{1}$$

where $\mathcal{F}(\cdot)$ indicates the filtering function, while f_l and f_h define the lower and upper cutoff frequencies, respectively. The selected passband is intended to preserve the main frequency components associated with imagined motor movements.

The filtered EEG streams are then divided into trial-level epochs according to the task event markers. Each epoch corresponds to a short time window in which the subject performs a specific motor imagery task. Formally, one EEG epoch is expressed as

$$X \in \mathbb{R}^{C\times T} \tag{2}$$

by C be the number of selected EEG channels and T be the number of time samples in epoch. Before applying FBCSP, epoch-wise normalization is performed to reduce amplitude differences caused by subject-specific signal strength, session variation, and recording conditions.

C. Filter Bank Common Spatial Pattern

Filter Bank Common Spatial Pattern or FBCSP method is used to transform EEG epochs into spatial features that are more informative for motor imagery classification. CSP procedure learns spatial projections that separate two motor imagery classes by emphasizing differences in signal variance. Through these projections, class-relevant neural activity is strengthened, while less informative background components are reduced.

Let $X \in \mathbb{R}^{C\times T}$ be an EEG epoch, where C be the number of channels and T be the number of temporal samples. For each motor imagery class, the spatial covariance of an epoch is normalized as

$$\Sigma = \frac{XX^T}{\mathrm{trace}(XX^T)} \tag{3}$$

where trace normalization reduces the effect of amplitude scaling across trials. The class-wise average covariance matrices are denoted by Σ_1 and Σ_2.

CSP determines a spatial projection vector $\mathbf{w}$ by maximizing the variance of one class while minimizing the variance of the other class:

$$\mathbf{w}^* = \arg\max_{\mathbf{w}} \frac{\mathbf{w}^T\Sigma_1\mathbf{w}}{\mathbf{w}^T\Sigma_2\mathbf{w}} \tag{4}$$

This objective is commonly solved as a generalized eigenvalue problem:

$$\Sigma_1\mathbf{w} = \lambda(\Sigma_1 + \Sigma_2)\mathbf{w} \tag{5}$$

where λ be the eigenvalue and $\mathbf{w}$ be the corresponding spatial filter. The projection matrix W is formed using the filters associated with the largest and smallest eigenvalues, since these filters provide the strongest class separation. The EEG epoch is then mapped into the CSP spatial space as $Z = W^TX$ where Z be the spatially filtered EEG signal. The feature value of each projected component is calculated using normalized log-variance:

$$f_i = \log\left(\frac{\mathrm{var}(Z_i)}{\sum_j \mathrm{var}(Z_j)}\right) \tag{6}$$

Afterwards, the feature vector represents the relative energy distribution of the spatially filtered EEG components and is suitable for separating motor imagery classes. FBCSP extends CSP by applying the same spatial filtering process over multiple frequency sub-bands. This is useful because motor imagery information may appear differently across the sensorimotor frequency range. By analyzing several bands separately, the model can obtain complementary spatial information from different rhythmic components.

For each frequency band $b \in B$, the EEG signal is filtered first, and CSP features are extracted from that band independently. The features from all bands are concatenated to construct the final representation:

$$\mathbf{f} = [f^{(1)}, f^{(2)}, \ldots, f^{(|B|)}] \tag{7}$$

where $f^{(b)}$ is the CSP feature vector obtained from frequency band b. When m spatial filters are selected for each band and $|B|$ is the total number of bands, the dimensionality of the final FBCSP feature vector is

$$d = m \times |B| \tag{8}$$

This filter-bank representation allows the classifier to use spatial information from several motor imagery-related frequency ranges, improving feature robustness before federated model training.

D. Federated Learning Framework

The proposed training scheme follows a federated learning setting, where model optimization is carried out across multiple EEG clients while keeping the original recordings local. In this study, each subject is regarded as one client with its own dataset. Let K be the total number of clients and let $\mathcal{D}_k$ denote the dataset stored by client k. After the FBCSP stage, the raw EEG epochs are represented as feature vectors, and each client uses these features with their labels to update a local classifier.

Training is organized as a sequence of server–client communication rounds. At round t, the server sends the current global parameter vector w_t to the participating clients. Each client then uses w_t as the initial model and performs local optimization on its own dataset $\mathcal{D}_k$. The local objective for client k is defined as

$$\min_{w} \ F_k(w) = \frac{1}{n_k} \sum_{i=1}^{n_k} \ell(w; x_i, y_i) \tag{9}$$

where n_k is the number of local samples, (x_i, y_i) denotes an FBCSP feature vector and its motor imagery label, and $\ell(\cdot)$ is the classification loss. Once local training is completed, client k obtains an updated parameter vector w_t^k.

The client does not transmit EEG recordings or trial-level data; only the learned parameters are returned to the server. The server combines the received client updates using the FedAvg rule:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k \tag{10}$$

where $n = \sum_{k=1}^{K} n_k$ be the total number of training samples across all clients. This sample-weighted aggregation assigns greater influence to clients with larger local datasets while still allowing all participating subjects to contribute to the global model.

The aggregated parameter vector w_{t+1} is then used as the global model for the next communication round. This procedure is repeated until the model reaches convergence or the maximum number of rounds is completed. Through this distributed optimization process, our method can learn from multi-subject EEG data while avoiding centralized storage of raw neural recordings.

III. Evaluation

In this section, we evaluate the performance of the proposed federated EEG classification framework using a large-scale motor imagery dataset. The experiments are designed to analyze the effectiveness of the proposed FBCSP feature extraction and federated learning under realistic multi-subject conditions. Specifically, we examine classification performance across distributed EEG clients and investigate the training dynamics of the federated optimization process. The evaluation focuses on three aspects: (i) the classification accuracy achieved by the proposed framework, (ii) the convergence behavior of the federated training process, and (iii) a comparison with conventional centralized.

A. Experimental Setup

We evaluated the proposed framework using the EEG Motor Imagery Dataset from PhysioNet. This dataset contains EEG recordings collected from 100 subjects performing motor imagery tasks. During each recording session, participants were instructed to imagine left-hand or right-hand movements while EEG signals were recorded using a multi-channel acquisition system.

In this study, we focused on motor imagery runs corresponding to imagined hand movements. Each subject was treated as an independent federated client, resulting in a total of $K = 100$ clients in the federated learning framework. The EEG signals were segmented into epochs aligned with motor imagery cues, and only channels associated with the sensorimotor cortex were selected to capture relevant neural activity.

The EEG signals were band-pass filtered and segmented into epochs following the preprocessing procedure described in Section III. For feature extraction, the Filter Bank Common Spatial Pattern (FBCSP) method was applied across five frequency bands: 8–12 Hz, 12–16 Hz, 16–20 Hz, 20–24 Hz, and 24–30 Hz. For each band, $m = 6$ spatial filters were selected, and the resulting features were concatenated to form the final feature vector.

TABLE I
PERFORMANCE OF THE PROPOSED FEDERATED FRAMEWORK

Method	Precision	Recall	F1-score
Local LDA (per-subject)	0.81	0.82	0.81
Federated Logistic Regression	0.77	0.78	0.77
Proposed Federated FBCSP	**0.84**	**0.85**	**0.84**

Each subject was treated as an independent federated client. The classifier used in this study was a multinomial logistic regression model trained using stochastic gradient descent. Federated learning was performed using FedAvg algorithm over multiple communication rounds.

The main training parameters were configured as follows. The federated learning framework consisted of 100 clients, corresponding to individual EEG subjects in the dataset. Training was conducted for 50 communication rounds, with each client performing 5 local training epochs during every round. The learning rate was set to 0.05, and a batch size of 32 was used for local optimization. All experiments were implemented in Python using the MNE library for EEG signal preprocessing and Scikit-learn for machine learning model training.

We evaluated the proposed framework using standard classification metrics including accuracy, macro-averaged precision, recall, and F1-score. These metrics provide a comprehensive assessment of classification performance across different motor imagery classes. Accuracy measures the proportion of correctly classified samples relative to the total number of predictions, while precision and recall evaluate the model's ability to correctly identify each class. The macro-averaged F1-score combines precision and recall into a single metric and provides a balanced evaluation across classes, particularly in scenarios where class distributions may vary.

B. Model Performance

Table I summarizes the classification performance of the evaluated approaches. First, the baseline federated regression model achieves lower accuracy compared to the local LDA approach, indicating that naive federated training without appropriate feature representation may suffer from cross-subject variability in EEG signals. Since EEG patterns differ significantly between individuals, directly aggregating model parameters across heterogeneous clients can reduce the discriminative capability of the global model.

Second, the proposed federated FBCSP framework achieves the highest performance across all evaluation metrics, improving accuracy from 0.78 to 0.85 compared with the basic federated baseline. This improvement highlights the importance of incorporating domain-specific signal processing techniques into federated learning pipelines. By extracting spatially discriminative features prior to model training, FBCSP reduces the variability of EEG representations across subjects and provides a more stable feature space for distributed optimization.

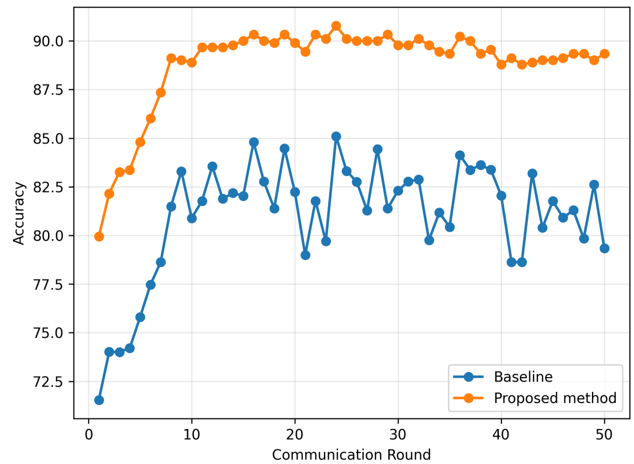

Fig. 3. Training convergence of federated EEG classification models

Furthermore, the results demonstrate that the proposed approach slightly outperforms the local LDA model despite operating in a distributed setting. This suggests that federated training can effectively leverage complementary information from multiple subjects while preserving data privacy. Overall, these findings indicate that combining classical EEG feature extraction methods with federated learning can significantly enhance the robustness and performance of distributed EEG classification systems.

C. Model Convergence

As shown in Fig. 3, both models exhibit progressive performance improvements as model updates from distributed clients are aggregated. However, the proposed federated FBCSP framework demonstrates faster convergence and consistently higher accuracy throughout the training process. In the early stages of training, the proposed model achieves an accuracy of approximately 79.9% after the first few communication rounds, while the baseline federated model starts at around 73.1%.

As training progresses, the proposed method rapidly improves and stabilizes after approximately 35–40 communication rounds, reaching a final accuracy of about 89.3%. In contrast, the baseline federated model converges more slowly and stabilizes at approximately 81–82% accuracy. On average, the proposed approach achieves a mean accuracy of 88.83%, whereas the baseline model achieves 80.95%.

This performance gap highlights the importance of integrating domain-specific feature extraction techniques into federated learning frameworks. By incorporating FBCSP-based spatial filtering, the proposed method generates more discriminative and stable feature representations, which improves the effectiveness of parameter aggregation across heterogeneous clients. Furthermore, the convergence behavior indicates that the federated optimization process remains stable despite the non-IID nature of EEG data across subjects.

We demonstrate that the proposed federated FBCSP framework not only achieves higher classification accuracy but also exhibits faster and more stable convergence compared with the baseline federated learning approach. Specifically, the integration of FBCSP-based spatial filtering enables the extraction of discriminative neural patterns associated with motor imagery tasks, thereby reducing the impact of inter-subject variability in EEG signals. This improved feature representation facilitates more consistent parameter updates during the federated optimization process, leading to more effective aggregation of client models. Consequently, the proposed framework benefits from both improved classification performance and enhanced training stability across distributed clients, highlighting the advantage of combining domain-specific EEG feature extraction techniques with federated learning.

IV. Conclusion

In this paper, we presented a privacy-preserving framework for distributed EEG motor imagery classification using a federated learning integrated with Filter Bank Common Spatial Pattern (FBCSP) feature extraction. The proposed system treats each EEG subject as an independent federated client, enabling collaborative model training without requiring the exchange of raw neural recordings. By combining classical EEG signal processing techniques with distributed optimization, the framework leverages information from multiple subjects while preserving the privacy of local EEG data.

Experimental results on the PhysioNet EEG motor imagery dataset involving 100 subjects demonstrate the effectiveness of the proposed approach. The proposed federated FBCSP framework achieved a classification accuracy of approximately 89.3%, significantly outperforming the baseline federated model which converged at around 81–82% accuracy. On average, the proposed method achieved a mean accuracy of 88.83%, compared with 80.95% for the baseline approach. In addition, the federated training process demonstrated stable convergence after approximately 35–40 communication rounds. The improved performance can be attributed to the integration of FBCSP-based spatial filtering, which extracts discriminative neural patterns from EEG signals and reduces cross-subject variability before federated optimization. By providing a more stable and informative feature representation, the proposed approach enables more effective parameter aggregation across heterogeneous clients.

Our future work will focus on extending the proposed framework in several directions. First, more advanced federated optimization strategies such as adaptive aggregation and client selection mechanisms could be explored to further improve training efficiency under heterogeneous data distributions. Second, integrating lightweight deep neural architectures such as EEGNet into the federated pipeline may enable richer feature representations for more complex EEG patterns.

Finally, evaluating the framework in real-world multi-device brain–computer interface (BCI) environments and investigating communication-efficient federated protocols will be important steps toward practical deployment of privacy-preserving EEG-based systems.

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