Horizontal Federated Learning For Brain-Computer Interface

Kairui Hu†
School of Computer Science and Engineering
Nanyang Technological University
Singapore
huka0001@e.ntu.edu.sg

Rui Liu†
School of Computer Science and Engineering
Nanyang Technological University
Singapore
rui.liu@ntu.edu.sg

Han Yu†
School of Computer Science and Engineering
Nanyang Technological University
Singapore
han.yu@ntu.edu.sg

ABSTRACT

Federated Learning (FL) is a decentralized training approach, allowing multiple clients to collaboratively improve models without directly exchanging raw data. This paradigm is particularly promising for EEG-based Brain-Computer Interfaces (BCI), where the transmission of sensitive neural data poses security risks. There is a pressing concern regarding the potential exposure of personal neurological insights. Addressing these challenges, we introduce the Federated Deep ConvNet (Fed-DCN) for Motor Imagery (MI) classification tasks in EEG-based BCI. Our method ensures data remains local, enhancing privacy and security. Results from our experiments, using the BCI 2014-001 Motor Imagery dataset with 9 subjects across 4 motor imagery tasks, demonstrate that Fed-DCN not only effectively addresses data privacy concerns but also consistently outperforms traditional DCN with subject-dependent setting in accuracy, emphasizing the potential of FL in advancing EEG-based BCI applications.

KEYWORDS

Horizontal Federated Learning, Deep ConvNet, Brain-Computer Interface, Electroencephalography

1 Introduction

Federated Learning is a decentralized deep learning approach that allows multiple clients to train a model collaboratively while keeping the data locally [1]. It ensures that the raw data remains on the local clients, thus prioritizing data security. Our work focuses on the application of FL in electroencephalography (EEG)-based brain-computer interfaces (BCI), which translates brain signals into commands for output devices. One of the main tasks in BCI is Motor Imagery (MI), which aims to detect the subjects' motor imagery intents based on their EEG signals [2].

A paramount challenge of EEG-based BCI is data security. EEG signals, as personal private data contains the brain's activities, thereby raising concerns about data protection [3]. This motivates us to incorporate FL into EEG-based BCI. FL ensures that training process is decentralized, where raw EEG data maintains locally without sharing among multiple clients, thereby enhances data security. Currently, there are very few works done to apply FL in the field of EEG-based BCI.

Below are our main contributions in this work:

- We propose a new deep learning framework for MI in EEG-based BCI, named Federated Deep ConvNet (Fed-DCN).
- We demonstrate that Fed-DCN can achieve better performance over the standalone DCN model in general, while enhancing data security during the training process.

2 Methodology

Our study proposes Fed-DCN, a new FL framework for the traditional DCN model [4]. In the proposed FL framework, each client is assigned with one subject's data. By applying the FedAvg algorithm [5], Fed-DCN trains the local DCN models for each subject without sharing their raw EEG data. An illustration of Fed-DCN is shown in Figure 1 below.

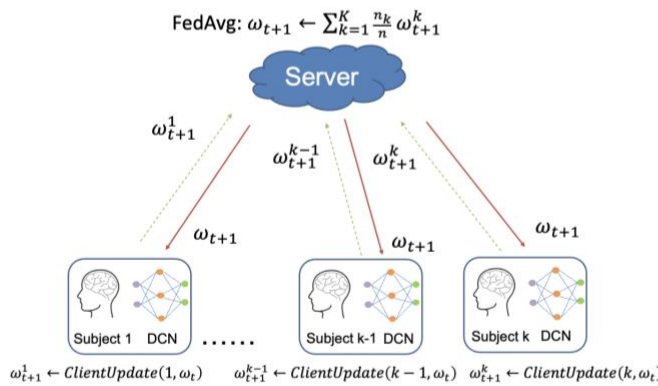

Figure 1: The Architecture of Fed-DCN

Fed-DCN optimizes the following loss function:

$$\min f(\omega) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(\omega)\,, \qquad (1)$$

$$where\ F_k(\omega) = \frac{1}{n_k} \sum_{i \in S_k} l(\omega; x_i, y_i)$$

n_k is the number of samples of subject k, i is the sample index and S_k is the sample of subject k. ω are the model weights of DCN, x_i is the input EEG signal sample, y_i is the label and $l(\omega; x_i, y_i)$ is the cross-entropy loss. The detailed training procedure for one training round in Fed-DCN is presented below:

1. Initial training: In each round t, the central server broadcasts the global model weights ω^t to Client 1 to Client K.

2. Local training: Client 1 to K receive global model weights ω^t and make a local copy of ω^t: referred to as ω_1^t, ω_2^t,..., ω_K^t

respectively. Each client then trains the local DCN model with its own training data D_1, D_2, ... D_K, for a total of E local epochs, and obtains updated model weights $\omega_1^{t+1}, \omega_2^{t+1}, \ldots, \omega_K^{t+1}$ respectively.

$$\omega_k^{t+1} = \omega_k^t - \eta \nabla l(\omega_K; b) \qquad (2)$$

where local data D_k is divided into b batches, and η is the learning rate.

3. Client-server communication: Client 1 to K upload their updated model weights $\omega_1^{t+1}, \omega_2^{t+1}, \ldots, \omega_K^{t+1}$ to the central server.

4. Averaging: The central server updates the global model weights by averaging uploaded local model weights $\omega_1^{t+1}, \omega_2^{t+1}, \ldots, \omega_K^{t+1}$ from clients:

$$\widetilde{\omega}^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \omega_k^{t+1} \qquad (3)$$

where n is the total number of samples. The updated global model $\widetilde{\omega}^{t+1}$ is broadcasted to each client as the step 1 in the next round. The process repeats until the global model converges.

3 Experiment

Dataset: Our research utilizes the BCI 2014-001 Motor Imager dataset, which consists of four motor imagery tasks: imagining movements of the left hand, right hand, both feet, and tongue. The dataset encompasses raw EEG data from nine subjects. The goal is to classify the raw EEG signals into one of the four categories.

Experiment Setup: In our baseline setup, we employ the DCN model for the subject-dependent setting, training it on each of the nine subjects for 200 epochs. In Fed-DCN, each local client retains the same network architecture as the baseline DCN. For a balanced comparison, we have 50 communication rounds with 4 epochs of local training in each round, totaling 200 round*epochs, same as the baseline setting. Both setups undergo the same preprocessing, and maintain consistent hyperparameters, with a learning rate of 0.004 and a batch size of 36.

4 Result

Table 1 showcases the results of our Fed-DCN model compared to the baseline DCN model. Employing the FL framework for the MI classification task has yielded promising outcomes. As demonstrated in Table 1, most subjects, through collaborative training of the global model using data from various clients, achieved enhanced testing accuracy with the Fed-DCN model compared to the standalone DCN model. This process successfully leverages collective datasets while ensuring individual data privacy. However, it's notable that certain subjects, specifically 1 and 7, saw marginal performance dips. Subject 3 experienced a notable 0.076 drop in accuracy upon employing FL. These anomalies are potentially attributed to the dataset's non-IID nature, where data distributions for these subjects diverge from the overarching dataset pattern. Such discrepancies, compounded by imbalances in local distributions, can render the global optimum less appropriate for certain local models. This data heterogeneity among subjects can inadvertently make the aggregated model less fitting for some participants.

Subjects	DCN	Fed-DCN	Increase
1	0.648	0.646	-0.002
2	0.305	0.327	**+0.019**
3	0.803	0.727	-0.076
4	0.451	0.465	**+0.014**
5	0.262	0.387	**+0.125**
6	0.389	0.427	**+0.038**
7	0.584	0.583	-0.001
8	0.652	0.678	**+0.026**
9	0.679	0.691	**+0.012**
Avg	0.530	0.548	**+0.018**

Table 1: Performance Comparison of DCN and Fed-DCN

5 Conclusion

Harnessing the power of Federated Learning, we have championed the dual objectives of leveraging local data for enriched model training and ensuring paramount data privacy, especially critical in the realm of EEG-based BCI. Our introduced Fed-DCN model, tailored for MI classification in EEG-based BCI, has showcased superior performance and heightened data security compared to its standalone counterpart. Further improvement like Personalized FL can be employed to mitigate the impact of non-IID data, increasing the overall robustness and adaptability of FL.

Acknowledgement

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Horizontal Federated Learning For BCI

Kairui Hu, Rui Liu, Han Yu
School of Computer Science and Engineering, Nanyang Technological University

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Motivation

- Brain-computer interfaces (BCIs) acquire humans' brain signals, translate them into commands relayed to output devices that carry out desired actions. Such applications with direct access to users' raw electroencephalography (EEG) signals have raised privacy concerns.
- Conventional machine learning algorithms require aggregating the raw data to a centralized data center (cloud) for training, in which individuals' data are exposed and privacy issues arise.
- To solve the privacy issues in BCI, we apply Federated Learning algorithm to BCI dataset. And our main contributions include:
  - We propose a new deep learning framework for MI in EEG-based BCI, named Federated Deep ConvNet (Fed-DCN).
  - We demonstrate that Fed-DCN can achieve better performance over the standalone DCN model in general, while enhancing data security during the training process.

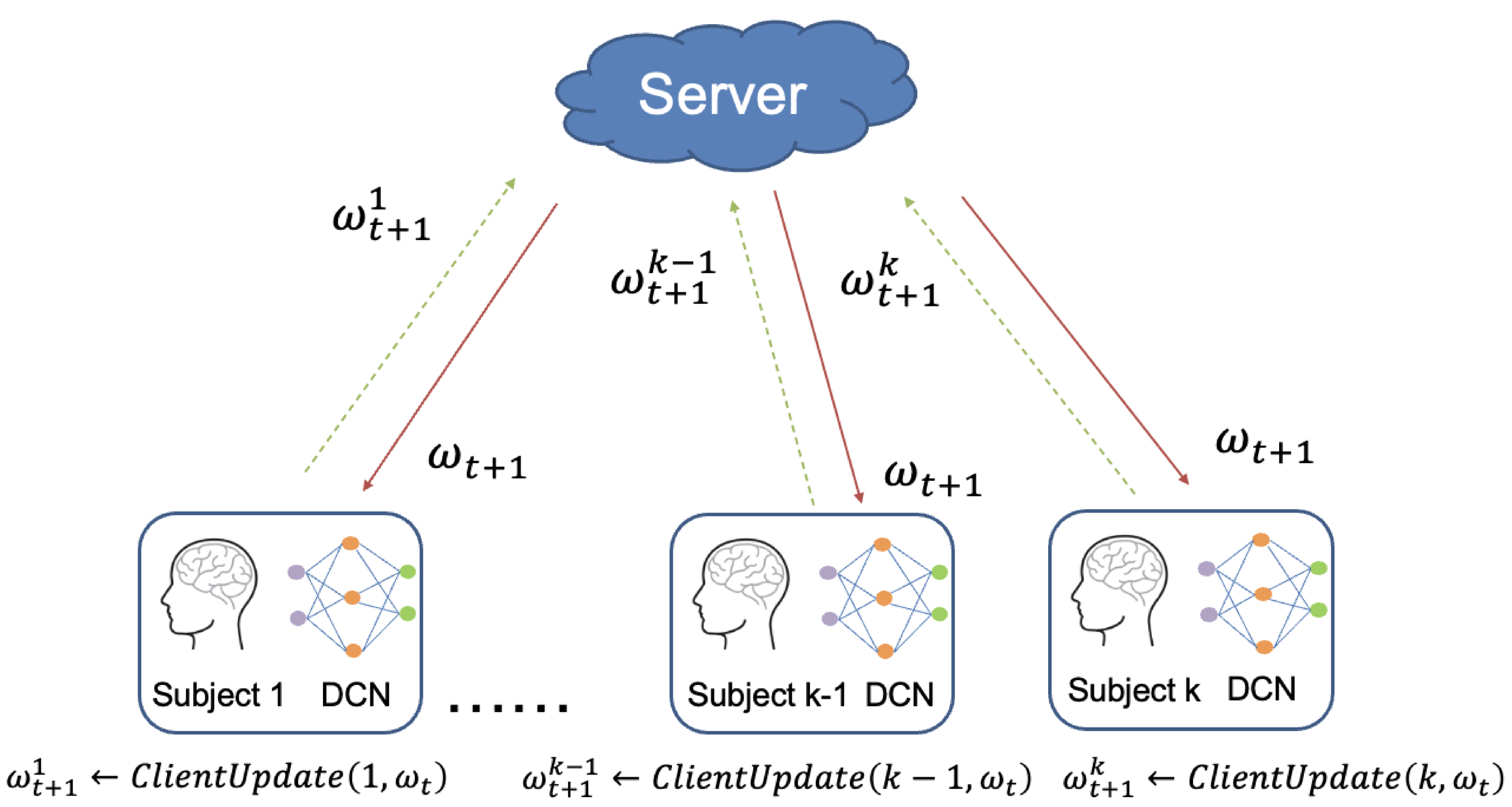
Experiment

Dataset: We used the BCI 2014-001 Motor Imager dataset, which consists of four motor imagery tasks: imagining movements of the left hand, right hand, both feet, and tongue.

Experiment Setup:

	Baseline DCN	Fed-DCN
Input	Raw EEG signals from 9 subjects	
Output	1 of the 4 imagining movements	
Train Set, Test Set	Session T, Session E	
Bandpass Filter	8 Hz – 32 Hz	
Round of Communication	1	4
Epoch per round	200	50
Total epoch	200	
Learning rate	0.004	
Batch size	36	

Model: Fed-DCN



Result

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Methodology

Fed-DCN optimizes the following loss function:

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$$where\ F_k(\omega) = \frac{1}{n_k} \sum_{i \in S_k} l(\omega; x_i, y_i)$$

The detailed training procedure for one training round in Fed-DCN:

1. **Initial training:** In each round t, the central server broadcasts the global model weights ω^t to Client 1 to Client K.
2. **Local training:** Each client then trains the local DCN model with its own training data and obtains updated model weights
$$\omega_k^{t+1} = \omega_k^t - \eta \nabla l(\omega_K; b) \quad (2)$$
3. **Uploading:** Clients upload their updated model weights to the server.
4. **Averaging:** The central server updates the global model weights by averaging uploaded local model weights from clients:
$$\tilde{\omega}^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \omega_k^{t+1} \quad (3)$$

The process repeats until the global model converges.

Acknowledgement

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