FEDEEG: FEDERATED EEG DECODING VIA INTER-SUBJECT STRUCTURE MATCHING

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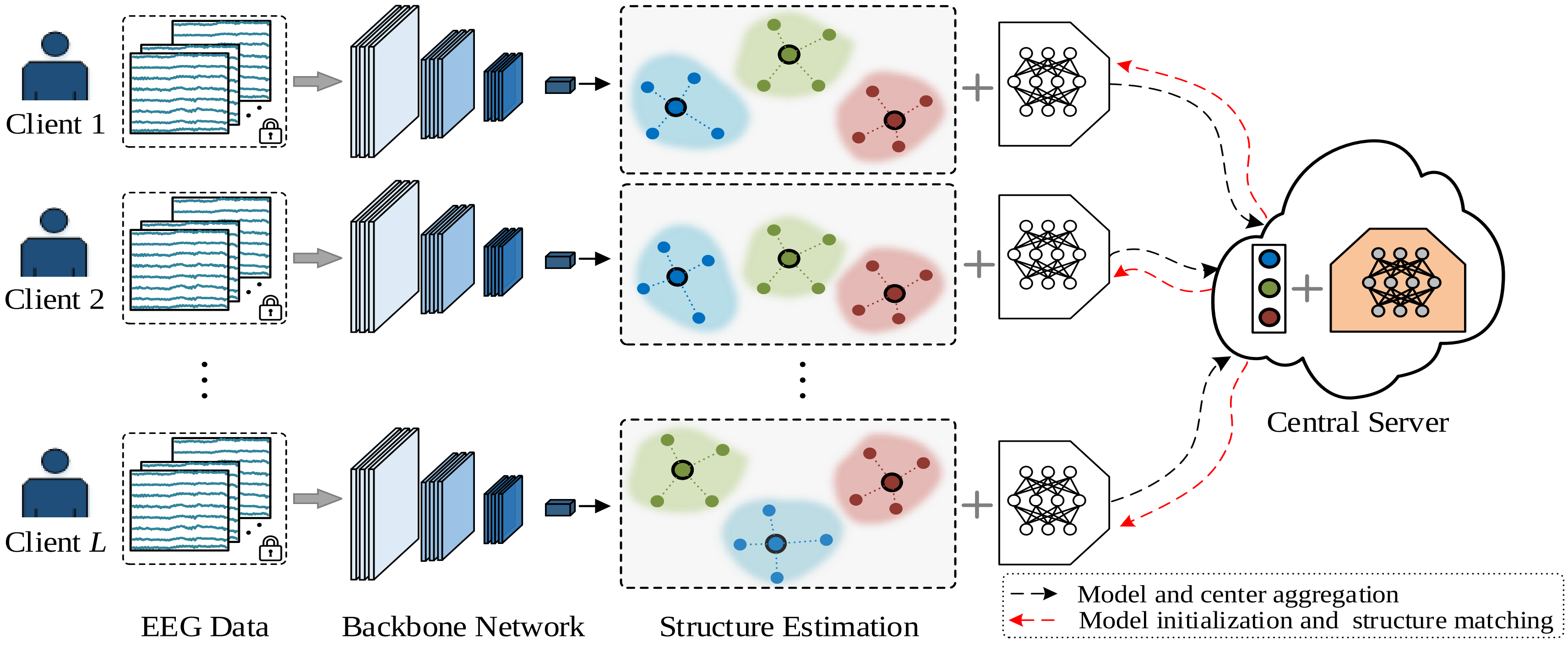
Motivation

- It is difficult to obtain abundant EEG data because collecting EEG training data is time-consuming and labor-intensive;
- Because of the particularity of EEG data structure, the existing federated learning method can not perform well in EEG decoding;
- We aim to exploit a federated EEG decoding framework by utilize the structure consistency among the local data to solve client drift in federated EEG learning.

Framework Overview

FedEEG Framework

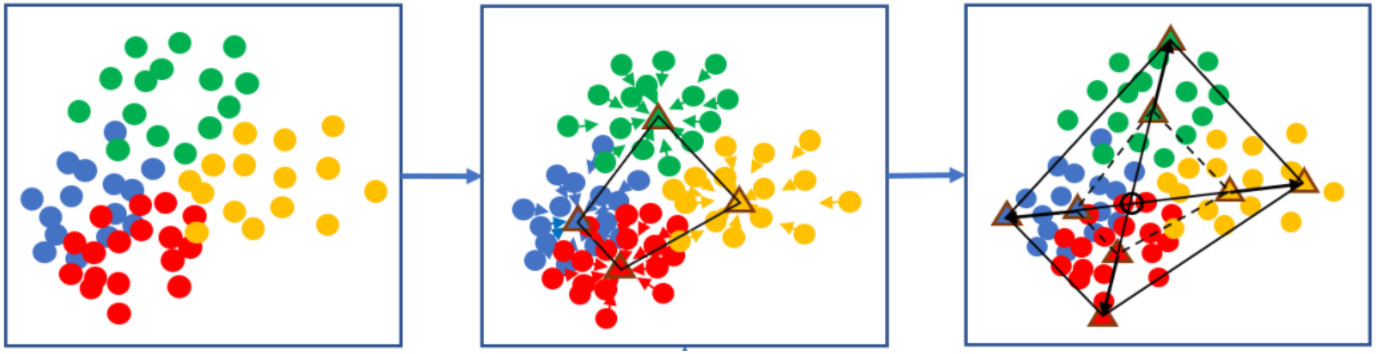


Structure estimation

- Multiple virtual class centers of each client are extracted by averaging the class specific EEG deep features.;
- Minimize the distance between the EEG deep features and their corresponding virtual class center to promote discriminative feature learning；
- Make different virtual class center points away from each other.

Center Loss：

$$\mathcal{L}_d = \frac{1}{C}\sum_{c=1}^{C}\frac{1}{N_c^l}\sum_{i=1}^{N_c^l}\left\|\mathbf{z}_i^l - \mathbf{v}_c^l\right\|^2$$



Inter-subject structure matching

- The central server collects the virtual class centers from each client and averages the centers from all subjects to compute the global virtual class centers representing the general inter-subject structure information;
- The central server sends the global virtual class centers to each client to rectify the local training of each client.

Structure matching loss：

$$\mathcal{L}_s = \frac{1}{C}\sum_{c=1}^{C}\left\|\mathbf{v}_{g,c}^{l} - \mathbf{v}_{c}^{l}\right\|^2$$

The objective function of local training for each client：

$$\mathcal{L} = \mathcal{L}_{ce} + \lambda_d \cdot \mathcal{L}_d + \lambda_s \cdot \mathcal{L}_s$$

Experiments

- **Dataset**
  - BCI Competition IV IIa;
  - BCI Competition III IIIa:
  - We used the EEG signals during the time interval [2.5s,6s] of each trial to evaluate the classification performance. Besides, EEG signals were band-pass filtered using the 5-order Butterworth filter in the frequency range of 4-38 Hz. Finally, we normalized all the EEG data to [-1, 1].
  - Each subject acts as a client, for each client, the dataset was randomly divided such that 50% of which was for used training, 20% for validation and 30% for testing.

Experiments

- **Experimental Setting**
  - The upperbound: DeepAll
  - State-of-the-art Federated learning methods:FedAvg[1], FedProx[2], MOON[3], FedFIRM[4] , FedBN[5]

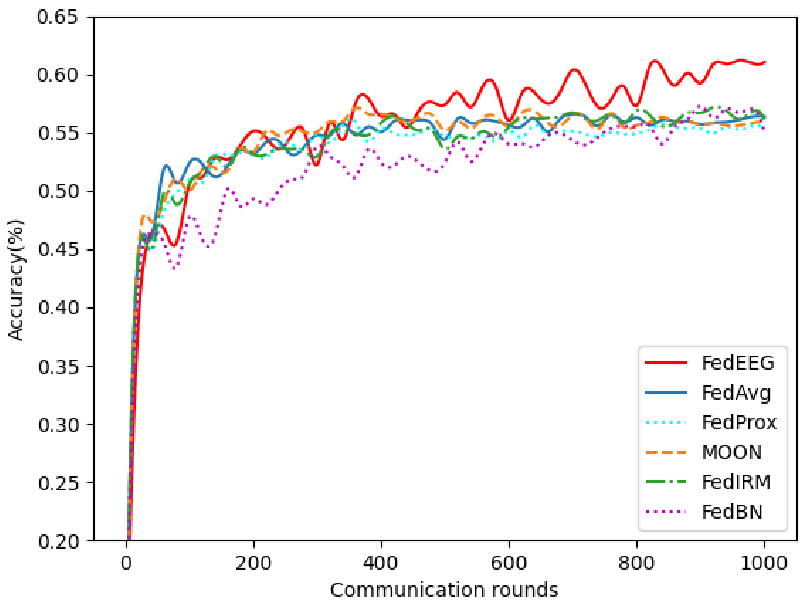
[1]Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas,"Communication-efficient learning of deep networks from decentralized data," in Artificial intelligence and statistics. PMLR, 2017, pp. 1273–1282.
[2]Tian Li, Anit Kumar Sahu, Manzil Zaheer, Maziar Sanjabi, Ameet Talwalkar, and Virginia Smith, "Federated optimization in heterogeneous networks," Proceedings of Machine Learning and Systems, vol. 2, pp. 429–450,2020.
[3]Qinbin Li, Bingsheng He, and Dawn Song, "Modelcontrastive federated learning," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2021, pp. 10713–10722.
[4]Quande Liu, Hongzheng Yang, Qi Dou, and PhengAnn Heng, "Federated semi-supervised medical image classification via inter-client relation matching," in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, 2021,pp. 325–335.
[5]Xiaoxiao Li, Meirui Jiang, Xiaofei Zhang, Michael Kamp, and Qi Dou, "Fedbn: Federated learning on non-iid features via local batch normalization," arXiv preprint arXiv:2102.07623, 2021.

Experimental Results

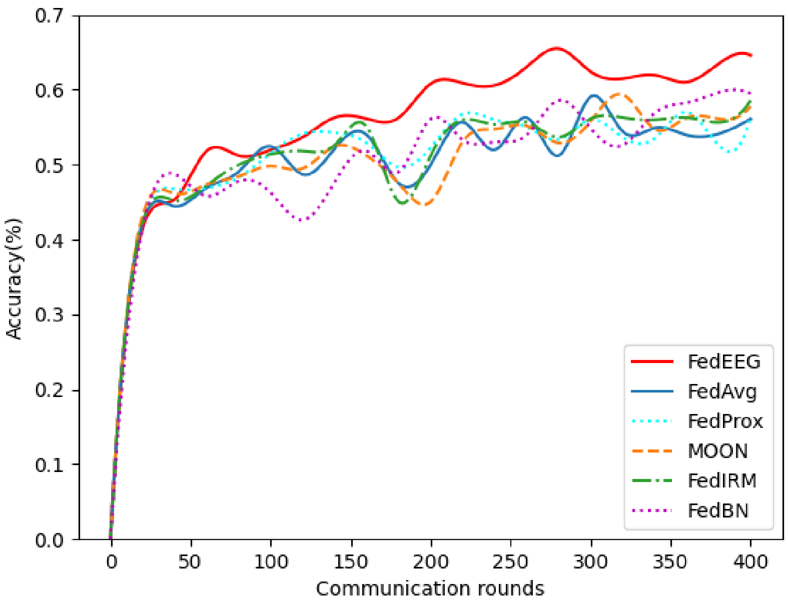
Table 1: Classification accuracy of the proposed FedEEG and the state-of-the-art methods on two MI-based EEG datasets.

Methods	*Dataset 1*										*Dataset 2*			
	A01	*A02*	*A03*	*A04*	*A05*	*A06*	*A07*	*A08*	*A09*	*Avg.*	*B01*	*B02*	*B03*	*Avg.*
DeepAll	79.77	52.02	81.50	50.87	46.24	41.62	67.74	78.03	76.30	63.79	88.99	72.22	73.61	78.27
FedAvg [9]	79.19	36.42	80.08	34.99	31.21	38.15	60.12	75.46	57.05	54.74	75.23	33.33	59.72	56.09
FedProx [10]	79.77	36.42	80.92	36.99	27.75	34.68	66.47	78.12	66.47	56.40	74.31	30.56	65.97	56.94
MOON [15]	79.77	36.99	**84.39**	34.10	29.48	34.10	66.47	73.41	64.16	55.88	74.31	37.50	63.89	58.57
FedIRM [13]	81.50	**39.31**	83.97	35.83	30.06	30.63	65.90	**78.61**	65.32	56.79	74.31	34.72	**66.67**	58.57
FedBN [16]	79.46	37.84	82.08	34.68	30.06	**43.20**	44.51	72.63	**76.34**	55.64	79.82	40.28	59.72	59.94
FedEEG	**82.66**	36.42	**84.39**	**41.05**	**46.42**	38.57	**73.41**	75.72	73.41	**61.34**	**86.24**	**55.56**	51.39	**64.40**

Experimental Results

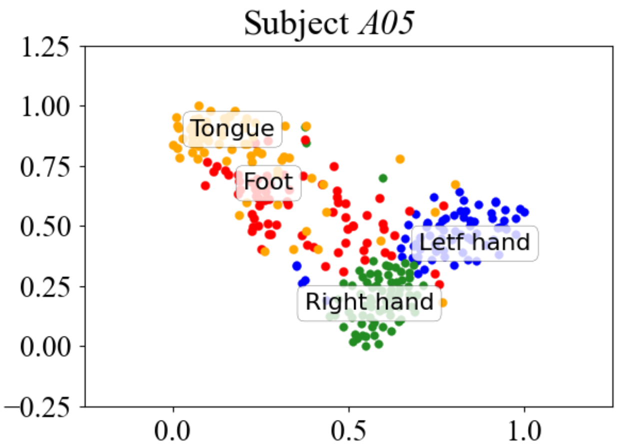


Dataset1

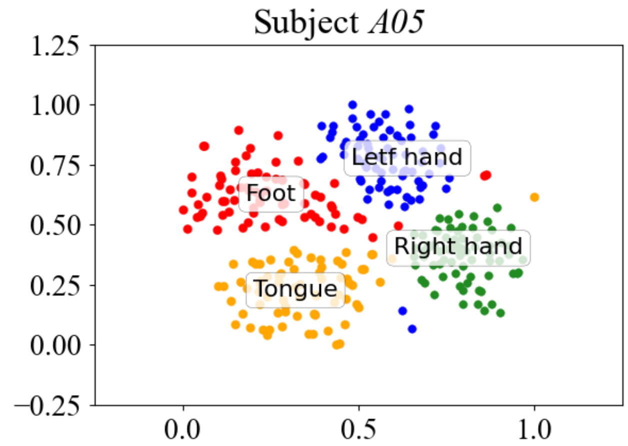


Dataset2

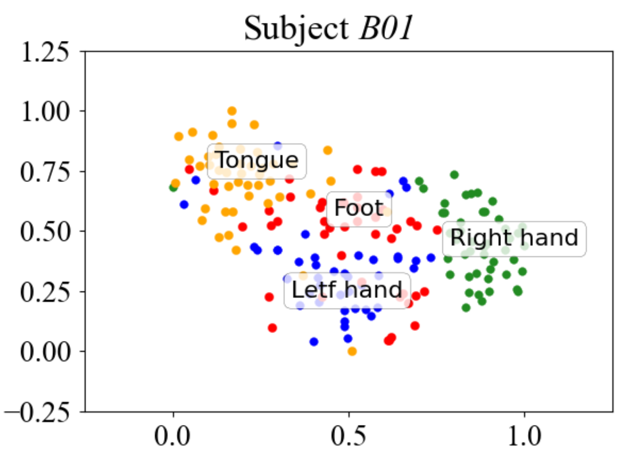
Experimental Results



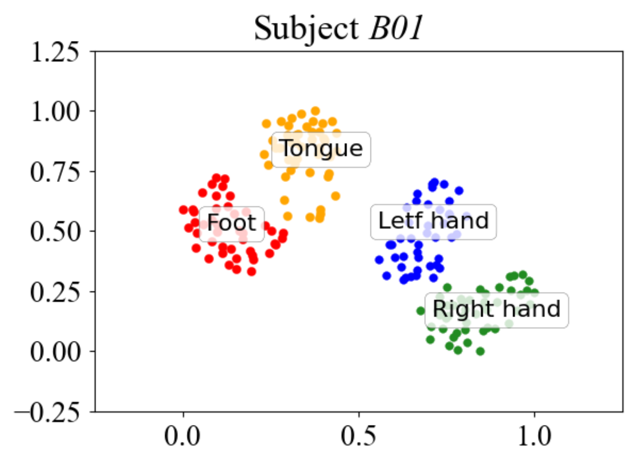
(a) Fedavg



(b) FedEEG



(c) Fedavg



(d) FedEEG

Summary

- **A novel federated learning framework for EEG decoding.**
  - Our key idea is that consistency in inter-subject structure is helpful to correct the local training of individual subject;
  - we devise a center loss to extract the virtual class centers and promote the discriminative feature learning in local client and introduce an inter-client structure matching scheme to rectify client drift.

Thank you for listening