Federated Transfer Learning for EEG Signal Classification

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Abstract—The success of deep learning (DL) methods in the Brain-Computer Interfaces (BCI) field for classification of electroencephalographic (EEG) recordings has been restricted by the lack of large datasets. Privacy concerns associated with EEG signals limit the possibility of constructing a large EEG-BCI dataset by the conglomeration of multiple small ones for jointly training machine learning models. Hence, in this paper, we propose a novel privacy-preserving DL architecture named federated transfer learning (FTL) for EEG classification that is based on the federated learning framework. Working with the single-trial covariance matrix, the proposed architecture extracts common discriminative information from multi-subject EEG data with the help of domain adaptation techniques. We evaluate the performance of the proposed architecture on the PhysioNet dataset for 2-class motor imagery classification. While avoiding the actual data sharing, our FTL approach achieves 2\% higher classification accuracy in a subject-adaptive analysis. Also, in the absence of multi-subject data, our architecture provides 6\% better accuracy compared to other state-of-the-art DL architectures.

I. INTRODUCTION

Brain-Computer Interface systems aim to identify users’ intentions from brain states. BCI has a prominent potential in the medical domain but its use has been limited by moderate decoding accuracies. In the era of deep learning, the success of BCI models for classification of electroencephalographic (EEG) recordings have been restricted by the lack of large datasets. Due to the high data collection costs, EEG-BCI data is present in the form of multiple small datasets that are scattered around the globe. Moreover, due to privacy concerns, it is difficult to create a large enough dataset by combining multiple small datasets. As EEG signals reflect brain activities in numerous aspects, the potential abuse of EEG data may lead to severe privacy violations and hence acts like General Data Protection Regulation (GDPR)\textsuperscript{1} prohibit organizations from exchanging data without explicit user approval. Therefore, it is significant to conduct a joint EEG signal analysis while protecting user privacy. Hence, to solve this problem, we propose to use federated learning framework\textsuperscript{2, 3}. Federated learning is an emerging and powerful technique which enables joint training of machine learning models using data from multiple sources without the need of actual data sharing between sources.

Existing federated learning mainly focuses on the homogeneous dataset, where the different parties share the same feature space. For EEG signal collection, even the same equipment manufacturer may develop EEG signal acquisition equipment with varying electrode numbers, position and sampling rate let alone different equipment vendors. Such device diversity further exacerbates the scarcity of training data and yields numerous distributed heterogeneous datasets in EEG classification. Heterogeneous domain adaptation by linking different feature spaces based on labels has been studied\textsuperscript{4}. However, existing solutions assume a presence of multiple source domains with abundant labeled instances and one target domain with limited labeled instances as well as unlabeled instances. When applied to our problem setting, existing heterogeneous domain adaptation approaches will face accuracy drop. The reason for the accuracy drop is that in our setting, there are numerous clients each with limited labeled data, and none of them can be a source domain in a source-target domain pair.

In this paper, we propose a novel neural network-based covariance method in BCI for the subject-specific analysis, and adapt it to the transfer learning setting for cross-subject learning in a subject-adaptive BCI analysis based on a federated learning framework. We call our method as Federated Transfer Learning (FTL). Specifically, the architecture of our model is of deep neural networks, whose inputs are spatial covariance matrices of EEG signals, with the domain adaptation technique for adaptive analysis.

In summary, following are the the major contributions of this paper: we propose a novel DL architecture based on the EEG spatial covariance matrix. Our approach is adapted to multi-devices for transfer learning setting based on the federated learning framework to protect data privacy. We perform subject-specific and subject-adaptive analysis on PhysioNet EEG Motor Movement/Imagery Dataset. We show that FTL can match the classification accuracy of state-of-the-art methods while avoiding the sharing of EEG data.

II. RELATED WORK

1) Covariance Methods in BCI: When we process and classify EEG signals, one cutting edge technology is to directly estimate and manipulate covariance matrices of EEG signal for source extraction instead of subspaces methods, such as principal component analysis (PCA), independent component analysis (ICA) and common spatial pattern (CSP)\textsuperscript{5, 6}. The covariance methods, also called Riemannian approach, encapsulates signal energy-based information of EEG signals. Covariance methods in BCI are promising methods to classify EEG signals, one cutting edge technology is to directly estimate and manipulate covariance matrices of EEG signal for source extraction instead of subspaces methods, such as principal component analysis (PCA), independent component analysis (ICA) and common spatial pattern (CSP)\textsuperscript{5, 6}. The covariance methods, also called Riemannian approach, encapsulates signal energy-based information of EEG signals. Covariance methods in BCI are promising methods to
III. METHODOLOGY

The raw data is represented in the spatial covariance matrix as the input for our FTL architecture. Specifically, let $X \in \mathbb{R}^{E \times D}$ be a short-time segment trial of EEG signal, where $E$ is the number of electrodes and $D$ is the epoch durations discretized as a number of samples. The spatial covariance matrix $S$ of segment trial $X$ is an $E \times E$ SPD matrix given by $S := \frac{1}{N} \cdot X \cdot X^T$.

Our proposed architecture consists of following 4 layers: manifold reduction layer (III-B), common embedded space (III-C), tangent projection layer (III-D) and federated layer (III-E). The purpose of each layer is as follows:

- **Manifold reduction layer (M):** Spatial covariance matrices are always assumed to be on the high-dimensional SPD manifolds. This layer is the linear map from the high-dimensional SPD manifold to the low-dimensional one with undetermined weights for learning.

- **Common embedded space (C):** The common space is the low-dimensional SPD manifold whose elements are reduced from each high-dimensional SPD manifolds, which is designed only for the transfer learning setting.

- **Tangent projection layer (T):** This layer is to project the matrices on SPD manifolds to its tangent space, which is a local linear approximation of the curved space.

- **Federated layer (F):** Deep neural networks are implemented in this layer. For the transfer learning setting, parameters of neural networks are updated by the federated aggregation.

Based on the above layers, we design transfer version and non-transfer version FTL architectures for subject-adaptive analysis and subject-specific analysis respectively. For the transfer version, our FTL architecture consists of M, C, T and F. For the non-transfer version, our FTL architecture only consists of M and T. The outputs of either architecture are predicted labels. The architecture of the transfer version FTL refers to Figure 1.

A. Notation

EEG device captures signals from $m$ subjects, and we always assume that the EEG signals have been band-pass filtered. For the $i$ th subject, his/her filtered EEG signal is separated as a sequence of trials $\{X_j\}_{j=1}^{N_i}$, where $N_i$ is the number of trials. The basic assumption of Riemannian approach for signal processing is that spatial covariance matrices $\{S_j\}_{j=1}^{N_i}$ of trials $\{X_j\}_{j=1}^{N_i}$ are distributed on an embedded SPD submanifold $\mathcal{M}_i \hookrightarrow \mathbb{R}^{E_i \times D_i}$, where $\hookrightarrow$ represents an embedding map in differential geometry [22].

B. Manifold Reduction Layer

For spatial covariance matrices $\{S_1, \ldots, S_m\}$ of the $i$ th subject on $\mathcal{M}_i \hookrightarrow \mathbb{R}^{E_i \times D_i}$, we build its own reduction $\mathcal{R}_i$ to map SPD submanifold $\mathcal{M}_i$ to the common SPD manifold $N \hookrightarrow \mathbb{R}^d$, where $d$ is the embedding dimension of $N$. Figure 1 illustrates the manifold reduction layer. We approximate these reductions $\mathcal{R}_i$ with neural networks approach. Suppose $W_i \in \mathbb{R}^{d \times E_i}$ is the weight matrix of neural network, the manifold reduction layer is constructed as a bilinear mapping, $\mathcal{R}_i(S_j) := W_i \cdot S_j \cdot W_i^T$.

C. Common Embedded Space

Upon the establishment of manifold reductions, we require that spatial covariance matrices from different subjects should fall closely onto the common embedded space $N$. One way to measure the distances between two probability distributions is as follows, reduced spatial covariance matrices on common embedded space $N$ is maximum mean discrepancy (MMD) [23]. Suppose each projected matrices $\mathcal{R}_i(\{S_1, \ldots, S_N\}) \sim Q_i$, where $Q_i$ is the probability distribution over common manifold $N$. For a feature map $\psi : N \hookrightarrow \mathcal{H}$, where $\mathcal{H}$ is a reproducing kernel Hilbert space (RKHS). Hence, the MMD distance between two probability distributions is as follows,

$$MMD_{\psi}(Q_i, Q_j) := \|\mathbb{E}_{\mathcal{R}_i(S) \sim Q_i} \psi(\mathcal{R}_i(S)) - \mathbb{E}_{\mathcal{R}_j(S) \sim Q_j} \psi(\mathcal{R}_j(S))\|_{\mathcal{H}},$$

where random variable $S \in \{S_1, \ldots, S_m\}$ ($i = 1, \ldots, m$). Notice that the small MMD yields closed reduced matrices on $N$.

D. Tangent Projection Layer

For any reference matrix $P$ on common embedded SPD manifold $N$, we consider the associated tangent space $T_P N$. Let $V_1$ and $V_2$ be two tangent vectors on tangent space $T_P N$ with the inner product defined as $\langle V_1, V_2 \rangle_P := tr(V_1 \cdot P^{-1} \cdot V_2 \cdot P^{-1})$. Logarithmic map LOG on manifolds locally project the spatial covariance matrix $P$ onto the tangent space of reference matrix $P$ by

$$V := LOG_P(P) = P^{\frac{1}{2}} \cdot \log (P^{-\frac{1}{2}} \cdot P \cdot P^{-\frac{1}{2}}} \cdot P^{\frac{1}{2}},$$
where \( \log \) is the logarithm of SPD matrix \( P = U \cdot \text{diag}(\sigma_1, \cdots, \sigma_E) \cdot U^T \), such that

\[
\log(P) := U \cdot \text{diag}(\log(\sigma_1), \cdots, \log(\sigma_E)) \cdot U^T.
\]

Specifically, the reference matrix \( P = I_E \) yields a compact expression of tangent vector \( V = \log(P) \). Hence, we let the tangent projection layer \( \mathcal{P}_N \) on common space \( \mathcal{N} \) be \( \mathcal{P}_N(X) := \log(X) \), where \( X \) is the set of all reduced spatial covariance matrices from different subjects on \( \mathcal{N} \).

### E. Federated layer

The tangent space of common manifold \( \mathcal{N} \) is locally homeomorphic in the Euclidean space of dimension \( d \). Hence, we establish typical neural networks as the classifier from tangent space. The architectures of each subject’s classifier in federated layer are assumed to be the same including fully connected layer, flatten layer and activation function.

At training round \( i \), we adopt federated averaging method[24] to train the model weights \( w_i \) in federated layer. Federated averaging is conducted over clients of each subject for feature map aggregation and over all the clients for classifier aggregation. Specifically, the techniques of federated learning follows a server-client setting. A server acts as model aggregator. In each round, the server collects updated local models from each client for model aggregation. After model aggregation, the server sends the updated global model to each client as follows,

\[
\mathcal{F} : w_{k+1} \leftarrow \frac{1}{m} \sum_{i=1}^{m} w_i^t
\]

When a client receives the model sent by server, it updates the model with its local data distributed on the reduced common manifold \( \mathcal{R}_i(\mathcal{M}_i) \subset \mathcal{N} \hookrightarrow \mathbb{R}^d \). The training process continues until the model converges.

### 4. Architecture and Loss

There are two classes of loss in our approach including the classification loss and the domain loss as follows,

- **Classification Loss**: the cross entropy loss between predicted label and ground truth, write as \( \mathcal{L}_C(\bar{Y}, Y) \), where \( \bar{Y}, Y \in \{1, \cdots, K\} \) is predicted label and ground truth respectively.
- **Domain Loss**: MMD distance with pre-set feature map \( \psi \) between any two of probability distributions \( Q_i^Y \) and \( Q_j^Y \), for \( 1 \leq i < j \leq m \) and \( Y \in \{1, \cdots, K\} \).

For the non-transfer version, the architecture includes repeated manifold reduction layer, tangent projection layer and typical neural networks with only the classification loss, i.e.

\[
\mathcal{L} := \sum_{i=1}^{m} \mathcal{L}_C(\bar{Y}_i, Y),
\]

where subscript \( i \) represents each subject.

For the transfer version, the architecture includes two classes of losses as follows,

\[
\mathcal{L} := \sum_{i=1}^{m} \mathcal{L}_C(\bar{Y}_i, Y) + \sum_{1 \leq i < j \leq m}^{K} \lambda_{i,j}^Y : \text{MMD}_\psi(Q_i^Y, Q_j^Y),
\]

where \( \lambda_{i,j}^Y \) are pre-set weights for each domain loss term.

### IV. EXPERIMENTS

#### A. Experimental Setup

The EEG data used in our experiments is from PhysioNet EEG Motor Imagery(MI) Dataset [25].

1) **MI Dataset Description**: The PhysioNet EEG dataset is recorded from 109 subjects. In our experiments, we consider the 2-class MI data, i.e. imagined left and right hand movements. The EEG data is recorded using 64 electrodes at 160Hz sampling frequency.
2) Evaluated Algorithms: We evaluated FTL against the following subspaces methods, covariance methods and DL methods:

- CSP + linear discriminant analysis (LDA)/support vector machines (SVM): CSP spatial filtering algorithm with an LDA/SVM classifier [5], [9].
- FBCSP: Best-performing CSP method for motor imagery classification [26], [27].
- MDM: Classification algorithm based on computing the geodesic distances on SPD manifolds [9].
- Tangent Space Mapping (TSM): Classification algorithm on the tangent space of SPD manifolds [9].
- Riemannian-based Kernel Method (R-Kernal): Kernel method with the specific kernel derived from Riemannian geometry of SPD matrices [10].
- EEGNet: A compact CNN architecture for EEG-based BCIs [21].
- DeepConvNet: A new discriminative spectral–spatial input to represent a diversity of brain signal patterns across the subjects and sessions [28].

3) Architecture of FTL in Experiments: All the experiments are conducted on a machine with 2.6 GHz 6-Core Intel Core i7 with Memory 16 GB 2400 MHz DDR4.

- Subject-specific Analysis: The architecture of FTL in this analysis includes three-manifold reduction layers (i.e. $W_1 \in \mathbb{R}^{32 \times 4}$, $W_2 \in \mathbb{R}^{4 \times 4}$ and $W_3 \in \mathbb{R}^{4 \times 4}$), tangent projection layer and federated layer without federated aggregation. The learning rate is initialized to 0.1 with a decay after 50 epochs. We stop the training procedure when the training loss is less than 0.1.
- Subject-adaptive Analysis: The architecture of FTL in this analysis includes two clients, i.e. source domain (good subjects) and target domain (bad subjects). For the source domain (27 good subjects), we design three-manifold reduction layers (i.e. $W_1 \in \mathbb{R}^{32 \times 16}$, $W_2 \in \mathbb{R}^{16 \times 8}$ and $W_3 \in \mathbb{R}^{8 \times 4}$). For the target domain (1 bad subject), we design a small two-manifold reduction layers (i.e. $W_1 \in \mathbb{R}^{32 \times 8}$ and $W_2 \in \mathbb{R}^{8 \times 4}$). According to our construction, common space $\mathcal{N}$ is a SPD manifold with dimension $4 \times 4$. The kernel in RKHS of $\mathcal{N}$ is Gaussian kernel with a mean of 0 and a population standard deviation 2. The federated layer is a simple fully-connected structure $W \in \mathbb{R}^{16 \times 2}$ with federated aggregation. In the loss, the pre-set weights are as follows: $\lambda_{1/2} = \lambda_{1/2} = 0.1$. Additionally, the learning rates are initialized to 0.1 with a 2% decay after 50 epochs. We stop the training procedure when the training loss is less than 1.5.

B. Experimental Results and Analysis

Our experimental section includes a subject-specific analysis and a subject-adaptive analysis. All experiments are evaluated in 5-fold cross-validation settings with 4 folds being used for training and 1 fold for testing. Trials were randomly assigned to different folds and this allocation was maintained constant across the classification methods. The result is plotted in Figure 2, and it demonstrates that no competing classifier outperforms others. The specific experimental setting is as follows,

1) Subject-specific Analysis for 2-class MI Classification: Table I demonstrates that the average performance for each classifiers of 109 subjects is around 0.60. It is worthy to

![Fig. 2: Average accuracy of classifiers on 109 subject in subject-specific analysis: horizontal axis represents the subject number from 1 to 109, and vertical axis represents the average accuracy.](image)

| Alg. /Setting   | Bad Subject | Good Subject | Transfer Learning |
|-----------------|-------------|--------------|------------------|
| CSP+LDA         | 0.489       | 0.869        | 0.528            |
| CSP+SVM         | 0.488       | 0.876        | 0.527            |
| FBCSP           | 0.532       | 0.805        | 0.525            |
| MDM             | 0.478       | 0.842        | 0.522            |
| TSM             | 0.519       | 0.868        | 0.547            |
| R-Kernel        | 0.514       | 0.840        | 0.537            |
| EEGNet          | 0.487       | 0.719        | 0.513            |
| DeepConvNet     | 0.505       | 0.721        | 0.520            |
| FTL             | 0.513       | 0.837        | 0.549            |

### Table I: Cross-validation average accuracy (Avg Acc.) of 9 classifiers on 109 subjects. We have 3 subspaces methods, 3 covariance methods and 3 DL methods in the table.
mention that subspace methods and covariance methods usually perform better than DL methods on a small sample size dataset. However, our approach FTL takes advantage of the covariance methods, and outperforms other two state-of-the-art DL methods in this experiment.

We pick good and bad subjects from 109 subjects for the following subject adaptive analysis, where the word good and bad are in the following sense that the classification accuracy of CSP+LDA classifiers is in Top 25% and Bottom 25% of 109 subjects respectively. According to this construction, we have 27 good subjects and 28 bad subjects.

2) Subject-adaptive Analysis for 2-class MI Classification: In subject-adaptive analysis experiment, we have three experimental settings, i.e. bad subject setting, good subject setting and transfer learning setting. Bad and good subject settings refers to the average of results in subject-specific analysis for bad and good subjects respectively. Transfer learning setting refers to the subject-adaptive analysis in BCI that the training data for every bad subject is good subject data combined with 4 folds of the bad subjects data, and the testing data is the rest 1 fold. The results of the transfer learning setting, listed in the third column of Table II, demonstrates that modeling with signals from good subjects yields better accuracy than modeling only with the bad subject (the results in the first column). Furthermore, FTL is an effective classifier, which is equipped with the techniques of domain adaptation, for transfer learning setting.

C. Discussion

Lack of adequate training data is a major challenge in the adaption of DL methods for EEG-BCI classification. In this paper, to mitigate this issue, we proposed a federated transfer learning based deep learning architectures for subject-adaptive EEG-MI classification. Furthermore, following the successful Riemannian approach [6], [7], [8], [9], [10], our architecture used signal covariance matrix as an input. With this architectures, in a subject-specific analysis, we achieved 6% better classification accuracy compared to the other two state-of-the-art DL architectures. This indicates that the covariance-based representation of EEG can be an effective input for DL architectures, particularly in the absence of adequate training data. Furthermore, in a subject-adaptive analysis, the proposed method achieved the best classification accuracy which shows that the use of domain adaptation in the FTL architecture can boost classification performance. Lastly, as done in this work, the federated learning framework can be effectively used to enable distributed training of EEG classifiers from multiple heterogeneous data configurations.

V. CONCLUSIONS

In this paper, we investigated the feasibility of the federated learning framework to enable a distributed training of BCI models from multiple datasets with heterogeneous configurations. The experimental results confirm the effectiveness of our approach and demonstrate the prominent potential of extracting knowledge from the heterogeneous BCI data.

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