Ultra Efficient Transfer Learning with Meta Update for Cross Subject EEG Classification

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Abstract

Electroencephalogram (EEG) signal is widely used in brain computer interfaces (BCI), the pattern of which differs significantly across different subjects, and poses a major challenge for real world application of EEG classifiers. We found an efficient transfer learning method, named Meta Update Strategy (MUPS), boosts cross subject classification performance of EEG signals, and only need a small amount of data from target subject. The model tackles the problem with a two step process: (1) extract versatile features that are effective across all source subjects, and (2) adapt the model to target subject. The proposed model, which originates from meta learning, aims to find feature representation that is broadly suitable for different subjects, and maximizes sensitivity of the loss function on new subject such that one or a small number of gradient steps can lead to effective adaptation. The method can be applied to all deep learning oriented models. We performed extensive experiments on two public datasets, the proposed MUPS model outperforms current state of the arts by a large margin on accuracy and AUC-ROC when only a small amount of target data is used.

Our code is publicly available at https://github.com/tiehangd/MUPS

Index terms—EEG classification, meta learning, convolutional neural network, gradient descent

1 Introduction

EEG signal is widely used to analyze the activities of human brain. The signal is recorded by placing electrodes on different regions of human scalp when the subject performs executive/imaginary tasks or perceives stimulus from outside [1]. EEG signal has proved to be effective for restoring motion capabilities of disabled people [2], human intention interpretation [3], emotion recognition [4] and enhanced experience in gaming control [5].

One major challenge in EEG signal analysis is the significant pattern variability across subjects, which makes it hard for the model to perform well on user previously unseen [6]. This challenge can be tackled with two steps: (1) extracting versatile features which are effective across different subjects from large standard dataset, and (2) adapt the classifier to fit on the new subject, denoted as the calibration process [1]. In our work, we utilize meta update mechanism to significantly reduce this calibration effort, i.e., using minimized amount of labeled target data and with just a few gradient update steps to adapt on target subject, which would increase the utility of BCI systems in real world scenarios.

Previous works extract versatile and subject invariant features with either signal processing techniques or deep learning models. [7] utilized filter bank (FB) and common spatial pattern (CSP) for effective feature extraction which are then sent to a fisher linear discriminator (FLD). [8] adopt multiple classifiers on top of CSP which are combined with $l_1$ regularized regression for an improved performance. And [9] extracted features from power spectral density (PSD) of EEG signals and used support vector machines (SVM) as the classifier. Models based on deep learning emerged as a promising approach as they alleviate the need for manual feature engineering and achieved state of the art

*Calibration-free approaches extract subject independent features without calibration on target. They have the privilege that no additional effort is required from the target subject, but performance improvement is still needed for challenging tasks, as 70% classification accuracy is generally deemed an acceptable threshold for BCI systems [4].
performance. EEGNet [10] is a compact convolutional neural network (CNN) that can be applied to different BCI paradigms, which involves both temporal convolution and depth convolution. CTCNN [11] is another widely used model based on CNN with a novel cropped training strategy. [12] introduced a cascade and parallel structure on CNN for improved performance. CRAM [6] is proposed recently which adopts LSTM with attention mechanism on top of convoluted features to help the model focusing on most discriminative temporal features, and achieved promising result.

Transfer learning techniques are utilized to transform models onto target subject for improved performance. Previous works have adopted classic transfer learning [13] [14] [15] or domain adaptation [16] [17] to transfer learned knowledge. [4] proposed an inter-subject transfer learning framework built on top of CNN model. [18] takes a probabilistic transfer approach by updating posterior of model weights based on new evidence from target subject. [16] and [17] explored performance of multiple domain adaptation methods including transfer component analysis (TCA-EEG), maximum independence domain adaptation (MIDA-EEG) and information theoretical learning (ITL) for emotion recognition. Recent emerged models on few shot learning such as Matching Nets [19] and Prototype Nets [20] can be adapted to the transfer process and we also included them for comparison in our experiments. We changed their base block to be EEGNet for a fair comparison with our model.

In this letter, we propose a simple and computationally efficient meta optimization strategy to tackle cross subject EEG classification, which achieves accuracy on par with intra subject classification utilizing minimized amount of labeled data from target subject. This Meta UPdate Strategy (MUPS) adopts its idea from meta learning [21][22] and is applicable to all deep learning oriented classifiers. It involves a meta training phase followed by meta test on target subject. The meta training phase is performed on the known source subjects. It extracts versatile features that are effective across different subjects, and push model weights to sensitive regions of parameter space such that a small number of gradient steps can yield adequate adaptation on target subject during meta test. Another desirable property of the model is that it doesn’t overfit even if target data is very limited, allowing it to properly function in low target-resource scenarios. We performed extensive experiments with the proposed method on two publicly available EEG datasets. It outperforms current state of the arts by at least 8% in accuracy when a small amount of target data is used.

2 Methodology

MUPS extracts broadly effective features from known subjects and then adapt onto target subject with fast adaptation speed and efficient in terms of target data usage. The difference between MUPS and classic transfer learning lies in the optimization process.

For traditional optimization, weights are sequentially updated after each time step, seeking sensible parameters with

$$\hat{\Theta} = \arg\max_{\Theta} \log p(\Theta|D_s, D_t)$$  \hspace{1cm} (1)$$

where $\Theta$ is the collection of model parameters, $D_s$ is training data from source subjects, and $D_t$ is the small amount of data from target subject.

MUPS decomposes the problem into two steps by setting up meta parameters $\Phi$. Given

$$\log p(\Theta|D_s, D_t) = \log \int_{\Phi} p(\Theta|D_t, \Phi) p(\Phi|D_s) d\Phi \hspace{1cm} (2)$$

Maximizing the log likelihood is approximated to first finding meta parameters that maximizes $\log p(\Phi|D_s)$

$$\hat{\Phi} = \arg\max_{\Phi} \log p(\Phi|D_s) \hspace{1cm} (3)$$

Then approximates eq. 1 to be

$$\arg\max_{\Theta} \log p(\Theta|D_s, D_t) \approx \arg\max_{\Theta} \log p(\Theta|D_t, \hat{\Phi}) \hspace{1cm} (4)$$

The meta update mechanism can thus be interpreted as helping the model learn a prior of transferable knowledge on the subjects. This prior is later used to infer the posterior parameters in the network after the model sees a small amount of data from the new subject. The prior learned during meta training act as an inductive bias for minimizing the generalization error

\footnote{Intra subject EEG classification is significantly easier than cross subject classification as model are trained and tested on data from the same subject.}
during evaluation, which allows the EEG classifier to properly functions on the new subject after a few gradient updates.

The MUPS model involves interaction between a base learner and a meta learner, each formed with a feature extractor and a top layer classifier.

Feature extractor can be any form of deep learning networks that extracts effective features from raw EEG signal. We adopt convolutional layers of EEGNet\cite{10} in our study for its compactness, versatility across different BCI paradigms and state of the art performance.

It is built up with three convolutional layers, with the first layer being temporal convolution to learn frequency filters, then another layer of depthwise convolution for temporal specific spatial filters. The third layer performs pointwise convolution which has reduced number of parameters compared to classic convolutional layers. Please refer to \cite{10} for more details on the network structure. Compactness is important for feature extractor as less parameters allow easier adaptation and also needs less data from target subject. Parameters in the feature extractor are pretrained to have a warm start before meta update begins.

**Algorithm 1:** MUPS for Cross Subject EEG Classification

| Input | data from source subjects $\mathcal{D}_s$, data from target subject $\mathcal{D}_t$, base learning rate $\alpha$, meta learning rate $\beta$ |
|-------|-------------------------------------------------------------------------------------------------------------------------------------|
| Output: | optimal meta learned model |
| 1 for samples in $\mathcal{D}_s$, do | 2 pretrain $\phi$ based on $\mathcal{L}_{\mathcal{D}_s}(\phi)$ |
| 3 end | 4 while not done do |
| 5 sample a batch of tasks $\{\mathcal{T}_{1\sim K}\} \in \mathcal{E}_{meta}$ | 6 for meta episode $k$ from 1 to $K$ do |
| 7 Split $\mathcal{T}_k$ into $\mathcal{T}_b$ and $\mathcal{T}_m$ | 8 for number of base updates do |
| 9 optimize $\{\theta, \phi\}$ with $\mathcal{T}_b$ by Eq. 5 | 10 end |
| 11 optimize $\{\theta^*, \phi^*\}$ with $\mathcal{T}_m$ by Eq. 6 | 12 $\{\theta, \phi\} \leftarrow \{\theta^*, \phi^*\}$ |
| 13 end | 14 end |

The meta update process is defined as follows:

An ensemble of $M$ meta tasks $\mathcal{E}_{meta} = \{\mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_M\}$ is created from source dataset $\mathcal{D}_s = \{(x_1, y_1), ..., (x_N, y_N)\}$ with a total of $L$ source subjects. Each meta task $\mathcal{T}_i = \{(x^i_1, y^i_1), ..., (x^i_m, y^i_m)\}$ contains $m$ data points from $l$ subjects, where $m \ll N$ and $l < L$.

Each cycle of meta update is called an episode, including two phases: base learning and meta learning. In each episode, a meta task $\mathcal{T}_i$ is sampled from the task pool $\mathcal{E}_{meta}$, with $p$ data points for base learning $\mathcal{T}_b$, $q$ data points for meta learning $\mathcal{T}_m$ (omitted indexing on $i$ here for conciseness), and $p + q = m$.

MUPS adopts a two stage optimization approach with two sets of optimizers, one for optimizing base learner and the other for optimizing meta learner. Parameters of base learner includes feature extractor $\phi$ and top layer classifier $\theta$. Meta learner keeps another set of parameters $\{\phi^*, \theta^*\}$. During initialization, $\{\phi, \phi^*\}$ is adopted from the pretrained feature extractor to have a warm start, and $\{\theta, \theta^*\}$ is randomly initiated. In later episodes, both base learner and meta learner inherit parameter values from meta learner of previous episode.

In base learner, gradient is evaluated with $\nabla_{\{\theta, \phi\}} \mathcal{L}_{\mathcal{T}_b}(\theta, \phi)$, with the loss function $\mathcal{L}_{\mathcal{T}_b}(\theta, \phi)$ being cross entropy for classification tasks. Parameters of base learner is updated as

$$\{\theta, \phi\} \leftarrow \text{Adam}\left(\{\theta, \phi\}, \nabla_{\{\theta, \phi\}} \mathcal{L}_{\mathcal{T}_b}(\theta, \phi), \alpha\right)$$ (5)

where $\alpha$ is the learning rate for base optimizer. Here Adam can be replaced by any optimizer based on first order gradient. After base learning loop ends, meta task $\mathcal{T}_m$ is applied to get meta gradient $\nabla_{\{\theta, \phi\}} \mathcal{L}_{\mathcal{T}_m}(\theta, \phi)$, and parameters of meta learner get updated accordingly

$$\{\theta^*, \phi^*\} \leftarrow \text{Adam}\left(\{\theta^*, \phi^*\}, \nabla_{\{\theta, \phi\}} \mathcal{L}_{\mathcal{T}_m}(\theta, \phi), \beta\right)$$ (6)

where $\beta$ is the learning rate for meta optimizer. Note this meta optimization is performed over the meta learner, whereas the objective gradient is computed using the updated base learner parameters for its gradient descent direction is broadly effective on different subjects. Meta learner is kept between different episodes and then adapt to target subject during evaluation, while base learners are set up inside each episode. The algorithm is outlined in Algorithm\cite{11}

Please note while MUPS borrows its idea from model agnostic meta learning (MAML) \cite{21}, the task
and model settings are both different. The work on MAML aims to learn a model that performs well on previously unseen classes, and MUPS aims to get classifier perform well on unseen subjects. For cross subject EEG classification, meta tasks are sampled from different subjects, instead of different classes.

3 Experiments

3.1 Dataset and Implementation

3.1.1 Dataset

The proposed model is evaluated on two public datasets, namely BCI competition IV dataset 2a (abbreviated as BCI IV-2a below) [25] and DEAP dataset [26].

BCI IV-2a involves 9 subjects doing 4 class motor imaginary tasks. Each subject is tested in two sessions and each session consists 288 trials. Signals are recorded with 22 electrodes at 250Hz sampling rate.

DEAP dataset is for emotion recognition, with a total of 32 subjects. 40 trials are recorded for each subject as they watched music videos with different types of arousals. The signal comprises 32 channels at a sampling rate of 512Hz.

For our cross subject classification scenario, we split the data to leave one subject out for testing each time. The recording is processed with each segment has a window size of 400 and step size is 50 for neighboring segments.

3.1.2 Implementation

The model is implemented with Pytorch. Feature extractor is pretrained on SGD optimizer with learning rate set to 0.01. Adam optimizer is adopted during meta training for adaptation of base learner and meta learner, with learning rate set to 0.001. The learning rate is discounted by 0.2 every 5 steps. We run 10 epochs for feature extractor pretraining, and 20 epochs for meta training. Each meta episode involves ten iterations of base learner update and one meta update. For more details, please refer to the publicly available code [3].

3.2 Result Analysis

Result on BCI IV-2a dataset and DEAP dataset are presented in table [1] and table [2] respectively. We did a comprehensive comparison to models that perform well on cross subject classification tasks with code publicly

![Figure 1: Illustration of MUPS’s convergence speed during meta training on BCI IV-2a dataset. Baseline is our base learner (EEGNet) training on intra subject classification task. Intra subject EEG classification is significantly easier than cross subject classification as model are trained and tested with data from the same subject. MUPS model fully converges after 10 epochs of meta training, using 43 seconds with a single GPU.](http://bnci-horizon-2020.eu/database/data-sets)

![Figure 2: MUPS performance on BCI IV-2a dataset with different amount of target subject data. We observed both Accuracy and AUC-ROC score converge with 20 seconds of target subject data.](https://www.eecs.qmul.ac.uk/mmv/datasets/deap/download.html)
which justifies their relatively lower performance.

The first three models are subject independent and don’t use any target subject data. For the other transfer learning approaches we used the same amount of target subject data (20 seconds of EEG recording) for a fair comparison. MUPS outperforms these three models by a large margin with its efficient meta adaptation mechanism.

Table 1: Comparison of Accuracy and ROC-AUC on BCI-Competition IV 2a dataset. With a total of nine subjects in the dataset, the models are trained on eight subjects and tested on the subject left out. The first three models are subject independent and don’t use any target subject data. For the other transfer learning approaches we used the same amount of target subject data (20 seconds of EEG recording) for a fair comparison. MUPS outperforms comparison methods by a large margin with its efficient meta adaptation mechanism.

| Criterion | Comparison Method | Test Subject (the remaining subjects used as training) | Mean |
|-----------|-------------------|-------------------------------------------------------|------|
| Accuracy  |                   | A01  A02  A03  A04  A05  A06  A07  A08  A09 |      |
|           | EEGNet [10]       | 0.538 0.395 0.549 0.430 0.518 0.490 0.607 0.614 0.478 | 0.513 ± 0.052 |
|           | CTCNN [11]        | 0.559 0.260 0.707 0.455 0.332 0.354 0.410 0.613 0.601 | 0.477 ± 0.151 |
|           | CRAM [2]          | 0.610 0.424 0.731 0.504 0.507 0.515 0.673 0.697 0.669 | 0.591 ± 0.108 |
|           | MIDA-EEG [16]     | 0.646 0.452 0.718 0.556 0.561 0.529 0.684 0.643 0.557 | 0.594 ± 0.084 |
|           | TCA-EEG [17]      | 0.629 0.463 0.694 0.526 0.557 0.531 0.676 0.668 0.528 | 0.586 ± 0.082 |
|           | Deep-Transfer [23]| 0.674 0.382 0.692 0.551 0.452 0.517 0.621 0.693 0.487 | 0.563 ± 0.116 |
|           | RA-MDRM [24]      | 0.743 0.506 0.815 0.516 0.512 0.546 0.752 0.731 0.716 | 0.649 ± 0.125 |
|           | Matching Net [19] | 0.616 0.442 0.765 0.581 0.522 0.576 0.659 0.663 0.659 | 0.614 ± 0.093 |
|           | Prototype Net [20]| 0.731 0.502 0.794 0.659 0.553 0.614 0.678 0.740 0.722 | 0.661 ± 0.096 |
| ROC-AUC   | MUPS              | 0.767 0.712 0.868 0.775 0.782 0.814 0.782 0.768 0.743 | 0.779 ± 0.043 |
|           | EEGNet            | 0.772 0.677 0.81 0.729 0.784 0.743 0.831 0.827 0.748 | 0.772 ± 0.048 |
|           | CTCNN             | 0.826 0.57 0.935 0.699 0.644 0.711 0.772 0.912 0.863 | 0.768 ± 0.124 |
|           | CRAM              | 0.83 0.685 0.937 0.76 0.769 0.761 0.872 0.899 0.853 | 0.819 ± 0.081 |
|           | MIDA-EEG          | 0.808 0.703 0.876 0.753 0.754 0.737 0.880 0.869 0.842 | 0.802 ± 0.067 |
|           | TCA-EEG           | 0.822 0.738 0.862 0.763 0.772 0.769 0.867 0.882 0.836 | 0.812 ± 0.053 |
|           | Deep-Transfer     | 0.831 0.658 0.847 0.726 0.677 0.751 0.823 0.874 0.762 | 0.772 ± 0.076 |
|           | RA-MDRM           | 0.844 0.739 0.893 0.752 0.746 0.790 0.836 0.901 0.869 | 0.823 ± 0.064 |
|           | Matching Net      | 0.771 0.688 0.859 0.788 0.752 0.733 0.806 0.863 0.840 | 0.789 ± 0.057 |
|           | Prototype Net     | 0.824 0.731 0.872 0.827 0.734 0.772 0.825 0.882 0.875 | 0.816 ± 0.073 |
| ROC-AUC   | MUPS              | 0.855 0.840 0.913 0.863 0.875 0.926 0.847 0.919 0.878 | 0.880 ± 0.032 |

available. The first three comparison models (EEGNet, CTCNN, CRAM) don’t involve the transfer process and no target data is used. For the other transfer learning approaches, we used the same amount of target subject data (20 seconds of EEG recording) to have a fair comparison.

For BCI-IV 2a dataset, MUPS has an improvement of at least 11.8% on accuracy and 5.7% on AUC-ROC compared with other models. The classification accuracy varies across individual subjects. MUPS classified all 9 subjects to above 70% accuracy, which is generally deemed an acceptable threshold for application of BCI systems. This significantly outperforms the best comparison model which gets 5 out of 9 subjects to above 70% of accuracy. For DEAP dataset, MUPS outperforms other approaches by at least 8.3% in accuracy and 5.3% in AUC-ROC. This performance improvement comes from MUPS’s ability to rapidly adapt onto the target domain with a small amount of target data.

MUPS differs from the other models in its optimization process, and we further investigated its convergence speed shown in Figure 1. Baseline is our base learner (EEGNet) directly training on intra subject classification with classic Adam optimizer. MUPS fully converges after 10 epochs of meta training, and takes 43 seconds on a single TITAN-V GPU. In comparison, it takes baseline model nearly 50 epochs and 5 minutes with same computational resource. Figure 2 shows the influence on model performance with different amount of target subject data. The performance is positively correlated with target data, and we observed both accuracy and AUC-ROC converges with 20 seconds of EEG recording from target subject.

These three models adopt a more challenging problem setting which justifies their relatively lower performance.
Table 2: Performance Comparison on DEAP Dataset. The cross subject classification is performed by leaving one subject out for testing each time.

| Comparison Method | Accuracy  | ROC-AUC  |
|-------------------|-----------|-----------|
| EEGNet            | 0.459 ± 0.073 | 0.627 ± 0.044 |
| CTCNN             | 0.396 ± 0.095 | 0.603 ± 0.048 |
| CRAM              | 0.565 ± 0.117 | 0.731 ± 0.078 |
| MIDA-EEG          | 0.496 ± 0.123 | 0.638 ± 0.078 |
| TCA-EEG           | 0.512 ± 0.109 | 0.640 ± 0.062 |
| Deep-Transfer     | 0.478 ± 0.146 | 0.651 ± 0.083 |
| RA-MDRM           | 0.553 ± 0.117 | 0.718 ± 0.074 |
| Matching Net      | 0.547 ± 0.078  | 0.724 ± 0.047 |
| Prototype Net     | 0.589 ± 0.102  | 0.754 ± 0.055 |
| MUPS              | 0.672 ± 0.063  | 0.807 ± 0.037 |

4 Conclusion

EEG pattern variability across different subjects is a major challenge for cross subject EEG classification. We found a highly efficient transfer learning model built on meta update mechanism is effective for solving the problem. The two step meta update approach functioning on meta tasks enables the model to learn general features across different subjects and then rapidly adapt onto the target subject utilizing minimal target subject data. The model is computationally efficient and its convergence speed is several times faster than classic optimizers. We evaluate the model on two public datasets, where it significantly outperforms current state of the arts when a small amount of target subject data is used.

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