

EEG EMOTION RECOGNITION BASED ON CONTRASTIVE SELF-SUPERVISED LEARNING

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ABSTRACT

Domain adaption is crucial for EEG emotion recognition, which transfers the knowledge learned from a labeled source domain to an unlabeled target domain with a different data distribution. However, the training data in the source domain is required by most traditional methods, which is usually not available for EEG emotion recognition due to privacy-preserving policies. Thus, the source-free unsupervised domain adaption (SFUDA) problem emerges. To solve this problem, this paper proposes a Contrastive Self-Supervised Learning (CSSL) framework for online calibration of EEG recognition without using source data. The CSSL framework consists of two steps. In the first step, the source shared and personalized generator and classifier are trained, and contrastive learning tricks make the shared and personalized features closer when they are from the same data, thus making features more suitable for the cluster to generate pseudo labels in the second step. In the second step, the pseudo labels generated by the cluster or Gaussian mixture model (GMM) are applied to supervise the training of the target model. Experimental results indicate that our proposed method performs better than the state-of-art methods, and it achieves an accuracy of 89.2% and 61.6% on the SEED and DEAP datasets, respectively. The code is available at <https://github.com/heibaopei/DCIM>.

Index Terms— contrastive learning, self-learning, EEG, emotion recognition, emotion classification

1. INTRODUCTION

As an important emotion detection approach, electroencephalogram (EEG) is invisible and difficult to replicate, which makes EEG more reliable than other emotion detection methods [1]. However, inter-subject variance makes EEG-based emotion recognition models not friendly for new users. Also, due to the privacy protection policy, the problem of domain adaptation without using source data needs to be solved. In this case, source-free unsupervised domain adaption (SFUDA) has drawn much attention in the fields of

computer vision (CV) and natural language processing, but not in the EEG signal analysis field.

As for source-free self-supervised learning methods, Zhang et al. [2] proposed a data-augmented framework to generate high-quality and high-diversity simulated EEG samples for contrastive learning. Shen et al. [3] adopted contrastive learning to minimize the inter-subject variance by maximizing the similarity in EEG signal representations across subjects when they receive the same emotional stimuli. However, all self-supervised learning methods require pretext training, and the final task is in downstream learning.

The methods for solving the SFUDA problem only use source models and unlabeled target data, and there are state-of-art methods in the CV field. In SHOT[4], a generalized model is trained with all source data as a source model. Only the parameters of the source model are transmitted, and then the target subject data is fed into the source model to generate features, which are clustered to generate pseudo tags. Meanwhile, the parameters of the feature model are updated with the clustered pseudo tags. SHOT ++[5] exploits both information maximization and self-supervised learning for feature extraction. It divides the target data into two splits according to the confidence of predictions (label information) and then employs semi-supervised learning to improve the accuracy of less-confident predictions. So two challenges need to be overcome for SFUDA. **One challenge is how to establish a meaningful source model.** Emotional EEG is highly correlated with personality, living environment, and culture. This paper hypothesizes that the emotional features of EEG signals can be divided into domain-invariant features and domain-specific features. **The other challenge is how to improve the quality of the pseudo-labels generated by the clusters and optimize the training process.** Papers [4, 5] applied the IM loss [6, 7, 8] to make the target outputs individually similar and globally diverse. Lee et al. [9] proposed a Confidence score Weighting Adaptation using the JMDS (CoWA-JMDS) framework to solve the SFUDA problem.

In this paper, for the cluster feature, contrastive learning is applied to align domain-invariant features and domain-specific features. It is hoped that the two features are close when they are obtained from the same sample. For the feature cluster, three state-of-the-art methods for solving the SFUDA

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problem, namely SHOT [4], SHOT++[5], and CoWA [9] are adopted, implemented, and modified for EEG representation learning. Meanwhile, a comprehensive study is performed by comparing these methods when different pseudos labels are generated and different argument methods are applied. It is demonstrated that these methods can be effectively used in Brain-Computer Interface (BCI) for EEG emotion recognition, and features learned by minimizing the contrastive loss are more robust when generating pseudos-labels.

2. METHODS AND DATASETS

Let $\{(x_i^s, y_i^s)\}_{i=1}^n$ denote the dataset consisting of s pieces of source data and $\{(x_i^t, y_i^t)\}_{i=1}^n$ denote the target dataset, where $X_i \in R^{C \times T}$ represents the processed data, C represents the number of channels, T represents the data length, y corresponds to the condition (i.e., class) label, and $s_i \in \{1, 2, 3, \dots, k\}$ denotes the subject ID.

2.1. Training the shared feature extractor and the individual feature extractor

As shown in Fig1, in the first part, the shared feature extractor consists of three components: E_s a sharing feature extractor $f_1 = h_1(X; \theta_{f_1})$, a semantic classifier $c_1 = G_{y_1}(\cdot, \theta_{y_1})$, and a domain discriminator $d_1 = G_{d_1}(\cdot, \theta_{d_1})$. The classifier and the adversary network model satisfy the likelihoods $P_{\theta_{y_1}}(y|h)$ and $P_{\theta_{d_1}}(d|h)$, respectively. To extract the sharing feature, this paper proposes an adversarial game and applies Gradient Reversal Learning (GRL) to G_{d_1} . GRL maximizes the differential entropy $loss_{d_1}$ so that the model cannot discriminate the domains the data come from. Also, the feature extractor f_1 needs to avoid information loss and satisfy the likelihood $G_{y_1}(\cdot, \theta_{y_1})$. The following parameters are trained to fit the objective:

$$\hat{\theta}_{f_1}, \hat{\theta}_{y_1}, \hat{\theta}_{d_1} = \arg \min_{\theta_{f_1}, \theta_{y_1}} \max_{\theta_{d_1}} \mathcal{L}(\theta_{f_1}, \theta_{y_1}, \theta_{d_1}) \quad (1)$$

where the loss of the model is composed of two parts:

$$Loss_{sharing} = \alpha E_{h_1} E_{y_1} [-\log p_{\theta_{y_1}}(y_1|h_1)] + (1 - \alpha) E_{h_1} E_{d_1} [\log p_{\theta_{d_1}}(d_1|h_1)] \quad (2)$$

where α is a trade-off between the two loss functions, $1 > \alpha > 0$.

Due to each person's experience and long-term thinking style, a person's emotion EEG is unique and can be used for identification [10]. For the individual feature extractor, a multi-task approach is applied, the individual feature extractor $f_2 = h_2(X; \theta_{f_2})$, the semantic classifier $y_2 = G_{y_2}(\cdot, \theta_{y_2})$, and the domain discriminator $d_2 = G_{d_2}(\cdot, \theta_{d_2})$ are optimized by minimizing the loss of the label classifier

and the domain classifier to fit the likelihoods $P_{y_2}(y_2|h_2)$ and $P_{d_2}(d_2|h_2)$.

$$\hat{\theta}_{f_2}, \hat{\theta}_{y_2}, \hat{\theta}_{d_2} = \arg \min_{\theta_{f_2}, \theta_{y_2}} \min_{\theta_{d_2}} \mathcal{L}(\theta_{f_2}, \theta_{y_2}, \theta_{d_2}) \quad (3)$$

where the loss function is:

$$Loss_{individual} = \beta E_{h_2} E_{y_2} [-\log p_{\theta_{y_2}}(y_2|h_2)] + (1 - \beta) E_{h_2} E_{d_2} [-\log p_{\theta_{d_2}}(d_2|h_2)] \quad (4)$$

where β is the trade-off of the two losses, $1 > \beta > 0$.

To fully utilize the two types of features, the features from the same sample should be closer than those from different samples. Inspired by CLIP [11], $b_1 = h_2(x; \theta_{b_1})$ and $b_2 = h_2(x; \theta_{b_2})$, where b_1 and b_2 represent the shared feature and the individual feature, respectively. The following parameters are trained to fit the objective:

$$\hat{\theta}_{f_1}, \hat{\theta}_{f_2}, \hat{\theta}_{b_1}, \hat{\theta}_{b_2} = \arg \min_{\theta_{f_1}, \theta_{f_2}, \theta_{b_1}, \theta_{b_2}} \mathcal{L}(\theta_{f_1}, \theta_{y_1}, \theta_{d_1}, \theta_{d_2}) \quad (5)$$

where the loss function is:

$$Loss_{ctr} = \mathcal{L}(b_1 \cdot b_2', y') \quad (6)$$

where y' is the data index in a batch, b_2' is the transpose of b_2 , and the \mathcal{L} is the cross-entropy loss.

2.2. Unsupervised training without source data

SHOT and SHOT++ In both methods, the pseudo labels are generated by k-means clustering. For k-means, the initialized center point c_k^0 is calculated based on classification results $C1$ and $C2$ and the combined features. The features can be fused in two approaches: plus and stack together. After the center point in the k-means is updated, the pseudo labels \hat{y} are obtained, and the shared and private encoders can be updated by the loss:

$$\ell = l_{IM} - \gamma \cdot H((C(F(x_t)), \hat{y})) \quad (7)$$

where γ stands for the weight of the loss based on the clustering result. Meanwhile, the IM loss is adopted to avoid all the data clustering to a single class. $Loss_{ent}$ makes predictions more determined in a single result, while $Loss_{div}$ makes the result more dispersed among different categories. In SHOT++, data-augmented methods are integrated into the algorithm.

$$\begin{aligned} l_{IM} &= l_{ent} + l_{div}, \\ l_{ent} &= -E(x_t) \sum_{k=1}^K \delta(C(F(x_t))) \log \delta(C(F(x_t))), \\ l_{div} &= D_{KL}(\bar{p}_k, 1/K \cdot M_2) - \log K \end{aligned} \quad (8)$$

where K is the number of label classes, $\delta(C(F(x_t)))$ is the mean output embedding of the target data, and M_2 is a K -dimensional vector where all of the elements are 1. $\bar{p}_k =$

Table 1. The results of the state-of-the-art methods

Method	SEED	DEAP (valence)	DEAP (arousal)	DEAP (four class)
DGCNN [13]	0.7995±0.09	-	-	-
IAG [14]	0.863±0.07	-	-	-
DANN [15]	0.797±0.09	0.4982±0.13	0.502±0.21	0.303 ±0.12
Multi-task	0.799±0.08	0.523±0.09	0.534±0.16	0.272 ±0.21
DANN+contrastive-loss	0.863±0.01	0.577±0.14	0.61±0.16	0.403 ±0.02
Multi-task+contrastive-loss	0.873±0.02	0.586±0.12	0.613 ±0.14	0.412 ±0.01
SHOT(both)	0.883±0.01	0.537±0.01	0.565±0.08	0.372 ±0.01
SHOT++	0.892±0.02	0.546±0.01	0.616 ±0.01	0.383±0.01
CoWA	0.88±0.02	0.566±0.01	0.571±0.01	0.374±0.01

five bands (1-4 Hz, 4-8 Hz, 8-14 Hz, 14-30 Hz, 30-50 Hz) are calculated, and the moving average filter with a 10-second window is used. In the SEED test, the size of each sample is 310 (62 × 5). For this dataset, the feature extractor is a full network with three layers (310-128-64), the classifier is a one-layer network (64-3), and the domain classifier is also a one-layer network (64-14). In the DEAP dataset, the size of the input is 128 (32 × 4) with no 0-4 Hz band signal. After moving the baseline, a weight decay moving average is applied to the data. For this dataset, the feature extractor is also a network with three layers (128-96-64), the classifier is a one-layer network (64-2) for two-class and (64-4) for four-class, and the domain classifier is a one-layer network (64-31). The output size of the two bottleneck feature extractors is 64. Besides, in the DEAP dataset, the threshold of the label is set to 5 for valence and arousal binary classification, and four classification labels are generated by valence and arousal labels.

The default value for k-means clustering is set to 5 cycles. Meanwhile, the parameters including alpha, beta, and gamma are set to 0.1, 0.1, and 0.3, respectively. The learning rate is set to 0.0001, and the learning rate of anti-gradient recursion for training invariant features is set to 0.1. The batch size is set to 128. Additionally, the augmented data is generated by adding noise with a standard distribution. In the experiment, the proposed model is implemented by Pytorch and runs on an NVIDIA Geforce GTX GPU.

3.2. Results

The compared results are presented in Table 1. The first four methods are generalized learning models. **DGCNN** and **IAG** both generate adaptive graphs to adapt to variance subjects. To test the importance of the contrastive loss, the classification accuracy of **DANN** and **Multi-task** learning is compared in two conditions without self-supervised learning. **With the contrastive loss and the simplest neural network, both emotion recognition methods can achieve the best accuracy on the SEED and DEAP datasets, and they even perform better than the best generalization model.** The three unsupervised adaption methods also improve the

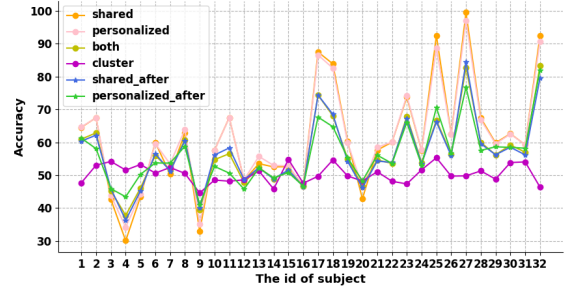


Fig. 2. The arousal EEG recognition accuracy of SHOT on the DEAP dataset. The “shared” and “personalized” denote the pre-training results.

accuracy of EEG emotion recognition on the SEED dataset. SHOT++ and CoWA achieve higher accuracy than SHOT, and the mixup trick and the high entropy weight optimization could improve the robustness of the model.

On the DEAP dataset, the classification accuracy of all three SFUDA methods drops significantly, but the EEG emotion recognition accuracy of 32 individuals is more stable. It can be seen from Figure2 that if the shared classifier and the personal classifier obtain a low accuracy for emotion recognition, K-means or GMM SFUDA methods could improve the accuracy little. Since these two methods are very sensitive to the initial center point, they are difficult to be corrected if the center points are in the wrong category area at the beginning. However, self-learning, augmented style recognition, and the mixup trick could make the same type of features more compact and improve accuracy.

4. CONCLUSION

This paper proposes a Contrastive Self-Supervised Learning (CSSL) framework for the online calibration of EEG recognition. Extensive experiments are conducted with three SFUDA methods, and our framework is evaluated on two public datasets. Meanwhile, the reasons for the results on different datasets are analyzed in detail. Experimental results

show that the contrastive pre-trained feature model can improve the accuracy of EEG emotion classification. However, this paper only uses noise-augmented data in self-learning, and more EEG data augmentation methods will be used in future work.

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