Conditional Domain Adaptation Based on Initial Distribution Discrepancy for EEG Emotion Recognition

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Abstract. How to integrate data in different feature spaces and distributions is a research hotspot in EEG-based emotion recognition. A novel source-domain adaptation strategy based on initial distribution differences for EEG emotion recognition is proposed, which selects several source domains that are most similar to the target domain for domain adaptation. Compared to the 'source-target pair' domain adaptation method using all source domains, this method improves accuracy by up to 10% and reduces computation time by up to 43%, based on the SEED-III and SEED-IV datasets.

Keywords: Emotion recognition · EEG · Transfer learning · Domain adaptation

1 Introduction

Emotions play an important role in the life of human-beings. EEG signals are one way to recognize people's emotions by machines [1,2]. The acquisition of EEG signals is affected by many factors such as individuals and equipment, resulting in different feature spaces and distributions across the data [3,4]. In practical application scenarios, it is usually required to use the original data to predict the emotional state of a new individual from their EEG signals. These cross-subject and cross-experiment data will result in low accuracy if trained and tested using a traditional machine learning model [5]. Therefore, how to integrate data for effective learning is a focus of research in this area.

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An important assumption that traditional machine learning relies on is that training data and future data must have the same feature space and distribution [6], but in many practical application scenarios, this assumption cannot be satisfied [7]. One solution is to introduce transfer learning in which data in the source learning system constitutes the source domain, and data in target learning system constitutes the target domain [8].

Domain Adaptation is a method of transfer learning, which is suitable for situations where the distributions of data features in the source and target domains are different [9]. This method inputs the data of the two domains into a feature transformer, thus changing these data into a new feature space. The distribution difference between the source domain and the target domain in this new feature space is then calculated by a specific distribution similarity criterion. The adaptation process is to train the feature extractor so that the distribution difference between the two target domains is as small as possible after transformation.

In this paper, a source-domain adaptation strategy based on initial distribution differences for EEG emotion recognition is proposed. This strategy does not use all source domains for domain adaptation, but selects those source domains that are most similar to the target domain for domain adaptation. The similarity criterion between target and source is the distribution difference without domain adaptation feature transformation. The target domain and each source domain respectively form a 'source domain-target domain pair' for domain adaptation. Based on the SEED-III and SEED-IV datasets, we test the accuracy and computation time for the proposed method using the chosen metric, and make comparisons with the original method.

2 Materials

Domain adaptation has been frequently used in the training of EEG-related models in recent years. Chai et al. [10] proposed a fast domain adaptation strategy that integrates marginal and conditional distributions into a single in a unified framework. Lin and Jung [11] explored a conditional transfer learning framework for sentiment classification by selectively applying data with similar feature spaces by evaluating the transferability of each sample. They use ReliefF [12] to form a feature space and use Pearson's correlation coefficient as an indicator of source domain selection, which, however, is not a specific strategy. Chen et al. [13] proposed a multi-source marginal distribution adaptation strategy (MSMDA), which pairs the target domain and each source domain one by one to form a 'source domain-target domain pair' for domain adaptation. The problem of information loss may be caused by merging all source domains into one source domain. However, using all source domains may lead to negative transfer due to too large gaps between some source and target domains.

Li-Ming et al. [14] devised a methodology called plug-and-play adaptation for cross-subject EEG-based emotion recognition, which can be used to enhance user experience and make EEG-based affective computing applications more practicable. Jinpeng et al. [15] proposed a multisource transfer learning method, where existing persons are sources, and the new person is the target. In the work of Dongdong et al. [16], a multiple source domain adaptation method is proposed to learn fault-discriminative but working condition-invariant features from raw vibration signals. Different known working conditions are assigned different weights, on the basis of their distributional similarities to the target working condition. Zirui et al. [17] compared two public datasets DEAP and SEED used in domain adapation, based on which in this paper SEED is chosen for its coverage.

The datasets used in this paper are SEED-III [18] and SEED-IV [19]. SEED is a series of datasets for EEG sentiment analysis, which uses discrete sentiment classification as labels, with three sentiment labels in SEED-III and 4 in SEED-IV. 15 subjects participated in the data collection. In order to ensure the universality of the data, each dataset is divided into three sessions, each session representing data taken in a period of time. There are 15 trails in a session. The device collected EEG data from 62 channels (electrodes) of the subjects (Fig. 1).

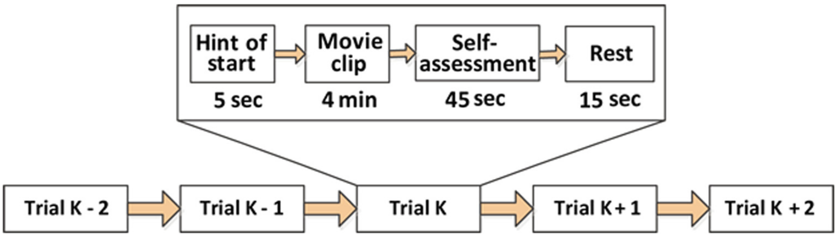

Fig. 1. The data collection process within a trail. In a trail, subjects watch a 4-min movie clip, and the emotional label corresponding to the 4-min EEG data is determined by the type of movie clip.

The collected data is firstly processed by down-sampling 200 Hz and filtered at 0 75 Hz, and then mapped to five commonly used frequency bands through Fourier transform. Finally, the differential entropy is used to process the data sequence. The relevant literature [20] proves that the differential entropy is more suitable for EEG data than other feature extraction methods.

3 Methods

Inspired by the work of Lin and Jung [11] and Chen [13], we propose two hypotheses: (1) conditionally selecting several source domains whose initial distribution is most similar to the target domain, and using these source domains, ideal classification results can be achieved; (2) since the contribution of each source domain to model training is different. The more similar a source domain and the target domain are in the initial distribution, the better the effect of using this source domain for domain adaptation, and the greater the accuracy of the model.

A series of experiments were conducted to test these hypotheses using SEED-III and SEED-IV, thus obtaining and validating a conditional source domain selection strategy based on initial distribution differences.

The model used is an improved version of MSMDA [13]. In Fig. 2, each source and target domain is the EEG data of a certain subject. Before performing domain adaptation, it is necessary to calculate the initial distribution difference (dist. discrepancy) between each source domain and the target domain. The blue source field in the figure indicates that the difference is acceptable, and the red one indicates it is not. The remaining domains including source and target are then sent to Common Feature Extractor to extract their common features. Source domains are paired one by one with the target domain and enter the Domain-specific Feature Extractor, where the distribution difference between the two is calculated as part of the loss function (dist. loss). Then, the output of each DSFE is fed into the corresponding domain-specific classifier. The magnitudes of the difference between results of these classifiers are also used as part of the loss function (disc. loss). Finally for each DSC, the difference (cls. loss) between their output and the actual label is calculated. The final output of the model is the average of all DSC outputs.

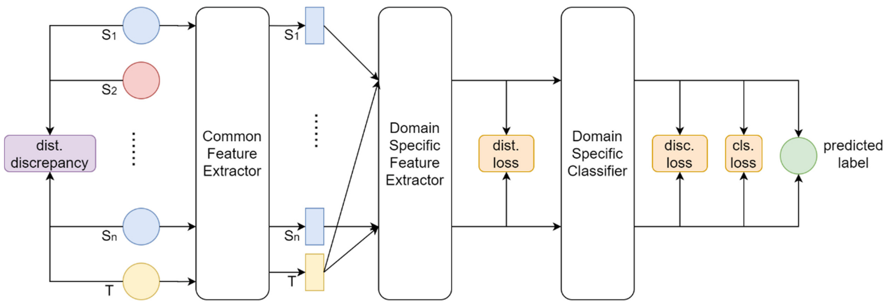

Fig. 2. The structure of the proposed model. The main difference from MSMDA is that the initial distribution difference between the source domain and the target domain is calculated before entering the model, thereby eliminating those source domains with large differences.

Step 1: Finding the Best Distribution Difference Metric. Currently, the most commonly used metric in domain adaptation is the Maximum Mean Discrepancy (MMD). The formula is as follows:

$$MMD(p, q, F) = \left\| \frac{1}{m} \sum_{i=1}^{n} f(x_i) - \frac{1}{n} \sum_{j=1}^{m} f(y_j) \right\|_H \tag{1}$$

However, the calculation of MMD needs to use a Gaussian kernel function, and the calculation process is relatively cumbersome. Note that the data in the source and target domains in the model have been transformed by DFE before dist. Loss is calculated. Therefore, the mean difference of norm 1 can be calculated directly on the transformed data (Mean Discrepancy, MD-L1). Its formula is as follows:

$$MD(p, q) = \left\| \frac{1}{n} \sum_{i=1}^{n} x_i - \frac{1}{m} \sum_{j=1}^{m} y_j \right\|_1 \tag{2}$$

It has also been proposed [21] that K-L Divergence (KLD) can be used to measure the distribution difference: the smaller the value of KLD, the more similar the two distributions are. KLD is defined as follows:

$$D_{KL}(p \| q) = \sum_{i=1}^{n} p\left(x_i\right) \log \frac{p\left(x_i\right)}{q\left(x_i\right)} \tag{3}$$

In order to choose the best metric, three metrics are used to compare the accuracy and computation time of the model. These three metrics are used in the model as dist. discrepancy and dist. loss.

Step 2: Calculate the Initial Variance of the Distribution. The initial distance between the source domain and the target domain is the criterion for selecting the source domain, so it needs to be calculated first. The distribution difference measure used here is the best metric obtained in the first step.

Step 3: Determine the Source Domain Selection Strategy. In the first session of SEED-III, 2 14 source domains are selected from small to large and built corresponding models to complete the training. The ones with higher accuracy are selected first, and when the difference in accuracy between the two source domains is below 2%, the one requiring less computation time is chosen, thus obtaining the optimal number of source domains. After this, the largest distances (i.e. distribution differences) of these source domains relative to the target domain can be obtained (d_{max}), and the average distance is d_{avg}. A ratio $p = d_{max}/d_{avg}$ between the largest distance and the average distance can be used to determine the optimal source domain selection strategy: for a new target domain, set its average distance to all source domains to be d'_{avg}, a predicted distance threshold $d'_{max} = p * d'_{avg}$ can be obtained; all source domains with distances less than this threshold can be selected for domain adaptation toward the target domain.

Step 4: Verify Source Domain Selection Policy. To validate our proposed conditional source domain strategy, data from other sessions of SEED-III and all sessions of SEED-IV is used. The accuracy and time-consuming between proposed method and MSMDA are compared [13].

4 Results

4.1 The Best Distribution Difference Metric

Table 1. The average and variance of the accuracy and calculation time of the three indicators

Metric	Average accuracy/%	Standard deviation	Average computation time/s	Standard deviation
MMD	82.87	8.56	2745	7
MD-L1	83.58	6.61	2606	6
KLD	74.12	8.11	2629	5

Table 1 shows the accuracy and calculation time corresponding to the three metrics in the first session of SEED-III with different subjects as the target domain. The remaining 14 subjects were used as the source domains. It can be seen that the accuracy of MMD and MD-L1 is comparable, and that of MD-L1 has less fluctuation among subjects. Among the three metrics, the computation time of MD-L1 is the lowest, KLD the second, and MMD the highest. Considering both accuracy and calculation time, MD-L1 is the best. Subsequent experiments will use MD-L1 as a measure of distributional differences.

4.2 Source Domain Selection Strategy

Table 2. The optimal number of source domains and related data for each subject

Subject number	Optimal number	The farthest distance	Average distance	p value
0	11	0.0547	0.0422	1.30
1	10	0.0328	0.0230	1.42
2	7	0.0145	0.0228	0.64
3	14	0.0871	0.0319	2.73
4	14	0.0531	0.0256	2.07
5	10	0.0357	0.0353	1.01
6	11	0.0505	0.0243	2.08
7	2	0.0230	0.0631	0.36
8	7	0.0438	0.0418	1.05
9	11	0.0531	0.0411	1.29
10	9	0.0316	0.0253	1.25
11	5	0.0076	0.0228	0.33
12	10	0.0390	0.0384	1.01
13	12	0.0475	0.0228	2.08
14	5	0.0078	0.0225	0.35

Table 2 shows the optimal number of source domains and related information. The p-value is the ratio of the largest source domain distance to the average domain distance. At the optimal number of source domains, most subjects had p-values between 1 and 1.5. Therefore, when p = 1.5, that is, when the largest distance of the selected source domain is 1.5 times the average distance from the target domain to all source domains, the accuracy and computation time reach the best balance. Combined with the selection order of the source domain, the optimal conditional source domain selection strategy can be obtained as Algorithm 1.

Algorithm 1. Optimal Conditional Source Domain Selection Strategy

Inputs:target domain T,source domains S_1,S_2,...,S_n
(1) Calculate the distance between each source domain and target domain $d(T, S_i)$,with the metric $MD - L1$.
(2) Sort the source domains according to $d(T, S_i)$ from small to large, and set the order of the source domain after sorting as $S_{d_1}, S_{d_2}, ..., S_{d_n}$.
(3) Suppose the set of selected source domains is $\mathcal{S} = S_(d_1)$,the average distance from the target domain to all source domains is $S_avg, i = 2$.
(4) if $d(T, S_(d_i)) \leq d_avg \times 1.5$, add $S_(d_i)$to $\mathcal{S}$,$i = i + 1$, repeat this step,otherwise end.
Outputs: set of source domains for domain adaptation $\mathcal{S}$

4.3 Verifying the Source Domain Selection Strategy

Table 3. Average accuracy of source domain selection strategy and original method

Data	The optimal strategy/%	The original method/%
SEED-III session2	77.49	77.21
SEED-III session3	80.09	78.80
SEED-IV session1	55.00	54.79
SEED-IV session2	62.43	55.79
SEED-IV session3	61.65	55.39

Table 4. Average computation time of source domain selection strategy and original method

Data	The optimal strategy/s	The original method/s
SEED-III session2	1963	2890
SEED-III session3	1643	2886
SEED-IV session1	531	697
SEED-IV session2	493	689
SEED-IV session3	466	690

In terms of accuracy (as shown in Table 3), the source domain selection strategy is slightly higher than MSMDA, and this advantage is more obvious in SEED-IV.

In terms of computation time (as shown in Table 4), the source domain selection strategy is greatly reduced compared to MSMDA. Validation experiments show that the conditional source domain selection strategy can achieve higher accuracy with a smaller number of source domains, and the required computation time is also greatly reduced.

5 Discussion

Effectiveness of Source Domain Selection Strategy. It can be concluded from the experiment that for most subjects, the peak of the accuracy rate does not appear when the number of source domains is 14, indicating that negative transfer occurred. Table 3 shows that the source domain selection strategy has a certain improvement in accuracy compared to the original method. Besides, since the conditional selection strategy reduces the usage of source domains, the scale of the model is also reduced, so the overall computation time is also significantly lower than the original method.

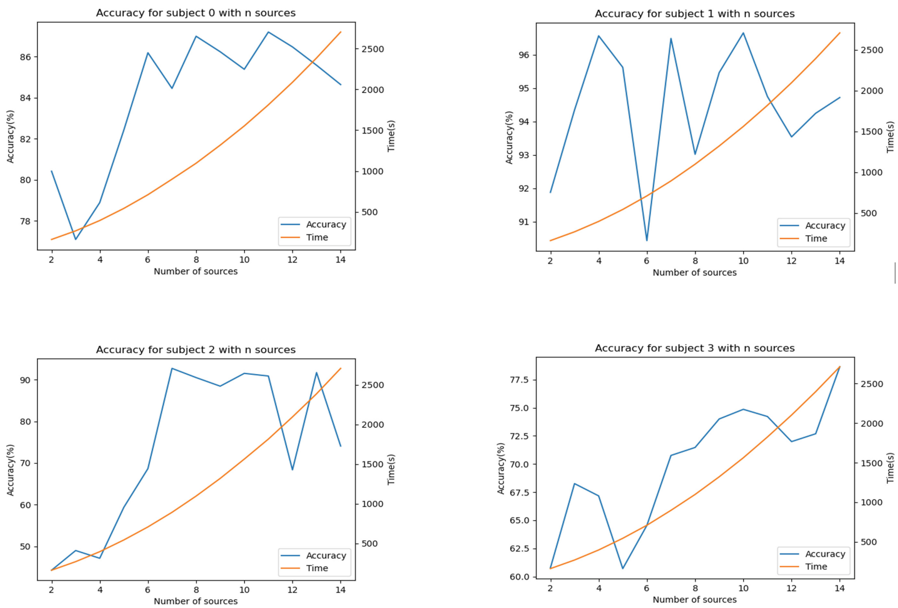

Fig. 3. The trend of accuracy and computation time of the top 4 subjects in the first session of SEED-III with number of source domains. The abscissa is the number of source domains, the blue line the accuracy, and the orange line the computation time. (Color figure online)

Extension of Source Domain Selection Strategy in Other Fields. The proposed source domain selection strategy is theoretically applicable to all domain adaptation tasks. As machine learning technology gradually penetrates into various applications, more tasks with data heterogeneity and data scarcity will appear in the future, and the proposed method is expected to improve the performance of machine learning models in those tasks.

Limitations of Source Domain Selection Strategy. For a new target domain (subject), the number of source domains to select is related to the optimal number of source domains for the existing data. In fact, it can be seen from Fig. 3 that the accuracy rate with the number of source domains is not a single peak, indicating that the initial distribution difference between source and target cannot completely determine the contribution of the source domain to the model. In order to obtain better source domain selection criteria, some mathematical analysis may need to be introduced. In validation experiments, only comparison with MSMDA is made, which can only show that the proposed method outperforms the 'source-target pair' full-source domain adaptation method. To further evaluate our method, it is necessary to compare the proposed method with those methods that combine all source domains into one.

6 Conclusion

In this paper, a conditional source domain selection strategy for EEG emotion recognition is proposed. On the SEED-III and SEED-IV datasets, this novel method improves accuracy by up to 10% and reduces computation time by up to 43% compared to the 'source-target pair' domain adaptation method using all source domains. Experimental results show that (1) using these source domains respectively, ideal classification results can be achieved. (2) the more similar a source domain and the target domain are in the initial distribution, the better the effect of using this source domain for domain adaptation, and the greater the accuracy of the model, which exactly are our hypotheses. The proposed source domain selection strategy is theoretically applicable to all domain adaptation tasks. In the future, we aim to introduce some mathematical analysis and also to compare the proposed method with other relevant methods that combine all source domains into one.

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