AU-Guided Unsupervised Domain Adaptive Facial Expression Recognition

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Abstract

The domain diversities including inconsistent annotation and varied image collection conditions inevitably exist among different facial expression recognition (FER) datasets, which pose an evident challenge for adapting the FER model trained on one dataset to another one. Recent works mainly focus on domain-invariant deep feature learning with adversarial learning mechanism, ignoring the sibling facial action unit (AU) detection task which has obtained great progress. Considering AUs objectively determine facial expressions, this paper proposes an AU-guided unsupervised Domain Adaptive FER (AdaFER) framework. In AdaFER, we first leverage an advanced model for AU detection on both source and target domain. Then, we compare the AU results to perform AU-guided annotating, i.e., target faces that own the same AUs with source faces would inherit the labels from source domain. Meanwhile, to achieve domain-invariant compact features, we utilize an AU-guided triplet training which randomly collects anchor-positive-negative triplets on both domains with AUs. We conduct extensive experiments on several popular benchmarks and show that AdaFER achieves state-of-the-art results on all the benchmarks.

1. Introduction

Facial expression is one of the most important modalities in human emotional communication. Accurately recognizing facial expressions helps understand various human emotions and intents, which is applied in wide-range applications, such as human-computer interaction [6], service robots [12], and medicine treatment [17]. Both in industry and academy areas, in the past decades, many well-labeled datasets [27, 38, 51, 10, 3, 32, 11, 23] and high-performance algorithms [41, 24, 40] have been proposed to automatically recognize facial expressions in the past decades.

In general, deep learning based facial expression recognition (FER) methods [32, 11, 23, 41, 24, 40] achieve high performance only when the training domain is identical or similar to the testing domain. However, due to the diversities of inconsistent annotation and different image collection condition, there inevitably exists domain gap among different datasets, which poses an evident challenge for adapting the FER model trained on one dataset to another one. As shown in Figure 1, a naive cross-domain method that deploying the trained model on different target domain often fails. To this end, many methods have been presented to mitigate the domain shift in FER [47, 43, 56], while almost all the methods follow general domain adaption algorithms and ignore the sibling facial action unit (AU) detection task. Action units represent the movement of the facial muscles, which are more objective than facial expressions and can be regarded as a type of domain-invariant cues.

In this paper, considering the remarkable progress of AU detection [34, 16], we propose an AU-guided unsupervised Domain Adaptive FER (AdaFER), to bridge the gap of dif-
different facial expression datasets. The AdaFER consists of two crucial modules: AU-Guided Annotating (AGA) and AU-Guided Triplet Training (AGT). Given two groups of images from source domain and target domain, we first use an advanced model for AU detection on both domains. Then, we perform AU-guided annotating as following. For each image on target domain, we use its AUs to query the source domain. All these images on source domain with the same AUs as the query image will be used for annotating. By default, the query image is assigned with a soft label which is the statistic label distribution of retrieval source images. Further, to achieve domain-invariant compact facial expression features, we perform the AU-guided triplet training. Each triplet is generated by comparing the AUs of source and target images. For example, when a source image is used as an anchor, we randomly sample a positive(negative) sample that has same(different) AUs as the anchor from all target images. With AdaFER, we are able to fine-tune a source-pretrained model on target domain with both pseudo soft labels and triplet loss, which effectively bridges the gap of FER datasets.

Overall, our contributions can be summarised as follow,

- We heuristically utilize the relationship between action units and facial expressions for cross-domain facial expression recognition, and propose AU-guided unsupervised Domain Adaptive FER (AdaFER).
- We elaborately design an AU-Guided Annotating module to assign soft labels for target domain and an AU-Guided Triplet Training module to learn compact and discriminative facial features.
- We conduct extensive experiments on several popular benchmarks and significantly outperform the state-of-the-art methods.

2. Related Work

2.1. Facial Expression Recognition

Recently, facial expression recognition has achieved a significant progress due to the well-designed feature extraction methods and high-performance algorithms. They first detect and align faces using several popular face detectors like MTCNN [49] and Dlib [1]. For feature extraction, a large number of methods focus on modeling the facial geometry and appearance features to help facial expression recognition. From the feature type view, these features can be generally divided into hand-craft feature and deep-learning feature. The hand-craft feature is used to extract the texture-based features and geometry-based features [33, 36, 8]. Hybrid features refer to that combine two or more texture-based and geometry-based features. For deep-learning feature, Tang [47] and Kahou et al. [18] utilize deep CNNs for feature extraction, and win the FER2013 and Emotiw2013 challenge, respectively. Zhou et al. [54] achieve a remarkable result in Emotiw2019 multi-modal emotion recognition challenge by using audio-video deep fusion method. To address the pose variant and occlusion in FER, Wang et al. [41] and Li et al. [24] design region-based attention network. Wang et al. [40] propose Self-Cure Network to suppress uncertain samples in FER datasets. Liu et al. [25] introduce a Facial Action Units (FAUs) based network for expression recognition. Daniel McDuff Daniel et al. [29] present a cross-platform real-time multi-face expression recognition toolkit using the (FAUs), which shows the robustness of FAUs in FER system.

2.2. Cross-Domain FER

It is inevitable to exist distribution divergences among different facial expression datasets due to the variant collecting conditions and annotating subjectiveness. In past decades, cross-domain FER (CD-FER) has got more attention [5, 22, 30, 35, 45, 46, 47, 52, 53, 56]. Generally, the CD-FER can be divided into semi-supervised-based, unsupervised-based, and generate-based methods. Semi-supervised-based methods [20, 45] apply Convolutional Neural Network (CNN) model to train a classification model using limited labeled samples from target domain. For unsupervised-based methods, Valstar et al. [39] use a Gabor-feature based landmarks detector to localize facial and track these points in each sequence to model temporal facial activation for facial expression recognition. They trained the recognition model using the CK database and performed the test in the MMI database for cross-validation. Zheng et al. [53] propose a transductive transfer subspace learning method using labeled source domain images and unlabelled auxiliary target domain images to jointly learn a discriminative subspace. For generate-based methods, Zong et al. [57] propose a domain regeneration framework (DR) that aims at learning a domain regenerator to regenerate samples from source and target databases, respectively. Wang et al. [42] introduce an unsupervised domain adaptation method using generative adversarial network (GAN) on the target dataset and give the unlabelled GAN generated samples distributed pseudo labels dynamically according to the current prediction probabilities. In order to understand the conditional probability distributions differences between source and target datasets, Li et al. [22] develop a deep emotion-conditional adaption network that simultaneously considers conditional distribution bias and expression class imbalance problem in CD-FER. Chen et al. [43] propose a Adversarial Graph Representation Adaptation (AGRA) framework that unifies graph representation propagation with adversarial learning for cross-domain holistic-local feature co-adaptation. Different from the above works, our work focus on bridging the gap in un-
3. Methodology

In this section, we first overview the AdaFER, and then present its key modules. We finally present the details of training and inference.

3.1. Overview of AdaFER

The goal of our method is to mitigate the domain gap including inconsistent annotations and different imaging conditions. Considering the relationship between subjective facial expression and objective Action Units, we propose a simple yet efficient AU-guided unsupervised Domain Adaptive Facial Expression Recognition (AdaFER) method. Figure 2 illustrates the pipeline of our AdaFER which mainly consists of two crucial modules: i) AU-Guided Annotating (AGA) and ii) AU-Guided Triplet Training (AGT). Given images from source domain and target domain, we first utilize a pretrained AU detection model to extract the AUs for images from both domains. Then the AGA module assigns a soft/hard pseudo label for each image in target domain by comparing the AUs between source and target domain. Meanwhile, we mine triplets among source and target domains according AUs and apply Triplet loss for training. We jointly train the FER model on source domain with ground-truths and target domain with pseudo labels and triplets. AdaFER makes full use of the objective AUs to bridge the gap of FER datasets caused by subjective inconsistent annotation and different imaging condition.

3.2. AUs are domain-invariant

To check whether features are domain-invariant among different datasets, a good way is to train a dataset classifier using these features. As shown in [22], both traditional shallow features and deep learned features are able to classify different dataset effectively. Here we leverage the detected AUs as features to train a SVM classifier for dataset classification. Figure 3 shows the confusion matrix. As can be seen, the dataset recognition performance is bad which suggests using AUs to classify different FER datasets is difficult. In other words, AUs are domain-invariant among FER datasets.

3.3. AU-Guided Annotating

We introduce the AU-Guided Annotating (AGA) module to assign pseudo labels for target domain images according to AU detection results. Specifically, we elaborately design several assignment schemes as follows.

Source-based hard label assignment (S-hard). Given an image $X^s_i$ and its detected AUs $E^s_i$ from source domain, the S-hard scheme utilizes $E^s_i$ as a query to search target domain images that have equal AUs. Meanwhile, we mine triplets among source and target domains according AUs. For example, given an anchor image in target domain, a positive image in source domain is the one with equal AUs and a negative image is the one with different AUs. We jointly train the FER model on source domain with ground-truths and target domain with pseudo labels and triplets.
can be defined as follows,

\[ [X^1_t, \ldots, X^k_t] = Q_{S-\text{hard}}(E^i_s), \] (1)

where \([X^1_t, \ldots, X^k_t]\) are the retrieval images from target domain, \(Q_{S-\text{hard}}\) represents the S-hard operation. S-hard assigns all the retrieval images with the label of \(X^i_s\).

**Target-based hard label assignment** (T-hard). Different from S-hard, the T-hard scheme uses target domain images as query images. Given an image \(X^i_t\) and its detected AUs \(E^i_t\) from target domain, the query process can be formulated as follows,

\[ [X^1_s, \ldots, X^k_s] = Q_{T-\text{hard}}(E^i_t), \] (2)

where \([X^1_s, \ldots, X^k_s]\) represents the retrieval images from source domain. With the ground truth of source domain images, T-hard assigns the most frequent label to the target domain image \(X^i_t\).

**Target-based soft label assignment** (T-soft). For a query image from target domain, besides the hard assignment scheme, the T-soft directly uses the label distribution of retrieval samples to assign each target domain image a soft label vector. It is worth noting that there does not exist a source-based soft label assignment since we do not have the labels of target domain images.

**Learning with AGA.** After assigning pseudo labels for target domain, we can train FER models in traditional ways. Suppose \(Y_s \in \mathcal{R}^{1 \times M}\) represents the labels of \(M\) source domain images, \(Y_{S-\text{hard}} \in \mathcal{R}^{1 \times N}, Y_{T-\text{hard}} \in \mathcal{R}^{1 \times N}, Y_{T-\text{soft}} \in \mathcal{R}^{C \times N}\) denote the labels of \(N\) target domain images in S-hard, T-hard, and T-Soft schemes, we use the following loss function by default to train with AGA model,

\[ L_c = \text{CE}(P_s, Y_s) + \beta(\text{CE}(P_t, Y_{S-\text{hard}}) + \text{KL}(P_t, Y_{T-\text{soft}})), \] (3)

where CE denotes the Cross-Entropy loss function, KL is the KL Divergence loss function, \(P_t\) and \(P_s\) represent the predictions of target and source domains images. \(\beta\) is the trade-off ratio between the two loss values that calculate by pseudo labels and ground truths.

### 3.4. AU-Guided Triplet Training

To achieve domain-invariant compact facial features, we perform the AU-Guided Triplet Training (AGT) to further narrow the gap of different domains. The key step is to sample triplets from source and target domain.

**Triplet Selection.** Intuitively, we can select triplets from the union of source domain and target domain. However, considering CD-FER is a classification task, we ignore the triplets in source domain since ground truths are available. Specifically, we only keep those cross-domain triplets. Given an anchor in source domain \((X^a_s)\) or target domain \((X^a_t)\), we first use it to retrieve the images of target domain or source domain that own the same AUs, and then we randomly select a positive sample from target domain \((X^p_t)\) or source domain \((X^p_s)\) according to the retrieval samples, and a negative sample \(X^n_t\) or \(X^n_s\) according to the rest samples of target domain or source domain. Thus, we mainly select two kinds of cross-domain triplets: \((X^a_s, X^p_s, X^n_s)\) and \((X^a_t, X^p_t, X^n_t)\). We conduct triplet selection in an offline manner. In addition, we also perform hard negative mining by sorting the similarities between the AU scores of anchor and all negative samples. We randomly select a sample from these with AU similarities larger than a threshold \(\tau\) (0.6 by default) will be added as the negative sample.

**AU-Guided Triplet Loss.** After the selection of triplets, we use triplet loss to learn discriminative and compact features as follows,

\[ L_{tri} = \max\{0, \gamma - (\|F_a - F_n\| - \|F_a - F_p\|)\}, \] (4)

where \(F_a, F_p,\) and \(F_n\) represent the L2-normalized features of anchor, positive, and negative images, respectively. \(\gamma\) is a margin which can be a fixed hyper parameter or a learnable parameter. We evaluate it in the experiment section. Training with these cross-domain triplets, we can obtain a cross-domain common feature space which makes similar facial images close and dissimilar ones far away.

Considering both pseudo annotations and triplets, the total loss function is \(L_{all} = L_c + \epsilon L_{tri}\) where \(\epsilon\) is a trade-off ratio. Our method utilizes the AUs as guided information for unsupervised domain adaptive facial expression recognition task to learn domain-invariant features, which is the reason why we call our method as AdaFER.
3.5. Implementation Details

**AU detection and FER backbone.** Face images are detected and aligned by Retinaface [9] and further resized to 224 × 224 pixels. We utilize an advanced AU detector that pretrained on EmotiNet dataset using MLCR [34] algorithm, to extract AUs for each image. We then evaluate the effectiveness of AdaFER using ResNet-18 [15] with Pytorch toolbox. The ResNet-18 is pre-trained on the MS-Celeb-1M face recognition dataset and the facial features for triplet training are extracted from the last pooling layer.

**Training.** We train our AdaFER in an end-to-end manner with 1 Tesla V100, and set the batch size as 128, i.e., 128 triplets with ground-truth labels or pseudo labels. In each iteration, all the images are optimized by Cross-Entropy loss, KLDiv loss and AU-Guided Triplet Loss. The ratio β is defaulted as 1 and evaluated in the ensuing Experiments. The triplet loss margin γ is empirically set at 1:1, and its influence will be studied in the ensuing ablation study of Experiments. The leaning rate is initialized as 0.001 with Adam optimizer using Exponential (gamma = 0.9) scheme to reduce the learning rate. We stop training at 40-th epoch.

4. Experiments

In this section, we first describe employed datasets. We then demonstrate the robustness of our AdaFER in cross-domain facial expression recognition task. Further, we conduct ablation studies to show the effectiveness of each module and the settings of hyper-parameters in AdaFER. We then compare AdaFER to related state-of-the-art methods. Finally, to obtain a better understanding of AdaFER, we visualize the statistical distributions of CK+ and FERPlus datasets.

4.1. Datasets

**RAF-DB.** [23] consists of 30,000 facial images annotated with seven basic expressions and 14 compound expressions by 40 trained students. In our experiments, we default set RAF-DB as source dataset and only images with seven basic expressions (neutral, happiness, surprise, sadness, anger, disgust, fear, neutral) are used which leads to 12,271 images for training.

**FER2013 & FERPlus** [2] contain 28,709 training images, 3,589 validation images and 3,589 test images, all of which are resized to 48×48 pixels. FER2013 is collected by Google Image Search API and annotated by seven facial expressions. However, the annotation of FER2013 is not accurate because the there are only two annotators. Therefore, FERPlus is extended from FER2013 as used in the ICML 2013 Challenges, it is annotated by 10 annotators and added contempt category.

**CK+** [32] contains 593 video sequences from 123 subjects. Among these videos, 327 sequences from 118 subjects are labeled with seven expressions (except neutral), i.e. anger, contempt, disgust, fear, happiness, sadness, and surprise. All the subjects start from neutral and increase their expression intensity to seven expressions. Therefore, we select the last three frames with peak formation from each sequence and the first frame (neutral face) of each sequence, resulting in 1236 images. We follow previous work [32] to choose 1108 images for training and 128 images for testing.

**ExpW** [50] contains 91793 images that are annotated by one of the seven expressions. Since the official ExpW dataset does not provide training/testing splits, we follow [43] to select 28848 for training, 28853 for validating and 28848 for testing.

**JAFFE** [28] collects 213 images from 10 Japanese females in lab-controlled condition. We here choose 170 images for training and 43 images for testing.

4.2. AdaFER for Unsupervised CD-FER

To evaluate the effectiveness of AdaFER, we compare several baseline methods with our proposed AdaFER using RAF-DB as source dataset and testing on CK+, JAFFE, ExpW, FER2013, and FERPlus. The first baseline method directly applies the trained model on source domain to target domain. Another clever baseline (Baseline+) method generates pseudo one-hot labels by applying the trained model and then fine-tuned it on target domain. As shown in Table 1, several observations can be concluded as follows.

Firstly, our AdaFER achieves the best performance and outperforms both baseline methods on all the datasets with a large margin. Specifically, AdaFER obtains more significant improvement when testing on lab-controlled CK+ and JAFFE datasets, with about 14% and 30% improvement over baseline method. For in-the-wild datasets, the improvements are from 9% to 15%. It illustrates the improvement of AdaFER is more obvious when the domain divergence is large. Secondly, Baseline+ also achieve dramatic improvement over baseline, which suggests that annotating the target datasets is useful for CD-FER task. Thirdly, AdaFER method obtain evident improvements over Baseline+ method, which shows the strong robustness of AdaFER in CD-FER tasks.

**Visualization of AU-Guided Annotating.** To further investigate AdaFER, we visualize the pseudo labels of target images annotated by AGA module and Baseline+ method. Note that, here we show the annotations using T-soft assignment. As shown in Fig 4, AGA achieves better results than Baseline+ method. To better understand the differences between those two annotations, we visualize the weights of top3 categories in AGA. In the first 6 images, AGA assigns the highest weights on the ground-truth category and the highest weights outperforms a larger margin than other categories’ weights. We also show two bad cases in Fig 4.

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Table 1: Performance (%) comparison between the proposed AdaFER and baseline methods with unsupervised cross-domain facial expression recognition. ‘Baseline’ represents training on the source domain dataset, and testing on the target datasets directly. *These results are trained using source domain FER model to annotate the target domain images.

| Method  | CK+   | JAFFE  | ExpW  | FER2013 | FERPlus |
|---------|-------|--------|-------|---------|---------|
| Baseline | 68.99 | 27.91  | 55.83 | 49.46   | 55.25   |
| Baseline* | 79.84 | 51.16  | 66.07 | 54.81   | 65.12   |
| AdaFER  | 81.40 | 61.37  | 70.86 | 57.29   | 78.22   |

Figure 4: Visualization the results of two kinds of annotation methods on FERPlus dataset: BSA represents using the source domain pretrained model to annotate images from target domain, AGA denotes the AU-Guided annotating method using target domain images as query. The ground truths of images are written on the orange bars. Gray bars are noted the predicted categories of BSA. We show the top3 voting results of AGA on three colorful bars. Note that, the voting results are processed by normalization, the numbers represent the weights of each category.

which is even extremely ambiguous for human. The seventh and eighth images’ ground truths are sadness and happy, but many people would agree with the labels given by AGA. Due to the objectiveness of AGA, which suffers smaller influences from domain shifting. That is why we utilize AGA to provide pseudo labels for target domain images.

4.3. Ablation Studies

We conduct ablation studies for the modules of our AdaFER and crucial hyper parameters.

**Evaluation of three types of assignments.**

In AGA, we introduce three kinds of assignment, namely S-hard, T-hard, and T-soft. We explore which combination of them is the best mode and show the results in Figure 5. T-soft and T-hard achieve comparable results on these four datasets. T-soft outperforms visible improvements on CK+, FERPlus and FER2013 datasets. The performances of ‘Baseline’* are very sensitive to different target domains. Jointly using T-hard and S-hard can not achieve improvement, because of these two assignments may lead to the inconsistent annotations for target domain. T-soft and S-hard assignments are complementary with each other, therefore, we default use this mode in the following experiments.

**Evaluate the source of anchor images.** After evaluate the influences of three types assignments, we find that both using T-soft and S-hard are the best option.

![Figure 5: Evaluation of pseudo assignment strategies.](image-url)
fore. As shown in Table 2, we default use the best assignment scheme and explore the influences of different anchor sources on CK+, ExpW, FER2013, and FERPlus datasets. Several observations can be concluded as follows. Firstly, sampling anchor images from source domain obtains obvious improvement than that anchors from target domain when the target domain size is small. It is mainly due to the number of triplet tuples is too small. Secondly, jointly using anchor from source and target domains achieves the best performance on CK+, ExpW, and FER2013.

AU-Guided Annotating (AGA) and AU-Guided Triplet Training (AGT), are two crucial modules in AdaFER which mainly leverages the pseudo labels for target domain images and constraints the distance structure of each triplet tuple. To explore the effectiveness of each module, we conduct the evaluation on CK+ (lab-controlled FER dataset), ExpW, FER2013, and FERPlus (in-the-wild FER datasets). As shown in Table 3, both AGA and AGT can improve the baseline by a large margin. AGA performs better on CK+ and FRRPlus datasets but AGT performs better on ExpW and FER2013 datasets. Due to CK+ is a lab-controlled dataset and FERPlus has more annotators than FER2013, CK+ and FERPlus have more reliable annotations than ExpW and FER2013. Therefore, Fig 3 suggests that AGA is more useful on well-labelled target datasets and AGT is more suitable on noisy target datasets.

**Evaluation the margin $\gamma$ of AGT.** $\gamma$ is a margin parameter to control the distance difference between anchor-positive pair and anchor-negative pair. We evaluate it both fixed setting and learnable mode on 4 FER datasets in Figure 6. For fixed setting, we evaluate margin from 0.25 to 1.5. On all the 4 FER datasets, our default margin $\gamma = 0.5$ achieve the highest performances. For learnable mode, $\gamma$ converges to 0.62 (±0.034), 0.37 (±0.067), 0.71 (±0.026), and 0.42 (±0.033) on CK+, ExpW, FERPlus, and FER2013. Meanwhile, the learnable $\gamma$ also obtains competitive results.

**Evaluation of trade-off ratios $\beta$ and $\epsilon$.** $\beta$ is the trade-off ratio between two types loss values calculated by pseudo labels and ground truths. $\epsilon$ is the other trade-off ratio between $L_c$ and $L_{tri}$. We evaluate them from 0.0 to 2.0 on FERPlus dataset and present the results with two colors line in Figure 7. From the blue line, our AdaFER’s performance increase gradually and reach the peak point when $\beta$ is 1.0. The red line in Figure 7 goes up from 0.0 to 1.0, but drops dramatically when $\epsilon$ is larger than 1.0, which illustrates $L_{tri}$ is as important as $L_c$.

**Evaluation of the ratio of anchors from two domains.** To investigate the contributions of anchor images from source an target domains, we conduct an evaluation by exploring different ratios of anchor images between source and target domains. As shown in Figure 8, we train the ratio from 0.1 to 0.9. AdaFER achieves the highest results on these four datasets when ratio is set to 0.5.
Table 4: Comparison to the state-of-the-art methods on CK+, JAFFE, FER2013, ExpW datasets. The results of upper part are taken from the corresponding papers, and the results of the bottom part are taken from a cross-domain facial expression recognition benchmark’s implementations. The last column shows the mean accuracy of performances on all the datasets.

| Methods          | Source Dataset | Backbones            | CK+   | JAFFE | FER2013 | ExpW | Mean  |
|------------------|----------------|----------------------|-------|-------|---------|------|-------|
| Da et al. [7]    | BOSPHORUS      | HOG & Gabor Filters  | 57.60 | 36.2  | -       | -    | -     |
| Hasani et al. [13]| MMI&FERA&DISFA | Inception-ResNet     | 67.52 | -     | -       | -    | -     |
| Hasani et al. [14]| MMI&FERA       | Inception-ResNet     | 73.91 | -     | -       | -    | -     |
| Zavarez et al. [48]| Six Datasets   | VGG-Net              | 88.58 | 44.32 | -       | -    | -     |
| Mollahosseini et al. [31]| Six Datasets | Inception           | 64.20 | -     | 34.00   | -    | -     |
| DETN [21]       | RAF-DB         | Manually-Designed Net| 78.83 | 57.75 | 52.37   | -    | -     |
| ECAN [22]       | RAF-DB 2.0     | VGG-Net              | 86.49 | 61.94 | 58.21   | -    | -     |
| CADA [26]       | RAF-DB         | ResNet-18            | 73.64 | 55.40 | 54.71   | 61.87|
| SAFN [44]       | RAF-DB         | ResNet-18            | 68.99 | 49.30 | 53.31   | 68.32|
| SWD [19]        | RAF-DB         | ResNet-18            | 72.09 | 53.52 | 53.70   | 65.85|
| LPL [23]        | RAF-DB         | ResNet-18            | 72.87 | 53.99 | 53.61   | 68.35|
| DETN [21]       | RAF-DB         | ResNet-18            | 64.19 | 52.11 | 42.01   | 43.92|
| ECAN [22]       | RAF-DB         | ResNet-18            | 66.51 | 52.11 | 50.76   | 48.73|
| AGRA [43]       | RAF-DB         | ResNet-18            | 77.52 | 61.03 | 54.94   | 69.70|
| AdaFER          | RAF-DB         | ResNet-18            | 81.40 | 61.37 | 57.29   | 70.86|

Table 5: Evaluation of the threshold for hard negative mining.

| Threshold | CK+  | ExpW | FER2013 | FERPlus |
|-----------|------|------|---------|---------|
| 0         | 68.99| 65.24| 52.21   | 66.68   |
| 0.25      | 72.03| 68.23| 56.23   | 74.23   |
| 0.5       | 81.40| 70.86| 57.29   | 78.22   |
| 0.75      | 80.96| 69.12| 55.80   | 77.72   |

Evaluation of the threshold for hard negative mining. We evaluate the threshold from 0 to 0.75 on four datasets. As shown in Table 5, the performances on these four datasets have the same trend that threshold as 0.5 achieves the best results. Too small threshold makes $L_{tri}$ invalid. Too large threshold adds difficulties to compact facial expression features learning.

4.4. Comparison to state-of-the-art methods

Table 4 compares our AdaFER with 13 state-of-the-art (sota) methods in CD-FER task. The results of the bottom part using RAF-DB as source dataset, and the results of the upper part using other datasets. Our AdaFER achieves competing results on all the datasets. Zavarez et al. [48] achieve the sota on CK+ using six datasets. ECAN [22] obtain sota on JAFFE and FER2013 using a model pretrained on VGGFace2 and then finetune on RAF-DB2.0. More importantly, RAF-DB2.0 has not yet been open-sourced. Therefore, to make fair comparison, we mainly focus on comparing with other state-of-the-art methods on the bottom part of Table 4 where the backbone and source dataset are the same. To illustrate the comprehensive performance among these datasets, we calculate the mean accuracy of all methods. Specifically, our AdaFER obtains the performances of 81.40%, 61.37%, 57.29%, and 70.86% on CK+, JAFFE, FER2013, and ExpW datasets, which are the new state-of-the-art CD-FER results on these datasets. Note that, our AdaFER does not increase the computing cost in both train-
ing and inference stages. AGRN [43] need to extract holistic and local features to initialize the nodes of target domain in inference stage, which is time-consuming. LPL [23] rely on the assumption of both source and target domains. More importantly, different from all the methods in Figure 4 we utilize the natural domain-invariant features (AU encodings) to bridge the gap of facial expression datasets.

Understand AU-Guided Learning To better understand the differences between baseline and our AdaFER, we utilize the T-SNE to show the feature distributions in Figure 9. We can find that our AdaFER can learn more compact feature than baseline method in unsupervised CD-FER tasks. For CK+, ‘Neutral’ samples are the most scattered ones using baseline method, AdaFER can cluster them dramatically. For FERPlus, the clusters of all the categories samples gather into a small area. AdaFER can obviously divide it into several clusters, which illustrates the reason why we can improve baseline with a large margin.

5. Conclusion

In this paper, we address the unsupervised domain adaptive facial expression recognition task with the auxiliary facial action units. Specifically, we proposed an AU-guided unsupervised Domain Adaptive FER (AdaFER) framework which includes an AU-guided annotating module and an AU-guided triplet training module. We evaluate several AU-guided annotating strategies and triplet selection methods. Extensive experiments on several popular benchmarks show that i) AdaFER achieves state-of-the-art results and ii) obtains discriminative and compact facial expression features.

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