

LETTER

Unsupervised Cross-Database Micro-Expression Recognition Using Target-Adapted Least-Squares Regression*

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SUMMARY Over the past several years, the research of micro-expression recognition (MER) has become an active topic in affective computing and computer vision because of its potential value in many application fields, e.g., lie detection. However, most previous works assumed an ideal scenario that both training and testing samples belong to the same micro-expression database, which is easily broken in practice. In this letter, we hence consider a more challenging scenario that the training and testing samples come from different micro-expression databases and investigated unsupervised cross-database MER in which the source database is labeled while the label information of target database is entirely unseen. To solve this interesting problem, we propose an effective method called target-adapted least-squares regression (TALSR). The basic idea of TALSR is to learn a regression coefficient matrix based on the source samples and their provided label information and also enable this learned regression coefficient matrix to suit the target micro-expression database. We are thus able to use the learned regression coefficient matrix to predict the micro-expression categories of the target micro-expression samples. Extensive experiments on CASME II and SMIC micro-expression databases are conducted to evaluate the proposed TALSR. The experimental results show that our TALSR has better performance than lots of recent well-performing domain adaptation methods in dealing with unsupervised cross-database MER tasks.

key words: cross-database micro-expression recognition, micro-expression recognition, domain adaptation, transfer learning, least-squares regression

1. Introduction

Micro-expressions are short duration of facial expressions

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that cannot be repressed when people try to conceal their genuine emotions [1]. Recognizing micro-expressions has shown its potential value in many application fields, e.g., clinical diagnosis [2] and criminal investigation [3]. In contrast to ordinary facial expressions, micro-expressions have several characteristics, i.e., shorter duration and lower intensity, which makes micro-expression recognition (MER) a challenging task [4]. Nevertheless, the MER research has attracted lots of attentions of researchers from different fields in recent years and lots of effective methods have been proposed [5]–[8]. For example, in the work of [5] Pfister et al. first used the spatiotemporal descriptor, local binary pattern from three orthogonal planes (LBP-TOP) [9], to describe micro-expressions. Wang et al. [6] proposed a color space decomposition method to investigate whether color information is beneficial for MER.

Although these methods achieved promising results in MER, it is noticed that nearly all the existing methods are evaluated in an ideal scenario that the training samples and testing samples come from the same micro-expression databases. However, in the practical scenario, the training and testing micro-expression samples may be recorded by different equipments or under different environments, which would easily bring the large feature distribution difference between them and hence degrade the performance of these methods. Consequently, it is urgent to investigate a challenging but interesting MER problem, i.e., unsupervised cross-database MER, in which the training and testing samples belong to different micro-expression databases and the label information of training (source) samples is provided while the testing (target) labels are completed not given. To solve this challenging problem, Zong et al. [10], [11] first attempted to treat it as a typical domain adaptation problem and propose several novel domain adaptation methods including target sample re-generator (TSRG) and domain regeneration framework. Before that, most researchers focused on the research of cross-database facial expression recognition (FER), which is a challenging topic closely related to cross-database MER and proposed lots of effective methods. For example, in the work of [12], Chu et al. proposed a simple yet effective methods called selective transfer machine (STM). STM aims to learn a set of weights to re-weight the source samples such that they can share the same or similar feature distributions with the target ones. Sangineto et al. [13] proposed transductive parameter transfer approach based on a regression framework, which learns

multiple person-specific classifiers and maps these classifiers' parameters to target samples to construct a target adaptive classifier. Recently, Yan et al. [14] leveraged the basic idea of common subspace [15] and developed a dictionary learning method called unsupervised domain adaptive dictionary learning (UDADL) to solve cross-database facial expression recognition problem and achieved satisfactory performance.

In this paper, we investigate unsupervised cross-database MER and propose an effective least-squares regression (LSR) method called target-adapted LSR (TALSAR). Different from the above mentioned methods, the proposed TALSAR not only aims to eliminate the feature distributions mismatch between the source and target micro-expression samples, but also considers the different contributions of facial regions in cross-database MER. To evaluate the performance of the proposed TALSAR method, we conduct extensive cross-database MER experiments between CASME II [16] and SMIC [17] micro-expression databases. The experimental results showed that our proposed TALSAR have better overall performance in coping with unsupervised cross-database MER.

2. Proposed Method

2.1 Notations

In this section, we address the proposed TALSAR in detail and its application in unsupervised cross-database MER. To begin with, we introduce some notations that are needed in what follows. Suppose we have N_s source micro-expression samples and N_t target micro-expression samples. Their corresponding feature matrices are denoted by $\mathbf{X}^s \in \mathbb{R}^{Md \times N_s}$ and $\mathbf{X}^t \in \mathbb{R}^{Md \times N_t}$, respectively. Note that M is the number of faical regions yielded by the preset grids, e.g., 8×8 , which is widely used in MER research, and d is the dimension of feature vectors. We also denote the source and target feature matrices corresponding to the i^{th} facial region by $\mathbf{X}_i^s \in \mathbb{R}^{d \times N_s}$ and $\mathbf{X}_i^t \in \mathbb{R}^{d \times N_t}$. In addition, according to the task setting of unsupervised cross-database MER, the label information of source samples is provided. The source label matrix is denoted by $\mathbf{L}^s \in \mathbb{R}^{c \times N_s}$, where c is the micro-expression number. The i^{th} column \mathbf{l}_i^s in \mathbf{L}^s is a binary-valued vector and describes the label information of i^{th} sample in \mathbf{X}_i^s . Only its j^{th} element will be one while others will be all zero if it belongs to the j^{th} micro-expression.

2.2 Target-Adapted Least-Squares Regression

The basic idea of the proposed TALSAR is to enable the regression coefficient matrix learned based on the source micro-expression samples and its label information to predict the micro-expression categories of target samples. Meanwhile, TALSAR would also consider the different contributions of facial regions in solving unsupervised cross-database MER. Following this idea, we design the optimization problem for the TALSAR model which targets at learning

such a regression coefficient matrix \mathbf{U} as follows:

$$\min_{\mathbf{U}} \mathcal{L}_s(\mathbf{U}) + \lambda_1 \mathcal{R}_U(\mathbf{U}) + \lambda_2 \mathcal{R}_{st}(\mathbf{U}), \quad (1)$$

where λ_1 and λ_2 are the trade-off parameter to balance the items in TALSAR.

From Eq. (1), it is clear to see that the objective function of TALSAR consists of three major terms. The first term $\mathcal{L}_s(\mathbf{U})$ is the least-squares loss function whose aim is to describe the relationship between the source micro-expression samples and their labels. $\mathcal{L}_s(\mathbf{U})$ can be written as:

$$\mathcal{L}_s(\mathbf{U}) = \|\mathbf{L}^s - \mathbf{U}^T \mathbf{X}^s\|_F^2 = \|\mathbf{L}^s - \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^s\|_F^2, \quad (2)$$

where $\|\cdot\|_F$ denotes the Frobenius norm of a matrix.

The second term \mathcal{R}_U targets at picking out the facial regions contributing to distinguishing different micro-expressions and meanwhile weakening the remaining ones. We are able to achieve this goal by resorting to the group sparse item proposed in [18] which can be formulated as:

$$\mathcal{R}_U(\mathbf{U}) = \sum_{i=1}^M \|\mathbf{U}_i\|_F. \quad (3)$$

The last one is the regularization term \mathcal{R}_{st} . \mathcal{R}_{st} is designed for enforcing the target micro-expression samples after projection with \mathbf{U} to abide by the feature distribution of the source micro-expression samples such that the learned \mathbf{U} is also applicable to the label prediction of the target samples. To this end, we borrow the idea of low-rank constraint in the work of [19] and design \mathcal{R}_{st} as the following formulation:

$$\mathcal{R}_{st}(\mathbf{U}, \mathbf{Z}) = \left\| \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^s \mathbf{Z} - \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^t \right\|_F^2 + \lambda \|\mathbf{Z}\|_*, \quad (4)$$

where \mathbf{Z} is a linear reconstruction coefficient matrix of the projected target micro-expression samples with respect to the projected source ones and $\|\cdot\|_*$ denotes the nuclear norm of a matrix.

By combining the above three terms in Eqs. (2), (3), (4), we can arrive at the final optimization problem of TALSAR whose formulation is as follows:

$$\min_{\mathbf{U}, \mathbf{Z}} \|\mathbf{L}^s - \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^s\|_F^2 + \lambda_1 \sum_{i=1}^M \|\mathbf{U}_i\|_F + \lambda_2 \left\| \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^s \mathbf{Z} - \sum_{i=1}^M \mathbf{U}_i^T \mathbf{X}_i^t \right\|_F^2 + \lambda_3 \|\mathbf{Z}\|_*, \quad (5)$$

where the trade-off parameter corresponding to $\|\mathbf{Z}\|_*$ is obtained by $\lambda_3 = \lambda_2 \times \lambda$.

2.3 Optimization of TALSAR

We optimize TALSAR with alternated direction method (ADM). Specifically, the objective function is iteratively

minimized with respect to one of parameters \mathbf{U} and \mathbf{Z} while fixing the other one. The updating rule can be summarized as the following two steps.

(1) Fix \mathbf{Z} and update \mathbf{U} : in this step, we can arrive at the following optimization problem:

$$\min_{\mathbf{U}_i} \|\mathbf{L}^s, \mathbf{0}\| - \sum_{i=1}^M \mathbf{U}_i^T [\mathbf{X}_i^s, \sqrt{\lambda_2} \Delta \mathbf{X}_i^{st}] \|_F^2 + \lambda_1 \sum_{i=1}^M \|\mathbf{U}_i\|_F, \quad (6)$$

where $\Delta \mathbf{X}_i^{st} = \mathbf{X}_i^s \mathbf{Z} - \mathbf{X}_i^t$ and $\mathbf{0}$ is the zero matrix with the size of $c \times N_t$.

(2) Fix \mathbf{U} and update \mathbf{Z} : the optimization problem in this step can be written as:

$$\min_{\mathbf{Z}} \|\mathbf{U}^T \mathbf{X}^s \mathbf{Z} - \mathbf{U}^T \mathbf{X}^t\|_F^2 + \frac{\lambda_3}{\lambda_2} \|\mathbf{Z}\|_*. \quad (7)$$

Note that the above two sub-optimization problem can be efficiently solved by the inexact augmented Lagrangian multiplier (IALM) [20] method. The detailed solving procedures can be referred to [18], [20], [21].

2.4 Unsupervised Cross-Database MER Based on TALSR

Suppose $\hat{\mathbf{U}}$ is the optimal solution of TALSR learned by using the above method. We can then predict the micro-expression category of target samples by resorting to $\hat{\mathbf{U}}$. Let \mathbf{x}_{te}^t be the feature vector of one testing sample from target micro-expression database. Its label can be predicted as the i^{th} micro-expression, where the i^{th} element is the maximal one in $\mathbf{I}_{te}^t = \hat{\mathbf{U}}^T \mathbf{x}_{te}^t$.

3. Experiments

3.1 Experiment Setting

In this section, we conduct extensive unsupervised cross-database MER experiments on two publicly available micro-expression databases including CASME II [16] and SMIC [17] to evaluate the performance of the proposed TALSR. SMIC has three subsets, i.e., SMIC (HS), SMIC (VIS) and SMIC (NIR). They are recorded by a high-speed camera, a visual camera, and a near-infrared camera, respectively, where SMIC (HS) consists of 164 samples from 16 subjects and SMIC (VIS) and SMIC (NIR) contain 71 micro-expression video clips belonging to eight subjects. These samples are divided into three micro-expressions including *Positive*, *Negative*, and *Surprise*. CASME II database has 256 samples from 26 participants, which are categorized into seven micro-expressions (*Happy*, *Disgust*, *Repression*, *Surprise*, *Others*, *Sad*, and *Fear*).

In order to enable the micro-expression categories of CASME II to be consistent with SMIC, we select the samples of *Happy*, *Disgust*, *Sad*, *Fear*, and *Surprise* from original CASME II and then relabel them with the

Table 1 Statistics of relabeled CASME II and SMIC databases used for cross-database MER experiments.

Database	Negative	Positive	Surprise
CASME II	73	32	25
SMIC (HS)	70	51	43
SMIC (VIS)	28	23	20
SMIC (NIR)	28	23	20

same micro-expression labels in SMIC. Specifically, the *Happy* samples are relabeled with *Positive*, and the samples of *Disgust*, *Sad*, and *Fear* correspond to *Negative* micro-expression. The labels of *Surprise* samples remain unchanged. We summarize the sample statistics of new CASME II and SMIC in Table 1. In the experiments, we crop and transform the face image in the micro-expression video clips to 112×112 . Then, temporal interpolation model (TIM) [22] is used to normalize the frame number to 16. The multi-scale LBP-TOP [8] (uniform LBP-TOP with $R = 3$, $P = 8$ together with a multi-scale spatial division grids including 1×1 , 2×2 , 4×4 , and 8×8) is served as the micro-expression feature.

Based on the new CASME II and SMIC, we design SIX unsupervised cross-database MER experiments, i.e., $C \rightarrow H$, $H \rightarrow C$, $C \rightarrow V$, $V \rightarrow C$, $C \rightarrow N$, and $N \rightarrow C$, where C , H , V , and N are short for new CASME II, SMIC (HS), SMIC (VIS), and SMIC (NIR). In the experiment of $S \rightarrow T$, S and T denote source and target micro-expression database, respectively. *Mean F1 score* and *Accuracy* widely used in MER are chosen as the evaluation metrics in the experiments. *Accuracy* is the normal recognition rate, while *Mean F1 score* is defined as $F1 = \frac{1}{c} \sum_{i=1}^c \frac{2p_i \times r_i}{p_i + r_i}$, where p_i and r_i denote the precision and recall of the i^{th} micro-expression respectively, and c is the category number of micro-expressions.

In the experiments, we compare the proposed TALSR with recently well-performing unsupervised domain adaptation methods including importance-weighted support vector machine (IW-SVM) [23], transfer component analysis (TCA) [24], geodesic flow kernel (GFK) [25], subspace alignment (SA) [26], transfer kernel learning (TKL) [27], (TSRG) [10], (DRLS) [11]. Linear SVM with parameter $C = 1$ is served as the classifier for all the domain adaptation methods. To offer a fair comparison, the domain adaptation methods involving kernel function all choose linear kernel as the kernel function. In addition, SVM without any domain adaptation is also included in the comparison to serve as the baseline. Since the target label information is entirely unknown, cross-validation strategy is not available to determine the optimal hyper-parameter, e.g., the optimal number of eigenvectors for TCA and λ_1 , λ_2 , and λ_3 for TALSR. Hence, we follow the grid searching strategy, which is widely used in unsupervised domain adaptation experiments [10], [11], [27], and report the best result for all the method in term of *Mean F1 score* corresponding to the optimal hyper-parameters. Note that we also calculate the average *Mean F1 score* and *Accuracy* among all

Table 2 Results (mean F1 score / accuracy) of all the methods in the unsupervised cross-database MER experiments between CASME II and SMIC.

Method	$C \rightarrow H$	$H \rightarrow C$	$C \rightarrow V$	$V \rightarrow C$	$C \rightarrow N$	$N \rightarrow C$	Average
SVM	0.3697 / 45.12	0.3245 / 48.46	0.4701 / 50.70	0.5367 / 53.08	0.5295 / 52.11	0.2326 / 23.85	0.4112 / 45.55
IW-SVM [23]	0.3541 / 41.46	0.5829 / 62.31	0.5778 / 59.15	0.5537 / 54.62	0.5117 / 50.70	0.3456 / 36.15	0.4876 / 50.73
TCA [24]	0.4637 / 46.34	0.4870 / 53.08	0.6834 / 69.01	0.5789 / 59.23	0.4992 / 50.70	0.3937 / 42.31	0.5177 / 53.45
GFK [25]	0.4126 / 46.95	0.4776 / 50.77	0.6361 / 66.20	0.6056 / 61.50	0.5180 / 53.52	0.4469 / 46.92	0.5161 / 54.34
SA [26]	0.4302 / 47.56	0.5447 / 62.31	0.5938 / 59.15	0.5243 / 51.54	0.4738 / 47.89	0.3592 / 36.92	0.4877 / 50.90
TKL [27]	0.3829 / 44.51	0.4661 / 54.62	0.6042 / 60.56	0.5378 / 53.08	0.5392 / 54.93	0.4248 / 43.85	0.4925 / 51.93
TSRG [10]	0.5042 / 51.83	0.5171 / 60.77	0.5935 / 59.15	0.6208 / 63.08	0.5624 / 56.34	0.4105 / 46.15	0.5348 / 56.22
DRLS [11]	0.4924 / 53.05	0.5267 / 59.23	0.5757 / 57.75	0.5942 / 60.00	0.4885 / 49.83	0.3838 / 42.37	0.5102 / 53.71
TALSR	0.4934 / 49.39	0.5366 / 57.69	0.6362 / 63.38	0.5966 / 60.00	0.5907 / 59.15	0.4622 / 47.69	0.5526 / 56.21

SIX experiments for each method such that we can make an overall comparison between the proposed TALSR and other comparison methods.

3.2 Experimental Results

The experimental results are given in Table 2. From the results, something interesting can be found.

Firstly, it is clear to see that compared with the baseline method (SVM without domain adaptation), nearly all the domain adaptation methods achieved significant improvement in term of both *Mean F1 score* and *Accuracy* in all the experiments. This indicate that domain adaptation methods provide an effective way to cope with unsupervised cross-database MER problem.

Secondly, as the average results showed, it can be seen that the proposed TALSR achieves the best result in term of *Mean F1 score* among all the methods, which is significantly better than the results of all the comparison methods. Although TSRG performs better than TALSR in term of *Accuracy*, their results are actually very competitive, which can be clearly seen from the comparison between 56.21% (TALSR) and 56.22% (TSRG).

Finally, we can also observe that the proposed TALSR outperforms all the comparison methods in terms of both *Mean F1 score* and *Accuracy* in TWO experiments ($C \rightarrow N$ and $N \rightarrow C$) among all SIX experiments. In a word, the proposed TALSR has an overall satisfactory and superior performance in dealing with unsupervised cross-database MER tasks. In addition, it is beneficial for developing unsupervised cross-database MER method to take the contributions of facial regions into consideration, which is worth of focusing on in the future.

4. Conclusion

In this letter, we have proposed an effective method called target-adapted least-squares regression (TALSR) to deal with the unsupervised cross-database MER problem. The main contribution of the proposed TALSR is that TALSR is able to eliminate the feature distribution difference between the source and target micro-expression samples and meanwhile pick out the facial regions having contributions to

distinguishing different micro-expressions. To evaluate the performance of TALSR, we conduct extensive unsupervised cross-database MER experiments on CASME II and SMIC databases. Compared with recent state-of-the-art unsupervised domain adaptation methods, the proposed TALSR has an overall superior performance.

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