26th International Conference on Pattern Recognition

ICPR 2022

Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition

Xingxun Jiang, Yuan Zong#, Wenming Zheng#, Jiateng Liu, Mengting Wei,
Key Lab of Child Development and Learning Science (MoE),
School of Biological Science and Medical Engineering,
Southeast University

Outline

I. Introduction
II. TGSR Method
III. Experiment
IV. Conclusion

Outline

I. Introduction
II. TGSR Method
III. Experiment
IV. Conclusion

I. Introduction

- Micro-Expression Recognition (MER) is widely used in various subjects.

Polygraph


Social Interaction


Education and health

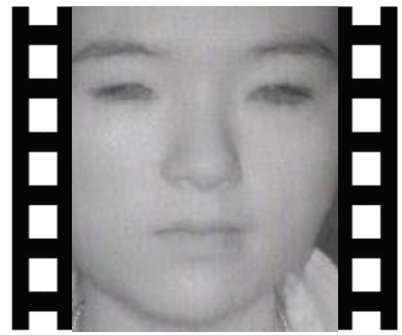
Practical MER required to be used in different domains, i.e., recognizing ME captured by various equipment from various subjects and scenes.
=> Practical application need a domain-robust MER model.

I. Introduction

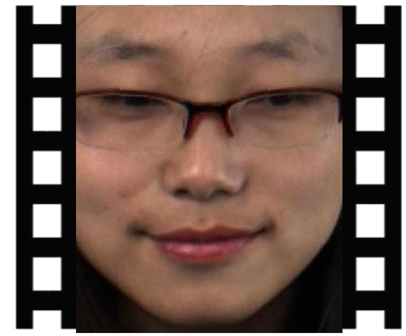
■ Cross-Database Micro-Expression Recognition (CDMER)

SMIC-HS

SMIC-VIS



SMIC-NIR



CASME II

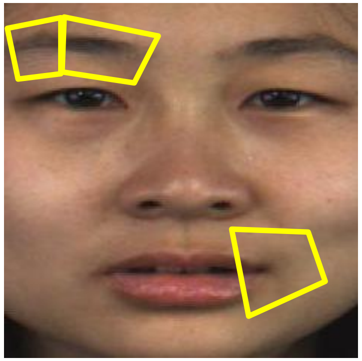
CDMER: evaluating the model’s adaptive ability operated by training the model in one database (source database) and testing in t he other (target database).

Two obstacles:

1) The severe feature distribution gap between the training and test databases.
2) The feature representation bottleneck of micro-expression such local and subtle facial expression, which requires professional knowledge.

I. Introduction

- Facial Region Selection Strategy



Selecting the salient ME regions conformed to anatomical definition (Facial Action Unit) for better CDMER.

1) promote a more precise measurement of the difference between the source and target databases by the operations in the feature level to alleviate this difference.
2) Improve the extracted hand-crafted feature to become more effective and explicable for better MER.

Outline

I. Introduction
II. TGSR Method
III. Experiment
IV. Conclusion

II. TGSR Method – Feature Generation

■ Extracting hierarchical micro-expression feature by grid-based multi-scale spatial division scheme

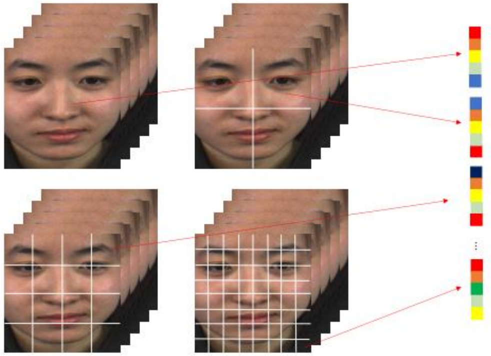


Fig. 1. The grid-based multi-scale spatial division scheme for extracting micro-expression feature.

1. A face is split into K local sequence (block);
2. Each spatial block: d dim feature $\boldsymbol{x}_k$;
3. Each micro-expression: $\boldsymbol{x}^\nu = \left[\boldsymbol{x}_1^{\mathrm{T}}, \cdots, \boldsymbol{x}_K^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{R}^{Kd}$;
4. Source database (N_s samples)
   - i-th facial block's feature is denoted by $\boldsymbol{X}_i^s \in \mathbb{R}^{d\times N_s}$;
   - Database's feature is denoted by $\boldsymbol{X}^s = \left[\boldsymbol{X}_1^{s\,\mathrm{T}}, \cdots, \boldsymbol{X}_K^{s\,\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{R}^{Kd\times N_s}$;
   - j-th sample's label is denoted by one-hot vector $\boldsymbol{l}_j^s = \left[l_{j,1}^s, \cdots, l_{j,C}^s\right]^{\mathrm{T}}$ which only $l_{j,c}^s$ equals to 1, indicating that sample belong to this category;
   - The label is denoted by $\boldsymbol{L}^s = \left[\boldsymbol{l}_1^s, \cdots, \boldsymbol{l}_{N_s}^s\right] \in \mathbb{R}^{C\times N_s}$, C is class number.
5. Target database (N_t samples)
   - i-th facial block's feature is denoted by $\boldsymbol{X}_i^t \in \mathbb{R}^{d\times N_t}$;
   - Database's feature is denoted by $\boldsymbol{X}^t = \left[\boldsymbol{X}_1^{t\,\mathrm{T}}, \cdots, \boldsymbol{X}_K^{t\,\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{R}^{Kd\times N_t}$.

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

II. TGSR Method – Proposed Method

- Transfer Group Sparse Regression Method

$$\min_{\boldsymbol{C}_i} \left\| \boldsymbol{L}^s - \sum_{i=1}^{K} \boldsymbol{C}_i^{\mathrm{T}} \boldsymbol{X}_i^s \right\|_F^2 + \underbrace{\boxed{\xi \left\| \frac{1}{N_s} \sum_{i=1}^{K} \boldsymbol{C}_i^{\mathrm{T}} \boldsymbol{X}_i^s \mathbf{1}_s - \frac{1}{N_t} \sum_{i=1}^{K} \boldsymbol{C}_i^{\mathrm{T}} \boldsymbol{X}_i^t \mathbf{1}_t \right\|_F^2}}_{①} + \underbrace{\boxed{\lambda \sum_{i=1}^{K} \|\boldsymbol{C}_i\|_F}}_{②} \quad (1)$$

① promote a more precise measurement of the feature different between the source and target databases in the label space to effectively alleviate this difference.
② improve the extracted hand-crafted feature to become more effective and explicable for better MER.

Note:
1. $\boldsymbol{C}_i \in \mathbb{R}^{C \times d}$ is such a domain-invariant regression matrix to bridge the feature of the i-th facial region from the source database and corresponding label; $\boldsymbol{C}_i$ is also shared with the source and target databases.
2. $\boldsymbol{C} = \left[\boldsymbol{C}_1^{\mathrm{T}}, \ldots, \boldsymbol{C}_K^{\mathrm{T}}\right]^{\mathrm{T}} \in \mathbb{R}^{Kd \times C}$ is the regression matrix, which is made of sub-matrix $\boldsymbol{C}_i$ to regress i-th facial local sequence.

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

II. TGSR Method – Optimization

- Solved by ADM and IALM

The problem can be rewritten into

$$\min_{C_i} \left\| \tilde{\boldsymbol{L}} - \sum_{i=1}^{K} \boldsymbol{C}_i^{\mathrm{T}} \tilde{\boldsymbol{X}}_i \right\|_F^2 + \lambda \sum_{i=1}^{K} \| \boldsymbol{C}_i \|_F, \quad (2)$$

where $\tilde{\boldsymbol{L}} = [\boldsymbol{L}^s, \boldsymbol{0}], \tilde{\boldsymbol{X}}_i = \left[\boldsymbol{X}_i^s, \sqrt{\xi}\left(\frac{1}{N_s}\boldsymbol{X}_i^s \boldsymbol{1}_s - \frac{1}{N_t}\boldsymbol{X}_i^t \boldsymbol{1}_t\right)\right]$.

Then we introduce a new variable, $\boldsymbol{D} = \left[\boldsymbol{D}_1^{\mathrm{T}}, \cdots, \boldsymbol{D}_K^{\mathrm{T}}\right]^{\mathrm{T}}$, which equals $\boldsymbol{C} = \left[\boldsymbol{C}_i^{\mathrm{T}}, \cdots, \boldsymbol{C}_K^{\mathrm{T}}\right]^{\mathrm{T}}$, thus the optimization of Equ. (2) can be converted in to Equ. (3)

$$\Gamma(\boldsymbol{C}_i, \boldsymbol{D}_i, \boldsymbol{P}_i, \mu) = \left\| \tilde{\boldsymbol{L}} - \sum_{i=1}^{K} \boldsymbol{D}_i^{\mathrm{T}} \tilde{\boldsymbol{X}}_i \right\|_F^2 + \lambda \sum_{i=1}^{K} \| \boldsymbol{C}_i \|_F + \sum_{i=1}^{K} \mathrm{tr}\left[\boldsymbol{P}_i^{\mathrm{T}}(\boldsymbol{C}_i - \boldsymbol{D}_i)\right] + \frac{\mu}{2} \sum_{i=1}^{K} \| \boldsymbol{C}_i - \boldsymbol{D}_i \|_F^2, \quad (3)$$

where $P_i \in \mathbb{R}^{d \times C}$ denotes the Lagrangian multiplier matrix corresponding to the i-th facial spatial local block sequence, and μ is the given trade-off coefficient.

II. TGSR Method – Optimization

■ Solved by ADM and IALM

To learn the optimal $\boldsymbol{C}_i$, we only need to minimize the Lagrange function of Equ. (3) while iteratively update $\boldsymbol{C}_i$ and $\boldsymbol{D}_i$.

1. Fix $\boldsymbol{C}, \boldsymbol{P}, \mu$ and update $\boldsymbol{D}$:

   In this step, the optimization problem with respect to the sub-matrix $\boldsymbol{D}_i$ of $\boldsymbol{D}$ can be written as Equ. (4), then solve its solution.

$$\min_{\boldsymbol{D}} \left\|\tilde{\boldsymbol{L}} - \boldsymbol{D}^{\mathrm{T}}\widetilde{\boldsymbol{X}}\right\|_F^2 + \mathrm{tr}\left[\boldsymbol{P}^{\mathrm{T}}(\boldsymbol{C} - \boldsymbol{D})\right] + \frac{\mu}{2}\|\boldsymbol{C} - \boldsymbol{D}\|_F^2, \tag{4}$$

   where $\boldsymbol{P}^{\mathrm{T}} = \left[\boldsymbol{P}_1^{\mathrm{T}}, \cdots, \boldsymbol{P}_K^{\mathrm{T}}\right], \boldsymbol{P} \in \mathbb{R}^{Kd\times C}, \boldsymbol{P}_j \in \mathbb{R}^{d\times C}$.

2. Fix $\boldsymbol{D}, \boldsymbol{P}, \mu$ and update $\boldsymbol{C}$:

   In this step, the optimization problem with respect to the sub-matrix $\boldsymbol{C}_i$ of $\boldsymbol{C}$ can be written as Equ. (5), then solve its solution.

$$\min_{\boldsymbol{C}_i} \lambda \sum_{i=1}^{K} \| \boldsymbol{C}_i \|_F + \sum_{i=1}^{K} \mathrm{tr}\left[\boldsymbol{P}_i^{\mathrm{T}}(\boldsymbol{C}_i - \boldsymbol{D}_i)\right] + \frac{\mu}{2}\sum_{i=1}^{K} \| \boldsymbol{C}_i - \boldsymbol{D}_i \|_F^2. \tag{5}$$

   We can convert Equ. (5) into Equ. (6), then solve its solution,

$$\min_{\boldsymbol{C}_i} \sum_{i=1}^{K} \left(\frac{\lambda}{\mu} \| \boldsymbol{C}_i \|_F + \frac{1}{2} \left\| \boldsymbol{C}_i - \left(\boldsymbol{D}_i - \frac{\boldsymbol{P}_i}{\mu}\right) \right\|_F^2\right). \tag{6}$$

3. Update $\boldsymbol{P}$ and μ.

4. Check the convergence of $\| \boldsymbol{C} - \boldsymbol{D} \|_\infty < \varepsilon$ (7)

II. TGSR Method – Optimization

- More details of the algorithm to solve the Equ.(3) for TGSR.

Algorithm 1: The algorithm to solve the optimal regression matrix $\boldsymbol{C}$ in TGSR model.

Input: $\tilde{\boldsymbol{L}}$, $\tilde{\boldsymbol{X}} = \left[\tilde{\boldsymbol{X}}_1^{\mathrm{T}}, \cdots, \tilde{\boldsymbol{X}}_K^{\mathrm{T}}\right]^{\mathrm{T}}$, salient region number κ , scalar parameter ρ and $\mu_{\max}$.

●Initializing the regression matrix $\boldsymbol{C} = \left[\boldsymbol{C}_1^{\mathrm{T}}, \cdots, \boldsymbol{C}_K^{\mathrm{T}}\right]^{\mathrm{T}}$, the Lagrangian multiplier matrix $\boldsymbol{P} = \left[\boldsymbol{P}_1^{\mathrm{T}}, \cdots, \boldsymbol{P}_K^{\mathrm{T}}\right]^{\mathrm{T}}$, and trade-off coefficient μ.

Repeating step 1) to 4) until convergence.

(1) Fix $\boldsymbol{C}, \boldsymbol{P}, \mu$ and update $\boldsymbol{D}$: $\boldsymbol{D} = \left(\mu \boldsymbol{I}_{Kd} + 2\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^{\mathrm{T}}\right)^{-1}\left(2\tilde{\boldsymbol{X}}\tilde{\boldsymbol{L}}^{\mathrm{T}} + \boldsymbol{P} + \mu\boldsymbol{C}\right)$

(2) Fix $\boldsymbol{D}, \boldsymbol{P}, \mu$ and update $\boldsymbol{C}$: Calculate $d_i = \left\|\boldsymbol{D}_i - \frac{\boldsymbol{P}_i}{\mu}\right\|_F$, and sort the value of d_i, such that $d_{i_1} \geq d_{i_2} \geq \cdots \geq d_{i_K}$, Let $\lambda = \mu d_{i_{\kappa+1}}$, then update C according to

$$\boldsymbol{C}_i = \begin{cases} \dfrac{d_i - \frac{\lambda}{\mu}}{d_i}\left(\boldsymbol{D}_i - \dfrac{\boldsymbol{P}_i}{\mu}\right), & \dfrac{\lambda}{\mu} < d_i \\ \boldsymbol{0}, & \dfrac{\lambda}{\mu} \geq d_i \end{cases}$$

(3) Update $\boldsymbol{P}$ and μ : $\boldsymbol{P} = \boldsymbol{P} + \mu(\boldsymbol{D} - \boldsymbol{C}), \mu = \min(\rho\mu, \mu_{\max})$.

(4) Check the convergence of $\| \boldsymbol{C} - \boldsymbol{D} \|_\infty < \varepsilon$.

Output: The solved $\hat{\boldsymbol{C}}$ of regression matrix $\boldsymbol{C}$.

II. TGSR Method – Application for CDMER

- Recognizing micro-expression using solved regression matrix.

We first extract the feature $\boldsymbol{x}_i^{te} \in \mathbb{R}^{Kd}$ of the micro-express to be predicted, then we can predict its label vector $\boldsymbol{l}^{\mathrm{te}}$ by solving the optimization problem as Equ.(8)

$$\min_{l^{te}} \left\| \boldsymbol{l}^{te} - \sum_{i=1}^{K} \hat{\boldsymbol{C}}_i^{\mathrm{T}} \boldsymbol{x}_i^{te} \right\|_F^2, \quad \text{s.t. } \boldsymbol{l}^{te} \geq 0;\ \mathbf{1}^{\mathrm{T}} \boldsymbol{l}^{te} = 1, \tag{8}$$

where $\hat{\boldsymbol{C}}_i \in \mathbb{R}^{d \times C}$ is the solved regression matrix of i-th facial spatial local region, and $\hat{\boldsymbol{C}}^{\mathrm{T}} = \left[\hat{\boldsymbol{C}}_1^{\mathrm{T}}, \cdots, \hat{\boldsymbol{C}}_K^{\mathrm{T}}\right], \hat{\boldsymbol{C}}^{\mathrm{T}} \in \mathbb{R}^{C \times Kd}, \boldsymbol{l}^{te} \in \mathbb{R}^{C}$. Then we can use Equ.(9) to assign its micro-expression label to the largest entry index of the predict label vector, i.e., micro-expression category $\hat{c}$.

$$\hat{c} = \arg\max_j \left\{\boldsymbol{l}_j^{te}\right\} \tag{9}$$

Outline

I. Introduction
II. TGSR Method
III. Experiment
IV. Conclusion

III. Experiment – Experimental Setup

- Database: Selected CASME II, SMIC;
  - SMIC: Positive, Negative, Surprise
  - Selected CASME II: Selected 4 category micro-expression to merge into 3 category; (Positive: Happiness), (Negative: Disgust, Repression), (Surprise: Surprise)
- Protocol:
  - TYPE-I: (Exp.1~Exp.6) between every two subsets of SMIC.
  - TYPE-II: (Exp.7~Exp.12) between Selected CASME II and every subset of SMIC.
- Evaluation Metrics: $Accuracy = \frac{T}{N}$ $Macro-F1 = \frac{1}{C}\sum_{c=1}^{C}\frac{2p_c r_c}{p_c + r_c}$
- Implementation Details:
  - Use Temporal Interpolation Model to fix each micro-expression sequence in to 16 frames; Then resize them into 112×112 pixels.
  - Use grid-based multi-scale spatial division scheme to divide the whole face into 1×1, 2×2, 4×4, 8×8, four scales totally $K = 85$ local facial sequence to extract and concatenate corresponding LBP-TOP features to serve as micro-expression representation.
  - MMD coefficient $\xi \in [0.001{:}\,0.0002{:}\,0.01\ \ 0.01{:}\,0.002{:}\,0.1\ \ 0.1{:}\,0.02{:}\,1\ 1{:}\,0.2{:}\,10\ \ 10{:}\,2{:}\,100\ \ 100{:}\,20{:}\,1000]$, salien region number $\kappa \in [1{:}\,1{:}\,85]$;

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

III. Experiment – Results and Analysis

- Results on TYPE-I (Exp.1~6) and TYPE-II (Exp.7~12) Experiment

Method	Exp.1(H→V)		Exp.2(V→H)		Exp.3(H→N)		Exp.4(N→H)		Exp.5(V→N)		Exp.6(N→V)	
	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC
SVM[39]	0.8002	80.28	0.5421	54.27	0.5455	53.52	0.4878	54.88	0.6186	63.38	0.6078	63.38
IW-SVM[40]	0.8868	88.73	0.5852	58.54	**0.7469**	**74.65**	0.5427	54.27	0.6620	69.01	0.7228	73.24
TCA[41]	0.8269	83.10	0.5477	54.88	0.5828	59.15	0.5443	57.32	0.5810	61.97	0.6598	67.61
GFK[42]	0.8448	84.51	0.5957	59.15	0.6977	70.42	0.6197	62.80	**0.7619**	**76.06**	0.8142	81.69
SA[43]	0.8037	80.28	0.5955	59.15	0.7465	**74.65**	0.5644	56.10	0.7004	71.83	0.7394	74.65
STM[44]	0.8253	83.10	0.5059	51.22	0.6628	66.20	0.5351	56.10	0.6427	67.61	0.6922	70.42
TKL[45]	0.7742	77.46	0.5738	57.32	0.7051	70.42	0.6116	62.20	0.7558	76.06	0.7580	76.06
TSRG[46]	0.8869	88.73	0.5652	56.71	0.6484	64.79	0.5770	57.93	0.7056	70.42	0.8116	81.69
DRLS[47]	0.8604	85.92	0.6120	60.98	0.6599	66.20	0.5599	55.49	0.6620	69.01	0.5771	61.97
Ours	**0.9150**	**91.55**	**0.6226**	**62.20**	0.5847	60.56	**0.6272**	**61.59**	0.6984	70.42	**0.8403**	**84.51**

Method	Exp.7(C→H)		Exp.8(H→C)		Exp.9(C→V)		Exp.10(V→C)		Exp.11(C→N)		Exp.12(N→C)	
	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC
SVM[39]	0.3697	45.12	0.3245	48.46	0.4701	50.70	0.5367	53.08	0.5295	52.11	0.2368	23.85
IW-SVM[40]	0.3541	41.46	0.5829	62.31	0.5778	59.15	0.5537	54.62	0.5117	50.70	0.3456	36.15
TCA[41]	0.4637	46.34	0.4870	53.08	**0.6834**	**69.01**	0.5789	59.23	0.4992	50.70	0.3937	42.31
GFK[42]	0.4126	46.95	0.4776	50.77	0.6361	66.20	0.6056	61.50	0.5180	53.52	0.4469	46.92
SA[43]	0.4302	47.56	0.5447	62.31	0.5939	59.15	0.5243	51.54	0.4738	47.89	0.3592	36.92
STM[44]	0.3640	43.90	**0.6115**	**63.85**	0.4051	52.11	0.2715	30.00	0.3523	42.25	0.3850	41.54
TKL[45]	0.4582	46.95	0.4661	54.62	0.6042	60.56	0.5378	53.08	0.5392	54.93	0.4248	43.85
TSRG[46]	**0.5042**	51.83	0.5171	60.77	0.5935	59.15	0.6208	63.08	0.5624	56.34	0.4105	46.15
DRLS[47]	0.4924	**53.05**	0.5267	59.23	0.5757	57.75	0.5942	60.00	0.4885	49.83	0.3838	42.37
Ours	0.5001	51.83	0.5061	56.92	0.5906	59.15	**0.6403**	**63.85**	**0.5697**	**57.75**	**0.4474**	**48.46**

Outperform those state-of-the-art methods on beyond half tasks.

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

III. Experiment – Results and Analysis

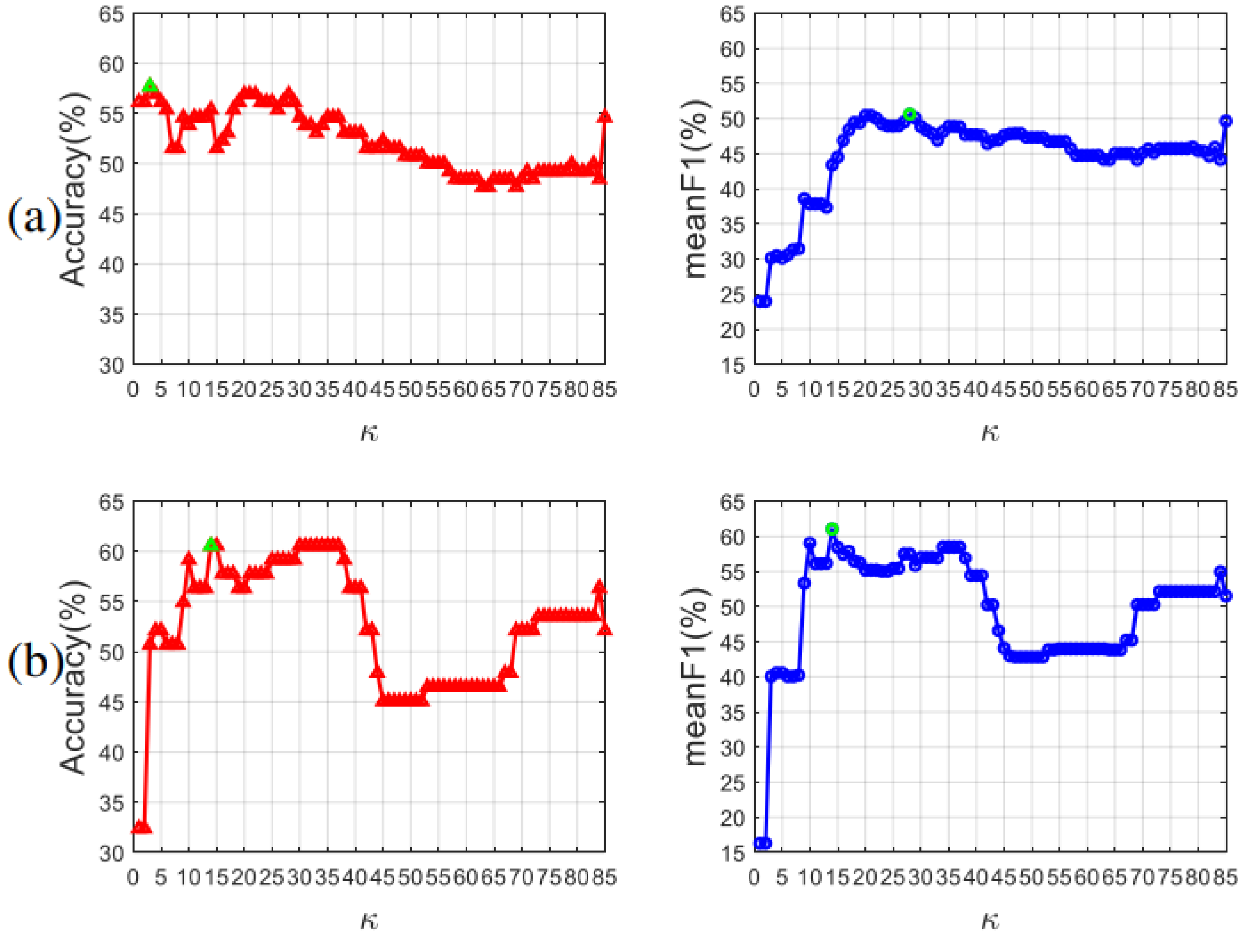
Results on TYPE-II Experiment

Method	Exp.1(H→V)		Exp.2(V→H)		Exp.3(H→N)		Exp.4(N→H)		Exp.11(C→N)		Exp.12(N→C)	
	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC	M-F1	ACC
SVM[39]	0.8002	80.28	0.5421	54.27	0.5455	53.52	0.4878	54.88	0.5295	52.11	0.2368	23.85
IW-SVM[40]	0.8868	88.73	0.5852	58.54	**0.7469**	**74.65**	0.5427	54.27	0.5117	50.70	0.3456	36.15
TCA[41]	0.8269	83.10	0.5477	54.88	0.5828	59.15	0.5443	57.32	0.4992	50.70	0.3937	42.31
GFK[42]	0.8448	84.51	0.5957	59.15	0.6977	70.42	0.6197	62.80	0.5180	53.52	0.4469	46.92
SA[43]	0.8037	80.28	0.5955	59.15	0.7465	**74.65**	0.5644	56.10	0.4738	47.89	0.3592	36.92
STM[44]	0.8253	83.10	0.5059	51.22	0.6628	66.20	0.5351	56.10	0.3523	42.25	0.3850	41.54
TKL[45]	0.7742	77.46	0.5738	57.32	0.7051	70.42	0.6116	62.20	0.5392	54.93	0.4248	43.85
TSRG[46]	0.8869	88.73	0.5652	56.71	0.6484	64.79	0.5770	57.93	0.5624	56.34	0.4105	46.15
DRLS[47]	0.8604	85.92	0.6120	60.98	0.6599	66.20	0.5599	55.49	0.4885	49.83	0.3838	42.37
Ours	**0.9150**	**91.55**	**0.6226**	**62.20**	0.5847	60.56	**0.6272**	**61.59**	**0.5697**	**57.75**	**0.4474**	**48.46**

1. Domain adaption tricks can promote method performance: [SVM]=>[IW-SVM].
2. TYPE-I generally perform better than TYPE-II: the tasks themselves cause it.
3. Experiment exchanging the source and target database has an obvious performance gap:
   - Exp.1 (H->V) outperform than Exp.2 (V->H) : high-speed camera
   - Exp.3 (H->N) outperform than Exp.4 (N->H) : color information
   - Exp.11 (C->N) outperform than Exp.12 (N->C) : color info & database gap

III. Experiment – Hyper-parameter Discuss

- Discussing the hyper-parameter of salient facial region κ



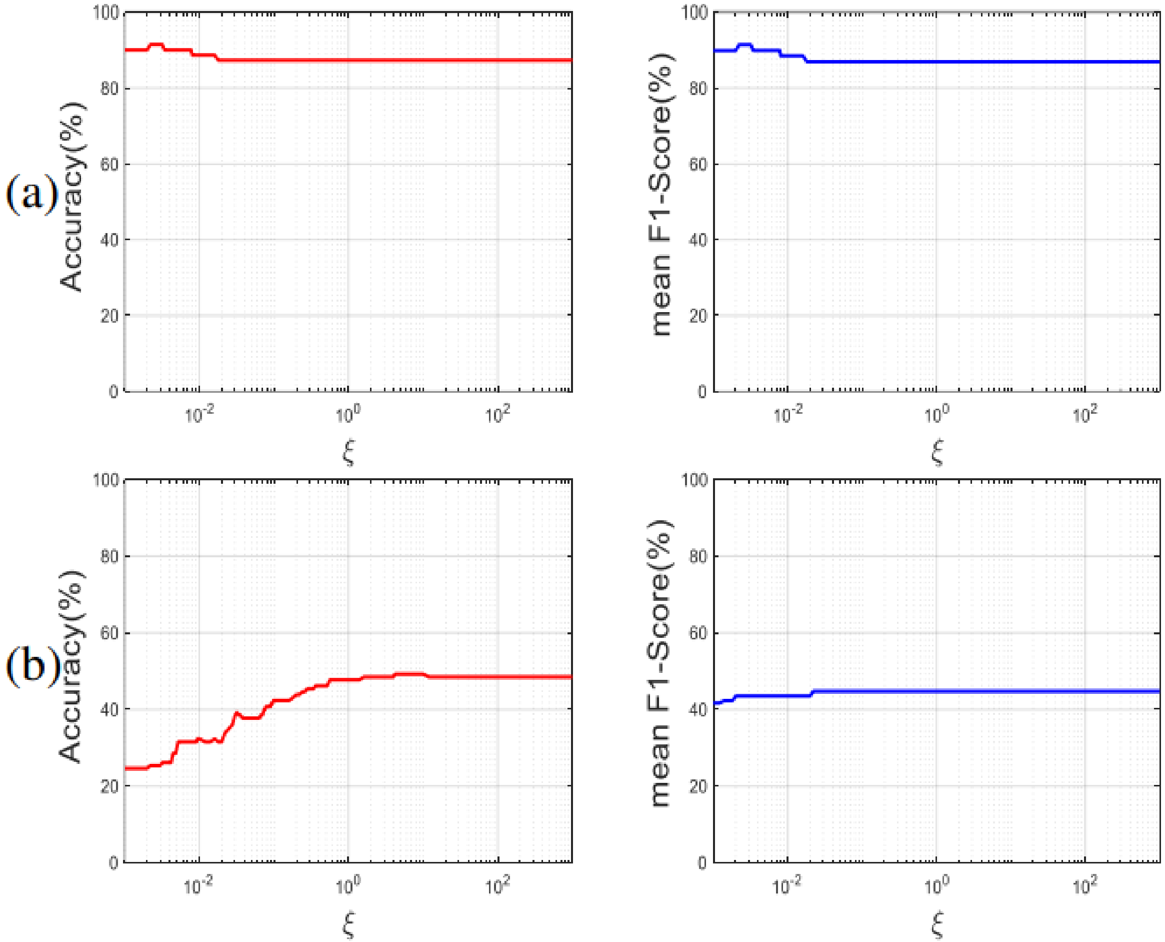
Salient facial regions for CDMER are exiguous and valuable feature may be drowned.

Fig. 3. The hyper-parameter discussion of selected facial local region number κ. (a) shows the experimental results of Exp.8(H→C) and (b) shows the experimental results of Exp.4(H→N).

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

III. Experiment – Hyper-parameter Discuss

- Discussing the hyper-parameter ξ of MMD term



MMD terms to improve model performance across a wide range of hyper-parameter ξ.

Fig. 4. The hyper-parameter discussion of trade-off coefficient ξ. (a) shows experimental results of Exp.1(H$\rightarrow$V), and (b) shows the experimental results of Exp.12(N$\rightarrow$C).

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

III. Experiment – Visualization

■ Competitive and Explicable Feature Learning

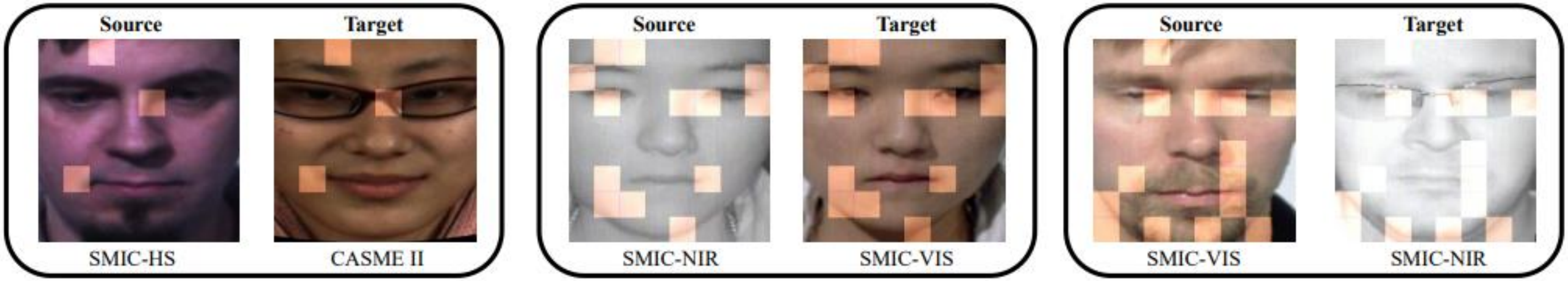


Fig. 2. The visualization of salient facial regions selected by proposed TGSR method for three cross-database micro-expression tasks. The salient facial regions are highlighted above and evidenced by the regression matrix C.

TGSR focuses on salient areas with apparent muscle movement, i.e., eye corners, mouth corners, which consistent with the micro-expression definition in anatomy.

TGSR achieved a competitive performance by learning an explicable feature.

Xingxun Jiang et al. Seeking Salient Facial Regions for Cross-Database Micro-Expression Recognition, ICPR22

Outline

I. Introduction
II. TGSR Method
III. Experiment
IV. Conclusion

Conclusion

- We propose a novel TGSR method.
  - TGSR seeks and selects the salient facial regions by learning a shared binary sparse regression matrix between the source and target databases.
  - TGSR promotes a more precise measurement for better alleviating the feature difference between the source and target databases in the label space.
  - TGSR improves the extracted hand-crafted feature to become more effective and explicable for better MER.
- We conduct experiments on CASME and SMIC databases.
  - Experiments and visualizations demonstrate that TGSR effectively learns well-designed features and outperform most state-of-the-art subspace-learning based domain adaption methods for CDMER.

Thanks for Listening

Our Lab: AIPL

Full paper

Contact Email: jiangxingxun@seu.edu.cn
Homepage: https://jiangxingxun.github.io/