LETTER

Micro-Expression Recognition by Leveraging Color Space Information*

Minghao TANG†, Yuan ZONG††, Wenming ZHENG†††, Jisheng DAI†, Jingang SHI††††, Nonmembers,
and Peng SONG†††,††††, Member

SUMMARY Micro-expression is one type of special facial expressions and usually occurs when people try to hide their true emotions. Therefore, recognizing micro-expressions has potential values in lots of applications, e.g., lie detection. In this letter, we focus on such a meaningful topic and investigate how to make full advantage of the color information provided by the micro-expression samples to deal with the micro-expression recognition (MER) problem. To this end, we propose a novel method called color space fusion learning (CSFL) model to fuse the spatiotemporal features extracted in different color space such that the fused spatiotemporal features would be better at describing micro-expressions. To verify the effectiveness of the proposed CSFL method, extensive MER experiments on a widely-used spatiotemporal micro-expression database SMIC is conducted. The experimental results show that the CSFL can significantly improve the performance of spatiotemporal features in coping with MER tasks.

key words: spontaneous micro-expression recognition, color space, fusion learning

1. Introduction

Micro-expressions were first discovered by Haggard and Isaacs in 1966 [1]. Subsequently, Ekman and Friesen [2] found them again in 1969 when they were watching a video of a depressed patient and formally name them micro-expressions. Compared with ordinary facial expressions, the duration of micro-expressions is very short often lasting for between $\frac{1}{25}$ and $\frac{1}{2}$ second [2] and meanwhile the intensity of micro-expressions is extremely low. Due to these two important characteristics, it is difficult for human beings to directly observe micro-expressions. However, detecting and recognizing micro-expressions has great values in lots of practical applications, e.g., emotion interfaces [3], clinical diagnosis [4], interrogation [5], and security field [6]. As a good example, micro-expressions in interrogation can be viewed as a “leakage” occurring on someone’s face when this person tries to conceal his hidden emotions [7]. Hence, it is urgent to investigate automatic micro-expression recognition (MER) and develop a high-quality MER system to assist human beings in recognizing different micro-expressions.

To this end, in recent years researchers form various filedes, e.g., affective computing, computer vision, and pattern recognition, have been devoted to MER research and proposed lots of effective MER methods [8]–[16]. For example, in the work of [8], Pfister et al. first used the widely-used spatiotemporal descriptor, local binary pattern from three orthogonal planes (LBP-TOP) [17], to describe micro-expressions and demonstrated its effectiveness in dealing with MER tasks. Subsequently, lots of spatiotemporal temporal descriptors are developed for describing micro-expressions. For example, Wang et al. [9] considered the redundancy of LBP-TOP and design a novel spatiotemporal descriptor called LBP with six intersection points (LBP-SIP). In addition to this, other types of spatiotemporal descriptors have been also designed such as main directional mean optical (MDMO) proposed by Liu et al. [12] and facial dynamics map (FDM) developed by Xu et al. [13].

Besides the design of spatiotemporal descriptors, some important cues existing in micro-expression samples, e.g., color space information and facial local region information, are considered to cope with MER [10]–[12], [15] as well. Specifically, Wang et al. [10] investigated whether color space information is helpful for MER by proposing a color space decomposition method. Moreover, the facial local region information has been also demonstrated to benefit MER problem. Wang et al. [10] and Liu et al. [12] respectively designed a set of region-of-interests (ROIs) which cover one or more action unit (AU) regions in the face. Their MER experiments showed that spatiotemporal descriptors together with ROIs would achieve superior performance.

In this letter, we will take full advantage of color space information in micro-expression samples to solve MER problem. Following this direction, we propose a novel feature learning method called color space fusion learning...
(CSFL) to fuse the spatiotemporal features extracted from different color channels in the color space such that the fused spatiotemporal features would be better to handle MER tasks. To evaluate the performance of the proposed CSFL, we conduct extensive experiments on a publicly available spontaneous micro-expression database (SMIC)\(^1\) [18]. The results showed that the CSFL can effectively improve the performance of spatiotemporal descriptors by leveraging the beneficial information from the RGB color space in dealing with MER tasks.

2. Proposed Method

2.1 Formulation of CSFL

Suppose we have a set of training micro-expression samples and their feature matrices in three different color channels (RGB color space) are denoted by \(X = \{x_1, \ldots, x_N\} \in \mathbb{R}^{d \times N}, Y = \{y_1, \ldots, y_N\} \in \mathbb{R}^{d \times N}, \) and \(Z = \{z_1, \ldots, z_N\} \in \mathbb{R}^{d \times N},\) where \(d\) is the feature dimension and \(N\) is the sample number. Note that the feature here can be any widely-used spatiotemporal feature used for describing micro-expressions, e.g., LBP-TOP [17]. Let \(L \in \mathbb{R}^{c \times N}\) be the label matrix corresponding to the above feature matrices, where \(c\) denotes the number of the micro-expression categories. Each column \(l = [l_1, \ldots, l_c]^T\) in the label matrix is a binary-valued vector. Only the \(i^{th}\) element is 1 whereas others are 0 if the corresponding sample of such label vector \(l\) belongs to the \(i^{th}\) micro-expression.

The basic idea of the proposed color space fusion learning (CSFL) model is simple and straightforward, i.e., learning three projection matrices for different color channels to extract the micro-expression discriminative information and meanwhile construct a compact relationship among them. Thus the extracted features by the projection matrices can be efficiently fused. Following this idea, we design the following optimization problem for CSFL model whose objective function consists of two corresponding terms:

\[
\min_{C, D, E} f_1(C, D, E) + \lambda f_2(C, D, E),
\]

where \(C, D,\) and \(E\) are the target learned projection matrices of our CSFL model and \(\lambda\) is the trade-off parameter controlling the balance between the terms of \(f_1\) and \(f_2.\) In what follows, we will introduce the details of these two terms.

The first term \(f_1\) aims to make the learned projection matrices have the ability to extract the discriminative information that can be easily used for distinguishing different micro-expressions from different color channels. To this end, we use the following regression objective function to build the relationship between the feature matrices \((X, Y\) and \(Z)\) and the label matrix \((L)\):

\[
f_1 = \|L - C^T X\|^F_2 + \|L - D^T Y\|^F_2 + \|L - E^T Z\|^F_2 + \mu (\|C^T\|_{2,1} + \|D^T\|_{2,1} + \|E^T\|_{2,1}).
\]

By minimizing Eq. (2), we are able to learn such satisfactory projection matrices \(C, D\) and \(E.\) It is notable that we also add the \(L_{2,1}\) norm of \(C, D\) and \(E\) for \(f_1\) to serve as the regularization term, which would result in the sparseness of several rows in the \(C, D,\) and \(E\) and hence enable them to pick out the important features contributing to MER in each color channel. Similar with \(\lambda, \mu\) is also a trade-off parameter which controls the sparsity of model.

As to the second term \(f_2,\) its target is to output a compact representation of the projected features in each color channel such that they can be better fused after projection by using the learned \(C, D,\) and \(E.\) To achieve this goal, we design a chain regularization term as \(f_2\) consisting of three mean projected vector difference between each other in all the color channels. By minimizing \(f_2,\) the projected features are hoped to compactly lie together. \(f_2\) is formulated as:

\[
f_2 = \|C^T \tilde{x} - D^T \tilde{y}\|^F_2 + \|C^T \tilde{x} - E^T \tilde{z}\|^F_2 + \lambda \|D^T \tilde{y} - E^T \tilde{z}\|^F_2,
\]

where \(\tilde{x} = \frac{1}{N} \sum_{i=1}^{N} x_i, \tilde{y} = \frac{1}{N} \sum_{i=1}^{N} y_i,\) and \(\tilde{z} = \frac{1}{N} \sum_{i=1}^{N} z_i.\)

Thus, we are able to arrive at our CSFL model whose final optimization problem can be written as:

\[
\min_{C, D, E} \|L - C^T X\|^F_2 + \|L - D^T Y\|^F_2 + \|L - E^T Z\|^F_2 + \lambda \|C^T \tilde{x} - D^T \tilde{y}\|^F_2 + \|C^T \tilde{x} - E^T \tilde{z}\|^F_2 + \|D^T \tilde{y} - E^T \tilde{z}\|^F_2 + \mu (\|C^T\|_{2,1} + \|D^T\|_{2,1} + \|E^T\|_{2,1}),
\]

2.2 Optimization of CSFL

The proposed CSFL can be efficiently solved by using alternating direction method (ADM) [19], i.e., iteratively updating one of three variables in CSFL while fixing others. More specifically, the updating rule for CSFL consists of the following three major steps: (1) fix \(D, E\) and update \(C;\) (2) fix \(C, E\) and update \(D;\) (3) fix \(C, D\) and update \(E.\) Note that the sub-optimization problems in all three steps are very similar and hence they can be solved by the same method. Herein, we detail the solving procedure for Step (1) as the example. The optimization problem in this step is:

\[
\min_{C} \|L - C^T X\|^F_2 + \lambda \|C^T \tilde{x} - D^T \tilde{y}\|^F_2 + \|C^T \tilde{x} - E^T \tilde{z}\|^F_2 + \mu (\|C^T\|_{2,1},
\]

and can be further rewritten as the following succinct formulation:

\[
\min_{C} \|\mathbf{L} - C^T \tilde{X}\|^F_2 + \mu (\|C^T\|_{2,1},
\]

where \(\mathbf{L} = \{L, \sqrt{\|D^T y\|}, \sqrt{\|E^T z\|}\}, \tilde{X} = \{X, \sqrt{\|\tilde{x}\|}, \sqrt{\|\tilde{x}\|}\}.

In this paper, we use an inexact augmented Lagrangian multiplier (IALM) approach [20] to solve Eq. (6). Specifically, we first convert the optimization problem in Eq. (6) to an unconstrained one by introducing an auxiliary variable \(P\) which equals \(C,\) which can be formulated as:

\[
\min_{C, P} \|\mathbf{L} - P^T \tilde{X}\|^F_2 + \mu (\|C^T\|_{2,1}, \ s.t. \ P = C.
\]
Table 1 The experimental results of using several spatiotemporal descriptors on SMIC database.

| Spatiotemporal Descriptor | Parameter Setting     | Method                        | Accuracy / mean F1-Score |
|---------------------------|-----------------------|-------------------------------|--------------------------|
|                           |                       |                               |                          |
| LBP-TOP [17]              | R = 1, P = 4          | Method I: Gray + No Fusion    | 43.90 / 0.4487           |
|                           | R = 1, P = 8          | Method II: RGB + No Fusion    | 40.24 / 0.4080           |
|                           |                       | Proposed: RGB + CSFL         | 43.90 / 0.4410           |
|                           | R = 3, P = 4          | Method I: Gray + No Fusion    | 39.02 / 0.3989           |
|                           | R = 3, P = 8          | Method II: RGB + No Fusion    | 39.63 / 0.3932           |
|                           |                       | Proposed: RGB + CSFL         | 42.07 / 0.4190           |
| LBP-SIP [9]               | R = 1                 | Method I: Gray + No Fusion    | 41.46 / 0.4222           |
|                           |                       | Method II: RGB + No Fusion    | 40.24 / 0.4097           |
|                           |                       | Proposed: RGB + CSFL         | 42.68 / 0.4283           |
|                           | R = 3                 | Method I: Gray + No Fusion    | 39.02 / 0.3989           |
|                           |                       | Method II: RGB + No Fusion    | 34.76 / 0.3473           |
|                           |                       | Proposed: RGB + CSFL         | 47.56 / 0.4840           |
| HOG-TOP [22]              | P = 4                 | Method I: Gray + No Fusion    | 32.32 / 0.3130           |
|                           |                       | Method II: RGB + No Fusion    | 36.59 / 0.3609           |
|                           |                       | Proposed: RGB + CSFL         | 39.02 / 0.3914           |
|                           | P = 8                 | Method I: Gray + No Fusion    | 38.41 / 0.3707           |
|                           |                       | Method II: RGB + No Fusion    | 35.98 / 0.3597           |
|                           |                       | Proposed: RGB + CSFL         | 42.68 / 0.4410           |

Algorithm 1 The updating rule for solving the optimization problem in Step (1).

Repeating steps 1) to 4) until convergence:
1) Fix $C$ and $T$, update $P$:
\[
\min_P \left[ \|L - P^T \hat{X}\|^2_F + tr(T^T(P - C)) + \frac{\kappa}{2} \|P - C\|^2_F \right].
\]
The close-form solution is
\[
P = \left[ \frac{2X\hat{X}^T}{\kappa} + I \right]^{-1} \left[ \frac{2XL^T - T}{\kappa} + C \right],
\]
where $I$ represents the identity matrix.
2) Fix $P$ and $T$, update $C$:
\[
\min_C \left[ \frac{1}{2} \|C^T - (P^T + \frac{T^T}{\kappa})\|^2_F \right],
\]
according to Lemma 4.1 in [20], we will obtain that
\[
c_i = \begin{cases} 
\frac{|y_i + \frac{1}{2}z_i| - \frac{1}{2}z_i}{|y_i + \frac{1}{2}z_i|} (p_i + \frac{1}{2}z_i) & \text{if } \frac{1}{2}z_i < \|p_i + \frac{1}{2}z_i\|_F \\
0 & \text{otherwise},
\end{cases}
\]
where $c_i$, $p_i$, and $t_i$ are the $i$th row of $C$, $P$ and $T$, respectively;
3) Update $T$ and $\kappa$: $T = T + \alpha(P - C), \kappa = \min(\rho_\kappa, \kappa_{max})$ where $\rho$ is a scaled parameter;
4) Check convergence: $\|P - C\|_{\infty} < \epsilon$, where $\epsilon$ denotes the machine epsilon and is suggested to fix at 1e-8.

Then, we are able to obtain its corresponding Lagrangian function of (6) which is expressed as follows:
\[
L(C, P, T, \kappa) = \|L - P^T \hat{X}\|^2_F + \text{tr}(T^T(P - C)) \\
+ \frac{\kappa}{2} \|P - C\|^2_F + \mu \|C^T\|_{l_2,1}, \quad (8)
\]
where $T$ is a Lagrangian multiplier, $\kappa > 0$ is a regularization parameter, and $\text{tr}()$ denotes the trace of the matrix.

Finally, by iteratively minimizing the Lagrangian function in Eq. (8) with respect to one of four variables while fixing others, the optimal $C$ can be learned. The updating rule is summarized in Algorithm 1.

2.3 Fusing Spatiotemporal Features in Different Color Channels with CSFL

Once the optimal projection matrices $\hat{C}$, $\hat{D}$, and $\hat{E}$ are learned, we can fuse the spatiotemporal features extracted in different color channels by concatenating them one by one to serve as the final micro-expression features, which can be expressed as follows:
\[
F = \begin{bmatrix} \hat{C}^T X \\ \hat{D}^T Y \\ \hat{E}^T Z \end{bmatrix}, \quad (9)
\]
where $F$ is the final fused feature.

3. Experiments

3.1 Databases and Experiment Setting

In this section, we conduct extensive experiments to evaluate the proposed CSFL method. A public available spontaneous micro-expression database SMIC[18] is adopted. SMIC has three datasets (HS, VIS, and NIR) recorded by three different equipments, i.e., high-speed camera, visual camera, and near-infrared camera. All the samples in SMIC are divided into three different micro-expressions (Positive, Negative, and Surprise). We use the HS dataset comprising 164 samples belonging to 16 subjects for the experiments. The face images in the micro-expression video clips are all cropped and then transformed to $112 \times 112$ pixels. The temporal interpolation model (TIM) [21] is used to normalize
the frame number of the video clips to 16.

In the experiments, leave-one-subject-out (LOSO) strategy is chosen to calculate the **Accuracy and mean F1-score** to report the performance of a MER method. To see whether the proposed CSFL is an effective method to enable the spatiotemporal descriptors to better describe micro-expressions, we choose three representative spatiotemporal descriptors including LBP-TOP[17], LBP-SIP [9], and HOG-TOP [22] with various parameter settings together with $8 \times 8$ spatial division grid to extract the features in each channel of RGB color space for CSFL to conduct the MER experiments under the LOSO strategy. As to the parameter settings of spatiotemporal descriptors, for LBP-TOP, the neighboring radius $R$ and the number of the neighboring points $P$ are set as ones of $[1, 3]$ and $[4, 8]$, respectively. Similarly, the neighboring radius $R$ of LBP-SIP is also set as $4$ and $8$, respectively. For HOG-TOP, the number of their feature vector bins $p$ is fixed at $4$ and $8$, respectively. Linear support vector machine (SVM) with fixed parameter $C = 1$ is served as the classifier throughout the experiments. The trade-off parameters of CSFL, i.e., $\lambda$ and $\mu$ are determined by the cross-validation method. In addition, to offer the comparison, we also conduct the experiments of using the above three spatiotemporal descriptors in the gray color space (Method I) and directly concatenated in the RGB color space without consideration of color information fusion (Method II), respectively. Note that the major difference between Method I and Method II is that Method I only considers to extract the spatiotemporal descriptors from the gray space of micro-expression samples, while Method II considers the color space of micro-expression samples and three color channel information are used for extracting micro-expression features.

### 3.2 Results and Analysis

The experimental results in terms of both **Accuracy and mean F1-score** are given in Table 1. From the results, it is clear to see that the proposed CSFL performs best among all three methods in the experiments of using any one of three spatiotemporal descriptors with fixed parameters as the micro-expression feature. It indicates that the proposed CSFL can effectively use make use of the color information and leverage the micro-expression discriminative information in the color space to enhance the performance of spatiotemporal descriptors in dealing with MER tasks. Moreover, although the RGB color space offers more beneficial information for MER than the Gray one, the spatiotemporal descriptors extracted from the RGB color space without fusion operation (Method II) seems mostly perform worse than Gray space (Method I), which can be clearly seen from the results of LBP-TOP ($R=1$, $P=4$), LBP-TOP ($R=3$, $P=4$), LBP-SIP ($P=4$), LBP-SIP ($P=8$) and HOG-TOP ($P=8$). We think this may attribute to the fact that compared with the Gray space, more redundant information also exist in the RGB color space, which degrades the performance of the spatiotemporal descriptors. However, we can find that the proposed CSFL is able to overcome the shortcoming of Method II (direct concatenation) and benefit from the beneficial information for MER in the RGB color space.

### 4. Conclusion

In this letter, we have investigated the micro-expression recognition (MER) problem and proposed a novel feature learning method called color space fusing learning (CSFL) model. By resorting to CSFL, existing spatiotemporal descriptors used for describing micro-expressions can benefit from the color space information. The spatiotemporal features corresponding to different color channels in the color space would be fused together resulting in a better feature representation for describing micro-expressions. Meanwhile, we have also given an efficient method solve the optimization problem of the CSFL model. Extensive experiments on SMIC micro-expression database has demonstrated the effectiveness and superior performance in MER.

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