Feature Extraction based on Local Directional Pattern with SVM Decision-level Fusion for Facial Expression Recognition

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Abstract

Facial expression recognition, as one of the important topics in pattern recognition and computer vision, has broad applications in fields of human-computer interaction, psychological behavior analysis, image understanding. This paper presents a novel facial expression recognition method based on global and local features extraction and facial recognition using decision-level fusion. We first extract Local Directional Pattern (LDP) global features of the whole face which can guarantee basic expression difference and decrease the influence of no-facial region meanwhile, and then the Local Directional Pattern Variance (LDPv) descriptor is used to extract local features of regions of eyes and mouth to extrude their contribution on expression changes. After feature extraction, PCA technique is utilized to reduce dimension of input feature space. Finally, in order to avoid redundant feature repeat we don't use feature fusion with simple concatenation, a decision-level fusion for global LDP feature and local LDPv feature by Support Vector Machine (SVM) is selected to recognition respectively. Furthermore, we also research the optimal parameters for regions-dividing and weight of LDPv. The proposed method is investigated on two standard databases Cohn-Kanade and JAFFE, and extensive experimental results indicate the effectiveness.

Keywords: *Facial expression recognition, Local directional pattern, SVM*

1. Introduction

Automatic facial expression analysis is an interesting and challenging problem[1], and impacts important applications in many areas such as human-computer interaction, data-driven animation, human psychology theory and emotional simulation study [2].Though much progress has been made[3-4], recognizing facial expression with high accuracy remains difficult due to the subtlety, complexity and variability of facial expressions [5]. Facial expression recognition generally contains three processes: image acquisition, feature extraction and expression classification, in which feature extraction is the key point. And the performance of an expression recognition method more critically depends on the extracted expression features with better discrimination capability [6]. For successful facial expression recognition, deriving an effective facial representation from original face images is a crucial step. There are two common approaches to extract facial features: geometric feature-based methods and appearance-based methods [7-11]. Because the geometric feature-based methods usually require accurate and reliable facial feature detection and tracking, which is difficult to accommodate in practical applications [12], the appearance-based methods are the most widely accepted at present [13].

Appearance-based methods deal with the whole face or specific face-regions to extract appearance changes of face using image filters such as Gabor-wavelet, Curvelet and local binary pattern (LBP)[12, 14, 15]. As one of potential appearance-based feature extraction method, LBP has many applications in the field of face detection, face recognition and facial expression recognition [14, 16]. Although LBP has advantages of efficient computation and robustness to monotonic illumination changes, it is sensitive to non-monotonic illumination variation and also shows poor performance in the presence of random noise. In order to overcome this weakness of LBP, recently Taskeed Jabid and others proposed Local directional pattern (LDP) method [17] which was a valid appearance-based feature extraction method and applied successfully in face recognition, object description, gender recognition and facial expression recognition [17-20],

LDP feature extraction method can represent facial curve, edge and texture characteristic well. Like most existing appearance-based method, they only consider the whole facial features to classify expressions. In the changes of facial expression, it is undeniable that the regions of eyes and mouth have powerful influence. Therefore, how to weaken the influence of no-facial region and highlight the local region which has more contribution on expression changes is particularly important. Paper [21] introduced contrast information to LDP operator, and proposed a weighted LDP method (Local Directional Pattern Variance, LDPv) for facial expression recognition. It adjusts the different contributions of LDP coding using the variance of local structure and account that texture with significant contract should impact more such as eyes and mouth that are more sensitive to high contract regions. That's just what we want but not for the whole facial face. So in this paper, we first extract global LDP features which can guarantee basic expression difference and decrease the influence of no-facial region meanwhile then LDPv descriptor is used to extract local regions of eyes and mouth to extrude the distinction between expressions. After feature extraction, we don't use feature fusion with simple concatenation, because if there is not an efficient fusion algorithm that may be only redundant repeat. Therefore we select decision-level fusion for global LDP feature and local LDPv feature by SVM to recognition respectively. Extensive results from two standard expression databases Cohn-Kanade and JAFFE demonstrate the effectiveness of our proposed method.

The structure of the paper is organized as follows. In Section 2, we will introduce local direction pattern and its variance and how to extract global and local features. Then we will present PCA dimension reduction method and SVM decision-level fusion for facial expression in Section 3. In Section 4, we will do extensive experiments on two benchmark datasets and analyze the results, and the conclusions are given in Section 5.

2. Facial Feature Extraction

2.1 LDP and global feature extraction

The LDP descriptor is an eight bit binary code assigned to each pixel of an input image that can be calculated by comparing the relative edge response value of a pixel in different directions. So that eight directional edge response values $\{m_i\}$, $i = 0,1, \cdots 7$ of a particular pixel are computed using Kirsch masks in eight different orientations $M_i$centered on its own position. These Kirsch masks are shown in the Figure 1, and Figure 2 shows eight directional edge response positions and LDP binary bit positions. Because different importance of the response values, the k most prominent directions are considered to generate the LDP. So the top k values $|m_j|$ are set to 1, and the other positions are set to 0. Finally, the LDP code is derived by formula (1), where m_k is the k-th most significant directional response value. Figure 3 shows an exemplary LDP code with k=3.

$$LDP_k = \sum_{i=0}^{7} b_i(m_i - m_k)\cdot 2^i,\ b_i(a) = \begin{cases} 1, & a \geq 0 \\ 0, & a < 0 \end{cases} \quad (1)$$

$$\underset{\text{East } M_0}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \quad \underset{\text{North East } M_1}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North } M_2}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \quad \underset{\text{North West } M_3}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{\text{West } M_4}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \quad \underset{\text{South West } M_5}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \quad \underset{\text{South } M_6}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \quad \underset{\text{South East } M_7}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

Figure 1. Kirsch edge response masks in eight directions

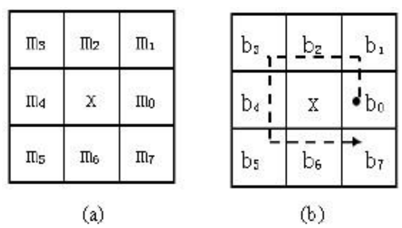

Figure 2. (a) Eight directional edge response positions; (b) LDP binary bit positions

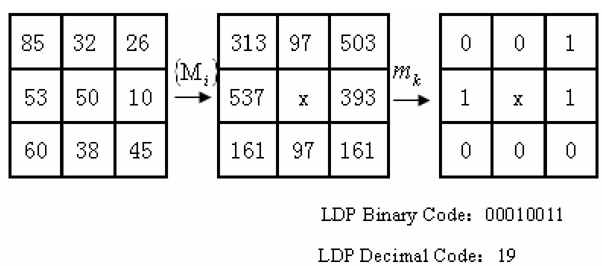

Figure 3. LDP Code with k=3

The input image of size $M \times N$ can be represented by an LDP histogram H using (2) after computing all the LDP code for each pixel(r, c), where *i* is the LDP code value.

$$H(i) = \sum_{r=1}^{M}\sum_{c=1}^{N} f(LDP_k(r,c), i),\ f(a,i) = \begin{cases} 1 & a = i \\ 0, & a \neq i \end{cases} \quad (2)$$

For a particular value k, there has C_8^k different number of bins for the histogram H. In essence, a resulting histogram vector size of $1 \times C_8^k$ is produced for the image.

LDP descriptor contains detail information of an image, such as edges, spots, corner, and other local textures [20]. Whereas computing LDP over the whole face image only considers the occurrences of micro-pattern without any information of their location and spatial relationship which usually represents the image content better. Hence, the image is divided into g regions $R_0, R_1, \cdots, R_{g-1}$ as shown in Figure 4 when using LDP, so that there will be a LDP_i histogram for every region R_i. Consequently, the resulting LDP descriptor is obtained via concatenating all the LDP_i histograms that is the global feature extraction in this paper.

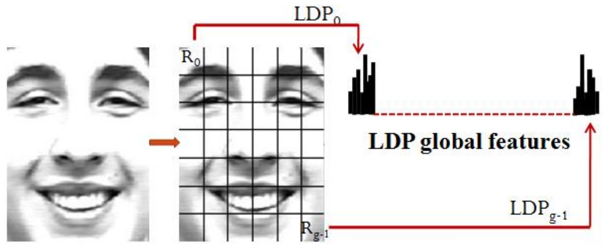

Figure 4. Expression image is divided into small regions from which LDP histograms are extracted histograms are extracted and concatenated into LDP global features

2.2. LDPv and local feature extraction

As described in section of introduction, local directional pattern variance (LDPv) method was proposed which considered contrast information to LDP operator. Therefore, the variance σ is introduced as an adaptive weight to adjust the contribution of the LDP code in the histogram generation. The proposed LDPv descriptor is computed as:

$$LDPv(\tau) = \sum_{r=1}^{M} \sum_{c=1}^{N} w(LDP_k(r,c), \tau) \tag{3}$$

$$w(LDP_k(r,c), \tau) = \begin{cases} \sigma(LDP_k(r,c)) & LDP_k(r,c) = \tau \\ 0 & otherwise \end{cases} \tag{4}$$

$$\sigma(LDP_k(r,c)) = \frac{1}{8} \sum_{i=0}^{7} (m_i - \overline{m})^2 \tag{5}$$

where, $\overline{m}$ is the average of all directional responses $\{m_i\}$ calculated for a position (r, c). Same as LDP descriptor, in order to represent spatial relationship, the image is divided into many regions. In this paper we want to extract LDPv feature on local regions of eyes($R_0 \sim R_{g-1}$) and mouth ($R_g \sim R_n$), as shown in Figure 5 shows, the formation of LDPv local feature. The final LDPv feature is obtained via concatenating all the $LDPv^i$ histograms which is built for each region R_i.

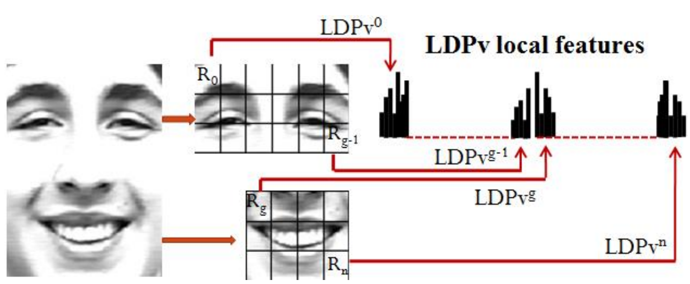

Figure 5. LDPv histograms are extracted from the regions of eyes and mouth and concatenated into LDPv local features

3. Feature dimensionality reduction and expression recognition

3.1. Feature dimensionality reduction using PCA

After feature extraction an inadequate number of feature vectors will be got, and if we use it directly, on the one hand a good classifier may work ineffectively; on the other hand many features increase time and complexities. Principal Component Analysis (PCA) has been widely applied to image processing to extract feature for recognition purpose [22-24]. Therefore, for global LDP features and local LDPv features we utilize PCA technique to reduce dimension respectively which transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. PCA successfully uncovers the latent structures in the datasets and shows optimality in the case of dimension reduction of the input feature space.

3.2. SVM and expression recognition

SVM is a well-founded statistical learning theory that has been successfully applied in various classification tasks in computer vision [25-27]. SVM performs an implicit mapping of data into a higher dimensional feature space and finds a linear separating hyper-plane with maximal margin to separate the data.

Given a training set of labeled examples$T = \{(s_i, l_i), i = 1,2,\cdots, L\}$ where $S^i \in \mathbb{R}_d$, and $l_i \in \{-1,1\}$, a new test data *x* is classified by

$$f(x) = sign\left(\sum_{i=1}^{L} \alpha_i l_i K(x_i, x) + b\right) \tag{6}$$

where α_i are Lagrange multipliers of the dual optimization problem, *b* is a bias or threshold parameter, and *K* is a kernel function. The training sample $x_i$with α_i> 0 is called the support vector, and the separating hyper-plane maximizes the margin with respect to these support vectors. Given a non-linear mapping function Φ that transforms the input data to the higher dimensional feature space, kernels have the form $K(x_i, x_j) = \langle\Phi(x_i), \Phi(x_j)\rangle$. Ofthe various kernels found in the literature, linear, polynomial and radial basis function (RBF) kernels are the most frequently used. SVM makes binary decisions, and multi-class classification can be achieved by adopting the on binary classification: “one-against-all,” “one-against-one,” and DAGSVM. Some research [28] indicated that the “one-against-one” and DAG methods are more suitable for practical use than the other methods. So in our work we used the one-against-one technique, which was constructs$k(k-1)/2$ binary classifiers where each one is trained on data from two class expressions (anger-happiness, anger-fear, *etc.*). Then voting strategy was adapted and the output is the “MaxWins” expression.

In the stage of recognition, we adopt decision-level fusion. That’s, we use global LDP features and local LDPv features to train SVM model and predict classification result respectively, and then the respective voting result are added to decide “MaxWins” one as the final expression. The benefit of this is that we not only consider the effect of global facial characteristic but also highlight the important contribution of local facial region which influence the changes of expression greatly. Figure 6 shows the algorithm flow chart.

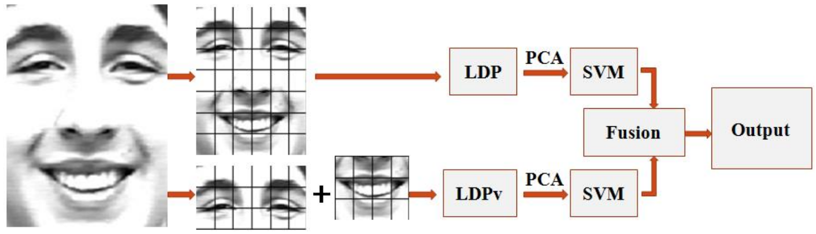

Figure 6. The Algorithm Flow Chart

4. Experimental results and analysis

4.1. Databases and experiment setup

We will evaluate the proposed method on two benchmark databases: the JAFFE databases [29] and the Cohn-Kanade databases [30]. The JAFFE database contains 213 gray images (256x256) of individual human subjects with a variety of facial expressions. In this database, 10 different Japanese females performed seven prototypical expressions: anger, disgust, fear, joy, sadness, surprise and neutral. We choose three samples per facial expression for each subject, and a total of 210 images among which every expression has 30 images. The Cohn-Kanade database includes video sequences of 97 subjects displaying distinct facial expression. We create a subset with 10 subjects for our experiments. All the subjects selected have six basic expressions: anger, disgust, fear, joy, sadness and surprise. Every expression is a sequence. From six sequences of expressions for a selected subject, we select the last four frames as six basic expressions and the first frame as neutral expression four of which are used. So there are 280 total images (640x490) in all. After choosing the images, they were cropped from the original one using the position of two eyes according to the distribution proportion of facial organs and resized into 150×110 pixels. The resulting expression images are shown in Figure 7.

Figure 7. Some expression samples from Cohn-Kanade (the first row) and JAFFE (the second row)

In our experiments 20 images per expression were selected randomly from JAFFE database for training and the rest images are used for testing, and it is the same for the Cohn-Kanade databases. For SVM the selection of kernel function is very important. In the three most frequently used kernel function mentioned in Section 2.2 we used polynomial kernel with the degree of 1, because the parameter setting and searching optimization for RBF with grid-search or geneticalgorithm spent a lot of time but the recognition rate of which is not much higher than liner and polynomial kernel. In order to verify the effectiveness of various methods and get persuasive conclusion for every method the designed experiment is repeated 10 times, and the average recognition accuracy with best PCA dimension was picked.

4.2. Results and analysis

It can be found that there have two parameter k and g (the number of blocks) will affect the forming of LDP features. In related research of LDP, k=3 and g=7x6 is proved best for Cohn-Kanade. Here we first affirm the best k and g again for Cohn-Kanade and JAFFE databases before comparing our proposed method with others. So we investigate LDP features with SVM classifier when k=3 with different number of blocks *g* as shown in Table 1.The results reflect that in Cohn-Kanade the best number of blocks is really g=7x6 with 94.93% but on JAFFE database g=9x8 is best with 88.43%. The reason may be the facial structure of JAFFE is different of Cohn-Kanade, and they belong to different human species.

Table 1.Recognitionperformance (%) for different number of blocks with k=3

blocks	Cohn-Kanade	JAFFE
g=3x3	90.43±4.4	76.71±4.2
g=5x5	92.64±3.4	80.86±5.0
g=7x6	**94.93**±3.5	87.29±2.8
g=9x8	94.42±4.4	**88.43**±5.0
g=12x9	93.78±5.1	87.29±4.8

With best parameter of LDP we can get our global features, and then we will find optimal weight for LDPv to obtain local features. Table 2 lists the result of the recognition performance of our proposed method with different weight σ for LDPv local features. From the result we can see that when weight is standard variance the best performance is achieved. Meanwhile, the recognition rate also improved when there has no weight or with forth root of variance but when the weight is variance. This only shows that overlarge weight will not improve the recognition rate instead.

Table 2. Recognition performance (%) with different weight

Weight	Cohn-Kanade	JAFFE
no weight	95.93±2.5	89.57±4.2
Variance	92.14±2.6	88.29±4.9
Standard variance	**96.86**±2.2	**92.14**±4.1
Forth root of variance	94.43±3.8	91.71±4.1

In order to verify the effectiveness of our proposed method with optimal parameter, we carry out experiments comparing with other existing methods described in the part of introduction on Cohn-Kanade, JAFFE and across-dataset (training on Cohn-Kanade and testing on JAFFE).Table 3 gives out the performance of various methods. The results indicate that the proposed method achieved better recognition accuracy. Furthermore, the recognition accuracy on across-dataset is all relatively low that still is the challenge of the future. Table 4 and Table 5 are confusion matrixes (CM) of 7-class expression recognition using our proposed on Cohn-Kanade and JAFFE of 96.86% and 92.14% respectively. There are 100 test images of every class for JAFFE and 200 test images of every class for CK in all with repeated 10 times randomly.

5. Conclusion

In this paper, we present a novel method for expression recognition based on global LDP features and local LDPv features with SVM decision-level fusion, which can retain the influence of global facial face and while highlight the local region with more contribution on expression changes. Extensive experimental results demonstrate the effectiveness of our proposed method. In future work we plan to increase the number samples on Cohn-Kanade and enhance the robustness and applicability especially with across-dataset.

Table 3. Recognition performance (%) with different methods on different databases

	Cohn-Kanade	JAFFE	Train:CK,Test:JAFFE
LBP	89.17	83.92	41.90
LDP	94.93	88.43	42.86
LDPv	95.12	89.28	43.33
Proposed method	**96.86**	**92.14**	**45.71**

Table 4. CM of 7-class expression recognition (%) on Cohn-Kanade

	Surprise	Disgust	Fear	Happy	Anger	Sad	Neutral
Surprise	100	0	0	0	0	0	0
Disgust	0	98	0	0	2	0	0
Fear	0	0	97.5	0.5	0.5	0.5	1
Happy	0	0	3.5	96.5	0	0	0
Anger	0	1.5	0	0	96.5	0.5	1.5
Sad	0	0	0	0	1	94	5
Neutral	0	0	0	0	0	4.5	95.5

Table 5. CM of 7-class expression recognition (%) on JAFFE

	Surprise	Disgust	Fear	Happy	Anger	Sad	Neutral
Surprise	95	0	0	1	0	3	1
Disgust	0	89	2	0	3	3	3
Fear	0	6	92	0	0	0	2
Happy	3	1	0	94	0	2	0
Anger	0	2	0	0	94	3	1
Sad	1	4	0	0	2	87	6
Neutral	1	1	1	0	0	3	94

Acknowledgements

This paper is supported by National Nature Science Foundation(61262071), Humanities and Social Sciences Research Project of Ministry of Education (12YJCZH053) and Funs of applied basic research of Yunnan province(2011FB044) (2010CD47).

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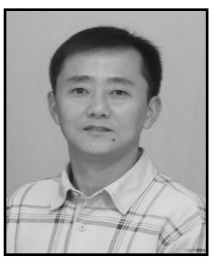

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