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Divided Local Binary Pattern (DLBP) Features Description Method For Facial Expression Recognition ⋆

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Abstract

This paper presents a new method for facial expression recognition using divided local binary pattern features. Motivated by Fourier's parity decomposition, we decompose a LBP descriptor into two sub-descriptors. This method reduces the amount of data of the feature extraction, reducing the data dimension effectively. Experimental results on JAFFE facial expression database show that the proposed method can get significant performance improvement in recognition rate, reduce the recognition time greatly.

Keywords: Divided; LBP; Facial Expression Recognition

1 Introduction

Human-computer Interface (HCI) is very popular in recent years. In similar way as human-human interaction, it is necessary for the computer to interact naturally with users. Face contains very rich information, one of the most important ways of human interacts with each other is though facial expression. Therefore, it is significant to develop a system which can automatically identify a variety of complex facial expression. For example, once a patient has a painful expression, a medical robot for the care can send an alert signal to inform the doctor for the treatment.

Even though much work has been done, recognizing facial expression with a high accuracy remains to be difficult due to the complexity and variety of facial expressions.

In the past few years, researchers have proposed many description of facial expression recognition algorithm. Commonly used methods for the usual static image feature extraction are: Principle Component Analysis (PCA) [1], Local Binary Pattern (LBP) [2], Gabor wavelet [3], model-based methods, etc. The model-based approaches include based on the Active Appearance Model (AAM) [4] and Point Distribution Model (PDM) [5]. LBP operator gradually draws attention of researchers for its simple calculation, extracting features fast, wide range of applications. In 1996, T. Ojala et al proposed local binary patterns to analysis image texture features as a kind

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of texture operator [6]. In 2002, T. Ojala et al proposed extending local binary patterns called circular LBP operator. Circular neighborhood is used rather than the usual eight neighborhood, and the number of sampling points and the radius can change. We can get different circular LBP operators by using different values of P and R [7]. Henceforth, the improvement work related to LBP operator and applications toward it emerge in endlessly. T. Ahonen applied the local binary pattern to face recognition [8]. In 2006, Marko Heikkilä proposed the central symmetry local binary pattern (CS - LBP) operator. The operator computes more easily and reduces the data dimension [9]. In 2007, Tan and his peers raised the Local Ternary Patterns (LTP). It extended the binary pattern, changed the two level qualifications into three level qualifications, and increased the LBP operator's robustness against noise [10]. In 2010, Guo putted forward a Complete LBP operator (CLBP) which enhanced the LBP operator's description ability of characteristics [11]. In 2007, Zhao Guoying presented (multiple frequency domain local binary pattern) Three Orthogonal Planes (LBP-TOP) operator. It was applied to facial image sequence recognition, and achieved more than 90 percents of classification success [12].

This paper proposed a novel improved method of LBP-decomposition Local Binary Pattern (DLBP). The improved method not only describes the details of face expression more effectively, but also greatly reduces the extracted feature's dimension, thereby lowering the facial expression recognition time. Through experiment, it proves that the improved method is effective by adopting block DLBP feature extraction for the face expression image on the JAFFE database and categorizing in accordance with the extracted combination feature histogram with the SVM classification.

2 LBP Operator

LBP was firstly presented by Ojala and Harwood in 1996 [6], and was proved a powerful means of texture description. The operator labels the pixels of an image by thresholding a 3×3 neighborhood of each pixel with the center value and considering the results as a binary number, see an illustration as in Fig. 1.

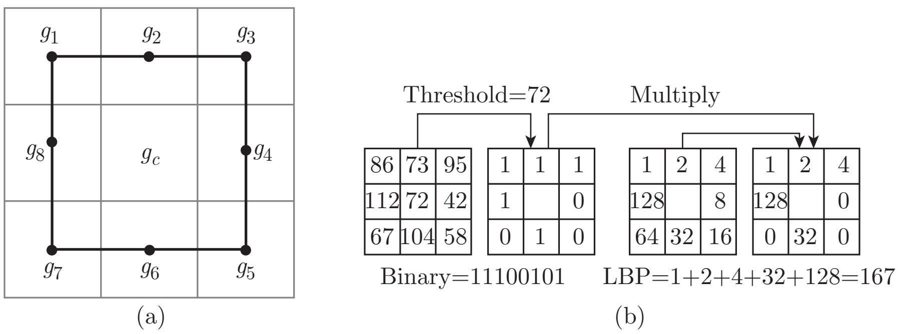

Fig. 1: The basic LBP operator

Lately, in order to adapt to the texture feature at different scales, in 2002, T. Ojala and his companions extended LBP's definition [7]. He extended 3×3 neighborhood to any size neighborhood, and used circular neighborhood instead of square based on double linear differential algorithm. Any numbers of pixel points in the radius R circular neighborhood are possible in the improved LBP operator. Assuming the central pixel is, we build a texture model with radius R

and sampling number P. In addition, P and R is variable, as in Fig. 2, (a), (b), (c), the value of P and R of LBP operator is ($P = 4$, $R = 1$), ($P = 8$, $R = 1$) and ($P = 8$, $R = 2$), respectively.

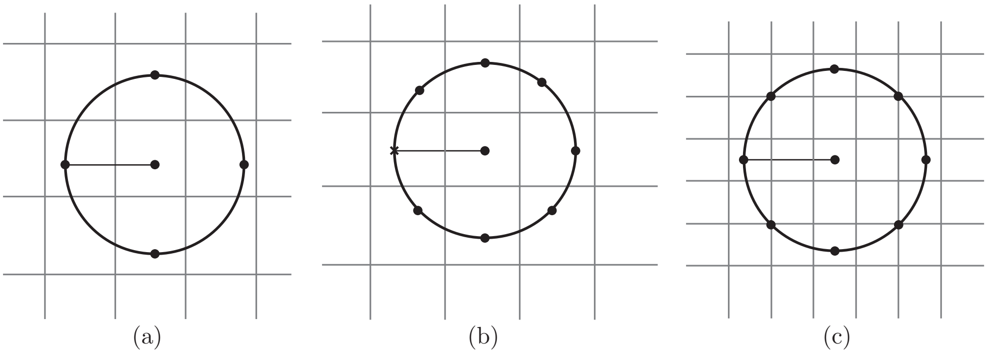

Fig. 2: Different LBP operator

The theory of circular LBP operator is as follows: Assuming the coordinates of center pixel is, in the radius R of circles, the P neighborhood points' position is (X_p, Y_p), then

$$X_p = \begin{cases} X_c & + R * cos\left(\frac{2\pi p}{P}\right), \\ Y_c & + R * cos\left(\frac{2\pi p}{P}\right). \end{cases} \tag{1}$$

So the local texture feature T of central pixel is

$$T = t(g_c, g_0 - g_c, ..., g_{p-1} - g_c) \tag{2}$$

Supposing g_c and g_p are independent of one another, then texture T turns into

$$T \approx t(g_c)t(g_0 - g_c, ..., g_{p-1} - g_c) \tag{3}$$

In addition, P is the entire sub-image's brightness. As result of brightness information has no related to the texture description, we can abandon it. It makes LBP operator have strong anti-interference ability against illumination. Texture feature T of abandoned brightness information is represented as follow,

$$T \approx t(g_0 - g_c, ..., g_{p-1} - g_c) \tag{4}$$

Definition function

$$s(x) = \begin{cases} 1 & if \quad x \geq 0, \\ 0 & if \quad x < 0. \end{cases} \tag{5}$$

Then

$$T \approx t(s(g_0 - g_c), ..., s(g_{p-1} - g_c)) \tag{6}$$

Distributing a quadratic coefficient 2^P for each $s(x)$, then the LBP value of pixel point (X_c, Y_c) can be counted by the follow formula

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) \times 2^P \tag{7}$$

2.1 LBP's Uniform Patterns

The LBP operator $LBP_{P,R}$ produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. If all the 2^P patterns are adopted, computation will be very complex. Studies find that some patterns appear in a low frequency; and some patterns contain more information than others. Therefore, it is possible to use only a subset of the 2^P Local Binary Patterns to describe the texture of images. This type patterns are called uniform pattern [7], the formula definition as follow:

$$U(LBP_{P,R}) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \leq 2 \tag{8}$$

Uniform pattern has a common point which there are two changes from 0 to 1 at most in the circular binary code, for example, 11111111 has none code changes, and 00111100 has two code changes. Uniform pattern with radius R and P sampling point can be expressed as $LBP_{P,R}$. $LBP_{8,1}$ has 256 possible pattern, however, uniform pattern $LBP_{8,1}^{u2}$ only has 59 possible patterns, greatly reduces the computation.

2.2 Decomposition LBP (DLBP)

We improve the basic LBP operator as follow: Decomposing the basic operator, as Fig. 3.

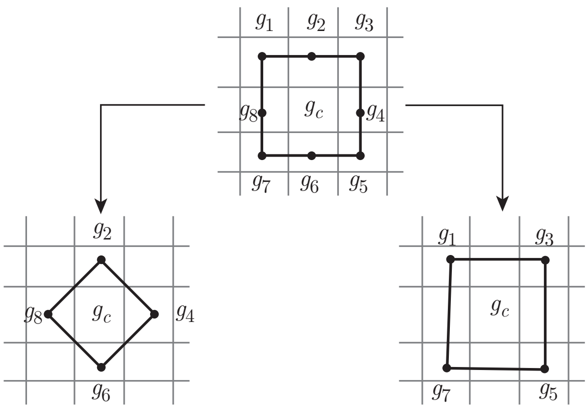

Fig. 3: Improved DLBP operator

Now, a LBP value is separated into two LBP value, see illustration in Fig. 4.

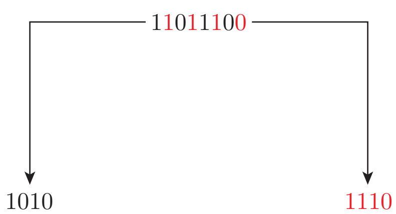

Fig. 4: The basic LBP decomposition

Formula as follows:

$$DLBP1 = \sum_{p=1}^{P-1} s(g_p - g_c) \times 2^P \qquad p \in (0, 4) \tag{9}$$

$$DLBP2 = \sum_{p=1}^{P-1} s(g_p - g_c) \times 2^P \qquad p \in (0, 4) \tag{10}$$

Now, $P = 4$, 4 sampling point surround the center point, dividing into 2 groups of LBP operators. Here offering the image which is extracted features with DLBP operator (see Fig. 5).

(a) Primary image (b) Image extracted feature (DLBP1) (c) Image extracted feature (DLBP2)

Fig. 5: (a) is a simple image, (b) and (c) is the image extracted features with DLBP1 operator and DLBP2 operator, respectively

According to the former introduction, $LBP_{8,1}^{u2}$ have 59 possible patterns. As for DLBP, the total pattern numbers are 16. The number of patterns reduces largely, and achieving excellent dimension reduction effect. In order to reduce noise, we improve DLBP with Uniform Pattern, defining as

$$U(DLBP) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \leq 2 \qquad p \in (0, 4) \tag{11}$$

Now, the quantities of DLBP patterns are reduced to 15.

2.3 Image Pre-processing and Block Feature Extraction

Here are several images in JAFFE database shown in Fig. 6. These facial expressions are sadness, angry, smile, fear, surprise, disgust, neutrality. As we know, facial expression feature is easily affected by hairstyle, clothes and so on, so pretreatment is necessary for the facial expression image. Here, we cut the images manually, and resize them into 100×100.

Fig. 6: Several images in JAFFE database

Fig. 7: Facial expression images after resizing

Cutting images as shown in Fig. 7.

For the sake of recognition accuracy, this paper divides the face expression image into blocks. Extracting each sub-regions' feature gradually with DLBP operator, and then attaining the features combination histogram. The processing is as in Fig. 8.

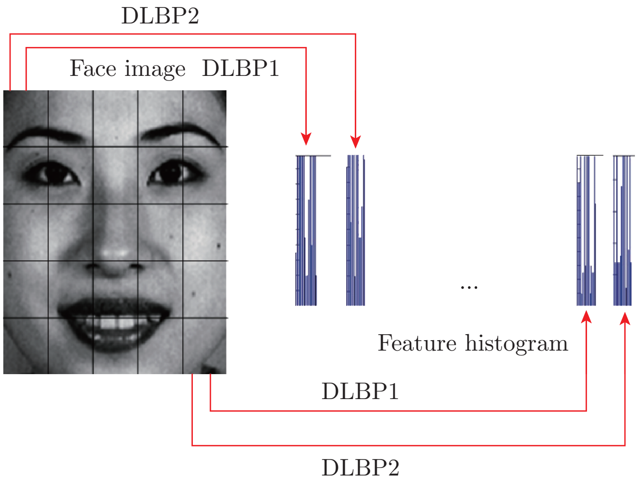

Fig. 8: Extracted features with DLBP1 and DLBP2 histogram and combination

3 Experimental Results

The experiment adopts JAFFE Expression Database which includes 213 images of 7 facial expressions of 10 women and each of them occupies 2-4 images for each expression. In addition, the experiment applies SVM classification to the processing related to people. The first experiment chooses 180 images of 6 expressions, wipes off the neutral expression images, and trains 2-3 images of each person. The second experiment chooses 210 images of 7 expressions, trains 2-3 images of each person and tests the rest.

If we use the features extracted by basic LBP as training samples, adopt the 5×5 blocking method in the paper and use the Uniform pattern of LBP operator, we get the features histogram with dimension of $59 \times 25 = 1475$. But if we extract features with DLBP, histogram dimension reduce to $15 \times 25 + 15 \times 25 = 750$, the dimensionality reduces about to half, so we save recognition time greatly.

Algorithm in this paper is compared with basic LBP and CLBP in paper [12]. Table 1 shows the 7-class expression dataset recognition rate. Seven expressions are sadness, angry, smile, fear, surprise, disgust, neutrality. Table 2 shows different dimensions in different methods of different number of blocks.

Table 1: Mean recognition comparison on JAFFE facial expression database of 7 expressions (%)

Methods	Different number of blocks				
	4×4	5×5	6×6	7×7	8×8
$LBP_{8,1}$	87.1	84.3	88.6	88.6	84.3
CLBP ([12])	81.4	90.0	85.7	91.4	88.6
Proposed DLBP	84.7	92.8	91.4	92.9	92.9

According to the comparison of the mean recognition in Table 1, we can see clearly that the recognition of DLBP is greater than LBP. That declares stronger recognition for DLBP. It can overcome the variance of different facial expression, and in the other hand, DLBP can extract the detail changes of facial expression, so it can distinguish different facial expressions.

According to the comparison of the different dimensions in Table 2, we can see that Proposed DLBP has the lowest dimensions. The dimensions of DLBP are nearly half of LBP and nearly one fourth of CLBP. Therefore, the features we extract by DLBP are effective and efficient.

Table 2: Different dimensions in different methods

Methods	Different dimensions				
	4×4	5×5	6×6	7×7	8×8
$LBP_{8,1}$	944	1475	2124	2891	3776
CLBP ([12])	1888	2950	4248	5782	7552
Proposed DLBP	480	750	1080	1470	1920

To further verify the effectiveness of the proposed algorithm of DLBP, we make changes in CLBP [12] by using DLBP. A further decomposition in CLBP like Fig. 9.

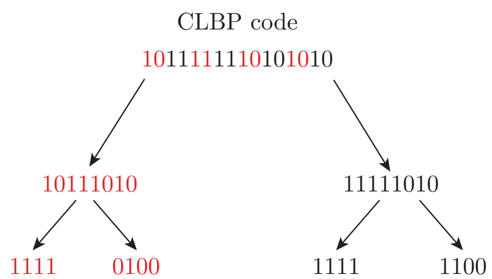

Fig. 9: CLBP+DLBP

The experiment result in CLBP by using DLBP is in Table 3.

The results in Table 3 show that high recognition rate and low dimensions by using the combination method of CLBP and DLBP. It confirms that the proposed method DLBP is effective and efficient again.

Table 3: CLBP by using DLBP method

Methods	CLBP+DLBP				
Blocks	4×4	5×5	6×6	7×7	8×8
Recognition rate(%)	88.6	91.4	88.6	95.7	92.8
Different dimensions	960	1500	2160	2940	3840

4 Conclusions

In this paper, a novel method for facial expression recognition is proposed. We can extract the better features for higher recognition and less time. Because of low dimension, the recognition time is much less than other methods. The dimension of DLBP is about half of LBP, so that the recognition time of DLBP shortens about 30 percents, and the dimension of CLBP is about four fold of DLBP, the recognition time of DLBP is about 1/3 of it. In all, we can prove the efficiency of the algorithm in this paper.

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