Journal of Information & Computational Science 8: 3 (2011) 412–421
Available at http://www.joics.com

LBP Feature Extraction for Facial Expression Recognition ⋆

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Abstract

The study of facial feature extraction based on Local Binary Patterns (LBP) is presented in this paper. As a nonparametric and computationally simple descriptor, LBP is broadly used in facial expression recognition for its invariant to monotonic grayscale transformation. First, the LBP descriptor is presented followed with the facial expression recognition framework using LBP. Aim for the facial expression recognition, the characters of global and local facial feature are analyzed. Then several LBP feature extraction methods with respect to different facial features are described. And the corresponding experiments based on different methods of LBP facial feature extraction are conducted. At last the conclusion is drawn based on the experimental results evaluation.

Keywords: LBP; Feature Extraction; Facial Expression Recognition; Local Feature

1 Introduction

Facial expression plays a great role in intelligent human computer interaction (HCI). Many techniques have been proposed in the literature for face expression recognition [1, 2, 3, 4, 5, 6, 7]. And research showed that local features play more important than global ones. LBP is one of the best local feature describer operator. The Local Binary Patterns is a nonparametric and computationally simple descriptor which describes the local spatial structure of an image. And recently LBP is introduced into facial image analysis research such face recognition and facial expression recognition.

The remainder of this paper is arranged as follows: in the second section, the Local Binary Patterns (LBP) is described followed with different forms of LBP feature in the third section. The fourth and fifth section presented the system framework of facial expression recognition based on LBP and some experiments respectively. And then some brief conclusions are drawn in the last section with discussion on future work.

⋆Project supported by the National Nature Science Foundation of China (No. 60873163).
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March 2011

2 Local Binary Patterns (LBP)

At a given pixel position (x_c, y_c) with the gray value g_c, define local texture $T = t(g_c, g_0, g_1, \cdots, g_7)$, where $g_i (i = 0, 1, \cdots, 7)$ correspond to the gray values of the 8 surrounding pixels. To compare the relative intensities between the center pixel and its neighbor pixels, T can be rewritten as a binary set $T \approx t(s(g_0 - g_c), \cdots, s(g_7 - g_c))$ where function $s(x)$ is defined as:

$$s(x) = \begin{cases} 1 & \text{when } x > 0, \\ 0 & \text{when } x \leqslant 0. \end{cases}$$

Then the LBP pattern [8, 9] at the given pixel is defined as an ordered set of the bi-nary comparisons and the resulting value can be expressed as:

$$LBP(x_c, y_c) = \sum_{i=1}^{7} s(g_i - g_c) 2^i.$$

Fig. 1 showed an example of the LBP operator.

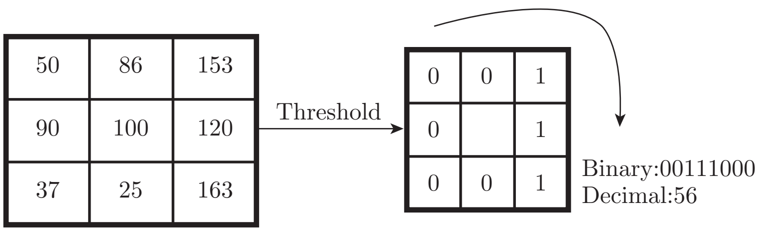

Fig. 1: An Example of the LBP Operator

An image can be transformed to the LBP map using LBP operator. Fig. 2 showed an example of the LBP map on a facial image.

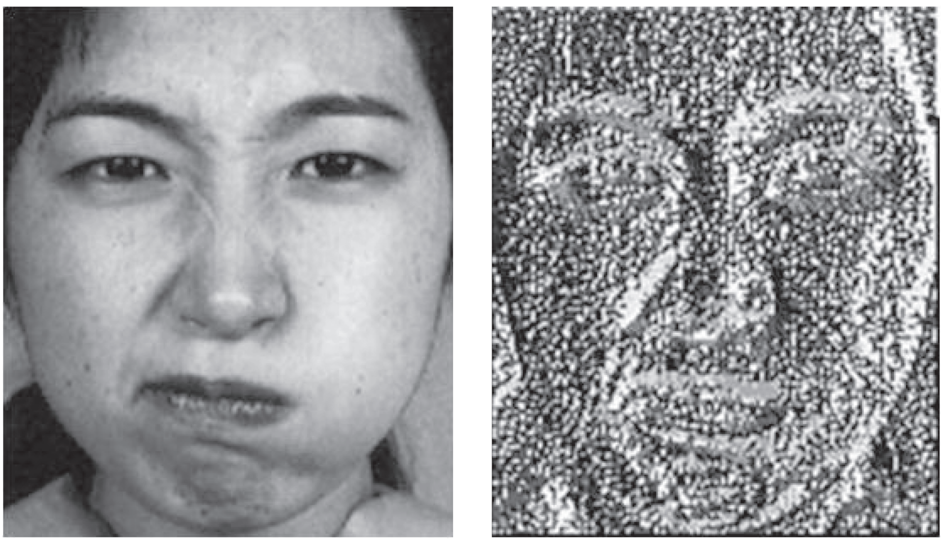

Fig. 2: An Example of LBP Map on A Facial Image

The image textual feature is often presented by the histogram of the LBP map of which the $i - th$ bin is defined as follows:

$$h_i = \sum_{x,y} I\left\{ fl(x, y) = i \right\}, i = 0, \cdots, n - 1$$

where n is the number of the LBP histogram bins (usually $n = 256 = 2^8$ as Fig. 1 showed), and function I is defined as:

$$I(A) = \begin{cases} 1, A = true \\ 0, A = false \end{cases}$$

Then the histogram of the LBP map is presented as $H = (h_0, h_1, \cdots, h_{n-1})$.

To describe the local feature, the LBP of an image is often divided into non-overlapping rectangle regions and the histogram is computed for each region. Then the whole LBP feature H is expressed as a concatenated sequence of histograms $H = (H^1, H^2, \cdots, H^r)$, where r is the number of the regions.

There are some approaches to measure similarity of two histograms (h^1, h^2) [10]. One of the most used is the histogram intersection measurement, which is defined as

$$\psi(h^1, h^2) = \sum_{i=1}^{n-1} \min(h_i^1, h_i^2)$$

3 Facial Feature Extraction Based on LBP

LBP is recently introduced into facial feature extraction for its excellent performance in describe local information [11, 12, 13, 14, 15, 16]. In following sections, the different LBP facial feature extraction methods are presented.

3.1 Global LBP Feature (GLBP)

Global LBP facial feature extraction method is a classical LBP feature application. The facial image is divided into non-overlapping rectangle regions (blocks). And the histogram is computed for each block of the whole facial image. Then the concatenated sequence of each block's LBP histogram constructs the facial features. Here the weight of each block of the whole facial image is equal in the histogram sequence. So we called Global LBP Feature of facial image. Fig. 3 showed the construction of the global LBP feature of a facial image. It should be noted that the recognition rate relates to the block size.

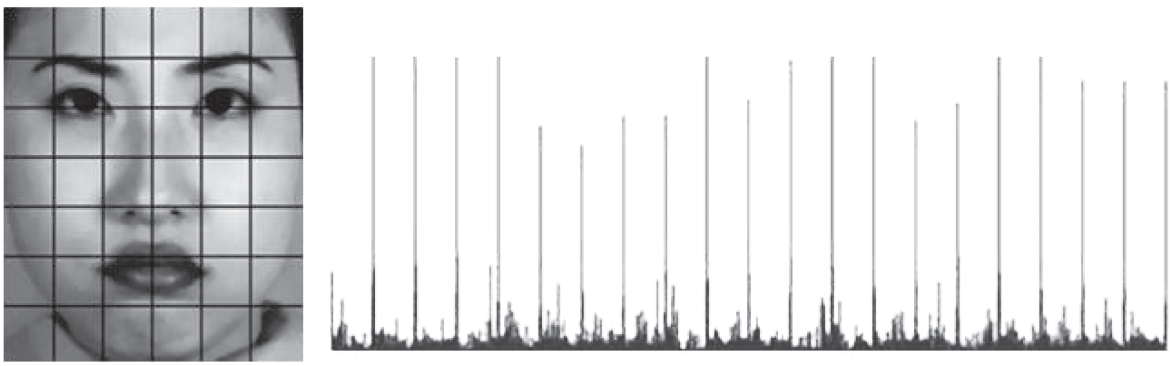

Fig. 3: The Partition of An Image (Left), Concatenate Each Block's LBP Sequence and Construct Feature (Right)

3.2 Local LBP Feature (LLBP)

For facial expression recognition, the experiments showed that some facial regions contribute more than others. For example, mouth contributes the most to facial expression, while canthus and eyebrow follow it. Therefore Local LBP selected some important regions such mouth neighborhood, eye neighborhood as facial mask.

The anatomy implied the arrangement of facial apparatus as shown in Fig. 4. Using the pre-knowledge of face structure and some eye position location algorithm [17], the local regions could be determinate automatically. As the LBP feature is operated on the facial regions the precise positions of eyeballs are not essential. Therefore, the integral projection method could cover the location problem of eyes and eyebrows as showed in Fig. 5.

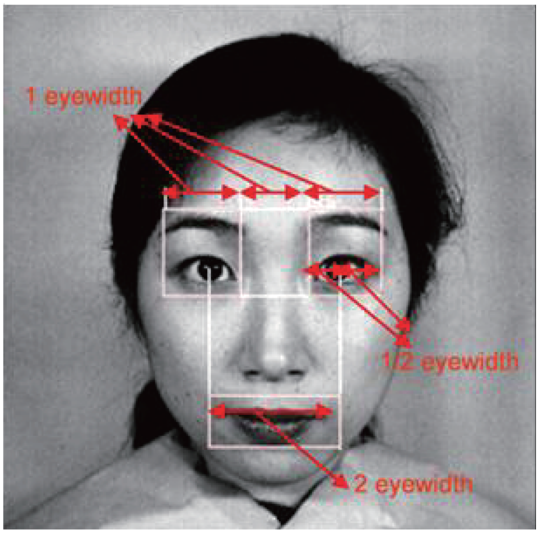

Fig. 4: The Facial Apparatus Arrangement

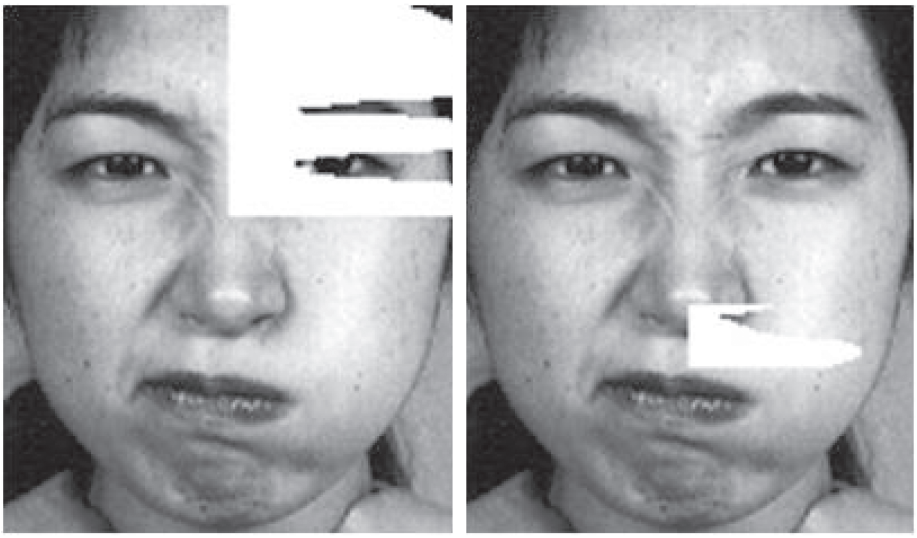

Fig. 5: Eye Location Based on Horizontal Projection

The local facial areas can be determined based on the arrangement of facial apparatus and the facial feature locations. An example of the local facial areas arrangement is showed in Fig. 6.

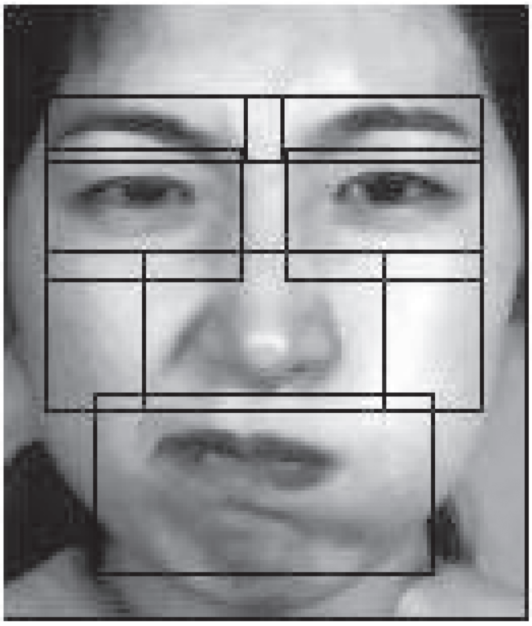

Fig. 6: Local Facial Areas Arrangement

Then the classical LBP operator is applied on the local areas. And the LBP features of these local areas formed the facial expression features for recognition.

3.3 LBP Difference Feature, Difference LBP Feature and Local Difference LBP Feature

An expressive face is often based on the facial feature movement as is well-known. So the difference between an expression face and the neutral face should be a better presentation of a facial expression. The difference between two images $f_1(x_i, y_i)$ and $f_2(x_i, y_i)$ is denoted as:

$$Sub(f_1 - f_2) = \sum_{i=0}^{N} \sum_{j=0}^{M} abs\left(f_1(x_j, y_i) - f_2(x_j, y_i)\right)$$

where $abs(\bullet)$ is the absolute function.

Then there would be some feature forms considering the combination of LBP and difference: (1) LBP Difference Feature (LBPD); (2) Difference LBP Feature (DLBP); and (3) Local Difference LBP Feature (LDLBP).

LBPD means the difference of LBP maps. First, the LBP map is obtained by applying LBP operator on an expressive facial image and the neutral facial image respectively. Then the difference between the two LBP maps is computed. Fig. 7 showed some examples of LBPD.

DLBP means the difference's LBP map. First, the difference between an expressive facial image and the neutral facial image is computed. Then the LBP operator is applied on the differential image to get the DLBP feature. Fig. 8 showed the DLBP with the same subjects in Fig. 7.

The concept of LDLBP is a combination of DLBP and LLBP (mentioned in section 3.2). LDLBP means the DLBP applied on the local regions of a face where full of more expressive information.

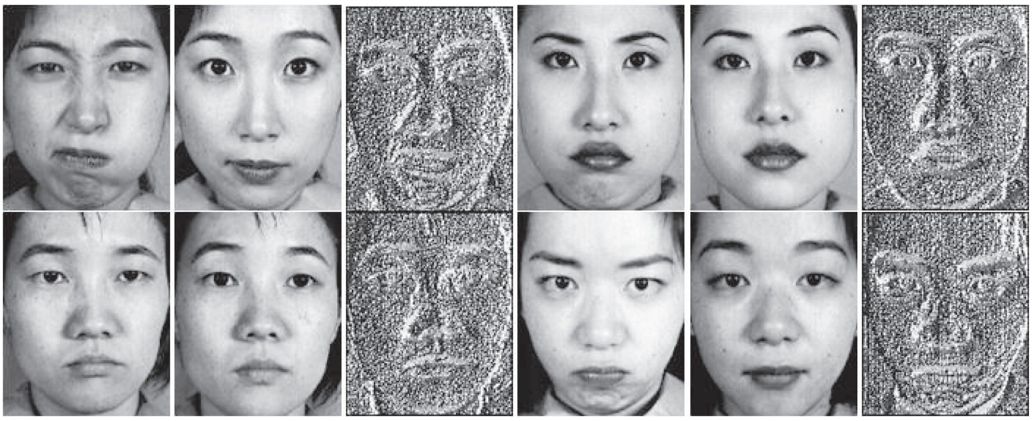

Fig. 7: Examples of LBPD, Expressive Image (Left), Neutral Image (Middle) and LBP Difference Images (Right)

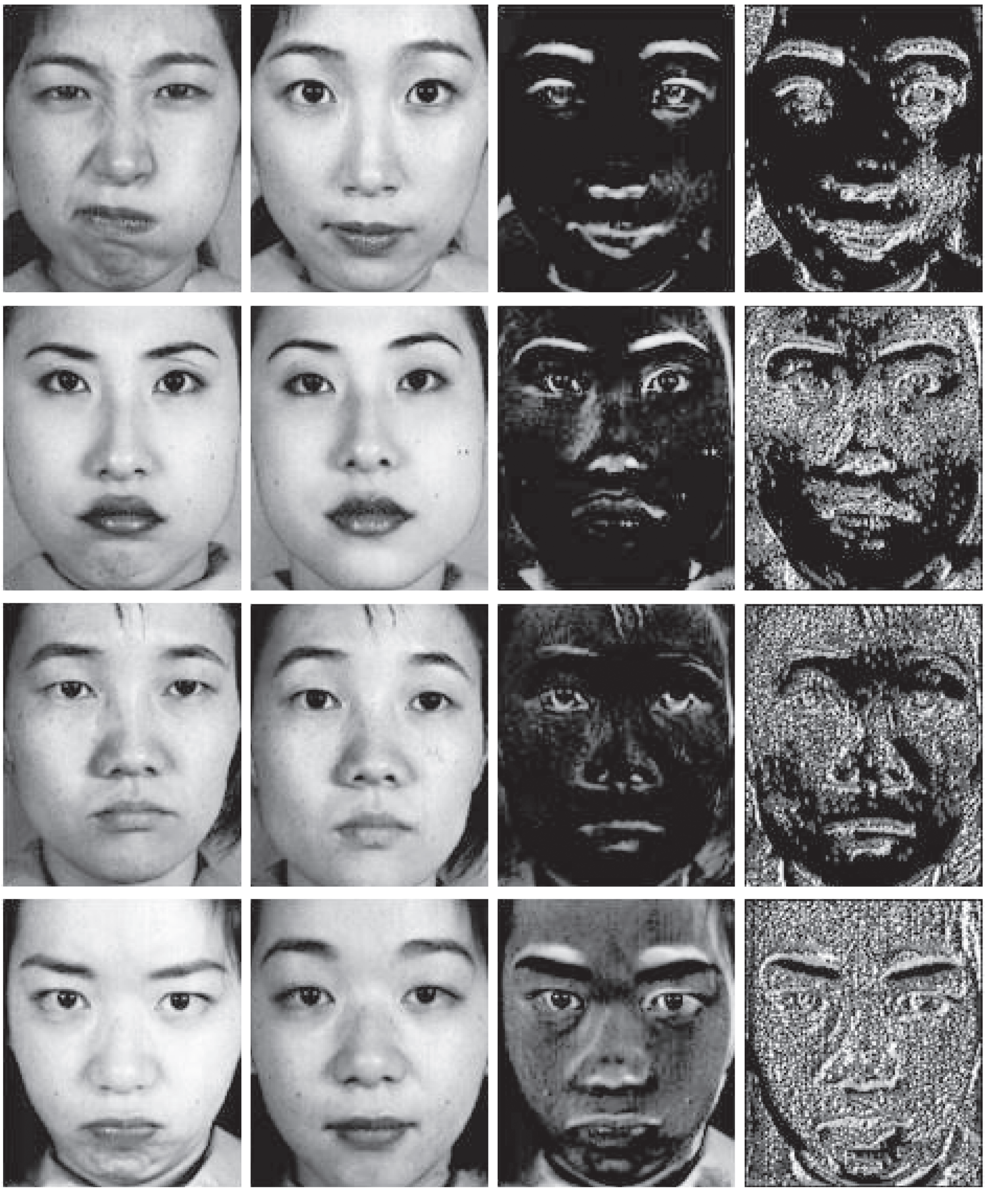

Fig. 8: Examples of DLBP, Expressive Images, Neutral Images, Difference and Difference's LBP Images (from Left to Right)

4 Facial Expression Recognition Based on LBP

The overall framework of facial expression recognition system based on Local Binary Patterns (LBP) is illustrated in Fig. 9. (1) A facial image is normalized; (2) The different form LBP features are extracted (i.e. GLBP, LLBP, etc.); (3) The LBP histograms of all the regions are concatenated to form histogram sequence as the input of the classifier; (4) The final decision is achieved by some classifier.

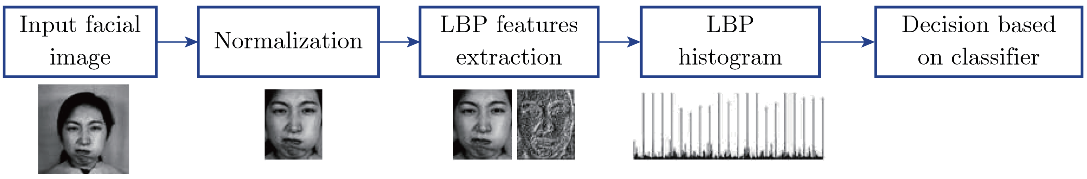

Fig. 9: Facial Expression Recognition Framework based on LBP Features

5 Experimental Evaluations

To evaluate the abilities of different LBP features for facial expression recognition, some experiments are conducted on JAFFE database which includes 3 or 4 examples for each of the six basic facial expressions and a neutral face image for each person, a total of 219 images of 10 persons.

Experiment 1: GLBP features. All the facial images are scaled to the size of, and then we adopted different partition methods to test the GLBP features, which means the block size for each partition method is different. The k-nearest neighbor classifier is used to make the final decision. And the average recognition rate for each partition method is showed in Table 1. The result showed that the best recognition rate is achieved when the image is divided into 67 blocks.

Table 1: Average GLBP Recognition Rate (%) of Different Partition

Partition	77	75	67	65	87	85
Average rate (%)	52.8	54.2	59	54.2	50.7	56.2

Experiment 2: LLBP feature. Two experiments conducted on JAFFE database using LLBP and GLBP. One is person-independent case which treats all persons equally. The other is person-dependent case which uses the training set and test samples of the same person. The comparison between LLBP and GLBP feature of each facial expression recognition rate is showed in Table 2. And the experimental results showed that the LLBP is better than GLBP for facial expression recognition.

Another experiment considered the comparison between LLBP and Local Gabor feature which is also often used to present image textures [18, 19]. The person-independent recognition test result is showed in Table 3. We can see that LLBP is better than Local Gabor feature in most expressions and obviously LLBP has less computation than Local Gabor.

Experiment 3: LBPD, DLBP and LDLBP. The third comparison experiment is conducted on Local Binary Patterns Difference (LBPD), Difference Local Binary Patterns (DLBP) and Local Difference Local Binary Patterns (LDLBP). And the average recognition rate is showed in Table 4.

Table 2: The Recognition Rate based on LLBP and GLBP

	Person-independent		Person-dependent	
	LLBP	GLBP	LLBP	GLBP
Anger	79.2	70.8	87.5	100
Disgust	54.2	37.5	87.5	91.7
Fear	54.2	25	100	79.2
Happy	87.5	83.3	100	91.7
Sad	45.8	45.8	95.8	66.7
Surprise	95.8	87.5	95.8	83.3
Average	68.1	59	94.3	85.4

Table 3: The Recognition Rate Based on LLBP and Local Gabor

	LLBP	Local Gabor
Anger	79.2	73.3
Disgust	54.2	26.7
Fear	54.2	33.3
Happy	87.5	63.3
Sad	45.8	53.3
Surprise	95.8	76.7
Average	68.1	53.3

Table 4: The Recognition Rate of LBPD, DLBP and LDLBP

Partition	77	75	67	65	87	85
Rates of LBPD	52.8	43.3	50	42.2	40.5	38.9
Rates of DLBP	47.2	51.1	52.2	52.2	50.7	51.2
Average rate of LDLBP	53.9					

We can see that DLBP performances better than LBPD in most cases. And the average rate of LDLBP is better than the best rate of DLBP and LBPD with different partitions.

6 Conclusion

LBP is an efficient local feature describe operator. Some comparison experiments of LBP are conducted for facial expression recognition in this paper. And some conclusions can be drawn from the experimental results. First, in facial expression recognition case the recognition rate is relevant to the partition block size. So an appropriate partition would be benefit for the recognition. Second, the Local LBP performances more than equal to Gabor feature with little computation. And third, the DLBP is a better facial feature than LBPD. We also noticed that the difference feature has not a better recognition result considering DLBP vs. LBP, and LDLBP vs. LLBP. The reason may lie in the normalization problem for the same facial feature points of different image are not at the same position in our experiment.

The future work is to explore the relation between facial image scale and the partition block size, and to study how to normalize the facial image based on still facial image.

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