The Face Recognition Algorithms Based on Weighted LTP

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***Abstract*—Local Ternary Pattern (LTP) is usually applied for texture classification problems. LTP extends the Local Binary Pattern using the custom threshold and encoding the small pixel difference into third state. Since the amount of information in different face regions is not equal, this paper proposes an approach of weighted LTP to show facial feature effectively. First, the original face image is divided into small blocks, and the LTP characteristic value and histogram of each piece of pixel are calculated. Then the weight of sub histogram is calculated by information entropy and the histogram of whole face image cascade of the histogram of all sub regions, finally, the weighted histogram of whole face image similarity are calculated by chi-square distance, the classification is performed by a nearest neighbor classifier. Experimental results show a better performance on ORL and Yale face database.**

***Index Terms*—local ternary pattern, local binary pattern, face recognition, histogram**

I. Introduction

Face recognition has received a great deal of attention from the scientific and industrial communities over the past several decades owing to its wide range of applications in information security, access control and law enforcement. The key to face recognition algorithm is extracting the facial features. LBP as a method of describing textures was applied to face recognition for the first time by Ahonen et al. But the original LBP method thresholds all pixels in the neighborhood based on the gray value of the central pixel [1]. As a result the original LBP becomes more sensitive to noise especially in near uniform or flat areas. In order to solve this problem, LTP that extract the features based on 3-valued texture operator was proposed by Tan *et al.* [2].

Both LBP and LTP method divided the facial image into some sub regions, but these regions has different amount of characteristic information, for example, eyes as an important characteristic of face contain more characteristic information than others regions of face. Therefore, that sub regions of face were given different weights can better performance characteristic of face. In this paper, we proposed weighted LTP algorithm that information entropy was introduced to calculate the weight of sub regions of face.

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II. Local Binary Pattern

The original LBP operator, introduced by Ojala *et al.*, was designed for texture description [3]. The operator labels the pixels of an image by thresholding the 3*3 neighborhood of each pixel with the center value and considering the result as binary number. Then, the histogram of labels can be used as a texture descriptor [1]. Formally, the LBP operator takes the (1):

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n S(p_n - p_c) \tag{1}$$

where in this case n runs over the 8 neighbors of the central pixel c, P_n and P_c are the gray-level values at c and n, and S(u) is 1 if $u \geq 0$ and 0 otherwise. See Fig. 1 for an illustration of the basic LBP operator.

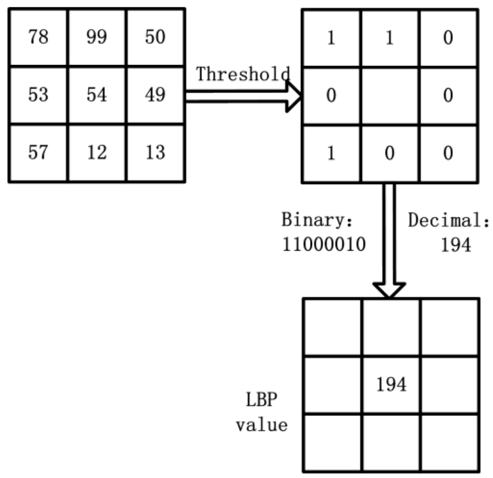

Figure 1. LBP operator.

Later the LBP operator was extended to use different size of neighborhood to deal with different scales of textures. Defining the neighborhood as a set of sampling points on circle centered at the pixel to be labeled allows any radius and number of sampling points [4]. However, after rotation, the result of LBP operator will have different value. Maenpaa extend the operator that the result of LBP is the minimum of rotated LBP operator [5].

Another extension to the operator is the definition of so-called uniform patterns. A local binary pattern is called uniform if it contains at most two bitwise transitions from 0 to 1or vice versa when the bit pattern is considered circular [6]. For example, the patterns

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11000011, 00111110 and 00000000 are uniform whereas the patterns 11001001 and 01010011 are not [7].

III. LOCAL TERNARY PATTERNS

Local Ternary Patterns are new 3-valued texture operator that can be considered as an extension to LBP. The LTP will define a threshold a threshold say t and any pixel value within the interval of –t and +t, thus assigns the value 0 to that pixel [8], while the user assigns the value 1 to that pixel if it is above this threshold and a value -1 if it is below it when compared to the central pixel value. The S(u) is replaced with function (2):

$$S(P_i, P_c, t) = \begin{cases} 1, & (P_i - P_c) \geq t \\ 0, & |P_i - P_c| < t \\ -1, & (P_i - P_c) < -t \end{cases} \tag{2}$$

To get rid of the negative values, the LTP values are divided into two LBP channels, the upper LTP (LTPU) and the lower LTP (LTPL). The LTPU is obtained by replacing the negative values in the original LTP by zeros. The LTPL is obtained in two steps, first, we replaced all the value of 1 in the original LTP to be zeros then we changed the negative values to be 1. See Fig. 2 for an illustration for procedure of the LTP operator.

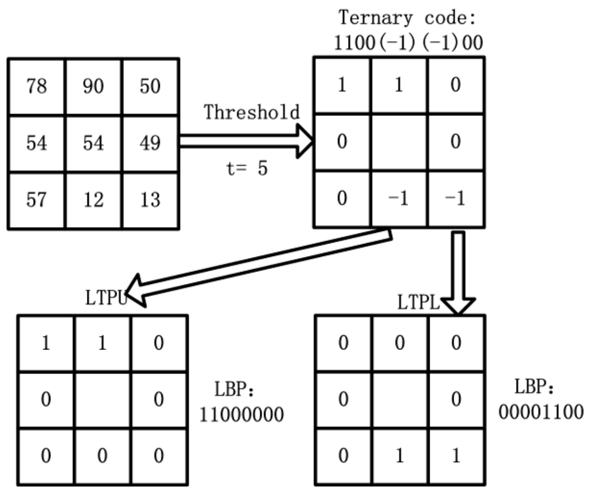

Figure 2. Procedure of the LTP operator.

IV. WEIGHTED LTP

About the weight of facial sub regions, in the references [2], the weights were selected without utilizing an actual optimization procedure and thus there are probably not optimal. In this paper, we applied information entropy to compute weight [4]. The information entropy is computed as in (3).

$$E_i = -\sum_{j=0}^{n} P_{i,j} \log P_{i,j} \tag{3}$$

where in this case j is the gray-level value, n is 255. $P_{i,j}$ represents probability of j-th gray value in i-th sub regions. $P_{i,j}$ is computed as in (4).

$$P_{i,j} = \frac{\sum_i T\{f(x,y) = j\}}{\sum_{i=1}^{m} \sum T\{f(x,y) = j\}} \tag{4}$$

Numerator represents number of j-th gray value in i-th sub regions, denominator represent number of j-th gray value in facial image. Thus, the weight of i-th sub regions was defined as (5).

$$\omega_i = \frac{E_i}{\sum_{i=1}^{m} E_i} \tag{5}$$

According to the theory of LTP, the LTP values of facial sub regions are divided into LTPU and LTPL. A LTP characteristic histogram of the whole face image is cascaded of LTPU characteristic histogram and LTPL characteristic histogram of all sub regions. The detailed process of extracting LTP features is shown in Fig. 3.

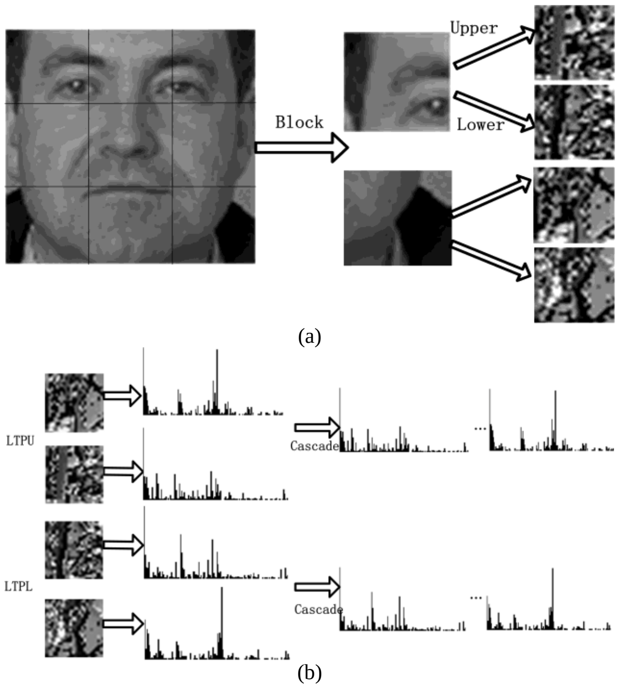

Figure 3. (a) Block face image and extend LTP features (b) cascade of histogram of all sub regions.

Finally, in the histogram matching, the weighted Chi square distance can be defined as (6).

$$\chi_\omega^2(H_1, H_2) = \sum_{i,j} \omega_j \frac{(H_{1i} - H_{2i})^2}{H_{1i} + H_{2i}} \tag{6}$$

in which H_1 and H_2 are the histograms to be compared, indices i and j refer to i-th bin in histogram corresponding to the j-th sub region and wj that calculated by (5) is the weight for region j.

V. EXPERIMENTAL RESULTS

This proposed approach is applied to ORL and Yale face database. The ORL face database have 400 images that consist of ten different images of each of 40 distinct subjects, the images were taken at different times, varying the lighting, facial expressions (open or closed eyes) and facial details (glasses or no glasses) [9]. The Yale face database contains 165 grayscale images of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: center-light, glasses, happy, left-light, wink and so on [9]. The ORL face database is shown as Fig. 4, and the Yale face database is shown as Fig. 5.

Figure 4. ORL face database.

Figure 5. Yale face database.

The block diagram for experiment is shown as Fig. 6.

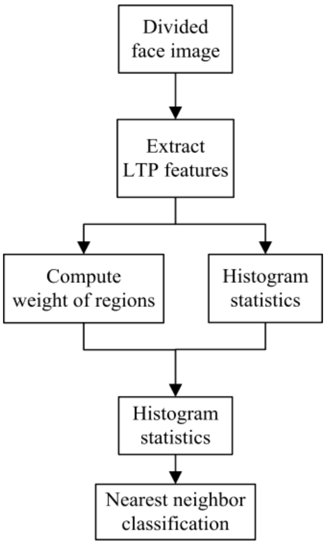

Figure 6. Block diagram of experimental.

To assess the performance of weighted LTP algorithm, we compare this algorithm with LBP and LTP in reference 2. In this work, 5 images are selected as training sample per subject, and the rest of images per subject are test images. Threshold t is set to 5 in the LTP operator, and there are three kind of dividing face images such as 3*3, 4*4 and 5*5.

The experimental object is the correct rate of face recognition [10]. The performance of the face recognition method can be measured with recognition rate, defined as follows:

$$\text{recognition rate} = \frac{number\ of\ correct\ recognition}{number\ of\ face} \times 100\%$$

The experimental results are shown in Table I and Table II.

TABLE I. EXPERIMENTAL RESULT IN ORL (%)

Method	Block Size		
	3*3	4*4	5*5
LBP	86.00	88.50	93.00
LTP in [2]	88.50	92.00	96.50
Weighted LTP	89.00	93.50	97.00

TABLE II. EXPERIMENTAL RESULT IN YALE (%)

Method	Block Size		
	3*3	4*4	5*5
LBP	87.78	91.11	93.33
LTP in [2]	90.00	93.33	96.67
Weighted LTP	91.11	96.67	97.78

We learn from Table I and Table II that the correct rate of weighted LTP is better than LBP and LTP in reference 2. The experimental result show that the correct rate of weighted LTP increase about 3%~4% in ORL face database and increase about 3%~5% in Yale face database. And the correct rate of block size of 5*5 more 8% than block size of 3*3 and more 3.5% than block size of 4*4 in ORL face database, while more 6.67% than block size of 3*3 and more 1.11% than 4*4 in Yale face database.

At the same time, we take a experiment that number of training sample produce an effect on the correct rate of weighted LTP. Where the threshold of weighted LTP is defined as 5 and block size is 5*5, and the number training is 2-9 of ORL face database, 2-10 of Yale face database, the results are described by Fig. 7 and Fig. 8.

With the increase in the number of training, the correct recognition rate of weighted LTP is gradually increased in ORL and Yale face database. When training number is increased from 2 to 5, the recognition rate increased quickly. While the recognition rate increased slowly with the training number increased from 5 to 9.

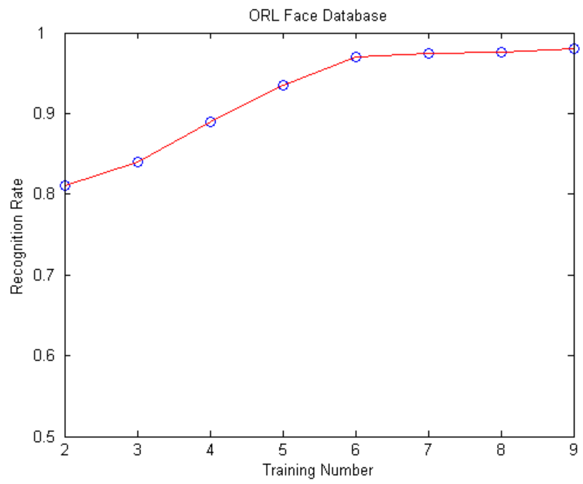

Figure 7. Experiment of ORL face database.

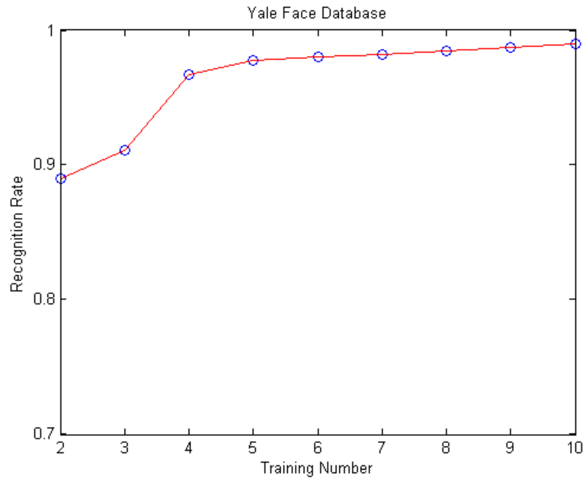

Figure 8. Experiment of Yale face database

VI. Conclusions

In this paper, we make an improvement that calculates histogram similarity combined with weight in LTP operator. So, the method can better to extract facial texture features and robustness to illumination. In order to validate the effective of our proposed method, we applied two face database for recognition. Experiment on the ORL and Yale face database show that the weighted LTP achieve much better performance than LBP and LTP in reference 2.

Unfortunately, defects still exist. We need new insights into the role of method of face recognition played in dealing with difficult lighting conditions and difficult noise in face image. For future work, more discriminative features will be researched to improve the robustness and accuracy of face recognition.

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