Face Recognition Based on Wavelet Transform and Regional Directional Weighted Local Binary Pattern

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Abstract—With the development of information technology, face recognition technology has been continuously developed. This technology has attracted the attention of many researchers, including institutions and production enterprises. Face recognition technology has become a relatively independent application technology area in various social services. This paper presents a face recognition algorithm based on wavelet transform and regional directional weighted local binary pattern. First of all, this algorithm puts forward a new basis for a face recognition, namely the level of detailed components of face images containing valid facial texture details, and the recognition rate is better than that of the vertical component information and diagonal component information. This is called Horizontal Component Prior Principle (HCPP). According to HCPP, the original image is decomposed with wavelet transformation. The algorithm extracts the scale and level of detailed components. To improve the original LBP operator, it presents the regional directional weighted local binary pattern (RDW-LBP). Using the RDW-LBP, it can calculate the histogram of scale components and detailed components decomposed by wavelet. The histogram feature vector of face image can be got with the different weighted sub-regions. The feature vector can be matched with Chi-Square distance. This approach further enhances the ability to extract face direction information effectively.

Index Terms—Face Recognition; Feature Extraction; Regional Directional Weighted Local Binary Pattern

I. INTRODUCTION

Face image is a kind of biological information which can achieve through non-contact. Personal identification has been a research hotspot in the field of pattern recognition and artificial intelligence. Over the years, researchers from all over the world have done many researches, but due to variability in the practical application environment such as the non-uniqueness and non-rigidity, face images make a certain distance between all kinds of recognition algorithm performance and practical business application requirements [1]. Therefore, further improving the recognition rate and robustness of face recognition algorithm become a main goal of face recognition research.

Pre-processing part of face image consists of four processes, namely the human face image normalization, scaling, illumination compensation and mask processing.

1. Face image normalization. According to the result of eye location, it can normalize the face database image to reduce the influence of deflection and scale change on recognition.

2. Scaling. Face image scaling can be realized by using bilinear interpolation algorithm for the calculation of wavelet decomposition. In this paper, a unified image scaling is 128 by 128.

3. Illumination compensation. Illumination change is one of the most important factors affecting the recognition rate. The problem of facial shadow caused by the uneven and excessive light will cause the recognition rate fall sharply. Adequate illumination compensation is particularly important to improve the recognition rate. Method to solve the illumination problem is divided into the following two categories. The first way is to start from the point of view of image enhancement, by the adjustment of brightness, contrast and facial image histogram distribution, to reduce the effect of illumination. Commonly used methods are histogram equalization, Gamma correction, logarithmic transformation, frequency filtering [9]. The second category is to recover the reflection component by splitting light components in the face image to effectively eliminate the effects of lighting [10-12]. In this paper, it uses the histogram equalization and LOG-DCT and Gamma correction algorithm for illumination preprocessing.

4. Mask processing. Mainly for compression and recognition of irrelevant or relatively changed areas, it uses mask processing which is assigned according to location algorithm or test library.

Basic Local Binary Pattern (LBP) was firstly put forward by Ojala [2] which was applied to the lines principle analysis and image retrieval. The late extension for unified mode circular neighborhood LBP descriptor [3] has been proposed to further reduce the dimension of the texture and to improve the ability of its portrayal of texture. Timo Ahonen [4] who firstly proposed LBP operator applied to face recognition expanded a new research idea in this field in 2004.

Without training, LBP algorithm has the strong promotion and classification ability. But for all the problems, it uses a single transformation which is not conducive to seek the classification hyperplane. At the
same time, extracting histogram vector in more images will inevitably lead to high vector dimensions which will make the computational complexity increases. If images are less, it will lose statistical significance. Otherwise, the robustness and illumination problems of LBP algorithm also limit the application.

By using basic LBP operator based on local texture feature, Timo Ahonen [5] introduced the idea of weighted sub-block on the basis of face image which further strengthened a lot of detailed characteristics of the eye and mouth area to affect recognition results. The method on FERET face database achieved good recognition performance. Shengcai Liao [6] proposed a method of multi-scale Block LBP, which separated image into blocks on the basis of calculating the first level scale image LBP map and used average grey value of subblocks to generate the second level scale image. Finally the multistage scale LBP histogram can be connected as a feature vector. The LBP feature histogram calculated by this way can contain both the micro and macro structure characteristics of the image, so the algorithm is more robust.

In order to improve the LBP operator’s ability to depict texture directionality, Mr Zhang proposed a method of combining LBP operator with Gabor wavelet for face recognition algorithm. First of all, this algorithm used multi-resolution Gabor wavelet filter for the normalized face image and extracted multiple Gabor amplitude domain mapping (Gabor Magnitude Map, GMM) corresponding to different directions and different scales, and then used LBP operator to calculate the local neighborhood relation on each GMM model. Combining with the Fisher discriminant classifier, the weighted matching HSLGBP binary was used for classification. Finally the algorithm on FERET face database also achieved good recognition performance. Wang wei extracted LBP feature spectra of two-stage low-frequency component by discrete wavelet decomposition, the test also achieved good recognition rate.

Xiaoyang Tan and Bill Triggs [7] [8] proposed a scalable LBP texture description operator—Local Ternary Pattern, (LTP). Threshold function of the LBP operator was modified by LTP operator. A original certain threshold value was improved to a set of threshold value intervals. And binary texture pattern of LBP was improved to the ternary texture patterns. At the same time, in order to reduce the complexity of the algorithm, the standard LTP texture model was divided into ULBP (Upper LBP) and LLBP (Lower LBP)-two LBP texture pattern for processing. The symmetry and noise threshold of LTP texture pattern can effectively eliminate the noise which improved the defects of LBP mode being sensitive to noise to improve the recognition rate. However, LTP has higher characteristic dimension problem, which makes the LTP feature need to take up more memory in storage and classification matching and makes the algorithm complex. It has seriously affected the further application of LTP.

So far, from previous research the following conclusions can be summarized. LBP operator describes the details of image, it has high distinguish ability to similar face images. But because LBP descriptor is small, it is more sensitive to noise and illumination. At the same time, the previous extension and improvement of LBP operator is proposed on the basis of the neighborhood pixel, they ignored the details of a microscopic scale and different direction which will affect recognition rate.

In the next section, we study process of face image preprocessing. In Section 3 we propose an improved optimization algorithm. In Section 4, we test the performance of proposed scheme and compare it with other face recognition algorithms. In Section 5 we conclude the paper and give some remarks.

II. PROCESS OF FACE IMAGE PREPROCESSING

Light, deflection, size, background and other objective factors are the enormous challenges for face recognition algorithms to improve the recognition rate. These factors must have certain robustness which is one of the main criteria for a practical recognition system. The effective pretreatment is a major method to reduce the influence of external factors. Pre-processing part of face image consists of four processes, namely the human face image normalization, scaling, illumination compensation and mask processing.

A series of different resolution sub-images by wavelet transform are obtained to form the original face image. Different sub images correspond to different frequency. The same level of the high frequency in sub-images reflects the decomposed images in different directions on the details. Low-frequency sub-images contain the main information in decomposed images. The eyes and the mouth have the main effect for recognition than other areas in a face image. After wavelet decomposition in face image, 3 detailed components can be obtained, and the horizontal detailed component contains the more features than other components in facial recognition. That’s the reason why the horizontal component is taken as the priority principle. 2D-Gabor function is defined as (1).

$$
\psi_{g,v}(x, y) = \frac{k^2}{\sigma^2} \exp\left( -\frac{k^2(x^2 + y^2)}{2\sigma^2} \right), \quad (1)
$$

$$
k = \begin{bmatrix} k_x \\ k_y \end{bmatrix} = \begin{bmatrix} k_x \cos \varphi_x \\ k_x \sin \varphi_x \end{bmatrix}, \quad k_x = 2 \frac{\sqrt{\pi} \sigma}{\sin \varphi_x}, \quad \varphi_x = \frac{\mu \pi}{K}.
$$

$$
x, y \text{ are Coordinate values of pixels. } \mu \text{ is direction of Gabor wavelet. } K \text{ is the number of total direction.}
$$

$$
v \text{ is scale factor of Gabor wavelet. } \frac{k}{\sigma} \text{ determines the size of Gaussian window. The convolution of } I(x, y) \text{ and } \psi_{g,v}(x, y) \text{ is (2).}
$$

$$
M(u, v, x, y) = \psi_{g,v}(x, y) \otimes I(x, y) = \int \psi_{g,v}(x, y) \cdot I(x, y) \, dx \, dy \quad (2)
$$
III. AN IMPROVED OPTIMIZATION ALGORITHM

A kind of algorithm based on wavelet transform and regional directional weighted local binary pattern is proposed for face recognition. First, the algorithm puts forward a new aspect for face recognition basis that the horizontal component details of the face image contain more effective facial textures than vertical component ones and also the level component details do more contribution than vertical component ones for recognition rate. Here is called a horizontal component prior principle (HCPP). According to the HCPP, algorithm uses wavelet transformation to the original image decomposition to extract the scale of the components and horizontal detail. To improve the original LBP operator, the regional directional weighted local binary pattern (RDW-LBP) is proposed. After the wavelet decomposition of the scale component and level detail component, its DW-LBP histogram can be calculated, and different sub areas are weighted in marco meaning, a character vector of RDW-LBP histogram is obtained corresponding to the face image. Finally, the Chi-Square distance is used for sequence histogram matching. By improving the primitive image calculation method of the LBP, RDW-LBP intensifies the ability to extract the facial texture information in effective direction.

LBP is based on the center pixel gray value and the local neighborhood pixel gray value to generate decimal code between two values and then calculate the histogram of LBP image to describe the texture details. The LBP operator basically consists of a 3 by 3 matrix which contains 9 pixel gray values. Suppose that gray value of the center pixel is $g_c$, 8 pixels around the center respectively are $g_0 \sim g_7$ (Fig. 1). The formula for the calculation of the basic LBP is Fig. 2.

$$LBP(g_c, g_i) = \sum_{k=0}^{7} 2^k S(g_i - g_c) \quad (3)$$

$$S(g_i - g_c \mid \delta, \tau) = \begin{cases} 1, & g_i > g_c \wedge g_i \leq \delta \tau \\ 0, & g_i < g_c \wedge g_i \leq \delta \tau \end{cases} \quad (4)$$

It can be promoted to coding pattern of circular neighborhood. Due to pixels symmetry of circular neighborhood, we can calculate threshold setting of $[0^\circ, \ 90^\circ]$ interval, then by symmetry transformation, we can get threshold distribution of the whole circle domain. It is supposed that there are $P$ number of sample pixel point, $P = 2^4$. A circle is divided into four intervals and take the IV interval for threshold sorting analysis. The point which is closer to number $g_{2i-2}$, the corresponding binary threshold $\delta_1, i = 1, 2, \ldots, k$ is less. The point which is closer to number $g_{2i-1}$, the corresponding binary threshold $\delta_1, i = 1, 2, \ldots, k$ is bigger and $\delta_0 \leq \delta_1 \leq \delta_2 \leq \cdots \leq \delta_k$.

In order to improve the rotation invariant of LBP operator, it is a good method to change the square neighborhood to circular neighborhood with arbitrary radius.

$$\begin{array}{c|c|c}
g_0 & g_1 & g_2 \\
g_3 & g_4 & g_5 \\
g_6 & g_7 & g_8 \\
\end{array}$$

Figure 1. LBP operator

$$\begin{array}{c|c|c|c}
134 & 143 & 156 & 0 & 0 & 0 \\
227 & 182 & 210 & 1 & 1 & 128 \\
208 & 182 & 180 & 1 & 1 & 64 \\
\end{array}$$

Binary:11101000

LBP=128+64+32+8+2=232

Figure 2. Calculation of LBP

So coding mode can be expressed as (5) to (7) and $BI(\cdot)$ represents bilinear interpolation calculation.

$$\{g_i \mid i = 0, 1, \ldots, k\} = BI(g_c, R, \theta) \quad (5)$$

$$DW-LBP(g_c) = \sum_{i=0}^{P-1} 2^i S(g_i - g_c) \quad (6)$$

$$S(g_i - g_c \mid i = 0, 1, \ldots, P - 1) = \begin{cases} 1, & g_i - g_c \geq \delta \tau \\ 0, & g_i - g_c < \delta \tau \end{cases} \quad (7)$$

From the definition of the LBP operator, it can be thought as a fusion of statistical method and structure analysis method for texture feature extraction. Each pixel in LBP will find a best matching code generated by original texture. LBP can overcome the deficiency of traditional statistical or structural method and has strong ability to describe the texture feature.

In this paper, binary local model RDW - LBP is proposed based on texture according to the different weighted directions. RDW - LBP thinks that the special texture of the face image, also is in line with the HCPP. So the local neighborhood pixels should not be assigned with equal weighting, and should be treated differently. Because horizontal direction information is more conducive to identify, horizontal direction should be given greater weight.

Figure 3. The original image and output with LBP

Take the eight neighborhood pixels of 3 by 3 matrix for example (Figure 1), $g_0$ and $g_4$ are located as the level...
adjacent pixels to the center pixel $g_c$. Their gray level difference with the center pixel represents brightness change of the local texture in the horizontal direction, thus it has maximum weight. $g_2$ and $g_6$ is directly below and above on the center pixel, and the weight takes second place. $g_1$, $g_5$, $g_3$ and $g_7$ have diagonal location with the center pixel, and they have minimum weight.

According to the algorithm, the weight is updated as shown in (8).

$$W_i, c = \exp(-\|g_i - g_c\|^2/t)$$ (8)

So the vector can be calculated as (9):

$$Q = \sum_{i=1}^{N} 2^k S(g_i - g_c) \cdot W_{i,c}$$ (9)

$N$ represents the number of the matrix. Based on RDW-LBP, different areas of the face image can be made with different weight. Fig. 3 shows that the $64 \times 64$ resolution of face images are divided into different number of blocks, as well as the weighting of the sub-block. According to the following situation, eye block has the maximum weight (dark grey), mouth weight (light gray) is smaller than eye block weight, cheeks and forehead weights (white) are smaller than mouth weight, and the weight of the rest parts is 0, which represents area not be included in the calculation. In practice, the weight can be adjusted according to the result of face positioning.

Here the function can be shown as follows:

$$P^{(n-1)} = (Q_1, Q_2, ..., Q_{n-1})$$ (10)

$$R^{(n-1)} = [P^{(n-1)}]^T D_n P^{(n-1)}$$ (11)

![Figure 4. Different areas of the face image with different weight](image)

$D_n$ is a matrix with $w$ dimension. When the best facial feature vector is extracted, it is needed to design an effective classifier to classify feature vector. It plays an important role of decision-making mechanism for classifier. If the classifier performance is good, it can achieve ideal classification results even though sometimes the extracted features are not good enough. On the contrary, if the classifier design is not good, it may not be able to achieve better classification results even the extracted characteristics are very good. Here are several kinds of classifiers.

The Euclidean Distance is usually a distance definition. It is the true distance between two points in the m dimensional space. The smaller the distance is, the more similar two histograms are.

$$d(H_1, H_2) = \sqrt{\sum (H_1(i) - H_2(i))^2}$$ (12)

The Bhattacharyya Distance is used to measure the correlation of two groups of feature histogram, which is commonly used for classifier algorithm.

$$d(H_1, H_2) = \sqrt{1 - \sum \frac{H_1(i) \cdot H_2(i)}{\sum H_1(i) \sum H_2(i)}}$$ (14)

$d(H_1, H_2)$ is a matrix with $w$ dimension. When the best facial feature vector is extracted, it is needed to design an effective classifier to classify feature vector. It plays an important role of decision-making mechanism for classifier. If the classifier performance is good, it can achieve ideal classification results even though sometimes the extracted features are not good enough. On the contrary, if the classifier design is not good, it may not be able to achieve better classification results even the extracted characteristics are very good. Here are several kinds of classifiers.

IV. EXPERIMENT AND ANALYSIS

In order to test the RDW-LBP algorithm, this paper selects the most commonly used two people face databases to test face recognition, which are AR face database and ORL face database respectively. In order to eliminate gender difference in recognition rate, this article from the AR face database randomly selects 50 people of the 70 men and 50 women face images for training and testing. Because this article focuses on testing recognition algorithm efficiency in shining environment, we select 12 images without shelter in each 24 pictures, 6 pieces are for training, and 6 copies are for testing. In ORL face database, it selects the volunteers in the experiment with odd number 5 images for training and even number 5 images for testing. TABLE I is recognition rate with three wavelet decomposition.

Based on horizontal component priority principle, Level details of face image do the largest contribution for recognition rate, which is greater than the vertical components and the diagonal components.

Because the different wavelet image decomposition can produce different results. In order to test the wavelet type influence on recognition rate, this paper compares the Haar wavelet, Daubechies wavelet and wavelet Sym-4 in AR and ORL face databases. TABLE I shows the wavelet’s impact on the final recognition rate. From each group of LL+LH, it can be seen in the column data, Haar wavelet shows the optimal effect. Its main reason is that, although the three low frequency component of the decomposed wavelet level LL, Haar wavelet information retention is incomplete, but it retained the most abundant high frequency LH details accordingly. For face recognition, different wavelet base for the low-frequency component are not obvious, the high frequency components provide the more detailed information, and the more conducive to improve recognition rate. The ultimate recognition rate of using Haar wavelet is optimal.
TABLE I. RECOGNITION RATE WITH THE THREE WAVELET DECOMPOSITION

<table>
<thead>
<tr>
<th></th>
<th>Haar (%)</th>
<th>Daubechies (%)</th>
<th>Sym-4 (%)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>LL+LH</td>
<td>LL</td>
<td>LL+LH</td>
</tr>
<tr>
<td>AR</td>
<td>97.2</td>
<td>96.2</td>
<td>96.5</td>
</tr>
<tr>
<td>ORL</td>
<td>99.2</td>
<td>98.7</td>
<td>98.3</td>
</tr>
</tbody>
</table>

Wavelet is an important tool for multi-scale analysis. Different decomposition layers can extract the details in different scales and can show different facial features. But because the LBP operator is the local texture feature, excessive decomposition layers may make the number of pixels too little in matrix, which will make LBP operator more sensitive to noise. Finally, it will affect the recognition. Therefore, this paper tests the effect of different wavelet decomposition layers on the final recognition rate. The Haar wavelet which has been tested with high recognition rate above is selected to test the recognition rate with different decomposition layers. TABLE II is recognition rate with different decomposition layers and TABLE III is recognition rate of different algorithms in the AR face recognition. TABLE II shows that the increase of Haar wavelet decomposition level can improve the recognition rate. But it is not the more the better. From the table II, it shows the recognition rate with 3 levels Haar wavelet decomposition is less than the recognition rate with 2 levels Haar wavelet decomposition. Also, the 3 level Haar wavelet decomposition increases the complexity and leads to the decrease of the calculation speed. So 2 levels Haar wavelet decomposition is used to extract features.

TABLE II. RECOGNITION RATE WITH DIFFERENT DECOMPOSITION LAYERS

<table>
<thead>
<tr>
<th></th>
<th>1 level</th>
<th>2 levels</th>
<th>3 levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>96.5%</td>
<td>96.67%</td>
<td>96.5%</td>
</tr>
<tr>
<td>ORL</td>
<td>98.4%</td>
<td>98.7%</td>
<td>98.3%</td>
</tr>
</tbody>
</table>

This article uses the Haar wavelet and RDW-LBP for human face feature extraction and Chi-Square for recognition test. On AR and ORL face databases, it is helpful to select the PCA, LBP and RDW-LBP recognition algorithm for recognition test and analysis. 500 pictures in AR face database are selected and added Gaussian noise the mean of which is 0 and the variance is 0.05, and the correct identified pieces are 489. The results increases by 4.1% and 1.8% respectively compared with PCA, LBP recognition rate (TABLE III); In ORL face database, 250 pictures are used for test and added Gaussian noise the mean of which is 0 and the variance is 0.05, the correct identified pieces are 243 pieces. The results increase by 5.5% and 3% respectively compared with PCA and LBP recognition rate (TABLE IV). Experimental data shows that RDW-LBP has strong face texture feature describing ability and robustness of facial expression.

As can be seen from Fig. 5 and Fig. 6, the red line represents the RDW-LBP algorithm, the blue line represents LBP algorithm. Number 1 represents matrix of 2*2, 2 represents matrix of 3*2, 3 represents matrix of 3*3, 4 represents matrix of 4*2, 5 represents matrix of 4*3, and 6 represents matrix of 4*4. With the increasing dimensions of the sample matrix, the two kinds of algorithm have greatly improved recognition rate. Under the same dimension, RDW-LBP algorithm recognition rate is superior to the recognition rate of LBP algorithm. After 3*3 matrix, the recognition rate is not obviously increased with the increase of dimensionality, but the increase of dimensionality decreases the speed of operation which will not be able to improve the efficiency. In the experiment, 3*3 matrix is selected as the sample matrix.

The recognition rate with noise in the yale face database is shown in Fig. 7 in which the red line represents the PCA algorithm, the green line represents LBP algorithm, and the blue line represents the RDW-LBP algorithm. Horizontal axis represents variance of Gaussian noise and vertical axis represents recognition rate. It clearly shows that the recognition rates with noise by PCA and LBP decrease with the increase of noise, but the recognition rate by RDW-LBP increases. With the Feret face database, the recognition rates with the three different algorithms have the same situation as is shown in Fig. 8. The experiments show that the RDW-LBP algorithm has good robustness.

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In order to increase the performance of face recognition algorithms, this paper has proposed an improved algorithm.

It has been a major research goal to improve the recognition rate and robustness of face recognition algorithms. At this goal, this paper first analyzes the influence of the directional details in face image and proposes the HCPP. Combining with HCPP, this paper puts forward a directional weighted based multi-scale regional type specification of binary local RDW-LBP texture description operator for robust face recognition algorithm. The Chi-Square is used to classify extracted characteristic vector. Experimental results indicate that HCPP is reasonable and correct, relative to the LBP operator. RDW-LBP operator proposed in this paper does not increase the calculation complexity, but effectively improves the recognition rate.

![Figure 8](image_url)

**REFERENCES**


