Face Recognition Algorithm Using Muti-direction Markov Stationary Features and Adjacent Pixel Intensity Difference Quantization Histogram

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***Abstract*—We have proposed a robust face recognition algorithm using adjacent pixel intensity difference quantization (APIDQ) histogram combined with Markov Stationary Features (MSF) so as to add spatial structure information to histogram features in our previous work. We named the new histogram feature as MSF-DQ feature. In this paper, we extend original MSF to multi-direction MSF by generating co-occurrence matrices with orientations of 0, 45, 90, 135 degrees, and then extract corresponding MSF-DQ features for every direction. Publicly available AT&T database of 40 subjects with 10 images per subject containing variations in lighting, posing, and expressions, is used to evaluate the performance of the proposed algorithm. Experimental results show face recognition using proposed multi-direction MSF-DQ features is more efficient compared with the original algorithm.**

Keywords-Face recognition; Adjacent pixel intensity difference quantization (APIDQ); Markov stationary feature (MSF); Multi-direction; Histogram feature.

I. INTRODUCTION

As a more natural and effective person identification method compared with that using other biometric features such as voice, fingerprint, iris pattern, etc., a lot of face recognition algorithms have been proposed [1]-[14] in the last two decades. These algorithms can be mainly categorized into two groups, that is to say, structure-based and statistics-based.

In the structure-based approaches [3][4], recognition is based on the relationship between human facial features such as eye, mouth, nose, profile silhouettes and face boundary. Statistics-based approaches [5][6][7] attempt to capture and define the face as a whole. The face is treated as a two dimensional pattern of intensity variation. Under this approach, the face is matched through finding its underlying statistical regularities. Principal component analysis (PCA) is a typical statistics-based technique [5]. However, these techniques are highly complicated and are computationally power hungry, making it difficult to implement them into real-time face recognition applications.

In [18][19], a very simple, yet highly reliable face recognition method called Adjacent Pixel Intensity Difference Quantization (APIDQ) Histogram Method is proposed, which achieved the real-time face recognition. At each pixel location in an input image, a 2-D vector (composed of the horizontally adjacent pixel intensity difference (dIx) and the vertically adjacent difference (dIy)) contains information about the intensity variation angle (θ) and its amount (r). After the intensity variation vectors for all the pixels in an image are calculated and plotted in the r-θ plane, each vector is quantized in terms of its θ and r values. By counting the number of elements in each quantized area in the r-θ plane, a histogram can be created. This histogram, obtained by APIDQ for facial images, is utilized as a very effective personal feature. Experimental results show a recognition rate of 95.7 % for 400 images of 40 persons (10 images per person) from the publicly available AT&T face database [20].

Li et al. [19] proposed Markov stationary feature (MSF), which can encode the relationships of intra-bin and inter-bin into histograms. Motivated by this consideration, we combine the APIDQ histogram with Markov stationary feature (MSF), so as to encode spatial structure information within and between histogram bins [17][18]. The MSF extends the APIDQ histogram features by characterizing the spatial co-occurrence of histogram patterns using the Markov chain models and improves the distinguishable capability of APIDQ features to extra-bin distinguishable level [19]. Experimental results demonstrated that the algorithm using the MSF-DQ features is more robust for face recognition evaluated by using the publicly available database of AT&T [20].

Pixel pairs in all directions are counted to generate a single co-occurrence matrix in original MSF algorithm. Considering that the co-occurrence matrices have been widely used in as a feature in registration and segmentation problems [23][24][24], we extend original MSF to multi-direction MSF by generating co-occurrence matrices with orientations of 0, 45, 90, 135 degrees, and then extract corresponding MSF-DQ feature for each direction. Therefore, more comprehensive personal feature information can be obtained by using multi-direction MSF-DQ features, which is named MDMSF-DQ.

In Section II, we will first introduce Markov stationary feature (MSF) as well as the Adjacent Pixel Intensity Difference Quantization (APIDQ) histogram feature which had been successfully applied to face recognition previously, and then describe proposed face recognition algorithm using multi-direction MSF-DQ features (MDMSF-DQ) in Section

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III. Experimental results will be discussed in Section IV. Finally, conclusions will be given in Section V.

II. RELATED WORKS

A. Markov Stationary features (MSF)

The Markov stationary feature (MSF) [19] extends the APIDQ histogram features by characterizing the spatial co-occurrence of histogram patterns using the Markov chain models and improves the distinguishable capability of APIDQ features to extra-bin distinguishable level. We will briefly introduce the MSF in this section.

Let p_k be a pixel in image I, the spatial co-occurrence matrix is defined as $C = (c_{ij})_{K\times K}$ where

$$c_{ij} = \#(p_1 = c_i, p_2 = c_j \| p_1 - p_2 | = d)/2, \tag{1}$$

in which d (d=1 in this paper) indicates L_1 distance between two pixels p_1 and p_2, and c_{ij} counts the number of spatial co-occurrence for bin c_i and c_j.

The co-occurrence matrix c_{ij} can be interpreted in a statistical view. Markov chain model is adopted to characterize the spatial relationship between histogram bins.

The bins are treated as states in Markov chain models, and the co-occurrence is viewed as the transition probability between bins. In this way, the MSF can transfer the comparison of two histograms to two corresponding Markov chains.

The elements of the transition matrix *P* are constructed from the spatial co-occurrence *C* by formula (2).

$$P_{ij} = c_{ij} / \sum_{j=1}^{K} c_{ij} \tag{2}$$

The state distribution after n steps is defined as $\pi(n)$, and the initial distribution is $\pi(0)$, the Markov transition matrix obeys following rules.

$$\pi(n+1) = \pi(n)P,\ \pi(n) = \pi(0)P^n; \quad P^{m+n} = P^m P^n \tag{3}$$

where $\pi(0)$ is defined as

$$\pi(0) = c_{ii} / \sum_{i=1}^{K} c_{ii} \tag{4}$$

According to the formula (3), we can get a distribution of π called a stationary distribution which satisfies

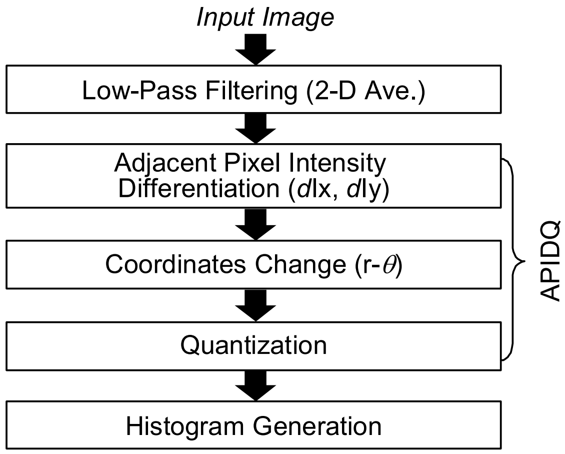

Figure 1. Processing steps of APIDQ histogram method.

$$\pi = \pi P \tag{5}$$

The stationary distribution becomes the final representation of MSF. Obtaining the MSF of each image, the comparison of two histograms is transferred to the comparison of two corresponding Markov chains.

B. Adjacent Pixel Intensity Difference Quantization (APIDQ)

The Adjacent Pixel Intensity Difference Quantization (APIDQ) histogram method [15] has been developed for face recognition previously. Figure 1 shows the processing steps of APIDQ histogram method. In APIDQ, for each pixel of an input image, the intensity difference of the horizontally adjacent pixels (*d*Ix) and the intensity difference of the vertically adjacent pixels (*d*Iy) are first calculated by using simple subtraction operations shown as formula (6).

$$\begin{aligned} dIx(i,j) &= I(i+1,j) - I(i,j) \\ dIy(i,j) &= I(i,j+1) - I(i,j) \end{aligned} \tag{6}$$

A calculated (*dIx*, *dIy*) pair represents a single vector in the *dIx*-*dIy* plane. By changing the coordinate system from orthogonal coordinates to polar coordinates, the angle θ and the distance *r* represent the direction and the amount of intensity variation, respectively. After processing all the pixels in an input image, the dots representing the vectors are distributed in the *dIx*-*dIy* plane. The distribution of dots (density and shape) represents the features of the input image.

Each intensity variation vector is then quantized in the r-θ plane. Quantization levels are typically set at 8 in θ-axis and 8 in *r*-axis (totally 50). Since *dIx*-*dIy* vectors are concentrated in small-r (small-*dIx*, -*dIy*) region, non-uniform quantization steps are applied in *r*-axis. The number

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of vectors quantized in each quantization region is counted and a histogram is generated. In the face recognition approach, this histogram becomes the feature vector of the human face.

The essence of the APIDQ histogram method can be considered that the operation detects and quantizes the direction and the amount of intensity variation in the image block. Hence the APIDQ histogram contains very effective image feature information. The MSF extends histogram based features with spatial structure information of images, and transfer the comparison of two histograms to two corresponding Markov chains.

III. PROPOSED FACE RECOGNITION ALGORITHM

A. Generation of 4 directions co-occurrence matrices

Pixel pairs in all directions are counted to generate a single co-occurrence matrix in original MSF algorithm. In this paper, we extend original MSF to multi-direction MSF by generating co-occurrence matrices with orientations of 0, 45, 90, 135 degrees as shown in Figure 2.

Because different MSF-DQ features are extracted with different direction co-occurrence matrices of the image, more comprehensive personal feature information can be obtained by combining multiple recognition results using 4 direction co-occurrence matrices.

In this paper, we employ 4 direction co-occurrence matrices for the facial image to extract more powerful personal feature. As shown in Figure 2, after APIDQ processing is carried out, MSF-DQ features at different directions are extracted from corresponding co-occurrence matrices. Recognition results are firstly obtained using MSF-DQ features at different directions separately and then combined by weighted averaging.

B. Proposed algorithm

The procedure of proposed face recognition algorithm using APIDQ histogram combined with MSF is shown in Figure 3. Low-pass filtering is first carried out before APIDQ using a simple 2-D moving average filter. This low-pass filtering is essential for reducing the high-frequency noise and extracting the most effective low frequency component for recognition. Then original APIDQ is implemented and quantization region number corresponding to each 2x2 image block is calculated. As shown in Figure 3, because each 2x2 image block can be regarded as a pixel of color c_i, the co-occurrence matrix for APIDQ can be computed according to formula (1). But instead of counting pixel pairs in all directions to generate a single co-occurrence matrix in original MSF algorithm, co-occurrence matrices at 4 different directions of 0, 45, 90, 135 degrees are generated.

The Markov transition matrix P for each direction of co-occurrence matrix is calculated by formula (2). Then the stationary distribution of corresponding direction can be

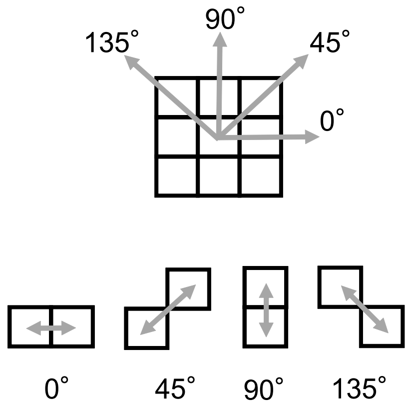

Figure 2. Extraction of Multi-direction pixel pairs .

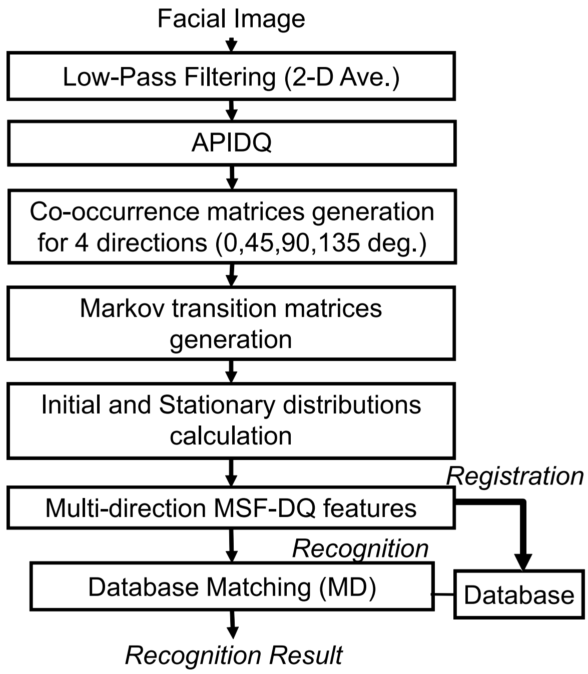

Figure 3. Proposed face recognition algorithm using multi-direction MSF-DQ features (MDMSF-DQ).

approximated by the average of each row $\vec{a}_i$ of A_n using formula (7).

$$\pi \approx \frac{1}{K} / \sum_{i=1}^{K} \vec{a}_i \text{, where } A_n = [\vec{a}_1, \cdots, \vec{a}_k]^T, \tag{7}$$

$$A_n = \frac{1}{n+1}(I + P + P^2 + \cdots + P^n) \tag{8}$$

n =50 is used as same as in [19]. The initial distribution $\pi(0)$ can be obtained by formula (4). As shown in formula (9), the Markov stationary feature in each direction is defined as the combination of the initial distribution $\pi(0)$ and the stationary distribution π after n steps.

$$\vec{h}_{MSF-DQ} = [\pi(0), \pi]^T \tag{9}$$

We call MSF extension of APIDQ histogram MSF-DQ feature. The MSF-DQ feature made from each direction is compared with those from the same direction in the database by calculating distances (d_i) between them using the same distance calculation formula as in [19]. Then the integrated distances (D) are obtained by weighted averaging as shown in the following formula (10).

$$D = \frac{\sum w_i d_i}{\sum w_i} \tag{10}$$

where w_i is weighting coefficient of the different directions, The best match is output as recognition result by searching the minimum integrated distance.

Figure 4. Samples of the database of AT&T Laboratories Cambridge.

IV. Experimental Results and Discussions

A. Data sets

The publicly available face database of AT&T Laboratories Cambridge [20], [21]is used for the analysis and recognition experiments. Forty people with 10 facial images each, (totaling 400 images), with variations in face angles, facial expressions, and lighting conditions are included in the database. Each image has a resolution of 92x112. Figure 4 shows typical image samples of the database of AT&T Laboratories Cambridge. From the 10 images for each person, five were selected as probe images and the remaining five were registered as album images. Recognition experiments were carried out for 252 ($_{10}C_5$) probe-album combinations using the rotation method.

B. Experimental results

Comparison of recognition results are shown in Figure 5. Recognition success rates are shown as a function of filter size. The filter size represents the size of the averaging filter core. A size of F3, for instance, represents the filter using a 3x3 filter core. Figure 5 shows the comparison between the recognition results using different direction MSF-DQ features separately and multi-direction MSF-DQ features. Average recognition rate is shown here. “bin 50 (original DQ)” stands for the case that original APIDQ utilizes quantization table containing the number of bins of 50 in [15][16]. “bin50_all_directions” stands for the case using pixel pairs in all directions counted to generate a single co-occurrence matrix in original MSF algorithm. “bin50_0:1:0:1”, “bin50_1:0:1:0”, and “bin50_1:1:1:1”, stand for the cases using combination of various direction MSF-DQ features of 0, 45, 90, 135 degrees respectively, which weighting coefficient at each direction level is set as 0 or 1.

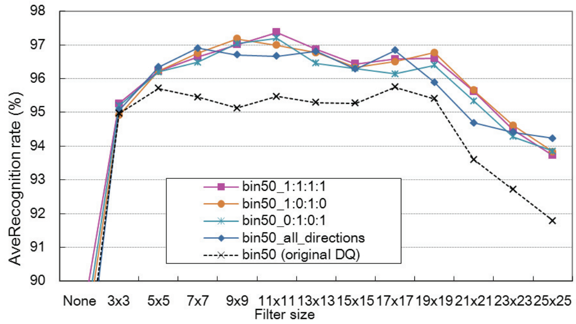

Figure 5. Comparison of results. Average recognition rate is shown here.

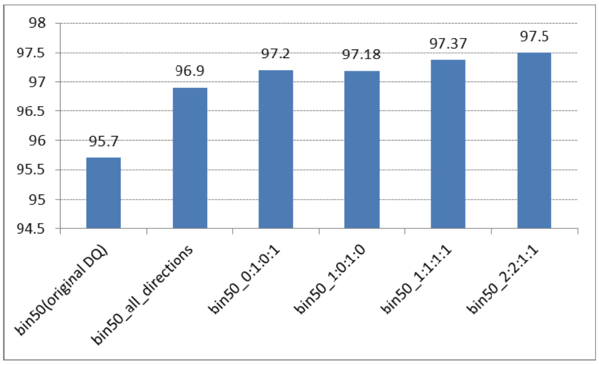

Figure 6. Comparison of results. Maximum average recognition rate is shown here.

The best performance of the average recognition rate 96.9% is obtained at original image size of 92x112 when using all-direction MSF-DQ features. By using multi-direction MSF-DQ features with the weighting coefficient at each direction level of 1, highest recognition rate increases to 97.37%. It can be said that multi-direction MSF-DQ features is more robust than original MSF-DQ features. We notice that the case that only using the combination of 0, 90 degrees or the combination of 45, 135 degrees can achieve similar recognition accuracy with that using 4 directions.

Figure 6 shows comparison results of the maximum average recognition rate using some combinations. Maximum of the average recognition rate 97.5% is achieved at the combination of weighting coefficients of 2:2:1:1 for 0, 45, 90, 135 degrees.

V. CONCLUSION AND FUTURE WORK

In this paper, we improved our face recognition using multi-direction MSF-DQ feature by generating co-occurrence matrices with orientations of 0, 45, 90, 135 degrees, and then extract corresponding MSF-DQ feature for each direction multi-direction for the facial image to extract more powerful personal feature. Excellent face recognition performance as large as a 97.5% recognition rate has been achieved by using the publicly available database of AT&T. It can be said that multi-direction MSF-DQ features is more is more robust for face recognition.

Because AT&T database is not a large face database, we will evaluate our proposed algorithm for practical application by using large database of FERET in our future work.

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