An Improved Face Recognition Algorithm Using Adjacent Pixel Intensity Difference Quantization Histogram and Markov Stationary Feature

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Abstract—**Previously, 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. We named the new histogram feature as MSF-DQ feature. In this paper, we employ multi-resolution analysis for the facial image to extract more powerful personal feature. After a set of multi-resolution pyramid images is generated using sub-sampling, MSF-DQ features at different resolution levels are extracted from corresponding pyramid images. Recognition results are firstly obtained using MSF-DQ features at different resolution levels separately and then combined by weighted averaging. 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-resolution features is very efficient. The highest average recognition rate of 98.57% is obtained.**

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

I. INTRODUCTION

In the last two decades, face recognition has been a hot research topic in artificial intelligence and pattern recognition area due to its potential applications in many fields such as law enforcement applications, security applications and video indexing, etc. 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]. These algorithms can be roughly divided into two main approaches, 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].

In [17][18], we combine the APIDQ histogram with Markov stationary feature (MSF), which was proposed in [19], so as to encode spatial structure information within and between histogram bins. 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]. The highest average recognition rate of 97.16% is obtained by using the publicly available database of AT&T [20]. It can be said that the extended MSF-DQ features is more robust for face recognition.

We can imagine that different MSF-DQ features are extracted with different resolutions of the image. Therefore, more comprehensive personal feature information can be obtained by combining multiple recognition results using multi-resolution analysis. In this paper, we employ multi-resolution analysis for the facial image to extract more powerful personal feature.

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-resolution MSF-DQ features in Section 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 [19].

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

where $\pi(0)$ is defined as

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

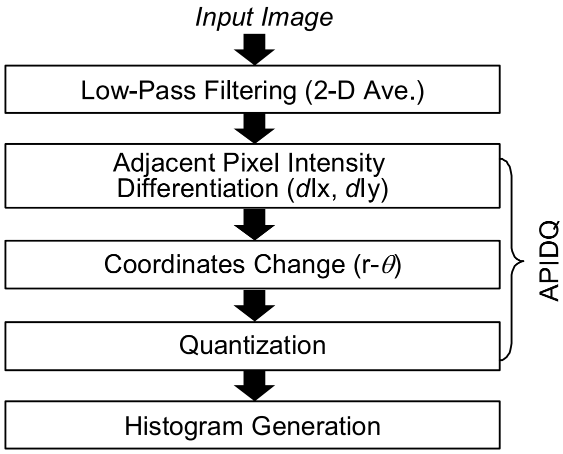

Figure 1. Processing steps of APIDQ histogram method.

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

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

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 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.

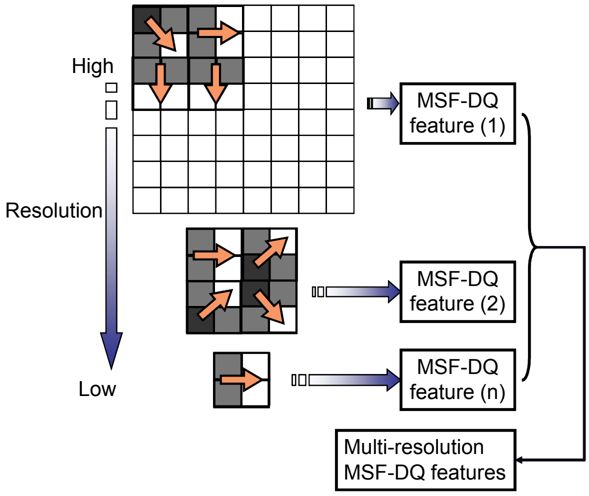

Figure 2. Multi-resolution MSF-DQ features.

III. PROPOSED FACE RECOGNITION ALGORITHM

A. *Multi-resolution analysis*

Because different MSF-DQ features are extracted with different resolutions of the image, more comprehensive personal feature information can be obtained by combining multiple recognition results using multi-resolution analysis. In this paper, we employ multi-resolution analysis for the facial image to extract more powerful personal features. As shown in figure 2, after a set of multi-resolution pyramid images is generated using sub-sampling, MSF-DQ features at different resolution levels are extracted from corresponding pyramid images. Recognition results are first obtained using MSF-DQ features at different resolution levels 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. After multi-resolution pyramid images are generated using sub-sampling, APIDQ operations are implemented on respective images with different resolution and quantization region number corresponded to each 2x2 image block is calculated. 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).

The Markov transition matrix P is calculated by formula (2). Then the stationary distribution can be approximated by the average of each row $\vec{a}_i$ of A_n using formula (7).

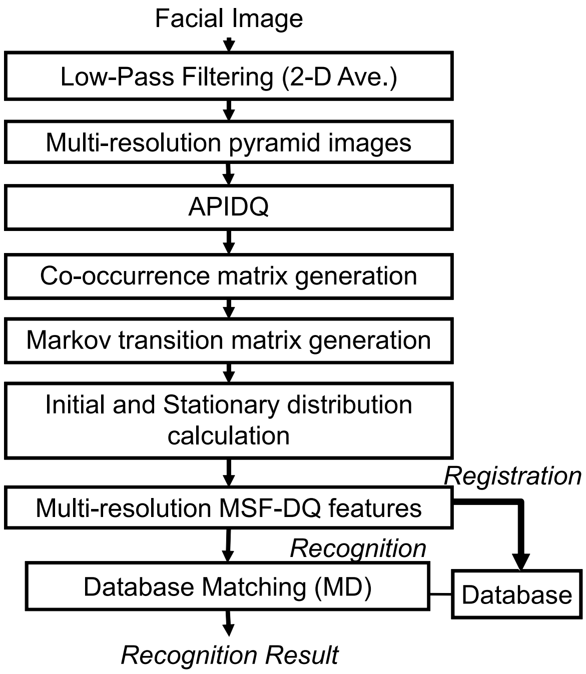

Figure 3. Proposed face recognition algorithm using multi-resolution MSF-DQ features.

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

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

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

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 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 as a MSF-DQ feature. The MSF-DQ feature made from each pyramid image is compared with those from the same resolution images 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 resolutions, The best match is output as recognition result by searching the minimum integrated distance.

IV. Experimental Results and Discussions

A. Data sets

The publicly available face database of AT&T Laboratories Cambridge [20] 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 resolution MSF-DQ features separately and multi-resolution 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]. “bin42_s92x112”, “bin42_s46x56”, “bin42_s23x28”, and “bin42_s11x14” stand for the cases

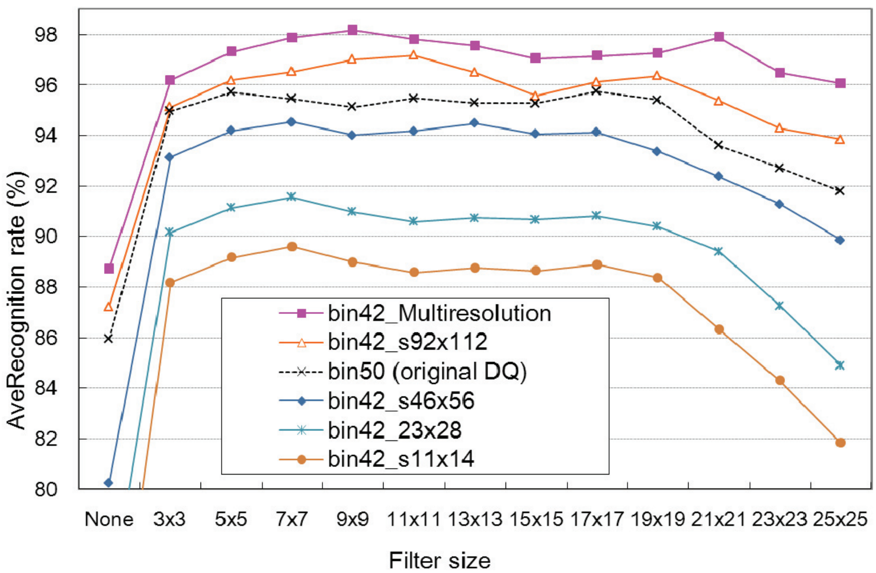

Figure 5. Comparison of results. Average recognition rate is shown here.

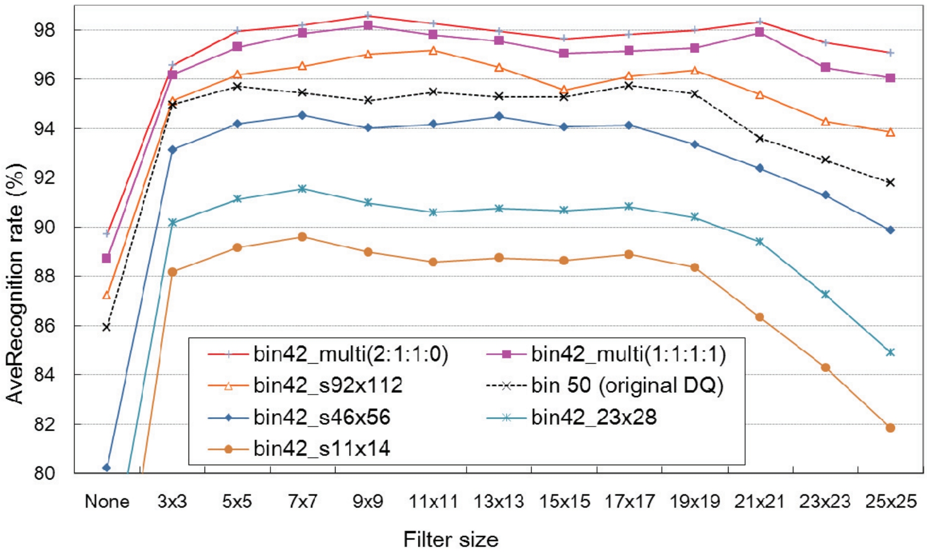

Figure 6. Comparison of results. Average recognition rate is shown here.

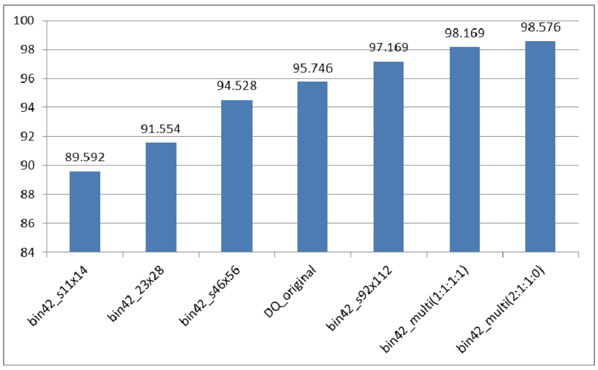

Figure 7. Comparison of results. Maximum average recognition rate is shown here.

using various resolution MSF-DQ features separately. “bin42_Multiresolution” stands for the case using multi-resolution MSF-DQ features proposed in this paper, which weighting coefficient at each resolution level is set as 1.

The best performance of the average recognition rate 97.16% [17][18] is obtained at original image size of 92x112 when using separate single-resolution MSF-DQ features. By using multi-resolution MSF-DQ features with the weighting coefficient at each resolution level of 1, highest recognition rate increases to 98.16%. It can be said that multi-resolution MSF-DQ features is more robust than single-resolution MSF-DQ features.

Figure 6 and 7 also show the results of using single-resolution solely, and those of using some combinations. Maximum of the average recognition rate 98.57% is achieved at the combination of weighting coefficients of 2:1:1:0 with the image resolutions of 92x112, 46x56, 23x28, 11x14, respectively. It can be considered too small image resolution give less contribution for feature generation.

V. Conclusion

In this paper, we improved our face recognition using MSF-DQ feature by employing multi-resolution analysis for the facial image to extract more powerful personal feature. Excellent face recognition performance as large as a 98.57% recognition rate has been achieved by using the publicly available database of AT&T. It can be said that multi-resolution MSF-DQ features is more robust for face recognition.

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