Face Recognition Algorithm Based on Adjacent Pixel Intensity Difference Quantization in Rectangular Coordinate Plane

Feifei Lee, Koji Kotani, Qiu Chen, and Tadahiro Ohmi

Abstract—**We have proposed a very simple yet highly reliable face recognition algorithm using Adjacent Pixel Intensity Difference Quantization (APIDQ) histogram previously. In this paper, we present a modified quantization method to improve recognition performance. After the intensity variation vectors for all the pixels in an image are calculated, each vector is quantized directly in (*d*Ix, *d*Iy) plane instead of *r*-θ plane. By counting the number of elements in each quantized area in the (*d*Ix, *d*Iy) plane, a histogram can be created. This histogram, obtained by APIDQ for facial images, is utilized as a very effective personal feature. Furthermore, by utilizing rough location information of facial parts, the facial area is divided into 5 individual parts, and then APIDQ is applied on each facial component. Recognition results are firstly obtained from different parts separately and then combined by weighted averaging. Experimental results show that the top of recognition rate of the whole research groups is achieved by using FB task of the publicly available face database of FERET.**

Index Terms—**Face recognition, adjacent pixel intensity difference quantization (APIDQ), histogram.**

I. INTRODUCTION

As a more natural and effective person identification method compared with that utilizing other biometric features such as voice, fingerprint, iris pattern, etc., face recognition has received significant attention in the last two decades due to requirement of security and law enforcement applications [1]. A lot of face recognition algorithms have been proposed [2-12]. These algorithms can be roughly divided into two main categories, namely, feature-based and appearance-based.

In the feature-based approaches [4], [5], recognition is based on the relationship between human facial features such as eye, mouth, nose, profile silhouettes and face boundary. Appearance-based approaches [6]-[9] 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 appearance-based technique [6], which casts about for a set of projection vectors projecting the facial image data into a subspace based on the variation in energy. Fisherface is another representative in this category, which incorporates linear discriminant analysis (LDA) to extract the most discriminant features and to reduce the dimensionality [7]. However, these techniques are highly complicated and are computationally power hungry, making it difficult to implement them into real-time face recognition applications.

Previously, we have developed a very simple, yet highly reliable face recognition method called *Adjacent Pixel Intensity Difference Quantization (APIDQ)* Histogram Method, which achieved the real-time face recognition [13]. At each pixel location in an input image, a 2-D vector (composed of the horizontally adjacent pixel intensity difference (*d*Ix) and the vertically adjacent difference (*d*Iy)) 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. By combining APIDQ with an appropriate low pass filter as pre-treatment of a facial image, the useful features for face recognition can be extracted. 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. In this paper, we focus on the quantization method of APIDQ. We found that quantization directly in (*d*Ix, *d*Iy) plane is more efficient in computation and can get higher recognition rate instead of r-θ plane.

In section II, we introduce proposed modified *Adjacent Pixel Intensity Difference Quantization (APIDQ)* histogram method. Experimental results will be discussed in section III. Finally, conclusions are given in section IV.

II. PROPOSED METHOD

Fig. 1 shows the processing steps of proposed modified Adjacent Pixel Intensity Difference Quantization (APIDQ) histogram method. 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. 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 (1).

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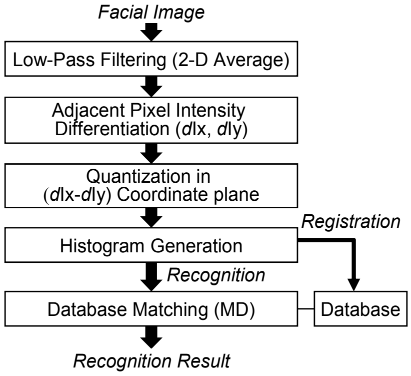

Fig. 1. Processing steps of modified APIDQ histogram method.

$$dIx(i,j) = I(i+1,j) - I(i,j)$$
$$dIy(i,j) = I(i,j+1) - I(i,j) \quad (1)$$

A calculated (dIx, dIy) pair represents a single vector in the dIx-dIy plane. After processing all the pixels in an input image, the dots representing the vectors are distributed in the dIx-dIy plane as shown in Fig. 2. The distribution of dots (density and shape) represents the features of the input image.

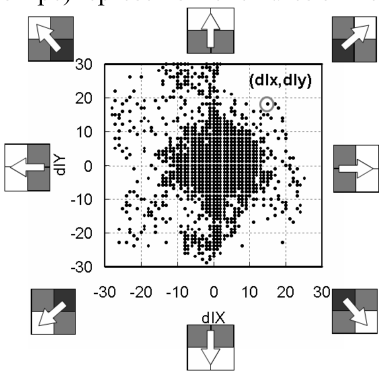

Fig. 2. Typical example of (dIx, dIy) vector distribution. The distribution of dots (density and shape) represents the features of the input image.

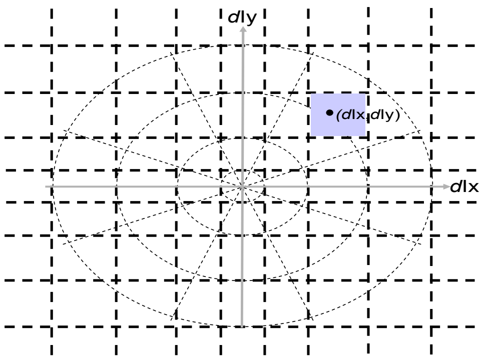

Fig. 3. Quantization in (dIx-dIy) plane.

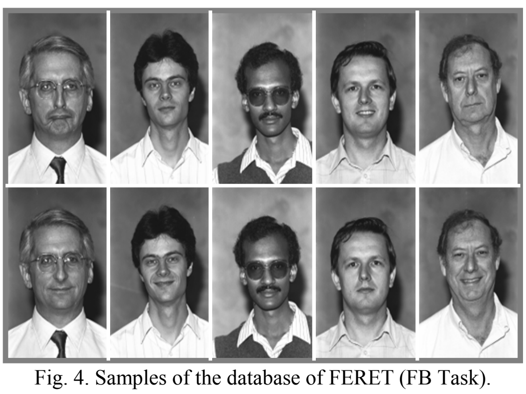

Fig. 4. Samples of the database of FERET (FB Task).

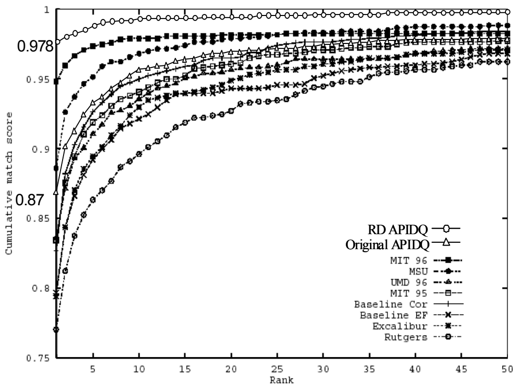

Fig. 5. Recognition results of FB task. Top1 recognition rate of 97.8% achieved is the top of the results among the all research groups

In original APIDQ [13], the coordinate system is then changed from orthogonal coordinates to polar coordinates, and each intensity variation vector is quantized in the r-θ plane as shown in Fig. 3. In this paper, we utilize the strategy that to quantize the intensity variation vectors directly in (dIx, dIy) plane without changing to polar coordinates as shown in Fig. 3. Since dIx-dIy vectors are concentrated in small-dIx, -dIy regions, non-uniform quantization steps are applied in axises. Quantization levels are set at 13 in dIx-axis and 13 in dIy-axis (totally 170) while the quantization steps are set to be the same as original steps of 1, 2, 4, 7, 12, 20, 30. The number of vectors quantized in each quantization region is counted and a histogram is generated. This histogram becomes the feature vector of the human face. In the registration phase, this histogram is saved in a database as personal identification information. In the recognition phase, the histogram is made from an unknown input facial image and is compared to registered individual histograms and the best match is outputted as the recognition result. The Manhattan distance (MD) between histograms is used as a matching measure.

APIDQ histogram method only uses the counted histogram as the feature information to identify the people and the location information of face are unused. So we cannot know which region of facial part the matched vector point belongs to. If we could combine the histogram features and location information of the human face, the integrated features of face will be more robust and effective. Based on this idea, we developed our algorithm to a region-division (RD) APIDQ histogram method. Based on the coordinates of two eyes, which are obtained by another eye location method, inclination-revision and size-scaling processes are done to normalize the face. Then the total face area is divided into 5 regions of facial parts (forehead, eye, nose, mouth, jaw) with respective sizes, and the histograms of every region of parts are generated by APIDQ operation respectively. The histogram made from each facial region is compared with the histograms from the same facial region in the database by calculating distances (d_i) between them (as shown in formula (3)). Then the integrated distances (D) are obtained by weighted averaging as shown in the following formula (2).

$$D = \frac{\sum w_i d_i}{\sum w_i}, \; i = forehead, eye, nose, mouth, jaw \quad (2)$$

$$d_i = \sum_{j=1}^{33} \left| \left(freq_j^{in(i)} - freq_j^{db(i)} \right) \right| \qquad (3)$$

where w_i is weighting coefficient of the facial regions, $freq_j^{in(i)}$, $freq_j^{db(i)}$ are the frequencies of dIx-dIy vectors that belong to a facial region of an input image and that belong to the same facial region of images registered in the database, respectively. The best match is output as recognition result by searching the minimum integrated distance.

III. Experiments and Discussions

A. Data Sets

The publicly available face database of FERET [14] for recognition experiments, which is one of the best-known databases and consists of 14051 eight-bit grayscale images with size 256x384 of human heads with views ranging from frontal to left and right profiles. The FERET database was constructed to develop automatic face recognition capabilities that can be employed to assist security, intelligence and law enforcement personnel. We utilize FB task in our experiments. FB (fafb) holds 1195 images, which mainly assess the effect on facial expression. All the tests used a single gallery containing 1196 images. Figure 4 shows typical image samples of the FERET database. To avoid the influence of eye detection accuracy, we utilize the coordinates of eyes supplied by FERET database to implement the region-division (RD) operation in our experiments. The total face area is divided into 5 regions of facial parts (forehead, eye, nose, mouth, jaw) with sizes of 146x65, 146x40, 146x30, 146x35, 146x30, respectively.

B. Experimental Results

Fig. 5 shows the recognition results of FB obtained by using the combination of APIDQ histogram method and region-division (RD) method to add rough location information. We get the top1 recognition rate of 87% by APIDQ histogram method directly in rectangular coordinate plane applied to the whole face area with the size of 146x200. By using RD-APIDQ histogram method with the weighting coefficient of 5 regions 1, 1, 0, 1, 1, the top1 recognition rate increases to 97.8%. Compared with the results of other research groups who are using the same task of the FERET database, the top1 recognition rate of 97.8% achieved is the top of the results of the whole research groups. It can be said that the modified APIDQ histogram method is a very reliable face recognition algorithm.

By applying a low pass filter, detailed facial features that degrade recognition performance, such as wrinkles, local hairstyle, image taking conditions and lapse in time, are excluded. Only the important personal facial features, such as the rough shape of facial parts, are extracted. Furthermore, APIDQ processing can effectively exclude the dc component of pixel intensity, which is simply varied by lighting conditions. By combining these two effects, the most important information for face recognition can effectively be extracted.

C. Processing Time

Recognition algorithm was programmed by ANSI C. To compare with the original APIDQ, the proposed method ran on the same conventional PC (3.2GHz) as the original method. Because of the table look-up method directly in the dIx-dIy domain at quantization step, the processing time for a single image in the database of FERET is 90 msec, which is composed of 50 msec for inclination-revision and size-scaling and low-pass filtering, 15 msec for APIDQ processing, and 25 msec for database matching.

IV. Conclusions

In this paper, a very fast and highly reliable modified APIDQ histogram method is proposed, which implements quantization directly in rectangular coordinate plane instead of r-θ plane. Excellent face recognition performance as large as a 97.8 % recognition rate has been achieved by using the publicly available database of FERET.

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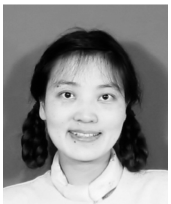

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