Face Recognition Using Adjacent Pixel Intensity Difference Quantization Histogram

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

†New Industry Creation Hatchery Center, Tohoku University, Japan
††Department of Electronics, Graduate School of Engineering, Tohoku University, Japan

Summary
This paper presents a very simple yet highly reliable face recognition algorithm using Adjacent Pixel Intensity Difference Quantization (APIDQ) histogram. 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. In this paper, we optimize the quantization method of APIDQ according to the maximum entropy principle (MEP), and determine the best parameters for APIDQ. Experimental results show maximum average recognition rate of 97.2% for 400 images of 40 persons from the publicly available face database of AT&T Laboratories Cambridge. 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. The experimental result shows that top 1 recognition rate of 97.6% is achieved when evaluated by FB task of the FERET database.
Key words:
Face recognition, Adjacent pixel intensity difference quantization (APIDQ), Maximum entropy principle (MEP)

1. Introduction

Face recognition has been studied for more than 20 years as an active research area. Especially, after the September 11 terrorist attacks on the United States, face recognition systems have become the subject of increased interest [1]. A number of face recognition algorithms have been proposed [2-11]. These algorithms can be roughly divided into two approaches, namely, structure-based and statistics-based.

In the structure-based approaches [4, 5], recognition is based on the relationship between human facial features such as eye, mouth, nose, profile silhouettes and face boundary. Statistics-based approaches [6, 7, 8] 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 [6]. 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 [12]. Although experimental results show APIDQ histogram method has achieved high recognition performance. It is still difficult to say such a quantization table is the most suitable because quantization is not optimized. In this paper, we firstly focus on the optimization of quantization in APIDQ based on the maximum entropy principle (MEP), and determine the best parameters for APIDQ [15].

Furthermore, APIDQ algorithm uses the counted histogram of whole human face as the feature vector to identify the people and the location information of face are unused. It can be considered as a simplified statistics-based approach. Although the APIDQ histogram method achieved high recognition rate using 40 persons' 400 images of publicly available database of AT&T Laboratories Cambridge [13], but the classification ability may decrease in the case of large face database due to the lack of structural information of human face. In this paper, we attempt to add some additional information of facial structure to improve the classification ability of APIDQ method. By utilizing the rough location information of the facial parts, the facial area is divided into 5 individual parts (forehead, eye, nose, mouth, jaw), and then APIDQ is applied on each facial part. Recognition results are firstly obtained from different parts separately and then combined by weighted averaging. By integration of statistical and structural information, namely, the APIDQ histogram and rough location information of facial parts,

Manuscript received August 5, 2009
Manuscript revised August 20, 2009

the accuracy of the APIDQ histogram method is expected to be improved [16].

In section 2, we introduce the *Adjacent Pixel Intensity Difference Quantization (APIDQ)* histogram method, and we then describe quantization optimization method according to the maximum entropy principle (MEP) we employ in section 3. The improved APIDQ method based on combinations of APIDQ histogram and rough location information of facial parts will be proposed in section 4.Experimental results will be discussed in section 5. Finally, conclusions are given in section 6.

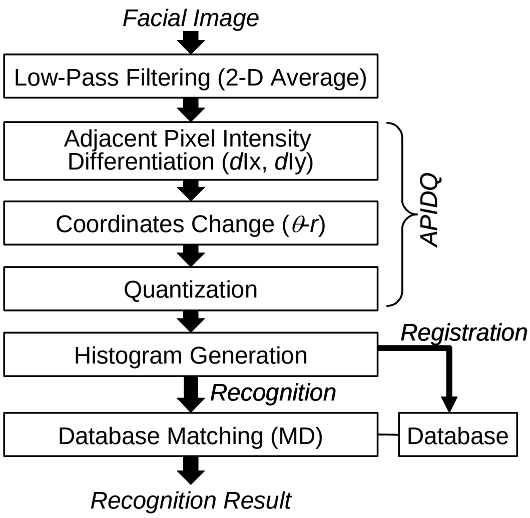


Fig. 1 Processing steps using APIDQ histogram method.

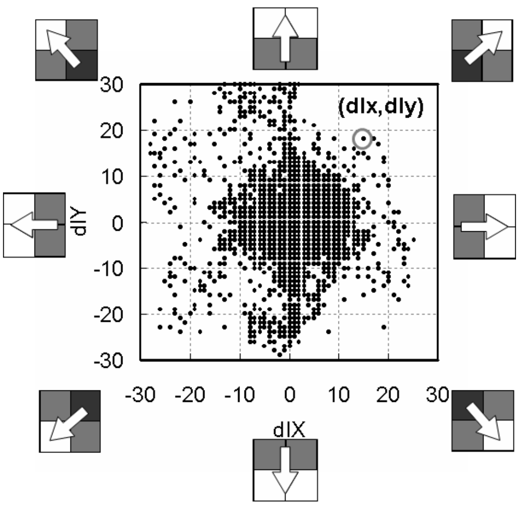


Fig. 2 Typical example of (*d*Ix, *d*Iy) vector distribution. The distribution of dots (density and shape) represents the features of the input image.

2. Review of Adjacent Pixel Intensity Difference Quantization

Figure 1 shows the processing steps of the 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).

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

A calculated (*d*Ix, *d*Iy) pair represents a single vector in the *d*Ix-*d*Iy 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 *d*Ix-*d*Iy plane as shown in Figure 2. 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. The quantization table is shown in Figure 3. The *italic* numbers in the table represent the index numbers of each quantization region. Quantization levels are set at 8 in θ-axis and 8 in r-axis (totally 50). Since *d*Ix-*d*Iy vectors are concentrated in small-r (small-*d*Ix, -*d*Iy) regions, 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. 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.

Experimental results show recognition rate of 95.7 % for 40 persons' 400 images of publicly available database of AT&T Laboratories Cambridge [13] containing variations in lighting, posing, and expressions.

In the next section, we will describe how to optimize the quantization method of APIDQ based on the maximum entropy principle (MEP), and determine the best parameters for APIDQ.

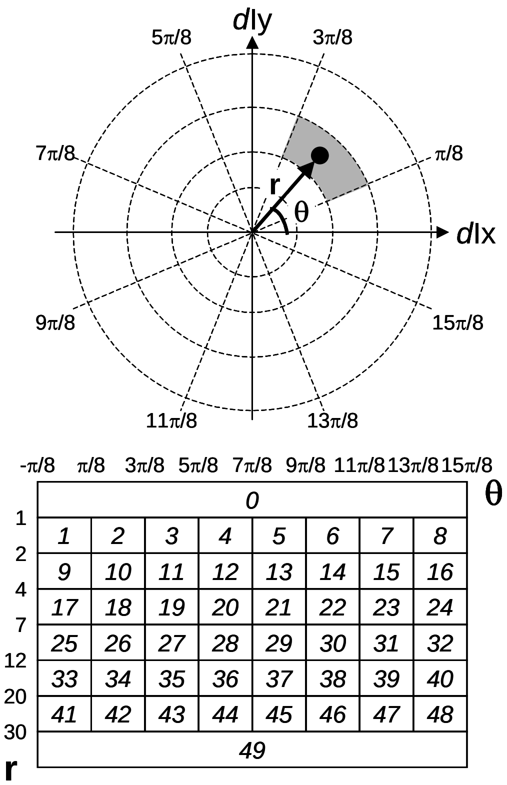


Fig. 3 Quantization table in r-θ plane. The *italic* numbers in the table represent the index numbers of each quantization region. Quantization levels are set at 8 in θ-axis and 8 in r-axis (totally 50). Since *d*Ix-*d*Iy vectors are concentrated in small-r (small-*d*Ix, -*d*Iy) regions, non-uniform quantization steps are applied in r-axis.

3. Optimization of quantization in APIDQ method

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. So the quantization in the r-θ plane is very important because it directly leads to different histograms. But how to determine the quantization level is not discussed in [12]. Although experimental results showed APIDQ histogram method had achieved high recognition performance. It is still difficult to say such a quantization table is the most suitable because quantization is not optimized and results in other cases should be examined. In this section, the maximization of information-theoretic entropy is used as a design criterion.

When the probability that a vector belongs to a certain bin ($b_1, b_2, \cdots, b_V$) is denoted to $P(B_1 = b_1, B_2 = b_2, \cdots, B_V = b_V)$ or simpler form $P(b_1, b_2, \cdots, b_V)$, the entropy of the histogram E can be defined as:

$$E = -\sum_{b_1}\sum_{b_2}\cdots\sum_{b_V} P(b_1, b_2, \cdots, b_V) \times \log P(b_1, b_2, \cdots, b_V) \qquad (2)$$

If $P(b_1, b_2, \cdots, b_V)$ comes to be equal probability towards to $b_1, b_2, \cdots, b_V$, the entropy of the histogram E will obtain maximum value according to the maximum entropy principle. The recognition performance can be expected be best because the average information content will be maximum at this point. Furthermore, if we assume that the bins of vector are independent of each other, we can get the following formula.

$$P(b_1, b_2, \cdots, b_V) = P(B_1 = b_1)P(B_2 = b_2)\cdots P(B_V = b_V) \qquad (3)$$

So we can see the average information content of the histogram will be maximized when $P(B_j = b_j)$ is constant (equal probability) towards to all of b_j (here $j = 1, 2, \cdots, V$).

Our strategy of the determination of quantization levels is that firstly we sub-sample the vectors, and then decide the boundary of bins so as to make the same amount of vectors to belong to different bins.

4. Region-division method

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 (5)). Then the integrated distances (D) are obtained by weighted averaging as shown in the following formula (4).

$$D = \frac{\sum w_i d_i}{\sum w_i}, \; i = forehead, eye, nose, mouth, jaw \qquad (4)$$

$$d_i = \sum_{j=1}^{33} \left|\left(freq_j^{in(i)} - freq_j^{db(i)} \right)\right| \qquad (5)$$

where w_i is weighting coefficient of the facial regions, $freq_j^{in(i)}$, $freq_j^{db(i)}$ are the frequencies of *d*Ix-*d*Iy 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.

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

5. Experiments and discussions

5.1 Experiments for Quantization Optimization

5.1.1 Data sets

The publicly available face database of AT&T Laboratories Cambridge [13] 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.

5.1.2 Investigation of the quantization structure

Ref. [12] used a quantization table which contains 50 bins in their recognition experiments. We will investigate the whole quantization structure of intensity variation vectors to optimize the quantization. At first, the quantization level is set to be only 1 from 0 to maximum value 30 while the number of quantization levels in θ-axis is fixed at 8 (totally 241), and then the number of vectors quantized in each quantization region is counted and a histogram of a facial image is generated.

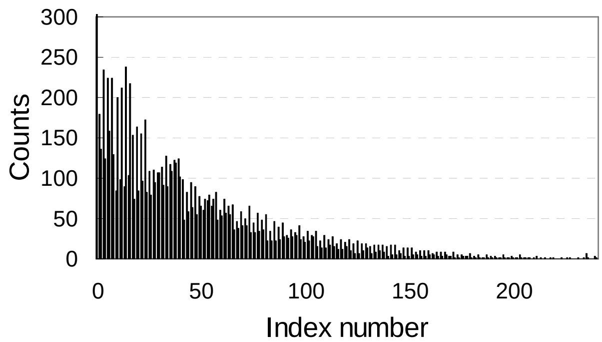


Fig. 5 Average histogram of 400 images. Quantization levels are set at 8 in θ-axis and 1 in *r*-axis (totally 241).

Figure 5 shows an average histogram of all 400 images in the database. This histogram shows *d*Ix-*d*Iy vectors are concentrated in small-r (small-*d*Ix, -*d*Iy) regions, and decrease in large-r regions. For a given quantization level 8 in *r*-axis, we change the boundary of bins dynamically so as to make the amount of vectors in each bin into equal value, then we can simply determine the adaptive boundary. In this case, we get quantization steps of r = 1, 2, 3, 5, 7, 10, 30 while the original steps are 1, 2, 4, 7, 12, 20, 30.

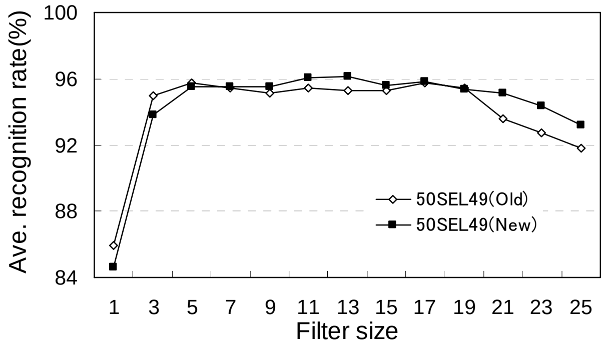


Fig. 6 Comparison of results. Average recognition rate is shown here.

Figure 6 shows the comparison between the recognition results using original one in [12] and new quantization table which contain the same number bins 50. Recognition success rates are shown as a function of filter size. Maximum of the average recognition rate increases from 95.7% to 96.29%. It can be said that the optimization method is effective.

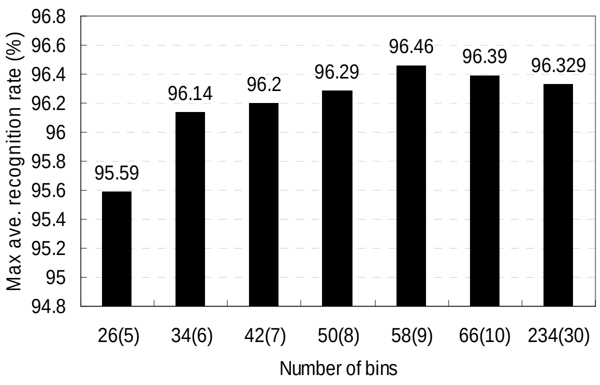


Fig. 7 Comparison of results in different total number of bins. The number of Quantization levels in θ-axis is fixed at 8.

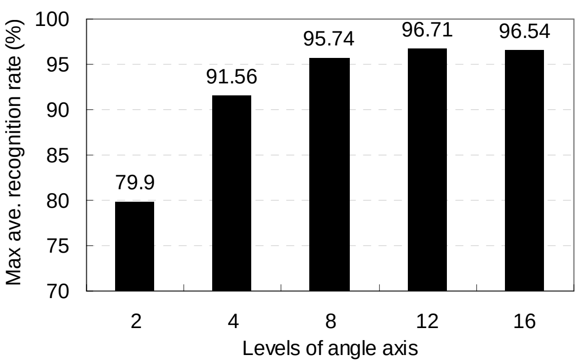


Fig. 8 Comparison of results in different levels of angle axis. The number of Quantization levels in r-axis is fixed at 8.

5.1.3 Variation of number of bins

In section 5.1.2, we only discussed the case that we assume that best number of bins is 50. It is necessary to choose a suitable number of bins. As the number of bins increases, the resolution of the histogram may become so sensitive that noise-corrupted vectors may significantly distort the histogram. On the contrary, if the number of bins is too small, the histogram can not sufficiently discriminate between different faces. In this section, we only discuss the cases that the number of quantization levels in θ-axis is fixed at 8.

We change the number of quantization levels in r-axis to be 5, 6, 7, 8, 9, and 30 where numbers of bins are 26, 34, 42, 50, 58, and 234, respectively. The maximum entropy principle is also applied in the quantization to generate histograms, and then recognition performance is evaluated.

Figure 7 shows the comparison between the recognition results using different quantization tables while quantization level in θ-axis is fixed at 8. The highest average recognition rates obtained in each number of bins are shown here. The best performance is obtained at number of 58 (here r = 9). Maximum of the average recognition rate 96.46% is achieved.

5.1.4 Variation of levels of angle axis

The discussion in last section assumed the number of quantization levels in θ-axis of 8 is the best choice. We also should consider the effect of the quantization in θ-axis. At this time, the number of quantization levels in r-axis is fixed at 8. The number of quantization levels in θ-axis is changed to be 2, 4, 8, 12, 16, and recognition results are shown in Figure 8. The best performance is obtained at the number of levels in angle axis of 12. Maximum of the average recognition rate 96.71% is achieved in this case.

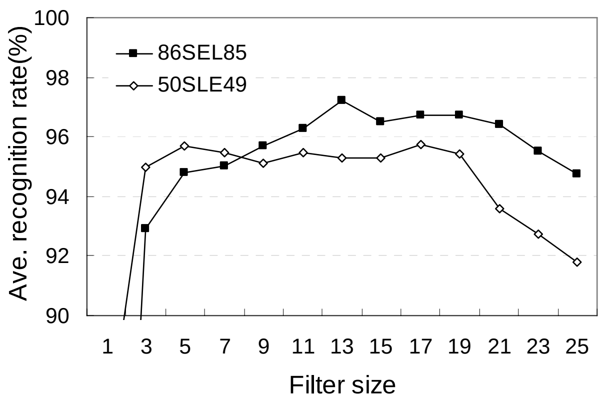


Fig. 9 Comparison of average recognition rate between total number of bins 86 and 50.

5.1.5 Optimization in both θ-axis and r-axis

By the method described above, we change the number of quantization levels both in θ-axis and in r-axis. We find the best combination appear in the numbers of quantization levels of 12 in θ-axis and 9 in r-axis (totally 86). Figure 9 shows the comparison between the recognition results using original one in [12] and new quantization table which contain the number of bins of 86. Recognition success rates are shown as a function of filter size. Maximum of the average recognition rate increases from 95.7% to 97.2%. It can be said that the optimization method is very effective.

Fig. 10 FERET database (FB task) samples.

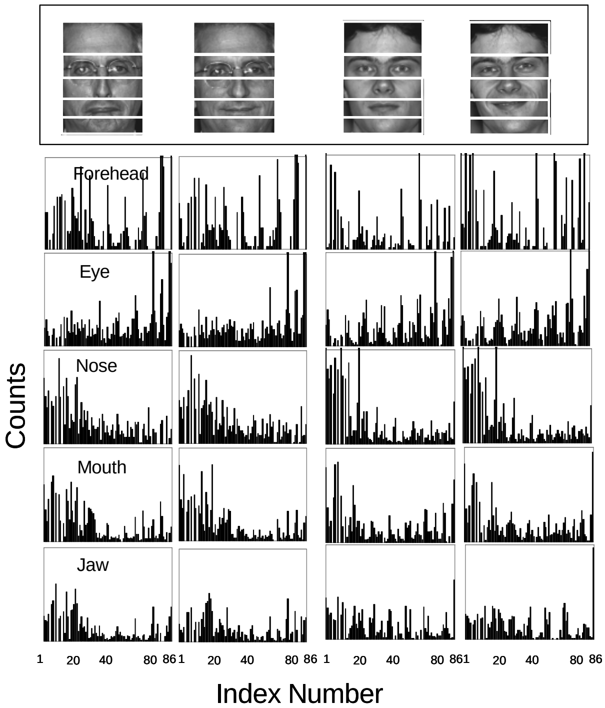


Fig. 11 Example of histograms. Histograms of different persons are clearly different. However, histograms of the same person are resembled, though there is a small difference in detail.

5.2 Experiments for Region division

As discussed above, based on the maximum entropy principle (MEP), we optimize the quantization in APIDQ. Maximum average recognition success rate of 97.2% is achieved when the number of quantization levels are set at 12 in θ-axis and 9 in r-axis (totally 86), which is higher than the original method using the quantization table of 50. We will utilize quantization table of 86 in latter experiments.

5.2.1 Data sets

We use a publicly available FERET database [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 10 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.

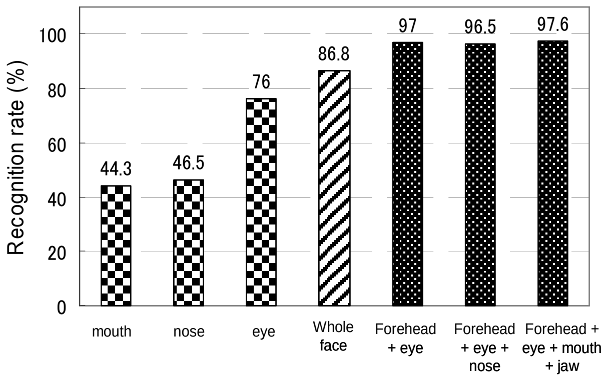


Fig. 12 Recognition results of RD histogram method (by using FB task). Top1 recognition rate of 86.8% is obtained by original APIDQ histogram method applied to the whole face. By using RD-APIDQ histogram method with the weighting coefficient of 5 regions 1, 1, 0, 1, 1, the top1 recognition rate increases to 97.6%.

5.2.2 Experimental results

Figure 11 shows typical examples of histograms of facial regions. Histograms of different persons are clearly different. However, histograms of the same person are resembled, though there is a small difference in detail. It can be said that histogram is very effective personal feature for discriminating persons.

Figure 12 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 86.8% by original APIDQ histogram method 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 97.6%, which is a little higher than another simlar approach in Ref. [17]. Fig. 12 also shows the results of using single facial region solely, and those of using some combinations. It was found by the actual experiments that among the regions of facial parts, the features of eyes seem the most important part for face recognition. Compared with the results of other research groups who are using the same task of the FERET database, the top1 recognition rate of 97.6% achieved is the top of the results of the whole research groups as shown in Figure 13. It can be said that the RD-APIDQ histogram method is a very reliable face recognition algorithm.

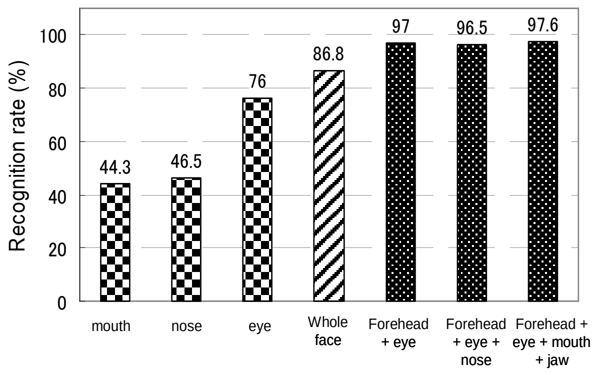


Fig. 12 Recognition results of RD histogram method (by using FB task). Top1 recognition rate of 86.8% is obtained by original APIDQ histogram method applied to the whole face. By using RD-APIDQ histogram method with the weighting coefficient of 5 regions 1, 1, 0, 1, 1, the top1 recognition rate increases to 97.6%.

Note that low-pass filtering is carried out before region-division operation using a simple 2-D moving average filter. Recognition success rates vary as a function of filter size. The highest top1 recognition rate of 97.6% is obtained at the filter size of 13x13. Low pass filter is effective for eliminating noise component and extracting important frequency component for recognition. By applying low pass filter, detailed facial features such as wrinkles and local hairstyle, which are easily varying with subtle facial expressions, image taking conditions and the lapse of time and degrade recognition performance, are excluded. Only the important personal facial features such as rough shape of facial parts can be extracted.

Recognition algorithm was programmed by ANSI C and was run on a conventional PC @ 3.2GHz (1G memory). Processing time for single image in FERET database is about 95 msec, which is composed of 50 msec for pretreatment including inclination-revision and size-scaling and filtering processes, 20 msec for block division, and minimum intensity subtraction, APIDQ processing, and 25 msec for database matching using a gallery containing 1196 images.

6. Conclusions

We have developed a very simple yet highly reliable face recognition method called APIDQ histogram method by applying APIDQ processing. Based on the maximum entropy principle (MEP), we optimize the quantization in APIDQ by changing the boundary of bins dynamically so as to make the amount of vectors in each bin into equal value, and then we can simply determine the adaptive boundary. Maximum average recognition success rate of 97.2% is achieved when quantization levels are set at 12 in θ-axis and 9 in r-axis (totally 86), which higher than the original method using the quantization table of 50.Combined by rough location information of the facial parts and APIDQ histogram method, excellent face recognition performance has been verified by using FERET database. Experimental results show top1 recognition rate of 97.6% in FB task. This region-division APIDQ histogram method has been proved very effective to extract the local features of the face robustly.

Acknowledgment

This research was partially supported by the Ministry of Education, Culture, Sports, Science and Technology of Japan, Grant-in-Aid for Young Scientists (B), No.20700074, 2008-2010.

References

[1] K. W. Bowyer, “Face Recognition Technology and the Security Versus Privacy Tradeoff”, IEEE Technology and Society, pp. 9-20, Spring 2004.

[2] R. Chellappa, C. L. Wilson, and S. Sirohey, “Human and machine recognition of faces: a survey”, Proc. IEEE, vol.83, no.5, pp.705-740, 1995.

[3] S. Z. Li and A. K. Jain, “Handbook of Face Recognition”, Springer, New York, 2005.

[4] R. Brunelli and T. Poggio, “Face recognition: features versus templates”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol.15, no.10, pp.1042-1052, Oct. 1993.

[5] L. Wiskott, J.M. Fellous, N. Kruger, and C. Malsburg, “Face recognition by elastic bunch graph matching”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol.19, no.10, pp.775-780, 1997.

[6] M. Turk and A. Pentland, “Eigenfaces for recognition”, Journal of Cognitive Neuroscience, vol.3, no.1, pp.71-86, Mar. 1991.

[7] W. Zhao, “Discriminant component analysis for face recognition”, Proc. ICPR’00, Track 2, pp. 822-825, 2000.

[8] K.M. Lam, H. Yan, “An analytic-to-holistic approach for face recognition based on a single frontal view”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol.20, no.7, pp.673-686, 1998.

[9] M.S. Bartlett, J.R. Movellan, and T.J. Sejnowski, “Face recognition by independent component analysis”, IEEE Trans. on Neural Networks, vol.13, no.6, pp.1450-1464, 2002.

[10] B. Moghaddam, A. Pentland, “Probabilistic visual learning for object representation”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol.19, no.7, pp.696–710, 1997.

[11] S. G. Karungaru, M. Fukumi, N. Akamatsu, “Face recognition in colour images using neural networks and genetic algorithms”, Int. Journal of Computational Intelligence and Applications, vol.5, no.1, pp.55-67, 2005.

[12] K. Kotani, F.F. Lee, Q. Chen, and T. Ohmi, “Face recognition based on the adjacent pixel intensity difference quantization histogram method”, 2003 Int. Symposium on Intelligent Signal Processing and Communication Systems, D7-4, pp.877-880, 2003.

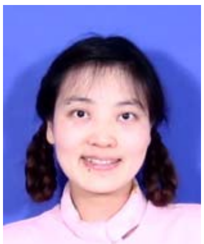
[13] AT&T Laboratories Cambridge, The Database of Faces, at http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

[14] P. J. Phillips, H. Wechsler, J. Huang, & P. Rauss. “The FERET database and evaluation procedure for face recognition algorithms,” Image and Vision Computing J, vol.16, no.5, pp.295-306, 1998.

[15] F.F. Lee, K. Kotani, Q. Chen, and T. Ohmi, “An improved fast face recognition algorithm based on adjacent pixel intensity difference quantization histogram,” Proc. of the 2008 Int. Conf. on Wavelet Analysis and Pattern Recognition, pp.316-320, Hong Kong, Aug. 2008.

[16] F.F. Lee, K. Kotani, Q. Chen, and T. Ohmi, “Face Recognition Based on the Combination of Histogram Features and Rough Location Information of Facial Parts,” Proc. of 9th Int’l Conf. on Signal Processing (ICSP2008), pp.2065-2069, Beijing, Oct. 2008.

[17] K. Kotani, Q. Chen, F.F. Lee, and T. Ohmi, “Region-division vector quantization histogram method for human face recognition”, Intelligent Automation and Soft Computing, vol.12, no.3, pp.257-268, May 2006.



Feifei Lee received Ph.D. degree in electronic engineering from Tohoku University, Japan, in 2007. She is currently an assistant professor at New Industry Creation Hatchery Center (NICHe), Tohoku University. Her research interests include pattern recognition and multimedia processing. Dr. F. Lee is a member of IEEE.

Koji Kotani received the B.S., M.S. and Ph.D. degrees all in electronic engineering from Tohoku University, Japan, in 1988, 1990 and 1993, respectively. He joined the Department of Electronic Engineering, Tohoku University as a research associate in 1993. From 1997 to 1998, he belonged to the VLSI Design and Education Center (VDEC) of the University of Tokyo. He is currently an associate professor at Department of Electronic Engineering, Tohoku University. He is engaged in the research and development of high performance devices/circuits as well as intelligent electronic systems. Dr. K. Kotani is a member of IEEE and a member of the Institute of Electronics, Information and Communication Engineers of Japan.

Qiu Chen received Ph.D. degree in electronic engineering from Tohoku University, Japan, in 2004. During 2004-2007, he was a COE fellow of Tohoku University 21st century COE program. He is currently an assistant professor at New Industry Creation Hatchery Center (NICHe), Tohoku University. His research interests include pattern recognition, computer vision, information retrieval and their applications. Dr. Q. Chen is a member of IEEE.

Tadahiro Ohmi served as a research associate in the Department of Electronics, Tokyo Institute of Technology, from 1966 until 1972.Then, he moved to Research Institute of Electrical Communication, Tohoku University and became an associate professor in 1976. In 1985 he became a professor at Department of Electronics, Faculty of Engineering, Tohoku University. Since 1998, he has been a professor at New Industry Creation Hatchery Center (NICHe), Tohoku University.

His research field covers whole Si-based semiconductor and flat panel display technologies in terms of material, process, device, circuit, and system technologies. He is known as an originator of "Ultra1clean Technology," which introduced ultraclean and scientific way of thinking into semiconductor manufacturing industry and became indispensable technology today. Dr. T. Ohmi is a fellow of IEEE and a fellow of the Institute of Electronics, Information and Communication Engineers of Japan.