Combined Histogram-based Features of DCT Coefficients in Low-frequency Domains for Face Recognition

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***Abstract*—Previously, We proposed an efficient algorithm using vector quantization (VQ) histogram for facial image recognition in low-frequency DCT domains. It can be considered that this algorithm is essential for utilizing the phase information of DCT coefficients by applying binary quantization on the DCT coefficient blocks. In this paper, we newly utilize energy histogram so as to add magnitude information of DCT coefficients. These two histograms, which contain both phase and magnitude information of a DCT transformed facial image, are utilized as a very effective personal value. Publicly available AT&T database is used for the evaluation of our proposed algorithm, which is consisted of 40 subjects with 10 images per subject containing variations in lighting, posing, and expressions. It is demonstrated that face recognition using combined histogram-based features of DCT coefficients in low frequency domains can achieve much higher recognition rate.**

Keywords-Face recognition; Vector quantizaiton (VQ); Energy histogram; DCT coefficients.

I. INTRODUCTION

Face recognition has been hot research topic for two decades due to its potential applications in many fields such as law enforcement applications, security applications and video indexing, etc. Many algorithms have been proposed for solving face recognition problem [1]-[11]. These algorithms can be roughly divided to two categories, namely, statistics-based and structure-based approaches. 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. Based on the use of the Karhunen-Loeve transform, PCA [5] is used to represent a face in terms of an optimal coordinate system which contains the most significant eigenfaces and the mean square error is minimal. However, it is highly complicated and computational-power hungry, making it difficult to implement them into real-time face recognition applications. Structure-based approach [3], [4] uses the relationship between facial features, such as the locations of eye, mouth and nose. It can implement very fast, but recognition rate usually depends on the location accuracy of facial features, so it cannot give a satisfied recognition result. There are many other algorithms have been used for face recognition, such as Local Feature Analysis (LFA) [11], neural network [1], local autocorrelations and multi-scale integration technique [2], and other techniques have been proposed.

Discrete Cosine Transform (DCT) is not only widely used in many image and video compression standards [12], but also for pattern recognition as a means of feature extraction [13]-[21]. The main merit of the DCT is its relationship to the KLT [18]. It has been demonstrated that DCT best approach KLT [23], but DCT can be computationally more efficient than the KLT depending on the size of the KLT basis set.

In our previous work [27], we present a simple, yet highly reliable face recognition algorithm using vector quantization (VQ) method for facial image recognition in compressed DCT domain. Feature vectors of facial image are firstly generated by using DCT coefficients in low frequency domains. Then codevector referred count histogram, which is utilized as a very effective facial feature value, is obtained by VQ processing.

This algorithm can be considered utilizing the phase information of DCT coefficients by applying binary quantization on the DCT coefficient blocks. If we could add magnitude information of DCT coefficients, the composite features of face are expected to be more robust and effective. In this paper, we utilize energy histogram to represent magnitude features of DCT coefficients. These two histograms, which contain both phase and magnitude information of a DCT transformed facial image, are utilized as a very effective personal value. Recognition results with different type of histogram features are first obtained separately and then combined by weighted averaging.

This paper is organized as follows. A brief introduction to DCT as well as energy histogram is given in Section II. Our proposed face recognition method will be described in detail in Section III. Experimental results will be discussed in Section IV. Finally, we make a conclusion in Section V.

II. RELATED WORKS

A. Discrete Cosine Transform (DCT)

Discrete Cosine Transform (DCT) is used in JPEG compression standard. The DCT transforms spatial

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Horizontal Frequency (Low → High) / Vertical Frequency (Low ↓ High)

	0	1	2	3	4	5	6	7
0	DC	AC01	AC02	AC03	23	-9	-14	19
1	AC10	AC11	AC12	AC13	-11	11	14	7
2	AC20	AC21	AC22	AC23	-18	3	-20	-1
3	AC30	AC31	AC32	AC33	-8	-3	-3	8
4	-3	10	8	1	-11	18	18	15
5	4	-2	-18	8	8	-4	1	-7
6	9	1	-3	4	-1	-7	-1	-2
7	0	-8	-2	2	1	4	-6	0

Figure 1. Generation of Low-frequency DCT coefficients (used as phase information)

information to decoupled frequency information in the form of DCT coefficients.

2D DCT with block size of N × N is defined as follows:

$$C(u,v)=\alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cdot\cos\left(\frac{(2x+1)u\pi}{2N}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (1)$$

$$f(x,y)=\sum_{u=0}^{N-1}\sum_{v=0}^{N-1}\alpha(u)\alpha(v)C(u,v)\cdot\cos\left(\frac{(2x+1)u\pi}{2N}\right)\cos\left(\frac{(2y+1)v\pi}{2N}\right) \quad (2)$$

where, $$\alpha(\omega)=\begin{cases}\frac{1}{\sqrt{N}} & : \quad for \quad \omega=0\\ \frac{2}{\sqrt{N}} & : \quad for \quad \omega=1,2,...,N-1\end{cases} \quad (3)$$

B. Face recognition using Binary vector quantization in low-frequency DCT domains

In our previous work [27], we proposed a feature extraction algorithm for face recognition using binary vector quantization (VQ) to generate feature vectors of facial image from DCT (Discrete Cosine transform) coefficients in low frequency domains.

First, low-pass filtering is carried out using 2-D moving filter. Block segmentation step, in which facial image is divided into small image blocks with an overlap, namely, by sliding dividing-partition one pixel by one pixel, is the following. Then the pixels in the image blocks (typical size is 8x8) are transformed using DCT according to the equation (1).

A typical sample of transformed block is shown in Figure 1. The DCT coefficients of the image block are then used to form a feature vector. From left to right and top to bottom, the frequency of coefficients changes from low to high as shown in Figure 1. Because low frequency component is more effective for recognition, we only use the coefficients on the left and above to extract features. The equation for calculation is shown below.

$$\begin{aligned}&a[0] = AC01;\\&a[1] = AC11;\\&a[2] = AC10;\\&a[3] = (AC02 + AC03 + AC12 + AC13) / 4;\\&a[4] = (AC22 + AC23 + AC32 + AC33) / 4;\\&a[5] = (AC20 + AC21 + AC30 + AC31) / 4\end{aligned} \quad (4)$$

where a[i] is the element of extracted feature vector, and d[i][j] is the coefficient value at point (i, j), respectively.

After that, quantization of the feature vectors is implemented. There are only 2 types of value for each a[i], so the number of combination of 6-dimensional vector is 64, which is very easy and fast to be determined. The number of vectors with same index number is counted and feature vector histogram is easily generated, and it is used as histogram feature of the facial image. In the registration procedure, this histogram is saved in a database as personal identification information. In the recognition procedure, the histogram made from an input facial image is compared with registered individual histograms and the best match is output as recognition result.

C. Energy histogram

A color histogram is obtained by counting the number of times a color occurs in an image. Similar to a color histogram, an energy histogram of the DCT coefficients is created by counting the number of times an energy level appears in a DCT blocks set of a DCT compressed image. An energy histogram (h_c) [30] of an 8x8 DCT block for a particular color component can be written as:

$$h_C[m]=\sum_{u=0}^{7}\sum_{v=0}^{7}\begin{cases}1 & if\ Q(F[u,v])=m\\0 & otherwise\end{cases} \quad (5)$$

with $Q(F[u,v])$ denotes the dequantized coefficient's energy level at the u,v location.

Energy histogram has been used in image retrieval in [30], and also reported to be used for face recognition algorithm [31].

III. Proposed Method

As described in Section II (B), we have proposed a face recognition algorithm by applying binary quantization on the low-frequency DCT coefficient blocks, which was demonstrated to be effective for face recognition by experimental results. Actually, it can be thought that phase information of low-frequency DCT coefficients is extracted by this algorithm. If we could add magnitude information of DCT coefficients, the composite features of face are expected to be more robust and effective.

We utilize energy histogram to represent magnitude features of DCT coefficients. In this paper, we propose an

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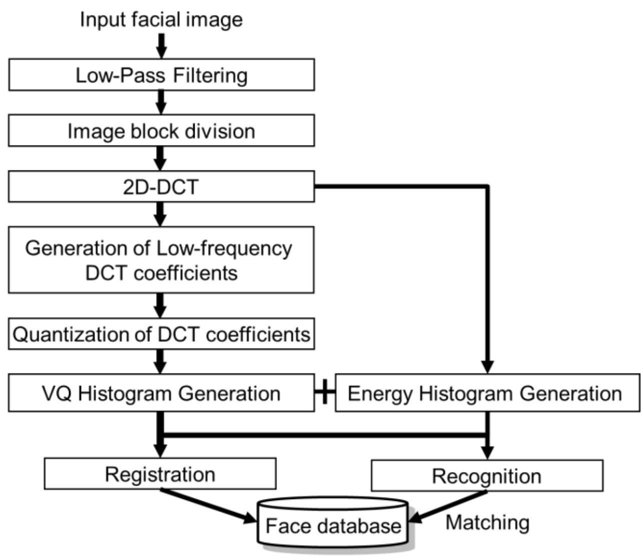

Figure 2. Face recognition process using combined histogram-based features.

Horizontal Frequency (0 Low → 7 High); Vertical Frequency (0 Low → 7 High)

	0	1	2	3	4	5	6	7
0	DC	AC01	AC02	AC03	23	-9	-14	19
1	AC10	AC11	AC12	AC13	-11	11	14	7
2	AC20	AC21	AC22	AC23	-18	3	-20	-1
3	AC30	AC31	AC32	AC33	-8	-3	-3	8
4	-3	10	8	1	-11	18	18	15
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6	9	1	-3	4	-1	-7	-1	-2
7	0	-8	-2	2	1	4	-6	0

Figure 3. Low-frequency DCT coefficients for energy histogram.

improved face recognition algorithm using combined histogram-based features. Figure 2 shows proposed face recognition process steps. First, low-pass filtering is carried out using 2-D moving filter. This low-pass filtering is essential for reducing high-frequency noise and extracting most effective low frequency component for recognition.

Block segmentation step, in which facial image is divided into small image blocks with an overlap, namely, by sliding dividing-partition one pixel by one pixel, is the following. Then the pixels in the image blocks (typical size is 8x8) are transformed using DCT according to the equation (1). After generations of low-frequency DCT coefficients, binary quantization of the feature vectors is implemented as described in Section II (B), and then VQ histogram of low-frequency DCT coefficients is created.

On the other hand, energy histogram of low-frequency DCT coefficients is also generated after 2D-DCT. Because low frequency component is more effective for recognition, we only use the coefficients on the left and above to extract features. This can also reduce computation time compared with using the whole DCT coefficients. In this paper, we use 4x4 coefficient blocks as shown in Figure 3, the same domain as VQ histogram used at the upper left corner of the DCT coefficient block which retain the higher energy level of the image. The DC coefficient is not included in the features to reduce the influence of the lighting conditions of the images. Once the features have been selected, the energy histogram is created by using formula (5).

These two histograms, which contain both phase and magnitude information of a DCT transformed facial image, are utilized as a very effective personal value. Recognition results with different type of histogram features are first obtained separately and then combined by weighted averaging.

IV. Experimental results and discussions

A. ORL database

Face database of AT&T Laboratories Cambridge [25], [26] is used for recognition experiments. In the database, 10 facial images for each of 40 persons (totally 400 images) with variations in face angles, face sizes, facial expressions, and lighting conditions are included. Each image has a resolution of 92x112. Five images were selected from each person's 10 images as probe images and remaining five images are registered as album images. Recognition experiment is carried out for 252 (${}_{10}C_5$) probe-album combinations by rotation method. The algorithm is programmed by ANSI C and run on PC (Pentium(R)D processor 840 3.2GHz).

B. Results and discussions

In our experiments, the bin size of energy histogram is set to 100. Figure 4 shows the comparison of the recognition results with different features. The average recognition rates obtained by each case with block size of 8x8 are shown here. Recognition success rates are shown as a function of filter size. Although recognition results only using energy histogram of low-frequency DCT coefficients ("N8_energy_hist") are not satisfied, average recognition rate increases combined with VQ histogram of low-frequency DCT coefficients ("N8_combined"). The maximum of the average rate 95.4% is achieved, which is 1.7% higher than that only using VQ histogram in our previous work ("N8_VQ_hist", the maximum of the average rate is 93.7%) [27].

Figure 5 shows recognition results using combined features with the same weighting coefficient of two

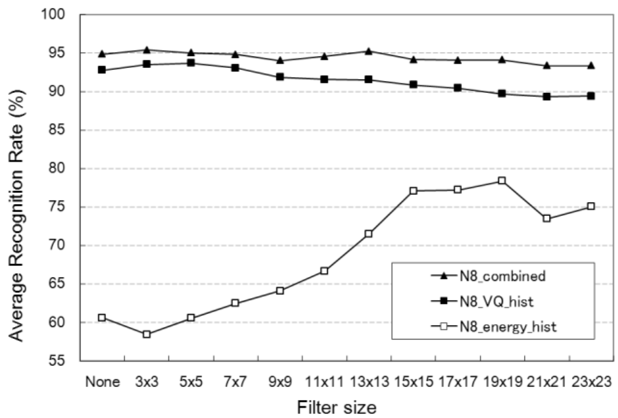

Figure 4. Comparison of recognition results

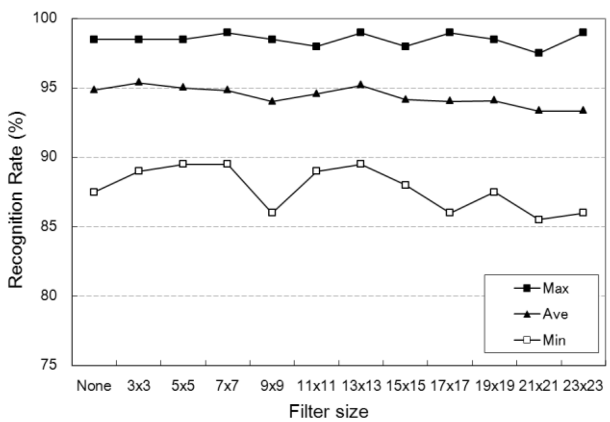

Figure 5. Recognition rate as a function of filter size (image block size is 8x8 here)

histogram features. Recognition success rates are shown as a function of filter size. "Max," "Min" and "Ave" stand for the best case, worst case, and average results in 252 ($_{10}C_5$) probe-album combinations, respectively. The highest average recognition rate of 95.38% is obtained at the filter size of 3x3. Low pass filter is effective for eliminating noise component and extracting important frequency component for recognition.

By combining these two different features, namely phase information and magnitude information of low-frequency DCT coefficient blocks, the most important information for face recognition can effectively be extracted.

V. CONCLUSIONS AND FUTURE WORK

We have developed a very simple yet highly reliable face recognition method using features extracted from low-frequency DCT domain, which is combined with VQ histogram and energy histogram. Excellent face recognition performance has been verified by using publicly available ORL database. The effect of the image block size will be discussed in our future work, as well as the performance evaluation of the face recognition using larger face database.

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REFERENCES

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

[2] S. Z. Li and A. K. Jain, "Handbook of face recognition," Springer, New York, 2005.

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

[4] 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, 1997, pp.775-780.

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

[6] W. Zhao, "Discriminant component analysis for face recognition," Proc. ICPR'00, Track 2, 2000, pp. 822-825.

[7] 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, 1998, pp. 673-686.

[8] 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, 2002, pp. 1450-1464.

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

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

[11] P. S. Penev and J. J. Atick, "Local feature analysis: a general statistical theory for object representation," Network: Computation in Neural Systems, vol. 7, no. 3, 1996, pp. 477-500.

[12] W. B. Pennebaker and J. L. Mitchell, "JPEG still image data compression standard," Van Nostrand Reinhold, New York, 1993.

[13] H. B. Kekre, T. K. Sarode, P. J. Natu, and S. J. Natu, "Transform based face recognition with partial and full feature vector using DCT and Walsh transform," Proc. of the Int'l Conf. & Workshop on Emerging Trends in Technology, 2011, pp. 1295-1300.

[14] Z. Liu and C. Liu, "Fusion of color, local spatial and global frequency information for face recognition," Pattern Recognition, vol. 43, Issue 8, Aug. 2010, pp. 2882-2890.

[15] H. F. Liau, K. P. Seng, L. M. Ang, and S. W. Chin, "New parallel models for face recognition," Recent Advances in Face Recognition, Edited by K. Delac etc., InTech, 2008.

[16] R. Tjahyadi, W. Liu, S. An and S. Venkatesh, "Face recognition via the overlapping energy histogram," Int'l Joint Conf. on Artificial Intelligence, 2007, pp. 2891-2896.

[17] D. Zhong and I. Defee, "Pattern recognition in compressed DCT domain," Proc. of Int'l Conf. on Image Processing, vol. 3, 2004, pp. 2031 - 2034.

[18] Z. M. Hafed and M. D. Levine, "Face recognition using the Discrete Cosine Transform," Int'l Journal of Computer Vision, vol. 43, no. 3, 2001, pp. 167-188.

[19] S. Eickeler, S. Müller and G. Rigoll, "Recognition of JPEG compressed face images based on statistical methods," Image and Vision Computing Journal, Special Issue on Facial Image Analysis, vol. 18, no. 4, Mar. 2000, pp. 279-287.

[20] S. Eickeler, S. Müller and G. Rigoll, "High quality face recognition in JPEG compressed images," Proceeding of Int'l Conf. on Image Processing, vol. 1, Oct. 1999, pp. 672-676.

[21] V. Nefian and M. H. Hayes, "Hidden Markov models for face recognition," Int'l Conf. on Acoustics, Speech, and Signal Processing, May 1998, pp. 2721-2724.

[22] M. Shneier and M Abdel-Mottaleb, "Exploiting the JPEG compression scheme for image retrieval," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 18, no. 8, Aug. 1996.

[23] A. Jain, Fundamentals of Digital Image Processing, Prentice: Englewood Cliffs, NJ, 1989.

[24] A. Gersho and R. M. Gray, "Vector quantization and signal compression," Kluwer Academic, 1992.

[25] AT&T Laboratories Cambridge, "The database of faces," at http://www.cl.cam.ac.uk/research/dtg/attarchive/ facedatabase. html.

[26] F. Samaria and A. Harter, "Parameterisation of a stochastic model for human face identification," 2nd IEEE Workshop on Applications of Computer Vision, 1994, pp. 138-142.

[27] Q. Chen, K. Kotani, F. F. Lee, and T. Ohmi, "Face recognition using VQ Histogram in compressed DCT domain," Journal of Convergence Information Technology, vol. 7, no. 1, 2012, pp. 395-404.

[28] K. Kotani, Q. Chen, F. F. Lee, and T. Ohmi "Region-division VQ histogram method for human face recognition," Intelligent Automation and Soft Computing, vol. 12, no. 3, 2006, pp. 257-268.

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

[30] J. A. Lay and L. Guan, "Image Retrieval based on energy histogram of the low frequency DCT coefficients," IEEE Int'l Conf. on Acoustics Speech and Signal Processing, vol. 6, 1999, pp. 3009-3012.

[31] R. Tjahayadi, W. Liu, and S. Venkatesh, "Application of the DCT energy histogram for face recognition," Proc. of 2nd Int'l conf. on Information Technology for Application (ICITA), Sydney, 2004, pp. 314-319.