Face Recognition Using Histogram-based Features in Spatial and Frequency Domains

Qiu Chen[1], Koji Kotani[2], Feifei Lee[3], and Tadahiro Ohmi[3]

[1] Department of information and Communication Engineering, Faculty of Engineering, Kogakuin University
[2] Department of Electronics, Graduate School of Engineering, Tohoku University
[3] New Industry Creation Hatchery Center, Tohoku University
e-mail: chen@cc.kogakuin.ac.jp

***Abstract*—Previously, we proposed an efficient algorithm using vector quantization (VQ) histogram for facial image recognition in low-frequency DCT domains. In this paper, we newly utilize Local Binary Pattern (LBP) histogram in spatial domain. These two histograms, which contain both spatial and frequency domain information of a facial image, are utilized as a very effective personal feature. 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 can achieve much higher recognition rate.**

Keywords-Face recognition; Vector quantizaiton (VQ); Local Binary Patterns (LBP); DCT coefficients.

I. INTRODUCTION

In recent years, face recognition has been hot research topic 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 into 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, the 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 combine spatial information of the facial image, the composite features of face are expected to be more robust and effective. In this paper, we utilize Local Binary Patterns (LBP) to represent facial features in spatial domain. These two histograms, which contain spatial and frequency domain information of a 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 LBP 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 information to decoupled frequency information in the form of DCT coefficients.

2D DCT with block size of $N \times N$ is defined as follows:

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
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)

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

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

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

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.

a[0] = AC01;

a[1] = AC11;

a[2] = AC10; (4)

a[3] = (AC02 + AC03 + AC12 + AC13) / 4;

a[4] = (AC22 + AC23 + AC32 + AC33) / 4;

a[5] = (AC20 + AC21 + AC30 + AC31) / 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.

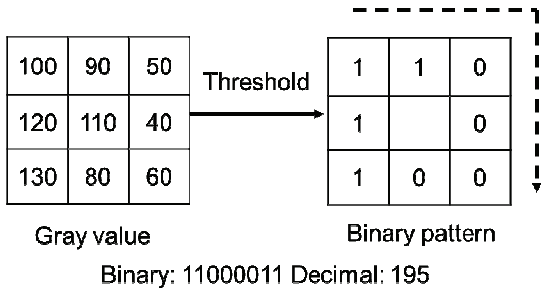

Figure 2. Fundamental LBP operator.

C. Local Binary Patterns (LBP) histogram

The original LBP operator proposed by Ojala et al. [28], is used for robust texture description. The operator labels the pixels of an image by thresholding the 3x3-neighbourhood of each pixel with the center value and considering the result as a binary number. Then the histogram of the labels can be used as a texture descriptor. Figure 2 shows an illustration of the basic LBP operator.

The limitation of the fundamental LBP operator is its small 3x3 neighborhood which can not capture dominant features with large scale structures. Hence, the operator later is extended to use neighborhood of different sizes. As shown in Figure 3, LBP(P, R) means P sampling points on a circle of radius of R to get LBP features. For instance, LBP(8, 2) means comparing a neighborhood of 8 on the circle of radius of 2 to get LBP features.

After labeling an image with the LBP operator, the histogram of the labeled image $p(x,y)$ can be defined as

$$H_u = \sum_{x,y} U(p(x,y) = u), u = 0,1,..., n-1 \quad (5)$$

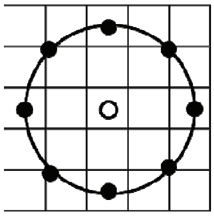

Figure 3. The circular (8,2) neighborhood.

Where n is the number of different labels produced by the LBP operator and

$$U(A) = \begin{cases} 1, A = ture \\ 0, A = false \end{cases} \quad (6)$$

A LBP histogram can effectively describe the distribution of the local micro-patterns over a whole face image without any indication about their locations. For efficient face representation, one should also retain spatial information. Thus, a face image can be equally divided into small regions. And then, the LBP features extracted from each sub-region are concatenated into a single histogram as

$$H_{u,v} = \sum_{x,y} U(p(x,y) = u) U\{(x,y) \in R_v\} \quad (7)$$

where $u = 0,1,..., n-1$ and $v = 0,1,..., m-1$.

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 combine spatial information of the facial image, the composite features of face are expected to be more robust and effective.

We utilize LBP to represent facial features in spatial domain. In this paper, we propose an improved face recognition algorithm using combined histogram-based features. Figure 4 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

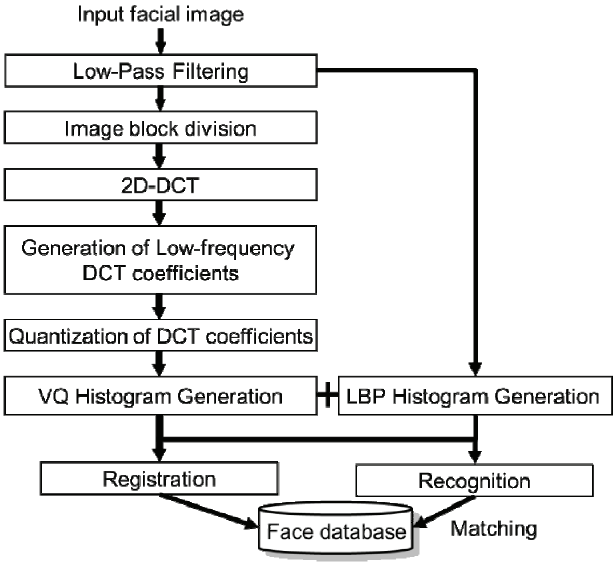

Figure 4. Face recognition process using combined histogram-based features.

described in Section II (B), and then VQ histogram of low-frequency DCT coefficients is created.

On the other hand, LBP histogram of facial image in spatial domain is generated after filtering processing. Once the features have been selected, LBP histogram is created by using formula (7) as described in Section II(C).

These two histograms, which contain both spatial and frequency domain information of a facial image, are utilized as a very effective personal feature. 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

Figure 5 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.

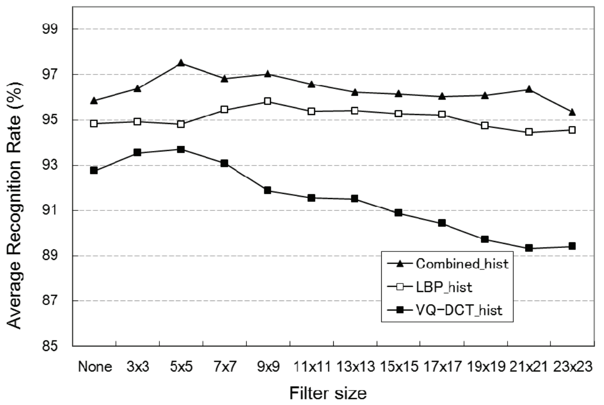

Figure 5. Comparison of recognition results

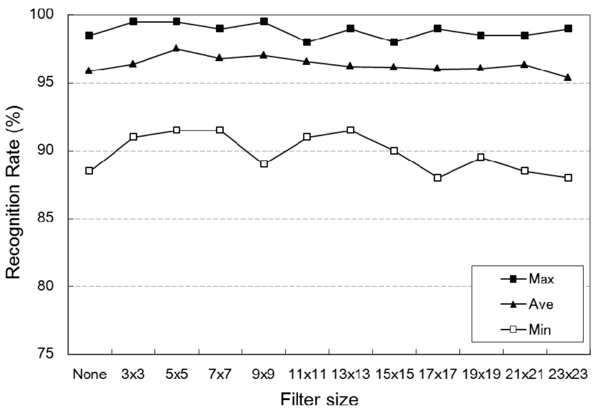

Figure 6. Recognition rate as a function of filter size (image block size is 8x8 for DCT coefficients here)

Recognition success rates are shown as a function of filter size. Recognition results only using LBP histogram ("LBP_hist") achieved 95.8% at the filter size of 9x9, average recognition rate increases combined with VQ histogram of low-frequency DCT coefficients ("Combined_hist"). The maximum of the average rate 97.5% is achieved, which is 3.8% 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 6 shows recognition results using combined features with the same weighting coefficient of two 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 97.5% is obtained at the filter size of 5x5. Low pass filter is effective for eliminating noise component and extracting important frequency component for recognition.

By combining these two different features, namely spatial and frequency domain information of a facial image, 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 and spatial domain of a facial image, which is combined with VQ histogram and LBP 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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 ISBN: 978-1-61208-320-9