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Iris Recognition Based on a Shift-Invariant Wavelet Transform

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Abstract

This paper describes a new iris recognition method based on a shift-invariant wavelet sub-images. For the feature representation, we first preprocess an iris image for the compensation of the variation of the iris and for the easy implementation of the wavelet transform. Then, we decompose the preprocessed iris image into multiple subband images using a shift-invariant wavelet transform. For feature representation, we select a set of subband images, which have rich information for the classification of various iris patterns and robust to noises. In order to reduce the size of the feature vector, we quantize.each pixel of subband images using the Lloyd-Max quantization method Each feature element is represented by one of quantization levels, and a set of these feature element is the feature vector. When the quantization is very coarse, the quantized level does not have much information about the image pixel value. Therefore, we define a new similarity measure based on mutual information between two features. With this similarity measure, the size of the feature vector can be reduced without much degradation of performance. Experimentally, we show that the proposed method produced superb performance in iris recognition.

Key words : iris recognition, shift-invariant wavelet transform, similarity measure

I. Introduction

Biometrics refers to the automatic authentification, identification, or verification of an individual based on physiological, behavioral and molecular characteristics. Research related to biometrics has developed rapidly in the last decades, and has led to various applications: security, smart card, and electronic commerce. Biometric techniques include recognizing faces, fingerprints, hands, iris, signatures, voices, DNA patterns, etc. Considering reliability and convenience, automated iris recognition is very attractive because human iris patterns are highly distinctive to an individual and the image of an eye can be taken at a distance.

Various iris recognition methods have been proposed for automatic personal identification and verification. Daugman [1] first presented a prototype system for iris recognition. For the feature representation, it makes use of a decomposition derived from application of a two-dimensional Gabor filter to the iris image. Quantized local phase angles yield the final representation. The similarity measure for feature classification is the Hamming distance between the acquired and data base representations. It reported good performance on a diverse database. However, the system employs carefully designed image acquisition devices and various pre-processes to get equal high quality iris images [2,3].

Wildes [3] presented another iris recognition system. It decomposes the iris pattern into the Laplacian pyramid using a Laplacian Gaussian filter. Quantized differences between a pyramid level and its next lower resolution level yield the final representation. The similarity measure is the normalized correlation between the acquired and data base representations. It reported as good performance as the system of Daugman.

Since wavelet sub-images at a high-resolution pyramid level is sensitive noises, Cho et al. [4] presented a method using a wavelet sub-image at a low-resolution pyramid level. The neural network is used to classify the extracted feature. However, discrete wavelet transform is sensitive to a small shift of a full-resolution iris image in the space domain [5,6,7]. Zhu et al. [8] presented a shift-invariant method, which decomposes the iris pattern into multiple bands using a two-dimensional Gabor transform or a wavelet transform. The means and variances of all bands are used for the shift-invariant feature representation. However, the means and variances do not contain much information on the shape of the iris pattern. This restriction limits the performance. Mallat [5] built a translation-invariant wavelet representation using wavelet zero-crossings, which was applied to the iris recognition by Boles et al. [9]. However, the number of zero-crossings can differ among iris image samples of an identical user due to the noise. This method was improved by Roche et al. [10].

In this paper, we decompose the preprocessed iris image into multiple subband images using two different wavelet transform, shift-variant and shift-invariant ones, respectively, and in each case, chose a set of subband images which have rich information for the classification of various iris patterns and robust to noises. When the shift-variant method is used for the decomposition, low-frequency subband images are chosen. However, when the shift-invariant method is used for the decomposition, a different set of subband images is chosen, and classification performance based on this set of subband images is much better. For the feature representation, the set of subband images is used.

Each pixel of the selected subband images is quantized

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using the Lloyd-Max method [11] to reduce the size of the feature vector. Since each pixel is represented not by its quantized value but by one of a few quantization levels, an appropriateformulation of similarity measure is defined for the classification. With this similarity measure, the size of the feature vector can be reduced without much degradation of performance.

This paper is constructed as follows: Section 2 starts with a brief review of the preprocessing and then, describes a new feature representation method for the iris recognition. Section 3 describes a new similarity measure and the verification method. Section 4 shows the experimental results. Finally, we conclude in Section 5 with a summary of the proposed method.

II. Feature Extraction and Representation

2.1 Preprocessing

Since acquired iris images have different contrast and non-uniform illumination due to the position and angle of the light source, the image is enhanced using local histogram equalization. A small change in the distance between a human eye and the image acquisition camera causes the iris sizeto shrink or to expand. For the iris pattern analysis, it is necessary to compensate the variation of the iris size. A common method is to map the disk-shaped iris to a rectangle block of a fixed size [3,5,8]. Fig. 1 shows an iris image in the rectangular form.

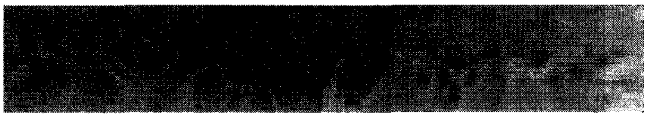

Figure 1. A preprocessed iris image.

2.2. Shift-Invariant Wavelet Decomposition

In order to find which wavelet components of the iris pattern have rich information and robust to noises such as iris localization error or iris pattern variation, we first decompose the iris image into multiple subband images using cascading horizontal and vertical wavelet filter banks. Fig. 2 shows the decomposition of the full band image into sixteen subband images. The location and strength of an edge in a subband image are sensitive to a small shift of the full-resolution image because of the aliasing noise. The shift-sensitive problem is reported in many papers on wavelet transform, and various solutions are proposed [5,6,7]. Using the M-band method of Liang et al. [7], we accomplish the subband decomposition over all possible space-shifts. When the full band image is decomposed into multiple subband images, each subband images has many different forms due to the shift of the full band image, which is shown in Fig. 3. Once all possible different forms are built, the form with maximum entropy among them is selected. The entropy is expressed as

$$E_{i,j} = -\sum_{k} h(k) \log h(k) \quad (1)$$

where $h(k)$ is the histogram of each form of a subband image. For the feature representation, we chose a set of subband images that has the best performance in verification of classification. The chosen subband images are f_{HILL} and f_{HILL} in Fig. 2.

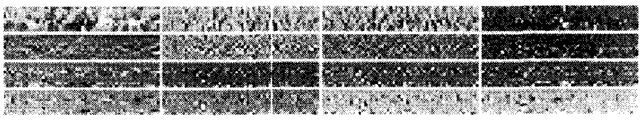

Figure 2. Sixteen subband images decomposed using Haar wavelets: from the top left, f_{LLLL}, f_{LLHL}, f_{HLLL}, f_{HLHL}, f_{LLLH}, f_{LLHH}, f_{HLLH}, f_{HLHH}, f_{LHLL}, f_{LHHL}, f_{HHLL}, f_{HHHL}, f_{LHLH}, f_{LHHH}, f_{HLLH}, f_{HHLH}, and f_{HHHH}.

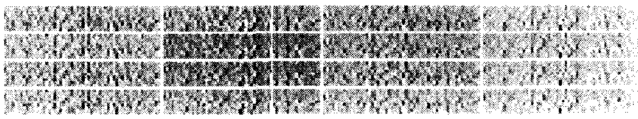

Figure 3. Sixteen different forms of a subband image, f_{HLLL}. Since f_{HLLL} contains horizontal mid-frequency and vertically low frequency components, four forms in each column have the same image pattern and four forms in each row have different image patterns.

III. Similarity Measure and Verification

3.1 Similarity Measure

We quantize each pixel value of an subband image to reduce the size of a feature vector using the Lloyd-Max quantization. Each feature element is represented by one of quantization levels such as 0, 1, ..., Q. A set of these feature element is the feature vector. When the quantization is very coarse, the quantized level does not have much information about the image pixel value. A simple similarity measure like L_p norm is not appropriate for the iris verification. Therefore, we define a new similarity measure based on mutual information between two feature x_a and x_b.

Let the probability that one feature element x_a has a quantization level j, be $P_a(j)$. When the other feature element x_b has a quantization level i, the probability that the quantization level of x_a is j is $P_{a,b}(j|i)$. When two features have large mutual information, $\frac{P_{a,b}(j|i)}{P_a(j)}$ has a meaningful value. Based on this fact, we define the similarity degree between two features a function of $\frac{P_{a,b}(j|i)}{P_a(j)}$.

$$SD(x_a = i, x_b = j) = \alpha \frac{P_{a,b}(j|i)}{P_a(j)} + \beta \quad (2)$$

We aim to define the similarity degree, $SD(x_a, x_b)$ that saisfies the following two conditions:

1. $SD(x_a, x_b) = 0$ when x_a and x_b are independent.
2. $SD(x_a, x_b) = 1$ when x_a and x_b belong to the same class.

Based on this fact, we define the similarity degree between x_b and x_a as an

$$SD(x_a, x_b) = \alpha \frac{P_{a,b}(j|i)}{P_a(j)} + \beta \tag{3}$$

where α, β are two parameters to be determined.

Under the assumption two features representing different classes are independent, we obtain

$$E[SD(x_a, x_b)] = \sum_{j=0}^{Q-1} \sum_{i=0}^{Q-1} SD(x_a = i, x_b = j) P_x(i) P_b(j) \tag{4}$$

where $P_x(i), P_b(j)$ is computed from the training set. From the second condition, we obtain

$$E[SD(x_a, x_b)] = \sum_{j=0}^{Q-1} \sum_{i=0}^{Q-1} SD(x_a = i, x_b = j) P_x(i) P_{a,b}(j|i) \tag{5}$$

where $P_x(i), P_{a,b}(j|i)$ is computed from the training set. From (4) and (5), α and β are determined.

3.2 Verification

For the verification, we first compute the similarity degree between the acquired and database feature vectors in each subband. Then, we verify the acquired feature vector using a Bayes decision rule [12]. Two feature vectors represent the same iris if

$$\sum_{i=0}^{F} P(\mathbf{x}_i \mid \Omega_{\mathrm{Intra}}) P(\Omega_{\mathrm{Intra}}) \geq \sum_{i=0}^{F} P(\mathbf{x}_i \mid \Omega_{\mathrm{Extra}}) P(\Omega_{\mathrm{Extra}}) \tag{8}$$

where N is the number of subband images used for feature represented, $P(\mathbf{x}_i \mid \Omega_{\mathrm{Intra}})$ is the probability that the similarity between two feature vectors obtained from the i-th subband imagesis $\mathbf{x}_i$ when two feature vectors represent the same iris, and $P(\mathbf{x}_i \mid \Omega_{\mathrm{Extra}})$ the probability that the similarity is $\mathbf{x}_i$ when two feature vectors represent different irises. $P(\Omega_{\mathrm{Intra}})$ is the probability that two feature vectors represent the same iris, and $P(\Omega_{\mathrm{Extra}})$ the probability that two feature vectors represent different irises. $P(\mathbf{x}_i \mid \Omega_{\mathrm{Intra}})$ and $P(\mathbf{x}_i \mid \Omega_{\mathrm{Extra}})$ are obtained from a training data. For the training $P(\mathbf{x}_i \mid \Omega_{\mathrm{Intra}})$ and $P(\mathbf{x}_i \mid \Omega_{\mathrm{Extra}})$, we computed the similarity degrees between 2,250,000 different sample pairs.

IV. EXPERIMENTAL RESULTS

The database used for the experiments consists of 1500 iris photos, 10 iris photos per each person. Among the photos that were taken from 150 persons in different hour during many weeks, 1500 photos passed an automatic quality check program were selected for the database.

The localized iris image is normalized to a 48-by-200 rectangular shaped image for the compensation of the iris variation. Since the normalized image size is relatively small, it is decomposed into sixteen subband images using Haar wavelet, of which the tap size is two. Each pixel of a subband image is quantized to one of four levels using the Lloyd-Max method.

For the comparison, we decompose the preprocessed iris image using two different wavelet transform, shift-variant and shift-invariant ones, respectively and compute the iris verification performance, FARs (false accept rate) and FRRs (false rejection rate), in each subband image. Table 1 shows the performance in the verification of 2,250,000 different sample pairs using each subband image. When the shift-variant method is used for the decomposition, horizontally or vertically low-frequency subband images result in relatively good performance. However, when the shift-invariant method is used for the decomposition, the verification performance based on a different set of subband images is much better. In the proposed shift-invariant method, most false acceptances and false rejections are due to the iris localization error, light reflections, and eyelid and eyelash obstruct. The proposed method takes more execution time than the shift-invariant method because multiple different forms are generated. However, the execution time for the iris localization and preprocessing steps is much larger than that for the shift-invariant wavelet decomposition and quantization steps. The amount of execution time from the raw image to the matching is about 800 milliseconds on an 800MHz Pentium III PC.

Finally, we compared the presented iris recognition method with two wavelet approaches: the Laplacian pyramid decomposition method of Wildes [3] and the wavelet zero-crossing method of Martin-Roche et al. [4]. Table 2 shows FARs and FRRs of three different methods. In the presented method, we use two subband images: f_{HILL} and f_{HILL}. The presented shift-invariant method yields far less FAR and FRR. The experimental results show that the presented shift-invariant method outperformed two conventional methods.

V. CONCLUSION

This paper has described a new iris recognition method based on a shift-invariant wavelet sub-images. In this paper, we decompose the preprocessed iris image into multiple subband images using two different wavelet transform, shift-variant and shift-invariant ones, respectively, and in each case, chose a set of subband images which have rich information for the classification of various iris patterns and robust to noises. When the shift-variant method is used for the decomposition, low-frequency subband images are chosen. However, when the shift-invariant method is used for the decomposition, a different set of subband images is chosen and classification performance based on this set of subband images is much better. Once a set of subband image is chosen for the feature representation, each pixel of subband images is quantized using the Lloyd-Max quantization method to reduce the size of the feature vector. Since each pixel is represented not by its quantized value but by a quantization level, an appropriate formulation of similarity measure is defined for the classification. With this similarity measure, the size of the feature vector can be reduced without much degradation of performance. The classification is basedon the Bayes decision rule. Finally, we compared the proposed method with two wavelet approaches and experimentally showed that the proposed method produced superb performance in iris recognition.

Table 1. FAR and FRR of iris verification in each subband image: (a) shift-variant method and (b) shift-invariant. The subband images with good performance are marked with dark gray.

(a)

FAR = 0.69% FRR = 0.49% TOT = 1.18%	FAR = 1.07% FRR = 0.12% TOT = 1.19%	FAR = 0.91% FRR = 0.13% TOT = 1.04%	FAR = 5.69% FRR = 1.01% TOT = 6.70%
FAR = 2.02% FRR = 0.50% TOT = 2.52%	FAR = 2.64% FRR = 0.79% TOT = 3.43%	FAR = 1.85% FRR = 0.34% TOT = 2.19%	FAR = 8.67% FRR = 1.12% TOT = 9.79%
FAR = 0.96% FRR = 0.47% TOT = 1.45%	FAR = 2.02% FRR = 0.34% TOT = 2.36%	FAR = 1.89% FRR = 0.31% TOT = 2.20%	FAR = 9.64% FRR = 1.15% TOT = 10.79%
FAR = 1.53% FRR = 0.45% TOT = 1.98%	FAR = 6.19% FRR = 1.06% TOT = 7.25%	FAR = 7.97% FRR = 0.64% TOT = 8.61%	FAR = 23.59% FRR = 4.02% TOT = 27.61%

(b)

FAR = 0.69% FRR = 0.27% TOT = 0.96%	FAR = 0.07% FRR = 0.06% TOT = 0.13%	FAR = 0.02% FRR = 0.08% TOT = 0.10%	FAR = 1.00% FRR = 0.24% TOT = 1.24%
FAR = 0.77% FRR = 0.51% TOT = 1.27%	FAR = 0.53% FRR = 0.15% TOT = 0.67%	FAR = 0.27% FRR = 0.13% TOT = 0.40%	FAR = 2.31% FRR = 0.62% TOT = 2.92%
FAR = 0.60% FRR = 0.49% TOT = 1.09%	FAR = 0.42% FRR = 0.08% TOT = 0.50%	FAR = 0.31% FRR = 0.15% TOT = 0.45%	FAR = 2.59% FRR = 1.16% TOT = 3.75%
FAR = 0.41% FRR = 0.22% TOT = 0.635	FAR = 1.82% FRR = 0.72% TOT = 2.54%	FAR = 2.40% FRR = 1.06% TOT = 3.46%	FAR = 12.79% FRR = 5.75% TOT = 18.55%

Table. 2. Verification performances of three methods: In the proposed method, we use two subband images: f_{HLLL} and f_{HHLL}.

Method	FAR	FRR
Wavelet zero-crossing method	1.12%	0.58%
Laplacian Pyramid method	0.41%	0.17%
The Proposed method	0.18%	0.06%

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