Neural-Network-Based Human Iris Recognition

Seongwon Cho*, Jaemin Kim*, Cheol Su Lim** and Robert Marks***

* School of Electronic and Electrical Engineering, Hongik University, 72-1 Sangsu-dong, Mapo-gu, Seoul 121-791, Korea

** Department of Computer Engineering, Seokyeong University, 16-1 Jungneung-dong, Sungbuk-gu, Seoul, 136-704, Korea

*** Department of Electrical Engineering, University of Washington Seattle, Washington 98195, USA

swcho@hongik.ac.kr jaemin@hongik.ac.kr cslim@skuniv.ac.kr

ABSTRACT

In this paper, we present human iris recognition, which is based on iris localization, feature extraction, and neural network.

The iris pattern is accurately segmented from the eye image using Canny filter. The features for iris recognition are extracted from the segmented iris pattern using two-dimensional (2-D) wavelet transform based on Haar wavelet. Experimental results show the accurate segmentation of the iris pattern and the usefulness of 2-D wavelet transform. In addition, we propose an efficient initialization method of the weight vectors and a new method to determine the winner in competitive learning neural network. The proposed methods have more accuracy than the conventional techniques.

Keywords : Neural Network, Iris Recognition, Learning Vector Quantization(LVQ).

1. Introduction

Each person has biologically distinctive features such as fingerprint, face, hand shape, palm, and iris. Technologies using biometrics have been developed for the automatic recognition of persons. Secure online authentification systems not only can replace passwords and secrete codes but also have many potential applications in surveillance and security systems [1].

The human iris is the pigmented, round, contractile membrane of the eye, suspended between the cornea and lens and perforated by the pupil. The visual pattern has two zones: the central pupillary zone with radiating spoke-like processes and frill and the surrounding ciliary zone with freckles, contractile lines and nevi. The zigzag circumferential collarette is placed between two zones [2].

The iris recognition is to analyze the iris pattern of an individual and to verify the individual's identity. Whereas most biological features (e.g., fingerprint, hand, and face) vary with age, the structure of iris is stabilized after two or three year old and is unique to an individual [3]. Due to high distinctiveness and stability, the iris pattern has been considered as the most reliable biometric measurement for the identification of individuals. Compared with the fingerprint recognition, the iris recognition does not require physical contact with a sensing device and is not invasive. However, the photo image of the iris pattern taken at a distance can have various artifacts due to long eyelashes and eyelid on the iris, reflection of illumination, and variation of the pupil size in different illumination. For reliable iris recognition, it is necessary to develop an efficient method for preprocessing the captured iris image, extracting the appropriate iris features, and classifying the extracted features.

In this paper, we address accurate localization of the iris pattern, efficient extraction of features vector using Haar wavelet transform, and successful classification of the extracted feature vectors using neural network. This paper is organized as follows: Section II describes the iris acquisition system and the accurate localization of the iris pattern. Section III explains how to extract compact feature vectors using Haar wavelet transform. In Section IV, a new initialization method of the weight vectors and an efficient winner-selection method for competitive learning neural network are proposed. Experiment results are discussed in Section V. Section VI is the conclusions.

2. Iris Acquisition and Localization

An iris acquisition system to automatically capture an iris image while remaining noninvasive to the human operator is shown in Fig. 1. When we take a photo of the iris pattern in a normal illumination condition, the photo is dark and does not have good contrast. To have good contrast in the interior iris pattern without annoying the operator, we use two infrared lamps, which consists of many light-emitting diodes (LED). By careful positioning of the light source, the reflection of the source can be placed inside the pupil. In this case, the major problem is the reflections of the point source off eyeglasses. To eliminate these artifacts in the acquired images, we use directional infrared LEDs and adjust the directional angles of them. We also put an infrared-passing filter in front of the lens to eliminate reflection of various illuminants. To make iris images well-framed without unduly constraining the operator, we put half mirror in front of the camera. Human operator can see what the camera is capturing and adjust his position accordingly. The captured image size is 320x240.

For the localization of the iris pattern, we detect the inner boundary of the iris pattern, the pupillary boundary and the outer boundary, the limbus using Canny filter[4].

3. Feature Extraction

For the extraction of features from the iris pattern, Gabor transform has been widely used [5,6]. Recently 1-D wavelet transform was also used [7]. In this section, we explain a new method for extracting feature from the iris pattern using 2-D Haar wavelet transform. We use Haar wavelet because it can be implemented easily and the computational cost can be saved.

To decompose a full-band 1-D signal into two subbands: L and H, a low-pass filter acts on the signal and the filtered signal is down sampled, which generates L subband, and a high-pass filter acts on the signal and the filtered signal is down sampled, which generates H subband. By using this decomposition in the x direction and in the y direction, a full-band 2-D signal is then decomposed into four bands: LL, LH, HL, and HH, where LH denotes one subband with L in the x direction and H in the y direction. This is shown in Fig. 2. For the pyramid decomposition, LL1 subband is decomposed into four bands: LL2, LH2, HL2, HH2. LL subbands are decomposed subsequently. This is shown in Fig. 3. The digital lowpass and highpass filters corresponding to Haar wavelet is [1,1] and [-1,1], respectively.

To analyze the iris image using Haar wavelet, the image, $I(r,\theta)$, in the polar coordinate is first transformed into the image, $I(x,y)$, in 2-D Cartesian coordinate and then is decomposed multiple subbands by the pyramid decomposition algorithm. Since sharp transition in the 2-D iris pattern is well represented by each HH subband, we can use each pixel intensity values of a HH subband as the feature vector for the classification. Since HH1 subband has too many pixels and is sensitive to the error of the iris location, we use a coarser HH subband such as HH4 or HH5. As the HH subband becomes coarser, the band becomes robust to the localization error but has less information.

To determine the best HH subband to be used, we checked whether a HH subband of one person could be classified from the same subbands of other persons. Fig. 4 and Fig 5 show the corresponding rates between feature vectors of 10 persons. Fig. 4 uses HH4 and Fig. 5 uses HH5. In Fig. 4 and Fig. 5, black dots represent the corresponding rate between feature vectors of the same person and white dots represent the corresponding rate between feature vectors of different persons. In Fig 4, we can find the decision boundary (such as 65% corresponding rate) that classifies the iris pattern of one person from the others. In Fig. 5, we cannot find any decision boundary. This means that HH5 band is too coarse to classify the iris pattern. Therefore, we extract most feature vectors from HH4 subband, which has 28x3=84 elements.

Other feature vectors are extracted from HH1, HH2, and HH3, where the mean value of each HH subband is used as a feature. The total number of the feature vectors is 84+3=87. Each feature is digitized into binary value. Only two levels are used for quantizing the feature values, and thus the feature vector is coded into 87 bits. This size is so small that the feature vector can be efficiently stored and processed.

4. Neural Network for Iris Recognition

Neural network is used to classify the extracted vectors. We use Learning Vector Quantization (LVQ) model due to its low complexity and high learning capability.

4.1. Initialization of the Weight Vectors

The LVQ is simple and faster than the error back-propagation algorithm, which is the most popular neural network model. However, the learning speed and classification performance of the LVQ are sensitive to the initial weight vectors. A simple method of initializing the weight vectors is to take the first m training vectors and use them as the initial weight vectors; the remaining vectors are then used for updating the weight vectors. Sometimes, the weight vectors are initialized to randomly selected training input vectors or the mean of the training vectors of each class. Other possible method of initializing the weights is to use K-mean clustering or CNN (condensed nearest neighbor) [8,9].

In the LVQ, an appropriate initial weight vector improves the learning time and classification performance. However, the distribution of initial weight vectors chosen by the previous initialization methods does not have large difference from the distribution of the training vectors. This is good for vector quantization. However, it is not appropriate for a pattern classifier based on a Nearest Neighbor method. When a nearest neighbor classifier is used, an input vector is classified to the class represented by the weight vector closest to it. Therefore, when we classify an input vector using reference (weight) vectors with uniform distribution, only reference (weight) vector close to decision boundaries between classes contribute to the classification performance. Accordingly, we can improve the performance of the LVQ by generating weight vectors close to decision boundaries and by removing unnecessary weight vectors.

Based on this fact, we propose a new weight initialization method for the LVQ, which generates the weight vectors close to decision boundaries. The proposed method is as follows:

[Step 1] Among training vectors of each class, take the first vector and use it as a weight vector for the class. The values of the remaining weight vectors for the classes are set to zero.

$$W_1^k = X_1^k \quad \text{for} \quad k = 1,2,\ldots,M \tag{1}$$

where X_1^k is the first training pattern of the k-th class, W_1^k is the first weight vector for the k-th class, and M is the total number of classes.

[Step 2] Feed a new training vector as an input vector into the network.

[Step 3] Compute the distances between the input vector and the weight vectors.

$$d(k,j) = \sum_{i=0}^{N-1} \left(X_i - W_{i,j}^k\right)^2 \tag{2}$$

where X_i is the i-th element of the input vector, $W_{i,j}^k$ is the i-th element of the j-th weight vector for the k-th class, and N is the dimension of the input vector.

[Step 4] Determine whether the class represented by the weight vector with minimum distance is the same with the class of the input vector. Only if two classes are different, the input vector is assigned as a new weight vector for the class of the input.

[Step 5] Repeat Steps 2-4 until all of the training vectors are processed.

Whereas for the original LVQ the number of the weight vectors for each class is to be predetermined, the proposed algorithm automatically determines the number of the weight vectors as the learning proceeds.

4.2. Dimensional Winner-Selection Method

As a distance measure, the Euclidean distance is used in the LVQ. However, when the dimension of the input vector is large like the iris feature vector, the winner selection based on the Euclidean distance can be wrong because of the loss of information about each dimension of the input vector. We propose a new winner selection method based on a new distance measure. For each training input vector, we do the following steps:

[Step 1] Compute the distance from an element of the input vector to the corresponding element of each weight vector.

[Step 2] Find the weight vector of which an element is closest to the corresponding element of the input vector, and then increase the winning count for the weight vector by one.

[Step 3] Repeat Steps 1-2 until all elements of the input vector are processed.

[Step 4] After all elements are processed, the weight vector with the largest winning count is the winner. Once the winning weight vector is determined, the weight vectors are updated using the well-known LVQ updating rule [8].

In determining the winner, the proposed dimensional winner-selection method can consider information about each element of the input vector (such as quality), and its computational complexity is less than the conventional winner-selection methods using other distance measures such as the Euclidean distance and 1-norm.

5. Experimental results

We use a database of 200 iris photographs for the experiments. The photographs were taken from 10 peoples in different hours and days. We used 100 iris photographs for learning and 100 for test. The parameter values for the LVQ are shown in Table 1.

5.1. Iris Localization

The proposed iris localization method successfully found the exact location of the inner and the outer boundaries for all of 200 photos. Fig. 7 shows the pupillary boundary and the limbus detected by the proposed method, respectively. The number of resolution levels is three.

5.2. Feature Extraction

We compared two different feature extraction methods based on Gabor transform and Wavelet transform. We used the same LVQ for two methods. The performance of two methods is shown in Table 2. As for the learning data, two methods result in the same performance. As for the test data, feature extraction based on wavelet transform results in slightly better performance.

5.3. Initialization of Weight Vectors

We compared classification performance of two methods: one based on the proposed initialization method and the other based on a random initialization method. Wavelet transform was used for feature extraction. The performance of two methods is shown in Table 3. The proposed initialization method results in better performance.

5.4. Winner Selection

We compared the proposed winner-selection methods and other ones. We used wavelet transform for feature extraction and the proposed initialization methods for the initialization of LVQ. 2-D Euclidean norm is generally used as a distance measure in the LVQ but it does not guarantee better performance than other norms. For improving classification performance, we tested various norms. However, other norms do not improve the performance, which is shown in Table 4.

To figure out the effect of each elements of the input vector on the classification performance, we computed the classification rate in each dimension of the input vector. This is shown in Fig. 6. If all elements have the similar contribution to the classification performance, we can use the Euclidean distance as a distance measure. However, some elements have more than 90% accuracy in the classification rate, and the other some elements have less than 85% accuracy in classification rate. This implies that the proposed dimensional-winner selection method is superior to the winner-selection method based on Euclidean norm, which is shown in Table 5

6. Conclusions

In this paper, we presented an iris recognition system with high classification rate. For the accurate localization of the iris pattern, Canny filer was used. For the feature extraction, we used Haar wavelet transform, which is experimentally shown to be better than Gabor transform in classification performance. To improve classification rate, we used a neural network based on the LVQ. For the learning of the LVQ for the iris recognition, we proposed a new initialization method and dimensional winner-selection method, which were experimentally proven to results in better performance. We also reduced the size of feature vector without degrade of performance.

References

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Learning rate	0.1
Update of learning rate	$\alpha(t)(1-1/\#\text{ of iteration})$
Total number of iteration	300

Table 1 Parameter values for LVQ

	Gabor transform	Wavelet transform
Learning data	98%	98%
Test data	93%	94%

Table 2 Classification rates of two different feature extraction methods

	Random initialization method	The proposed initialization method
Learning data	98%	100%
Test data	94%	98%

Table 3 Classification Rate of two different initialization methods

Norm	Classification rate	
1-norm	98%	$\lvert\cdot\rvert+\lvert\cdot\rvert+\Lambda$
2-norm	98%	$\sqrt{\lvert\cdot\rvert^2+\lvert\cdot\rvert^2+\Lambda}$
∞-norm	94%	$\max\{\lvert\cdot\rvert+\lvert\cdot\rvert+\Lambda\}$

Table 4 Classification rates of a known winner-selection method using various distance measures

	Winner-selection method using Euclidean distance	The proposed dimensional winner-selection method
Learning data	100%	100%
Test data	98%	100%

Table 5 Classification rates of two different winner-selection methods

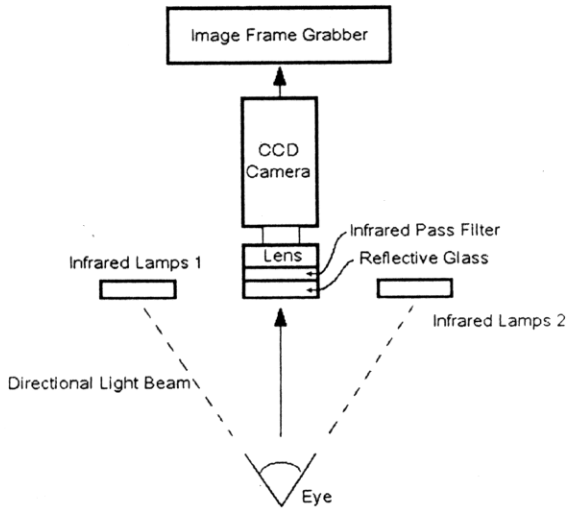


Fig. 1 The iris acquisition system viewed from the top. Two infrared lamps are placed at a higher position than the human eye.

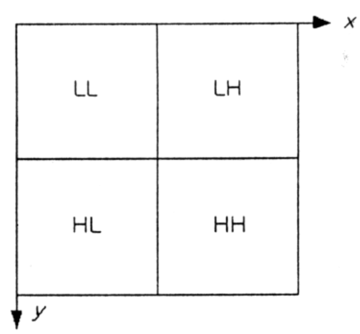


Fig. 2 Decomposition of 2D signal

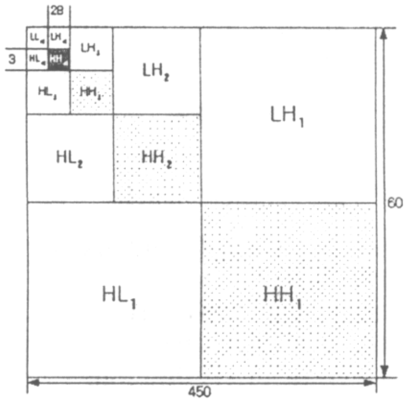


Fig. 3 Pyramid decomposition of the iris pattern

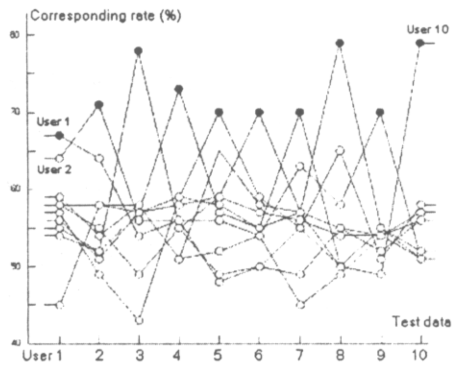


Fig. 4 The results using the feature vectors extracted HH4 obtained by 4 time decomposition.

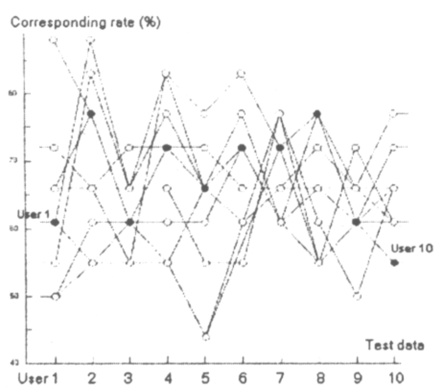


Fig. 5 The results using the feature vectors extracted HH4 obtained by 5 time decomposition.

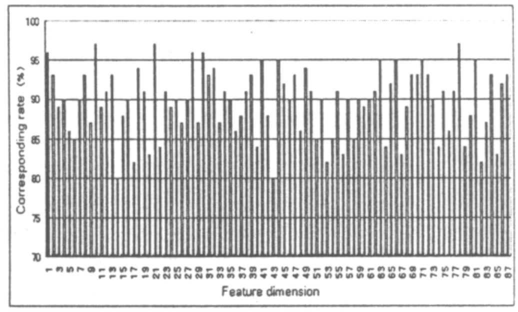
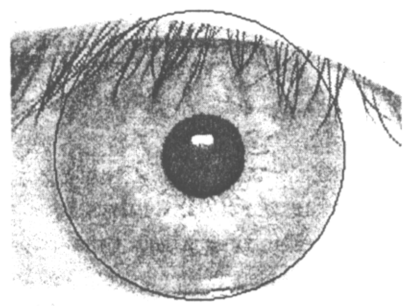
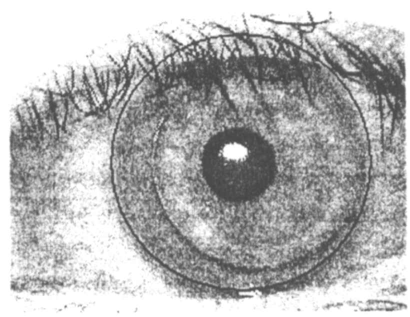


Fig. 6 Corresponding rate of each feature element



(a)



(b)

Fig. 7 The estimation results of the outer boundary of the iris, limbus