International Journal of Fuzzy Logic and Intelligent Systems, vol. 2, no. 3, December 2002 pp. 227-230

Iris Segmentation and Recognition

Jaemin Kim and Seongwon Cho

School of Electronics and Electrical Engineering, Hongik University

Abstract

A new iris segmentation and recognition method is described. Combining a statistical classification and elastic boundary fitting, the iris is first segmented robustly and accurately. Once the iris is segmented, one-dimensional signals are computed in the iris and decomposed into multiple frequency bands. Each decomposed signal is approximated by a piecewise linear curve connecting a small set of node points. The node points represent features of each signal. The similarity measure between two iris images is the normalized cross-correlation coefficients between simplified signals.

Key Words : iris segmentation, iris recognition, wavelet transform, expectation-maximization algorithm, active contour model

1. INTRODUCTION

Human iris patterns are highly distinctive to an individual [1]. Various iris recognition methods have been proposed for automatic personal identification and verification [2]-[6]. A prototype system for iris recognition presented by Daugman [2] reported its excellent performance on diverse database. Wildes et al. [3] described a prototype system for iris recognition, too. These prototype systems require high equal quality iris images, which is not easily satisfied in practical application. For robust iris recognition, a method using a zero-crossings of wavelet transform was presented by Boles et al. [4] and improved by Roche et al. [5]. Another robust method is to combine Gabor filtering and wavelet transform [6].

These methods require accurate iris segmentation for successful processing because the iris is small part of an acquired image. The iris is located between the pupil and the limbus. Some part of it can be covered by the eyelids. Since the iris boundaries have a wide range of edge contrast and irregular border shapes due to noises, the boundaries are modeled by circles or parabolic arcs and detected by various methods [3],[5],[6]. However, the assumption that the pupil contour can be fit to a circle is not always valid.

In this paper, we describe an accurate iris segmentation method and a robust iris recognition method.

2. IRIS SEGMENTATION

For robust and accurate iris segmentation, we combine statistical classification and elastic boundary fitting. A Gaussian mixture model (GMM) is successfully used for object segmentation, especially when objects have different intensity distributions [8]. The density function of the mixture model is

$$p(x) = \sum_{i=1}^{3} \omega_k f(x|\mu_k, \sigma_k) \quad (1)$$

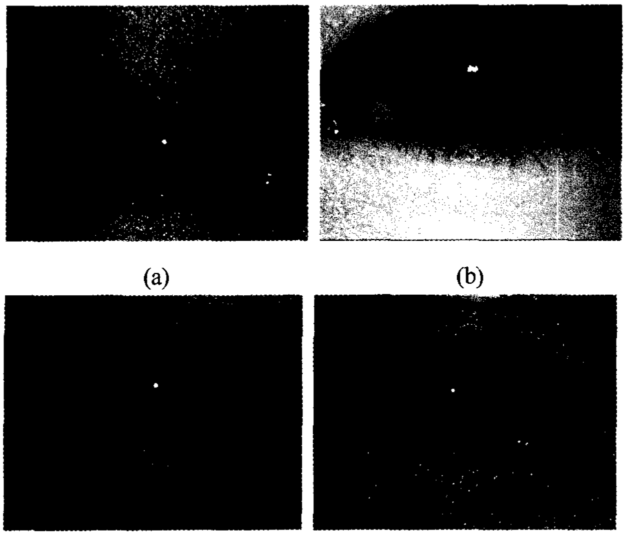
where x is the mixing parameters. $f(x|\mu_k, \sigma_k)$ is the Gaussian density function, (μ_k, σ_k) is the model parameters, and ω_k is the mixing parameters.

One common method for solving Gaussian mixture models is an EM algorithm [8]. EM is a general procedure for estimating model parameters when the data is incomplete. It iteratively updates model parameters to maximize expected value of log-probability of known observed variables and unknown hidden variables. In the E-step, compute the posterior for the hidden variables that indicate to which component an observation x belongs. In the M-step, compute the model parameters (μ_k, σ_k) and the mixing parameters ω_k. Generally, EM is sensitive to the initial values of the parameters. In our case, since the structural and intensity characteristics of the captured images are known, good initial values for $(\mu_k, \sigma_k, \omega_k)$can be chosen.

The segmentation based on the Gaussian mixture model has some errors like a speckle noise, which are removed by a spatial filtering described as:

If more than half of pixels in the neighborhood of the pixel to be filtered belong to one of three components, the pixel is classified as the component.

Since the image segmentation based on statistical classification can has some local error due to the noises such as the reflection of the light source and the eyelashes, we accurately detect the contour again using an elastic contour model. In the elastic contour model, the object boundary is represented by a sequence of nodes of which the positions are determined by minimizing an energy function [9]. For the real-time implementation of the elastic contour model, we adopt Greedy algorithm proposed by Williams and Shah [9]. This model is sensitive to noises such as the eyelashes and the reflection of the right source. The iris segmentation results are shown in Fig. 1.



(a) (b)

(a) (b)

Fig. 1. Segmentation results of images captures in various illumination conditions.

3. IRIS RECOGNITION

3.1 Preprocessing

Illumination normalization and histogram equalization is applied to the localized iris prior to feature extraction. For feature extraction, one-dimensional signals, $s_i(k)$ are generated as follows:

$$\begin{aligned} s_i(k) &= s[r_k \cos(\theta_i), r_k \sin(\theta_i)], \\ \theta_i &= 2\pi \cdot i/M, \\ r_k &= k \cdot \Delta R(\theta_i), \\ \Delta R(\theta_i) &= \| l(\theta_i) - p(\theta_i) \| / N, \end{aligned} \tag{2}$$

where $s_i(k)$ is a one-dimensional signal, θ_i is cyclic over $[0, 2\pi]$, $l(\theta_i)$ is a point on the limbus, $p(\theta_i)$ is a point on the pupillary contour. Since the most area between the upper eyelid and the pupil are covered by the eyelashes, one-dimensional signals in this area are ignored.

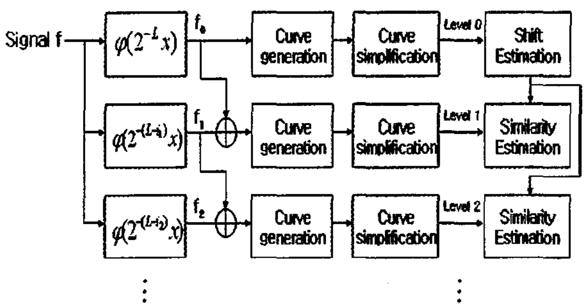


Fig. 2. Overall block diagram of signal decomposition and simplification.

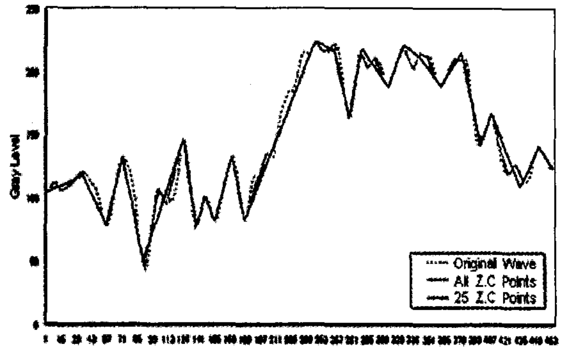


Fig. 3. 1-D iris signal computed over a circle, its approximated piecewise linear curve, and its simplified piecewise linear curve.

3.2 Feature Extraction

Each signal on a circle is decomposed into multiple frequency bands, which is shown in Fig. 2. For the decomposition, the input signal is first convolved with a filter bank, which consists of differently dilated Gaussian functions, and then the signal from each branch of the filter bank is subtracted from the signal from the next lower branch. Each subtracted output is approximated by a piecewise linear curve connecting node points. Each node corresponds to a local maximum or minimum point of a decomposed signal. This piecewise linear curve is simplified by iteratively contracting edges (vertex pairs) to their optimal targets with the minimum change of the shape. The approximation and simplification is shown in Fig. 3. The concept used in the 2-D mesh simplification method proposed by Garland et al [5] is applied to the piecewise linear curve simplification. An example of edge contraction is illustrated in Fig. 4. Each edge contraction is done by minimizing the error cost of contracting an edge (v_i, v_{i+1}) is given as

$$\min_{\bar{v}} \sum_{i=1} \omega_i (n_i \cdot \bar{v} + c_i)^2 \tag{3}$$

where $\bar{v}$ denotes the optimal contration target for the pair (v_i, v_{i+1}), n_i denotes the normal vector of a line l_i connecting the pair, $(n_i \cdot \bar{v} + c_i)$ represents the distance between $\bar{v}$ and l_i, and ω_i denotes a weighing factor proportional to the length of the edge.

The iterative edge contraction is as follows:

1. Select all vertex pairs and compute the optimal target for each pair and the contraction cost.
2. Place all the pair in a heap key on cost with the minimum cost pair at the top
3. Iteratively remove the pair of least cost from the heap, contract this pair, and update the

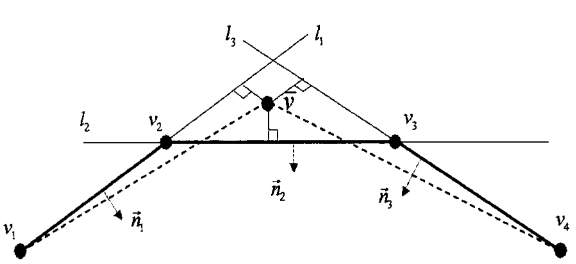


Fig. 4. An example of edge collapse.

3.3 Similarity Measure

The similarity meastHowever ure between two iris images is the normalized cross correlation coefficients between simplified signals, which are re-formed by linearly interpolating node points. The normalized cross correlation coefficient is given as

$$\langle \overline{f,g} \rangle = \frac{\langle f,g\rangle - \langle f\rangle\langle g\rangle}{\sigma_f, \sigma_g}$$
$$\langle f,g \rangle = \frac{1}{N}\sum_{i=1}^{N} f(i)g(i) \tag{4}$$

where $\langle\rangle$ is the average operator, σ is the standard deviation, and N is set a few times as large as the number of node points for the reduction of computation time.

2.4 Comparison with Zero-crossing Method

Zero-crossing points in [4,5] keep information about local signal variation of a lowpass signal. Similarity measure between two corresponding zero-crossing points is robust to a white Gaussian noise. The main problem of the zero-crossing method is that two compared representations can have different numbers of zero-crossings and some zero-crossing pairs used in computing the similarity may not be corresponding pairs in practical applications. To get around this problem, Roche et al. [5] use a binary Hamming distance between two nearest zero-crossing points.

In this paper, the similarity measure is the normalized cross-correlation coefficient between two bandpass signals, which are approximated by a piecewise linear curve connecting node points. The approximated linear curve is also robust to a white Gaussian noise because the approximation is some kind of lowpass filtering procedure. Making the approximate curve as close as possible to the original one, the present method still keeps the accuracy.

Code size of two methods are equal because a set of local maximum or mimimum points is used as a feature vector. As for the computation time, the presented method takes less computation times than the zero-crossing method.

4. EXPERIMENTAL RESULTS

The segmentation results in Fig. 1 show that the presented method can localize the iris very accurately and robustly. Fig. 1(b) shows that the pupil shape is different from the circle.

As for the feature extraction, each signal is analyzed into two components: the lowest resolution level f_0 and the next lower frequency band (f_1-f_0). In our experiments, f_0 is used to compute the rotation of the signal due to the head tilt and (f_1-f_0) is used to compute the normalized correlation coefficients. Since iris images used in the experiments are corrupted by various noises, the use of high frequency components (such as (f_2-f_1)) does not improve performance.

Finally, we compared the presented iris recognition method with a zero-crossing method. Fig. 5 shows the results of the zero-crossing method. The distribution illustrated by gray bars represents the binary Hamming distances between different irises. The distribution illustrated by black bars represents those between different images of identical irises. Two distributions overlapped by 2.5%. Fig. 6 shows the results of the present method. The distribution illustrated by gray bars represents the normalized cross-correlation coefficients between different irises. The distribution illustrated by black bars represents those between different images of identical irises. Two distributions are separated by a large margin. The experimental results show that the presented method outperformed the zero-crossing method.

5. CONCLUSION

This paper has described a new iris segmentation and recognition method. Combining statistical classification and elastic boundary fitting, the method segmented the iris robustly and accurately. For feature extraction, one-dimensional signals in the wavelet domain are approximated by a piecewise linear curve connecting a small set of node points. The set of node points is a feature vector to be stored. The approximation procedure reduces the feature vector size while keeping the recognition accuracy. Experimentally we showed that the proposed method gave good performance in iris segmentation and recognition.

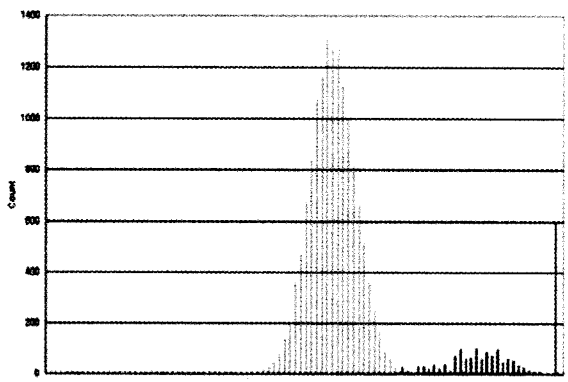


Fig. 5. Iris recognition results using a zero-crossing method: Black bars represent the binary Hamming distance between different images of identical irises, and gray bars represent those between different irises.

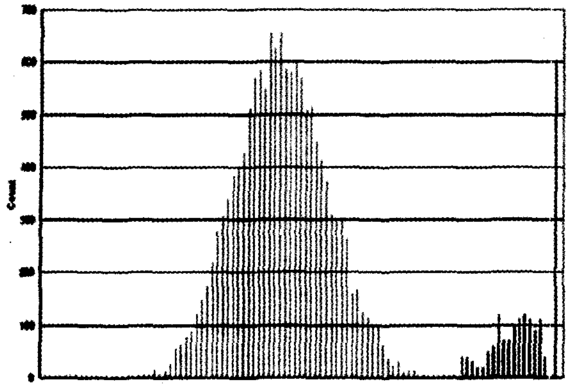


Fig. 6. Iris recognition results using the present method: Black bars represent the normalized cross-correlation coefficients between different images of identical irises, and gray bars represent those between different irises.

Reference

[1] F. H. Adler, Physiology of the Eye. St. Louis, MO: Mosby, 1965.

[2] J. Daugman, High Confidence Visual Recognition of Person by a Test of Statistical Independence, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, pp. 1148-1161, 1993.

[3] R. P. Wildes, Iris Recognition: An Emerging Biometric Technology, Proceedings of the IEEE, vol. 85, pp.1348-1363, 1997.

[4] W. W. Boles, and B. Boashah, A Human Identification Technique Using Images of the Iris and Wavelet Transform, IEEE Trans. on Signal Processing, vol. 46, pp. 1185-1188, 1998.

[5] D. de Martin-Roche, C. Sanchez-Avila, and R. Sanchez-Reillo, Iris Recognition for Biometric Identification using Dyadic Wavelet Transform Zero-Crossing, Security Technology, 2001 IEEE 35th International Carnahan Conference, pp. 272-277, 2001.

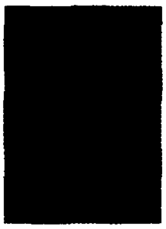
[6] Y. Zhu, T. Tan and Y. Wang, Biometric Person Identification based on Iris Pattern, ICPR2000, pp.805-808, 2000.

[7] S. Masahiko and K. Yuji, Iris Region Extraction and Individual Identifying Device, Japan Patent, JP2000189403A2, July 11, 2000.

[8] J. Li and A. Barron, Mixture Density Estimation, in Solla, Leen, and Mueller (eds.), Advances in Neural Information Processing Systems 12, The MIT Press, 2000.

[9] D. Williams and M. Shah, A Fast Algorithm for Active Contours and Curvature Estimation , CVGIP: Image Understanding. Vol. 55, No. 1, pp. 14-26. 1992.

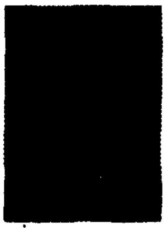
[10] M. Garland and P. Heckbert, Surface Simplification Using Quadric Error Metrics, Proceedings of Siggraph97, pp. 209-216, 1997.



Jaemin Kim

He received the B.S. and M.S. degrees in electrical engineering from Seoul National University in 1984 and 1986, respectively. He received the Ph.D. degree in electrical engineering from Rensselaer Polytechnic Institute in 1994. He is with Hongik University as an assistant professor at School of electronics and electrical engineering. His research interests are biometrics, image processing and compute vision.

Phone : +82-2-320-1634
Fax : +82_2-320-1110
E-mail : jaemin@hongik.ac.kr



Seongwon Cho

He received the B.S. and M.S. degrees in electrical engineering from Seoul National University in 1982. He received the M.S. and Ph.D. degrees in electrical engineering from Purdue university in 1987 and 1992, respectively. He is with Hongik University as an associate professor at School of electronics and electrical engineering. His research interests are biometrics, artificial intelligence, and pattern recognition.

Phone : +82-2-320-1493
Fax : +82_2-320-1110
E-mail : swcho@hongik.ac.kr