Improving Iris Recognition Accuracy via Cascaded Classifiers

Zhenan Sun, Yunhong Wang, Tieniu Tan, Jiali Cui

Center for Biometrics Authentication and Testing
National Laboratory of Pattern Recognition, Institute of Automation,
Chinese Academy of Sciences, P.O. Box 2728, Beijing, 100080, P.R. China
{znsun, wangyh, tnt, jlcui}@nlpr.ia.ac.cn

Abstract. As a reliable approach to human identification, iris recognition has received increasing attention in recent years. In the literature of iris recognition, local feature of image details has been verified as an efficient iris signature. But measurements from minutiae are easily affected by noises, which greatly limits the system's accuracy. When the matching score between two intra-class iris images is near the local feature based classifier's (LFC) decision boundary, the poor quality iris images are usually involved in matching. Then a novel iris blob matching algorithm is resorted to make the recognition decision which is more robust than the LFC in the noisy environment. The extensive experimental results demonstrate that the cascading scheme significantly outperforms individual classifier in terms of accuracy and robustness.

1 Introduction

With the increasing demanding of security in our daily life, reliable personal identification through biometrics is currently an active topic in the literature of computer vision. Biometric solutions, such as identification systems using fingerprint, iris, face, palmprint, etc., have many advantages over the traditional authentication techniques based on what you know or what you possess [1, 2]. Among them, iris recognition is tested as the most accurate manner of personal identification [3]. Therefore nowadays many automatic security systems based on iris recognition have been deployed world wide for border control, restricted access, and so on [4].

The iris of human eye is the annular part between the black pupil and the white sclera (Fig.1). There are lots of irregular small blobs, such as freckles, coronas, stripes, furrows and crypts, etc., overlaying on the iris region. Furthermore, the spatial distribution of these blocks in the iris is also random. Such randomly distributed and irregular blocks constitute the most distinguishing characteristics of the iris [22].

Since last decade, a number of researchers have worked on iris recognition with the ambition to improve the application's performance specifications, such as accuracy, processing speed, storage cost and robustness [5-23]. According to the various iris features utilized, these algorithms can be grouped into four main categories: phase-based method [5-9], zero-crossings representation [10-12], texture analysis [13-21], local intensity variation [22,23]. Because the distinctive iris information is essentially embedded in the fine spatial changes in the iris image, local feature based classifier (LFC) had achieved higher recognition accuracy compared with other methods. But on the other hand, the measurements from minutiae are easily affected by noises, such as occlusions by eyelids and eyelashes, localization error and nonlinear deformations, etc., which greatly limits the system's accuracy. In our experiments [22], about 90% false non-matches are incurred by all kinds of noises. Thus a blob matching algorithm, which attempts to establish the global correspondence between two iris images, is desirable to overcome the limitations of LFC, i.e. sensitive to photometric and geometric distortions.

For the purpose of improving iris recognition accuracy, a cascading strategy that combines the LFC and the global feature based classifier (GFC, because the global topological information is used in blob matcher) is proposed in this paper. The basic idea of this technique is to construct a two stage classification system with reject option. The LFC is implemented first and the GFC is seldom consulted unless the LFC is uncertain of its result. Because the large majority recognition tasks can be handled by LFC, the system's real-time performance is not essentially affected by the added GFC.

The remainder of this paper is organized as follows. Section 2 describes a novel iris blob matching algorithm. The multistage combination architecture will be introduced in Section 3. Section 4 provides the experimental results prior to conclusions in Section 5.

2 Alignment based iris blob matching method

A typical iris recognition system includes localization, normalization, feature extraction and matching. Fig. 1 illustrates the preprocessing results [5,14,17].

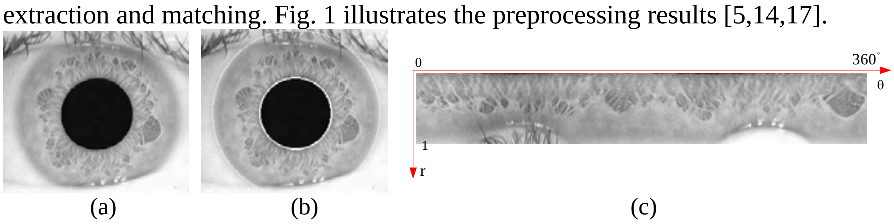


Fig. 1. Preprocessing of iris image; (a) Original image; (b) Result of iris localization; (c) Normalized iris image

Based on our observations, the block pattern in iris image is very informative for iris matching. The objective of blob matching algorithm is to find the spatial correspondences between the blocks in the input iris image and that in the stored model and quantitatively assess their similarity level based on the number of matched block pairs. The main steps of the blob matching algorithm are described as follows:

1) Blocks of interest (BOI) segmentation: Because the zero-crossings of wavelet transform often indicate the location of sharp variation points [24], the boundary of BOI can be efficiently detected after dyadic wavelet transform (DWT) performed on the input data. With local processing of edge linking, the closed-boundary regions are labeled. Because the pixels in the region of BOI always have lower intensity than

others, the object is labeled as foreground if the result of DWT at its region is negative (Fig. 2b).

2) Block pattern representation: In the coordinate system shown in Fig. 1(c), each BOI's centroid coordinates (R,θ), area (A) and the second order central moments $(MomentR,\ Moment\theta)$ are recorded as its attributes. Generally, there are nearly one hundred BOIs in an iris image. So each iris image can be represented with a block set $\{(R_i, \theta_i, Area_i, MomentR_i, Moment\theta_i) | i = 1, 2, \cdots, N\}$, where N denotes the total number of BOIs in the image.

3) Alignment of two block patterns: At first all corresponding block pairs (with similar R, A, $MomentR$ and $Moment\theta$) of the two iris patterns are explored. Each pair of corresponding blocks are supposed as the origins in their own images respectively, so blocks of other pairs should have relative angles ranging from 0° to 360° with respect to their reference blocks. In each temporary coordinate system pair, number of block pairs which have similar relative θ location is counted. After all iterations, the rotation parameter can be computed from the optimal coordinate system pair with maximum matching count N_m.

4) Similarity assessment: At last, a quantitative matching score of the two iris block patterns is defined as

$$MS = \min(\frac{M_1}{N_1}, \frac{M_2}{N_2}) \tag{1}$$

where M_i and N_i (i=1,2) denote the number of mated blocks (with similar location, area and moments) and all blocks in the i th iris block pattern respectively.

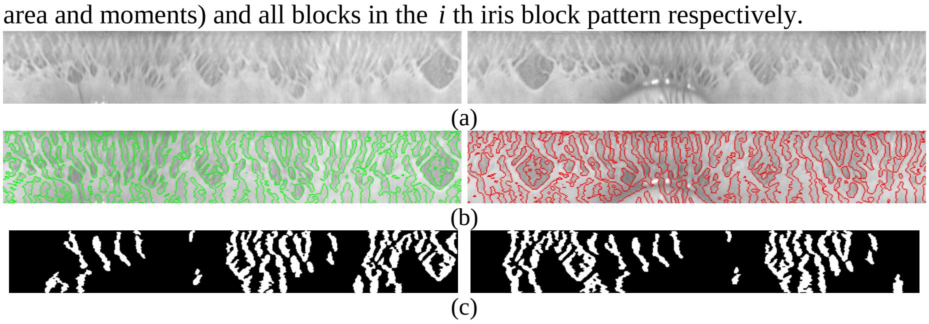


Fig. 2. Alignment based iris blob matching process; (a) Two normalized iris images from same eye; (b) Segmentation results, the contours denote zero-crossings of DWT; (c)The mated BOIs

3 Cascading architecture for accurate iris recognition

In this paper, we aim to reduce the positive identification system's false reject rate (FRR) when the system is operated in the status of low false accept rate (FAR). The cascading scheme is illustrated in Figure 3. This is a typical two stage classification system [25]. TL, TH and TB are the predefined thresholds, and TL is defined via

$$\mathrm{P}(SL < TL |\ \mathrm{Imposter}) = 0.9999 \tag{2}$$

and TH is defined by

$$P(SL < TH \mid \text{Imposter}) = 0.999999 \quad (3)$$

Thus TL and TH correspond to FAR 0.01% and 0.0001% respectively, which can be learned from the distribution of inter-class comparisons. We found that the majority of false rejections' matching scores fall into the interval between TL and TH. So the second session is introduced to give these false rejected subjects once more chance to provide another set of necessary evidences to verify their identities.

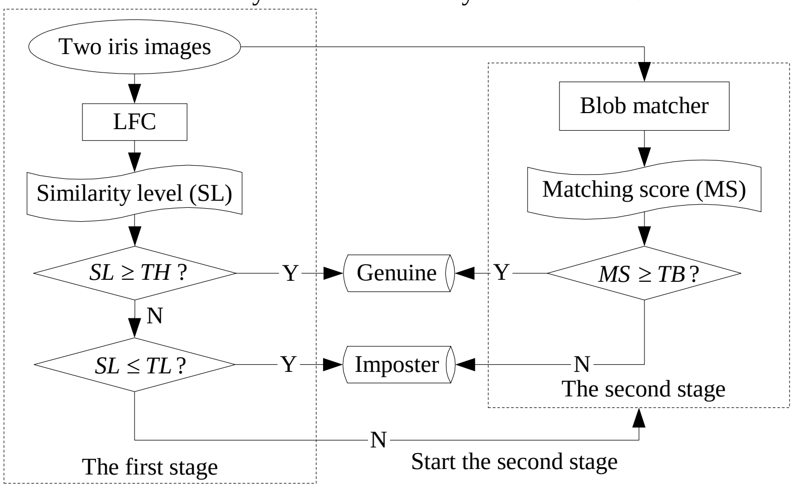


Fig. 3. Cascading scheme for iris recognition

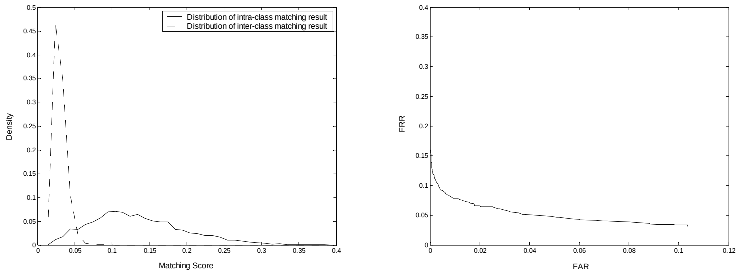
4 Experimental Results

4.1 Database

With the self made iris capture device, an iris database named CASIA has been constructed. This database has been worldwide shared for research purposes [26]. To test the proposed method, we make totally 1,135,566 comparisons between iris images captured in different time, including 3,711 intra-class comparisons and 1,131,855 inter-class comparisons.

4.2 Discriminating power of the blob matching algorithm

The distribution of matching scores of the proposed blob matcher is shown in Figure 4(a) and the ROC curve is drawn in Figure 4(b). From this experiment, we can see that it is difficult for two random block patterns to achieve high matching score. In this case, more than 98% inter-class matching scores are lower than 0.05, i.e. less than about 5 mated pairs. But accurate segmentation of blobs can not be guaranteed in all cases. So this method is generally worse than most of the existing iris recognition methods in terms of accuracy. However, it will be proved later that the blob matching method is much better than LFC in case of poor quality images because the elastic matching strategy make it accommodate localization error, distortion and occlusions of eyelids or eyelashes. What we need just is the complementary property of this method to the LFC.

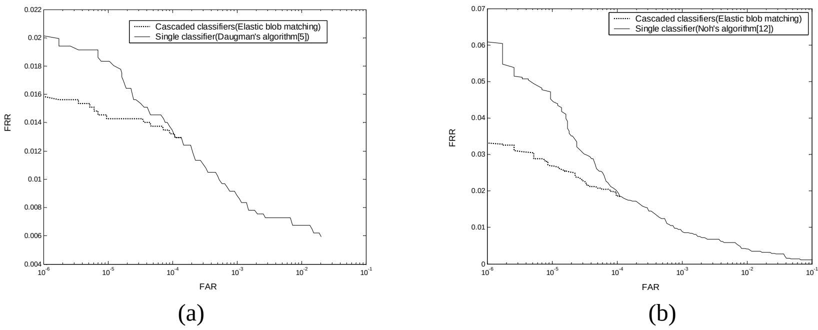


(a) (b)

Fig. 4. Performance of the blob matching algorithm; (a) Distribution of intra-class and inter-class matching scores; (b) ROC curve

4.3 Performance evaluation of cascaded classifiers

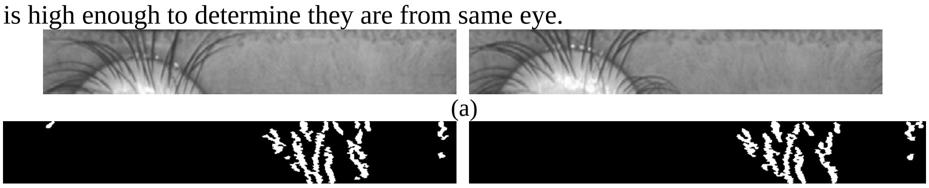
Both Daugman's phase demodulation algorithm [5,6] and Noh's wavelet decomposition method [12] are typical LFC. In this subsection they are both cascaded with the blob matching algorithm respectively as shown in Fig.3. The ROC curves of both LFC and the cascaded classifiers are demonstrated in Fig. 5 for comparison. We can see that when 10^{-6}<=FAR<=10^{-4} the cascaded system achieves the lower FRR, which demonstrate the GFC is better than LFC in recognizing poor quality iris images. The two curves overlay when FAR> 10^{-4} . It should be noted then the system's operation state (FAR/FRR) is controlled by the criterion of the GFC.



(a) (b)

Fig. 5. Performance of the cascaded classifiers; (a) Results of Daugman's algorithm; (b) Results of Noh's algorithm (only use the local feature).

One example is shown in Figure 6 which is a false rejection of LFC but correctly accepted by GFC. Because of the occlusions of eyelids and eyelashes, a test of statistical independence [5] of the two images is passed. But the blob matching score is high enough to determine they are from same eye.



(a)

(b)

Fig. 6. An example when GFC is more reasonable than LFC; (a) Two normalized iris images from same eye, the similarity level of Daugman's method is 0.58; (b) The mated BOIs by the blob matching algorithm, the blob matching score is 0.18.

From the experimental results, we can see that LFC and GFC are iris image quality-dependent. Although GFC is a weak classifier compared with LFC when the iris images are high quality, which does not affect its expertise in recognize noisy iris images (Fig. 6). In our case, the poor quality iris images are roughly detected by measuring whether their matching score of LFC is near the classifier's decision boundary. Therefore the system's ROC can be improved if the final decision is then provided by the GFC.

The computational cost of GFC is about two times of Daugman's, but its probability to be used is only about 1% empirically. So for Daugman's system, the average time cost only increases 2%. For Noh's algorithm, this number is about 3%. Compared with the cheap price paid for computation, the benefit in terms of the system's accuracy and robustness is deserved.

5. Conclusions

In this paper, a cascading scheme of multiple representations and matching algorithms for iris recognition is proposed. This method is also applicable in other biometric systems. Another contribution of this paper is a novel iris blob matching algorithm is presented. This method can register two intra-class iris images into sub-pixel precision. Although the experimental results show that blob matching algorithm alone is not promising for iris recognition directly, it has its own specialties for discriminating noisy iris images, which is complementary with LFC. Our further work is to exploit the mated blocks' area information to give a more accurate result. And another potential application of this blob shape based iris representation is to facilitate iris identification in large scale database by shape indexing technique, which is also an interesting research topic.

Acknowledgments

This work is funded by research grants from the Natural Science Foundation of China (Grant No. 60121302, 60275003, 60332010, 69825105) and the CAS.

References

1. A.K. Jain, R.M. Bolle and S. Pankanti, (eds.): Biometrics: Personal Identification in Networked Society, Norwell, MA: Kluwer (1999)
2. D. Zhang (ed.): Automated Biometrics: Technologies and Systems, Norwell, MA: Kluwer (2000)
3. T. Mansfield, G. Kelly, D. Chandler and J. Kane: Biometric Product Testing Final Report, issue 1.0, National Physical Laboratory of UK (2001)
4. http://www.iridiantech.com/solutions.php
5. J. Daugman: High Confidence Visual Recognition of Persons by a Test of Statistical Independence, IEEE Trans. PAMI, Vol.15, No.11 (1993) 1148-1161
6. J. Daugman: Statistical Richness of Visual Phase Information: Update on Recognizing Persons by Iris Patterns, IJCV, Vol. 45(1) (2001) 25-38
7. R. Sanchez-Reillo and C. Sanchez-Avila: Iris Recognition With Low Template Size, AVBPA (2001) 324-329
8. C. Tisse, L. Martin, L. Torres and M. Robert: Person Identification Technique Using Human Iris Recognition, Proc. of Vision Interface (2002) 294-299
9. J. Huang, L. Ma, Y. Wang, T. Tan: Iris Recognition Based On Local Orientation Description, ACCV (2004) 954-959
10. W.W. Boles and B. Boashash: A Human Identification Technique Using Images of the Iris and Wavelet Transform, IEEE Trans. on Signal Processing, Vol.46, No.4 (1998) 1185-1188
11. C. Sanchez-Avila, R. Sanchez-Reillo, et al.: Iris-based Biometric Recognition using Dyadic Wavelet Transform, IEEE Aerospace and Electronic Systems Magazine (2002.8) 3-6
12. S. Noh, K. Bae, J. Kim: A Novel Method to Extract Features for Iris Recognition System, AVBPA (2003) 838-844
13. Y. Zhu, T. Tan, Y. Wang: Biometric Personal Identification Based on Iris Patterns, ICPR (2000) Vol.II 805-808
14. L. Ma, T. Tan, Y. Wang and D. Zhang: Personal identification based on iris texture analysis, IEEE Trans. PAMI, Vol. 25, No.12 (2003) 1519-1533
15. L. Ma, Y. Wang, T. Tan: Iris Recognition Based on Multichannel Gabor Filtering, ACCV (2002) Vol.I 279-283
16. L. Ma, Y. Wang, T. Tan: Iris Recognition Using Circular Symmetric Filters, ICPR (2002) Vol.II 414-417
17. R.P. Wildes, J.C. Asmuth, et al.: A Machine-vision System for Iris Recognition, Machine Vision and Applications (1996) Vol.9 pp.1-8
18. B. Kumar, C. Xie and J. Thornton: Iris Verification Using Correlation Filters, AVBPA, (2003) 697-705
19. C. Park, J. Lee, M. Smith and K. Park: Iris-Based Personal Authentication Using a Normalized Directional Energy Feature, AVBPA (2003) 224-232
20. S. Lim, K. Lee, et al.: Efficient Iris Recognition through Improvement of Feature Vector and Classifier, ETRI Journal, Vol. 23, No. 2 (2001) 61-70
21. K. Bae, S. Noh and J. Kim: Iris Feature Extraction Using Independent Component Analysis, AVBPA (2003) 838-844
22. L. Ma, T. Tan, Y. Wang and D. Zhang: Efficient Iris Recognition by Characterizing Key Local Variations, IEEE Trans. Image Processing (Accepted)
23. L. Ma, T. Tan, D. Zhang, Y. Wang: Local Intensity Variation Analysis for Iris Recognition, Pattern Recognition (Accepted)
24. S. Mallat: Zero-Crossings of a Wavelet Transform, IEEE Trans. Information Theory, Vol.37, No.4 (1992) 1019-1033
25. P. Pudil, J. Novovicova, S.Blaha, J. Kittler: Multistage Pattern Recognition with Rejection Option, ICPR (1992) Vol.B 92-95
26. CASIA Iris Image Database, http://www.sinobiometrics.com/casiairis.htm