CASCADING STATISTICAL AND STRUCTURAL CLASSIFIERS FOR IRIS RECOGNITION

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ABSTRACT

Reliable human identification using iris pattern has recently gained growing interests from pattern recognition researchers. In literature of iris recognition, almost all algorithms are based on statistical information. In this paper, a structural iris image analysis method is proposed, which provides complementary information to statistical classifier. In order to save computational cost, the structural matcher is not consulted unless the statistical classifier is uncertain of its decision. At the second stage, the structural classifier may be combined with statistical classifier with different fusion strategies. The experimental results of decision-level classifiers combination are reported, which demonstrate that the cascaded classification system significantly outperforms single classifier.

1. INTRODUCTION

Automated personal authentication using biometric traits such as fingerprint, iris, face, palmprint, gait, voice, etc. has many important applications in modern society [1,2]. So biometrics attracts lots of researchers to make it feasible in practice. As an emerging biometric feature, iris pattern has the advantages of being non-invasive and highly unique, and it is more stable than most other human body signatures.

As seen in Figure 2, the iris of human eye is the annular part between the black pupil and the white sclera. It is clear that the iris pattern has both statistical and structural features. But due to the difficulties of segmentation, almost all existing iris recognition algorithms analyze iris image using random signal processing techniques, e.g. texture analysis [3-7], phase demodulation [8,9], wavelet transform [10-12] or moment description [13]. And for the complexity of iris pattern, the focus of these algorithms is on feature extraction, not classifier design. In this paper a shape-based iris image matching diagram is proposed to demonstrate the discriminating power of structural feature. For the purpose of optimal recognition accuracy, automatic iris recognition system should incorporate as many informative cues as available. So a cascading scheme is designed to combine the statistical iris feature with structural characteristics effectively. The overview of our ideas is illustrated in Figure 1. The well-developed statistical classifier has the ability to distinguish genuine irises from imposters confidently in most cases, but when the statistical distance between the input iris and the stored template is near its decision boundary (TL<dis<TH) it is uncertain of its result. Then the shape-based matcher is combined with statistical classifier to make the final decision because it is complementary to the statistical classifier. This paper only discusses the decision level intramodal fusion which is a popular method in biometrics literature.

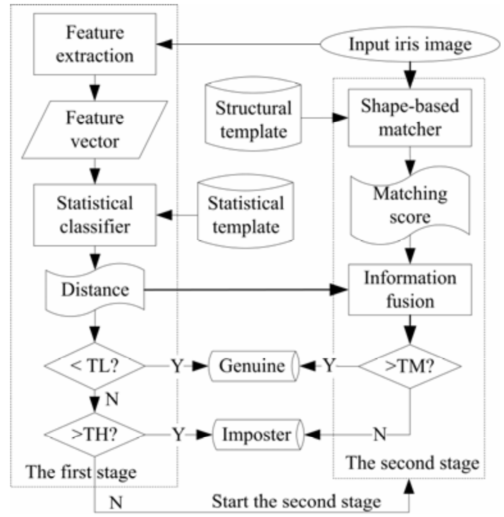


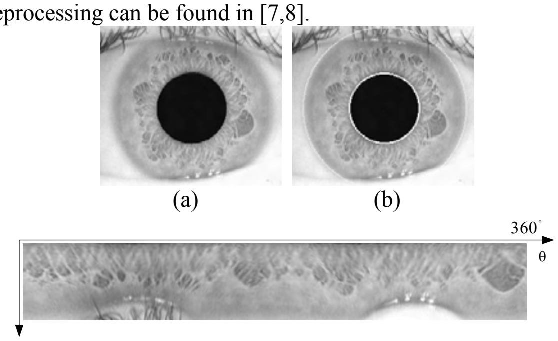
Figure 1 Overview of the proposed algorithm

The remainder of this paper is organized as follows. Section 2 describes a shape-based iris matching algorithm which attempts to establish the structural correspondence between two iris images. In Section 3, the recognition performance of the structural method is reported and it is serially combined with a typical statistical iris recognition algorithm. Section 4 concludes the overall paper.

2. SHAPE-BASED IRIS RECOGNITION METHOD

For human vision, the geometric shapes of the foreground objects play an important role in perception of a scene. So the shape of the blocks of interest (BOI) in iris image should also be valuable for iris recognition. The objective of shape-based iris recognition algorithm is to find the spatial correspondence between the BOI in the input iris image and that in the stored template based on their shape measurements, and quantitatively assess their similarity level. If each block is denoted by its centroid, then our task is a point pattern matching problem. It is well known that the fingerprint minutiae matching issue is essentially a typical point set matching problem. Using ideas from alignment based fingerprint minutiae matching [14], the whole process of the shape-based iris matching is described as follows:

1) Iris normalization: After iris localization, the iris ring can be normalized to the polar coordinate system (Fig. 2). The details of preprocessing can be found in [7,8].

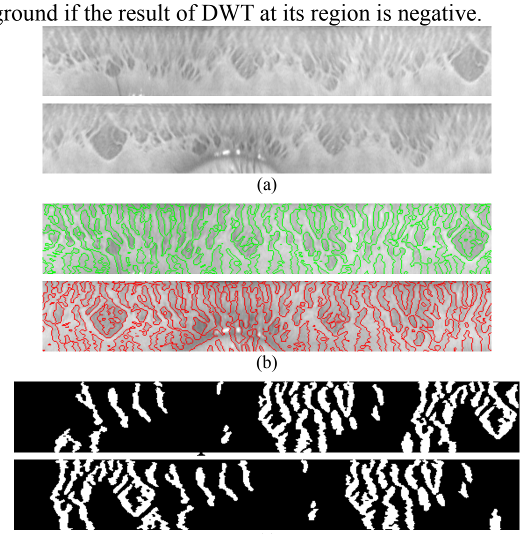


(a) (b)

(c)

Figure 2 Preprocessing of iris image; (a)Original image; (b)Result of iris localization, the white circles isolate iris portion from the whole image; (c)Result of normalization.

2) BOI segmentation: Because the zero-crossings of wavelet transform often indicate the location of sharp variation points [15], the boundary of BOI can be efficiently detected by implementing dyadic wavelet transform (DWT) of the normalized image. With local processing of edge linking, the closed-boundary regions are identified (Fig. 3b). 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.



(a)

(b)

(c)

Figure 3 Shape-based iris matching; (a) Two normalized iris images from same eye; (b) Segmentation results, the overlayed contours denote zero-crossings of DWT; (c)The mated BOIs.

3) Block pattern representation: In the coordinate system shown in Fig. 2c, we represent each BOI by a 2D function $f(r,\theta)$, which is defined as follows:

$$f(r,\theta)=\begin{cases}1, & (r,\theta)\in BOI\\ 0, & (r,\theta)\notin BOI\end{cases} \tag{1}$$

Then we record the centroid coordinates (R,θ), area (Area) and the second order central moments $(\mathrm{MomentR}, \mathrm{Moment}\theta)$ of each BOI as its attributes. In fact, the five features can all be described using geometric moments:

$$\mathrm{R}=\frac{m_{10}}{m_{00}}=\frac{\iint r^1\theta^0 f(r,\theta)drd\theta}{\iint r^0\theta^0 f(r,\theta)drd\theta} \tag{2}$$

$$\theta=\frac{m_{01}}{m_{00}}=\frac{\iint r^0\theta^1 f(r,\theta)drd\theta}{\iint r^0\theta^0 f(r,\theta)drd\theta} \tag{3}$$

$$\mathrm{Area}=m_{00}=\iint r^0\theta^0 f(r,\theta)drd\theta \tag{4}$$

$$\mathrm{MomentR}=\mu_{20}=\iint (r-\mathrm{R})^2(\theta-\theta)^0 f(r,\theta)drd\theta \tag{5}$$

$$\mathrm{Moment}\theta=\mu_{02}=\iint (r-\mathrm{R})^0(\theta-\theta)^2 f(r,\theta)drd\theta \tag{6}$$

Generally, there are nearly one hundred BOIs in an iris image. So each iris image can be represented with a block set $\{(\mathrm{R}_i,\theta_i,\mathrm{Area}_i,\mathrm{MomentR}_i,\mathrm{Moment}\theta_i)|i=1,2,\cdots,N\}$, where N denotes the total number of BOIs in the image.

4) Alignment of two block patterns: After iris localization and normalization shown in Fig.2, normalized iris image achieves position and scale invariant. However the rotation difference has not been complemented. So the rotation parameter between the two block patterns must be found first. Fortunately, the gravity centers of BOIs provide a good source of control points because they are stable under random noise. At first all corresponding block pairs of two iris patterns can be identified according to the following four criteria:

$$|R_1-R_2|<=T_R \tag{7}$$

$$\frac{|Area_1-Area_2|}{\min(Area_1,Area_2)}<=T_A \tag{8}$$

$$\frac{|MomentR_1-MomentR_2|}{\min(MomentR_1,MomentR_2)}<=T_{MR} \tag{9}$$

$$\frac{|Moment\theta_1-Moment\theta_2|}{\min(Moment\theta_1,Moment\theta_2)}<=T_{M\theta} \tag{10}$$

where the variables with subscript '1' denote the features of any block in input block pattern and '2' represents that in the stored block pattern. The four predefined thresholds T_R, T_A, T_{MR} and $T_{M\theta}$ construct the elastic bounding box. 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 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. Then a representation invariant to position, scale and rotation is obtained after all BOIs' θ coordinates are updated in the aligned coordinate system.

5) Similarity assessment: The registration of block patterns is

only based on 1 to 1 correspondence, but it is possible that physically one block is divided into several smaller regions during segmentation. So if the mapping relationship between M blocks and N blocks can be found, our result is more reasonable although it is a difficult problem. Fortunately, the proposed block pattern representation scheme facilitates this work because if k blocks are assumed to be one, the feature of the unified larger block can be derived from the features of its components:

$$\mathrm{R} = \frac{\sum_{i=1}^{k} R_i Area_i}{\sum_{i=1}^{k} Area_i}, \quad \theta = \frac{\sum_{i=1}^{k} \theta_i Area_i}{\sum_{i=1}^{k} Area_i}, \quad \mathrm{Area} = \sum_{i=1}^{k} Area_i \qquad (11)$$

$$\mathrm{MomentR} = \sum_{i=1}^{k} MomentR_i + \sum_{i=1}^{k} Area_i (R_i - \mathrm{R})^2 \qquad (12)$$

$$\mathrm{Moment\theta} = \sum_{i=1}^{k} Moment\theta_i + \sum_{i=1}^{k} Area_i (\theta_i - \theta)^2 \qquad (13)$$

where $(R_i, \theta_i, Area_i, MomentR_i, Moment\theta_i)$ $(i = 1, 2, \cdots, k)$ denotes the feature of the i th block and $(\mathrm{R}, \theta, \mathrm{Area}, \mathrm{MomentR}, \mathrm{Moment\theta})$ is the feature of the unified one. At last, a quantitative matching score of the two iris block patterns is defined as

$$MS = \min(\frac{M_1}{N_1}, \frac{M_2}{N_2}) \qquad (14)$$

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

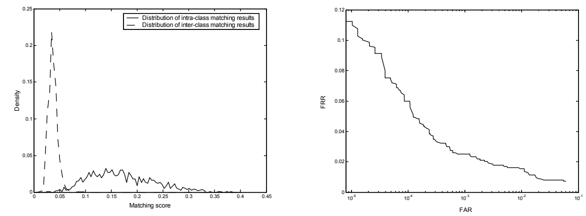
3. EXPERIMENTS

3.1. CASIA Iris Image Database

In order to evaluate the proposed algorithm, CASIA Iris Image Database is used as the test dataset, which has been worldwide shared for research purposes [13]. The used dataset includes 2,155 iris image sequences from 306 different eyes (hence 306 different classes) of 213 subjects. The images are separated to two sets: a training set of 918 template sequences (Three sequences per eye) and a testing set of 1,237 sequences of all people. For the images of the same eye, the time interval between the samples in the training set and the instances of testing set is more than one month and the longest interval is about six months. One image per each sequence is randomly selected to construct a challenging dataset.

3.2. Recognition performance evaluation

To evaluate the verification performance of the shape-based iris matching algorithm, each iris image in testing set is compared against the three templates of each class in training set respectively and the maximum matching score of the three results measures the similarity between the test data and the enrolled class. All possible comparisons are tried, so there are a total 1,237 intra-class matchings and 377,285 inter-class matchings. The distribution of all matching results is shown in Fig. 4a and the ROC (Receiver Operating Characteristic) curve, indicating the system's error rates under different threshold values, is drawn in Fig. 4b.



(a) (b)

Figure 4 Verification performance of shape-based iris matching algorithm; (a) Distributions of intra-class and inter-class matching scores; (b) ROC curve.

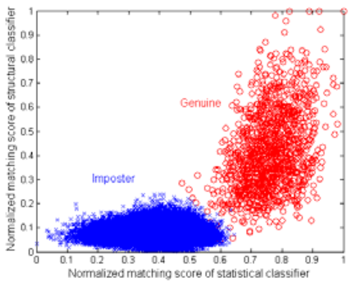
Because precise localization of BOI can not be guaranteed in all iris images, the shape-based method does not perform as well as the state-of-the-art statistical iris recognition algorithms [5,7,8,12]. But it is obvious in Fig. 4a that the matching score needed for confirmation of a genuine subject is very low, which indicates that the shape-based method is robust against local noises to some extent. For statistical classifier, if half region of iris image is smeared it almost can not verify the genuine subject, but the structural matcher still has the possibility to search the credible evidences in the minor region to authenticate the identification of the input image. And the elastic matching strategy makes it accommodate localization error, distortion and occlusions of eyelids or eyelashes. So the shape-based iris matcher is independent of statistical classifier and complementary to it. In order to test the proposed combination strategy in Fig.1, a typical statistical iris signature based on multi-channel texture information [5] is combined with the structural iris feature.

After linear transformation of the matching results, a 2D plot of genuine and imposters' matching scores, based on both statistical and structural classifiers, is shown in Fig. 5a. It is obvious that fusion of the two iris representations is helpful for classification. According to the classification scheme in Fig.1, we choose TL and TH based on the inter-class matching distance distribution of statistical classifier:

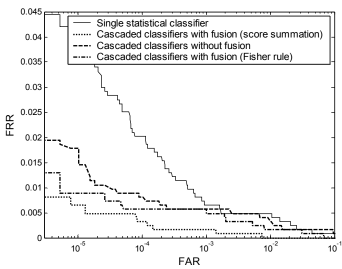
$$P(\text{distance}>\text{TH}|\ \text{Imposter})=0.9\,,$$
$$P(\text{distance}>\text{TL}|\ \text{Imposter})=0.999999 \qquad (15)$$

The reason is that in practice, when the statistical distance is smaller than TL we often consider the input iris is from genuine owner confidently and when the distance is larger than TH the subject is regarded as imposter without further consideration. We found that the majority of false rejections' matching distances fall into the interval between TL and TH. Then the second session is introduced to give these false rejected subjects once more chance to provide another set of authentic evidences to verify their identities.

Multiple classifier fusion for pattern recognition is currently a hot topic. Based on the posteriori class probabilities given by each classifier, Kittler et al. [17] developed a theoretical framework for combining classifiers. But in practice, we only have the matching score of each classifier, not the posterior probabilities. So in our case, the matching scores of the statistical and structural classifiers are regarded as the inputs of the higher level classification system. In the second stage of our classification system, three simple information fusion methods are adopted for comparison, i.e. score summation, Fisher linear discriminant and completely depending on the matching score of structural classifier (without fusion). Of course many other well developed classifier combination schemes could serve as this purpose. But the main focus of this paper is to show the potential improvement by combining statistical classifier and structural classifier for iris recognition without paying much computational costs. The ROC curves of both single classifier and cascaded classifiers based on different fusion methods are demonstrated in Fig. 5b for comparison.



(a)



(b)

Figure 5 Cascading texture filterbank based classifier and shape-based iris matcher; (a) A 2D plot of the matching results from the two matchers; (b) ROC curves of different classification systems.

Based on the experimental results, we can see that the structural feature in iris pattern is very informative for recognition. Despite the simplicity of our fusion schemes, the improvement is significant. And the fusion method based on score summation achieves the best accuracy, which tells us directly fusion of the comparable matching scores from distinct classifiers also is a good classifiers combination method. In all cascaded system, the system without fusion performs the worst. We can learn that although the statistical classifier is not confident to give the final decision sometimes, it still contributes important cues for recognition. So we can not discard its results in the second stage.

In terms of computational cost, it takes the structural classifier less than 1 second to extract shape features and elastically matching the similarity between two block patterns on a personal computer. Because in the cascaded system, the possibility of the structural classifier being used is less than 10%, the average overall computation time paid for the added module is less than 0.1 s. So the total diagram is very efficient.

4. CONCLUSIONS

In this paper, a novel shape-based iris matching algorithm is proposed and the potentiality of combining statistical classier with structural classifier is studied. Based on the cascading strategy, the accuracy of iris recognition is significantly improved with the cheap price paid for computational load.

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