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Adaboost and multi-orientation 2D Gabor-based noisy iris recognition

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ABSTRACT

In this paper, we present a noisy iris recognition frame which is learned by Adaboost on a 2D Gabor-based feature set. First, the irises are segmented and normalized by rubber sheet or simplified rubber sheet according to whether segmentations are accurate or not. Then, irises are divided into different amount of patches according to normalization. Moreover, a feature set is constructed based on 2D-Gabor for whole iris and patches. Finally, Adaboost learning is used for accurately and inaccurately segmented irises separately.

The proposed method was evaluated by the NICE:II (Noisy Iris Challenge Evaluation – Part 2). We were ranked 2nd among all of the 67 participants from 29 different countries/districts.

1. Introduction

Iris recognition is one of the most important biometrics. Since Daugman proposed the first iris recognition system based on 2D Gabor (Daugman, 1993), researchers have devoted great efforts to iris recognition (Daugman, 2007; Li et al., 2004; Ma et al., 2003; Proenca and Alexandre, 2007b; Sun and Tan, 2009; Wildes, 1997).

Noisy iris recognition is quite challenging. These images are captured in a natural environment and in visible light, without cooperation and illumination controlled, even at a distance or on-the-move.

This paper presents a noisy iris recognition method, which has been ranked 2nd in NICE:II contest. It is organized as follows: In Section 2, the proposed method of noisy iris recognition is presented. In Section 3, technical details and results of experiments are described. Finally, some conclusions are drawn in Section 4.

2. Proposed method

The proposed noisy iris recognition method mainly includes four steps: First, irises are segmented and the segmentations are evaluated. Second, they are normalized by rubber sheet or simplified rubber sheet according to whether segmentations are accurate or not. Then, a feature set is constructed based on 2D-Gabor. At last, Adaboost learning is used for accurately and inaccurately segmented irises separately for recognition.

2.1. Iris segmentation

Segmentation is one of the most important and difficult parts in noisy iris recognition. Accurate segmentation is necessary for an accurate iris recognition system (Proenca and Alexandre, 2006). This part presents our segmentation approach for iris and evaluation method for pupil segmentation.

2.1.1. Iris segmentation

Iris segmentation is quite challenging because of all kinds of drawbacks of iris images, such as motion blurred, glasses, eyelids, eyelashes and reflection etc. Generally, iris segmentation includes three parts (Daugman, 2007; He et al., 2009b): (1) determine pupillary and outer boundaries; (2) detect upper and lower eyelids; (3) separate noises from iris, which include eyelashes, reflection, shadow, etc. The four most important iris segmentation methods are integro-differential operator (Daugman, 1993), edge detection combined with Hough transform (Wildes, 1997), active contour integrated with Fourier series (Daugman, 2007) and edge detection followed by cubic smoothing spline fitting (He et al., 2009b).

In this paper, iris segmentation is processed as follows: first of all, the outer boundary of iris is coarsely estimated based on the binary segmentation mask which is given in NICE:II. Then, noises are detected by circular Gabor (Zhang et al., 2009). Furthermore, upper and lower eyelids are segmented by RANSAC (Random Sample Consensus) (Li et al., 2010). At last, we use circular integro-differential operator (Daugman, 1993, 2003) to determine pupillary and outer boundary for iris.

The experiments results on the training database of NICE:II show that outer boundaries could be estimated well in most cases, but pupillary boundaries is difficult to determine in some cases.

2.1.2. Evaluation of pupil segmentation

As we all know, the inaccuracy of pupil segmentation would lead to matching error, so it is essential to evaluate pupil segmentation before recognition. To accomplish this task, the error of pupil segmentation *Err* is proposed, which is similar to the segmentation

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error used in (Proenca and Alexandre, 2007a). *Err* is defined as follow:

$$Err = \sum_i \sum_j O(i,j) \cdot C(i,j) \Big/ \sum_i \sum_j O(i,j) \tag{1}$$

O is the pupillary binary mask of image *I*. It is generated by the proposed method in Section 2.1.1

$$O(i,j) = \begin{cases} 1, & (i,j) \text{ lies in pupil and } I(i,j) \text{ is not noise} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

C is the manually classified binary mask of the same iris which is offered in NICE:II. *O* and *C* have the same dimensions.

To evaluate the accuracy of pupil segmentation, *Err* is calculated. If $Err < T_{Err}$, pupil is considered to be accurately segmented, then the iris is judged as accurately segmented iris (AS-Iris). Otherwise, it is considered to be inaccurately segmented iris (IAS-Iris). T_{Err} is a given threshold here.

In the following parts of the paper, two iris recognition methods are proposed for AS-Iris and IAS-Iris separately.

2.2. Iris normalization

Because illumination and camera-to-eye distances may be different for each photograph, irises may be captured with different size. Generally, such deformation would lead to error in matching. So it is necessary to normalize the irises to the same size to obtain an accurate iris recognition approach.

In this part, rubber sheet and simplified rubber sheet are adopted for AS-Iris and IAS-Iris separately.

2.2.1. Rubber sheet for AS-Iris normalization

Daugman proposed rubber sheet model for iris normalization (Daugman, 1993). It maps Cartesian coordinates (x,y) to polar coordinates (r,θ) according to

$$x(r,\theta) = (1-r)x_{pupil}(\theta) + rx_{outer}(\theta) \tag{2.1}$$

$$y(r,\theta) = (1-r)y_{pupil}(\theta) + ry_{outer}(\theta) \tag{2.2}$$

where $r \in [0,1]$, $\theta \in [0,2\pi]$, $(x_{pupil}(\theta), y_{pupil}(\theta))$ and $(x_{outer}(\theta), x_{outer}(\theta))$ are the coordinates of pupillary and outer boundary in the direction θ.

Rubber sheet model is adopted for AS-Iris normalization in this paper.

2.2.2. Simplified rubber sheet for IAS-Iris normalization

Considering that pupillary boundaries are inaccurate for some noisy irises, we neglect the pupil boundary in normalization and transform rubber sheet to simplified rubber sheet, which is shown in (3.1) and (3.2)

$$x(r,\theta) = rx_{outer}(\theta) \tag{3.1}$$

$$y(r,\theta) = ry_{outer}(\theta) \tag{3.2}$$

The simplified rubber sheet only depends on outer boundary. So it could be used for IAS-Irises.

Intuitively, the simplistic solution would lead to great mistakes in recognition. But according to our experiment, it also works well. The details and results of the experiments would be described in Section 3.

2.3. Feature set construction

Each iris has a particular structure of texture. To represent global and local texture information, dissimilarities are calculated based on multi-directional Gabor for each pair of patches and whole irises. Feature set is composed of these dissimilarities.

2.3.1. Regional dissimilarity of texture

Texture is one of the most discriminative features in irises (Daugman, 1993; Ma et al., 2003). Daugman proposed a representation of the texture information based on 2D Gabor filter and adopted HD of codes to measure the dissimilarity of irises (Daugman, 1993, 2007).

Following this method, we use the regional HD of codes by Gabor filters to measure the dissimilarity of texture for any given region of iris. Firstly, the texture of iris is encoded by 2D multi-directional Gabor filter. The formula of 2D Gabor filter (Wang et al., 2008) is as follows:

$$G(x,y) = \frac{1}{2\pi\delta_x\delta_y} exp^{\left(-\frac{1}{2}((x')^2\delta_x^2 + (y')^2)\right)} \times exp^{\left(\sqrt{-1}\times 2\times\pi\times w\times x'\right)} \tag{4}$$

where $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\cos\theta$. θ is the orientation of Gabor. δ_x and δ_y indicate the effective width and length. Multi-directional Gabor filter could be obtained with changing θ. Fig. 1 shows the Gabor filters with eight orientations.

The encoding process (Daugman, 1993, 2004) is done as

$$C_{(Re,Im)}(x,y) = sgn_{(Re,Im)}[I(x,y) * G(x,y)] \tag{5}$$

where $sgn(x) = \begin{cases} 1, & x \geqslant 0 \\ 0, & x < 0 \end{cases}$, *I* is the normalized iris, *G* is Gabor filter and *c* is the binary code of *I*. Fig. 2 gives an example of encoding two whole irises with Gabor filter orientations 0 and $\pi/2$.

Then, HD is calculated for Gabor filter with different orientation by the following formula:

$$HD = \frac{\|XOR(code_A, code_B) \cap mask_A \cap mask_B\|}{\|mask_A \cap mask_B\|} \tag{6}$$

where $code_A$ and $code_B$ are the binary codes of iris A and B, $mask_A$ and $mask_B$ are the noise templates of A and B. "∩" is the boolean operator "And".

For two given irises, the smaller the HD is, the less the dissimilarity is. HD is adopted to measure the dissimilarity for each pair of regional patches in this paper.

2.3.2. Iris division

Generally, texture in inner circular part of an iris is much richer than that of outer part (Ma et al., 2003). So the inner circular part plays a more important role than the outer part in iris recognition. Proenca and Alexandre (2007b) and Zhaofeng et al. (2008) divided irises into small patches for recognition.

In this paper, the normalized iris is divided into $M \times N$ overlapping patches for recognition. Because normalizations are processed with rubber sheet and simplified rubber sheet according to pupillary segmentations in Section 2.2, two groups of (M,N) are designed for each case. Fig. 3(a) shows the division of AS-Iris. Fig. 3(b) shows the division of IAS-Iris. Fig. 3(c) and (d) is the normalization of Fig. 3(a) and (d) separately.

2.3.3. Feature set construction

To construct a feature set with enough discriminative information and a small amount of elements, both global and local texture information based on Gabor filters are selected in this paper. The construction process is described as follows.

Firstly, we compute the HD of codes on whole normalized irises. The codes are calculated by Gabor filter with different orientations. The orientation of the *i*th Gabor filter is $\theta_i = i\pi/L$, $i = 0,1,2,\ldots,L-1$. There would be only one HD_0^i for each θ_i. Let $F_{Whole} = \{HD_0^0, HD_0^1, \ldots, HD_0^{L-1}\}$. Obviously, $|F_{Whole}| = L$.

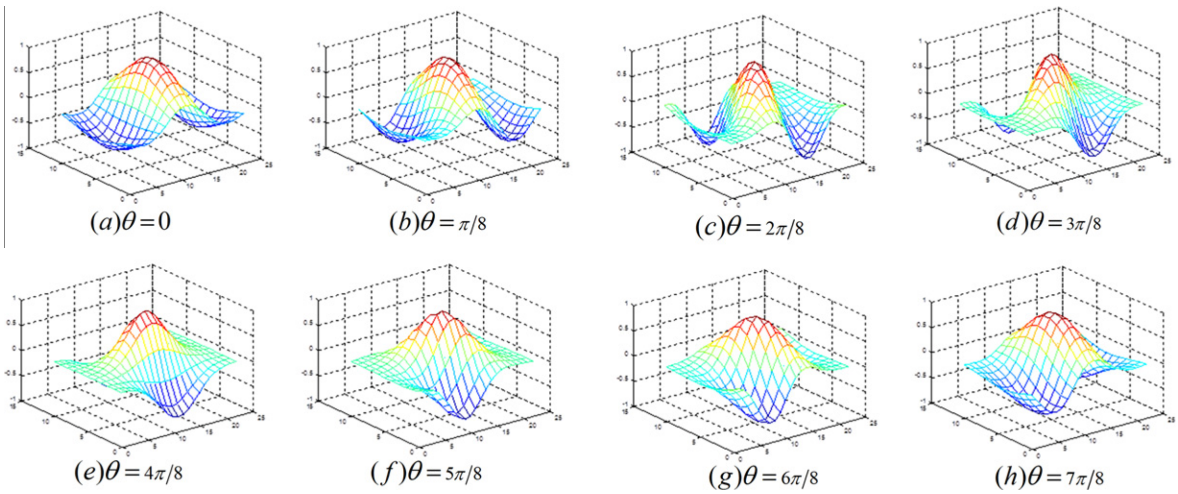

Fig. 1. Gabor filters with $\theta = i\pi/8$, $i = 0,1,2,\ldots,7$.

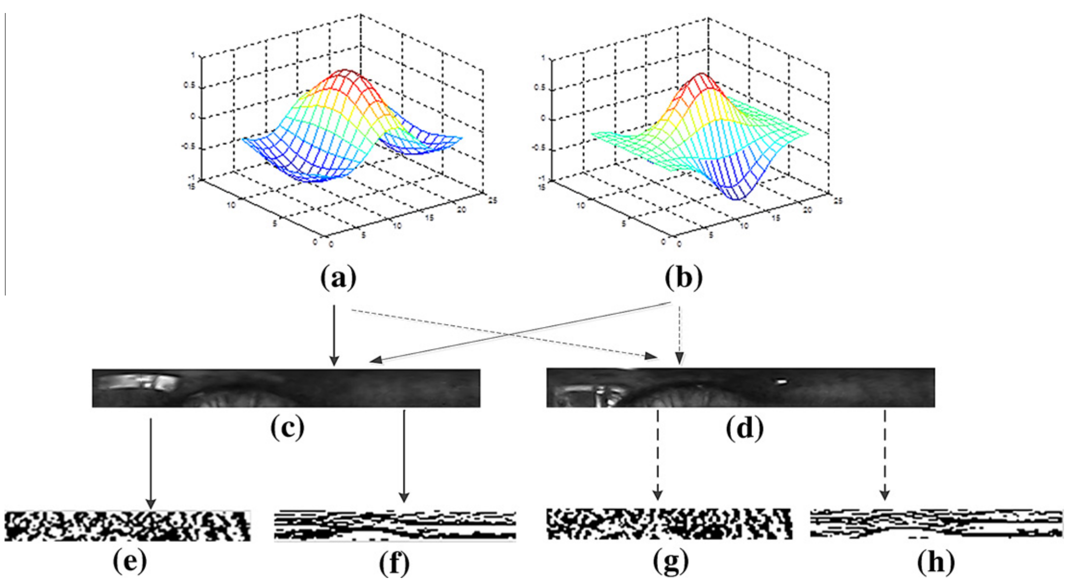

Fig. 2. Examples of Gabor filters with $\theta = 0$, $\pi/2$ and codes of normalized iris.

Secondly, we compute the HDs on divided $M \times N$ patches by the same method. Let $F_{patch} = \{HD_1^0, HD_1^1, \ldots, HD_1^{L-1}, \ldots, HD_{MN}^0, HD_{MN}^1, \ldots, HD_{MN}^{L-1}\}$. There are $M \times N$ patches for each iris and L orientations of Gabor, so $|F_{patch}| = M \times N \times L$.

The feature set $F_{WP} = F_{Whole} \bigcup F_{patch}$. Then, $|F_{WP}| = (M \times N + 1) \times L$. So the feature set F_{WP} is composed of $(M \times N + 1) \times L$ HDs, which represent both global and local texture information.

Because the amount of patches $M \times N$ is different for AS-Iris and IAS-Iris, the feature set F_{WP} is also distinct for each case. To discriminate the two cases, we use F_{WP}^{AS} to stand for the feature set for AS-Iris and F_{WP}^{IAS} for IAS-Iris.

2.4. Adaboost learning

Adaboost is a machine learning method. It is widely used in classification problems. It selects the best subset from a weak feature set and forms a strong classifier (Vaghela et al., 2009; Yin et al., 2005). It has been used for detecting iris in an image (He et al., 2009b). It is also used to detect fake irises (He et al., 2009a).

In this paper, Adaboost is applied to select and combine the most discriminative features from feature set F_{WP} for noisy iris recognition.

Given that $\{x_i, y_i\}$ is the ith labeled training samples with associated weights $\{w(x_i)\}$, where $x_i = \{x_{i1}, \ldots, x_{iM}\}$, $y_i \in \{+1, -1\}$, $i = 1,2,\ldots,N$, and M is the length of vector x_i. h_t is a component classifier, $t = 1,2,\ldots,T$.

Input: Given that the training samples $\{(x_1,y_1),\ldots,(x_N,y_N)\}$
Initialize: $w_1(x_i) = 1/N$, $i = 1,2,\ldots,N$.
For $t = 1,2,\ldots,T$

(1) Train the component classifier on the weighted training samples to obtain an estimation of $h_t : x \to \{-1,+1\}$.
(2) $\varepsilon_m = \sum_{i:h_t(x_{im}) \neq y_i} W_t(x_i)$, $m = 1,2,\ldots,M$ and $\varepsilon_t = min\,\varepsilon_m$. If $\varepsilon_t \geqslant 0.5$, then set $T = t - 1$ and abort.
(3) Calculate weight α_t, $\alpha_t = 0.5 \times ln[(1 - \varepsilon_t)/\varepsilon_t]$.
(4) Update: $W_{t+1}(x_i) = \frac{W_t(x_i)exp(-\alpha_t y_i h_t(x_i))}{Z_t}$, where Z_t is a normalization factor.

Output: $H(x) = sign\left(\sum_{t=1}^{t=T} \alpha_t h_t(x)\right)$.

More details about Adaboost could be found in (Vaghela et al., 2009; Yin et al., 2005).

In this paper, we label training samples according to whether the matches are intra-class or inter-class. x_i corresponds to the

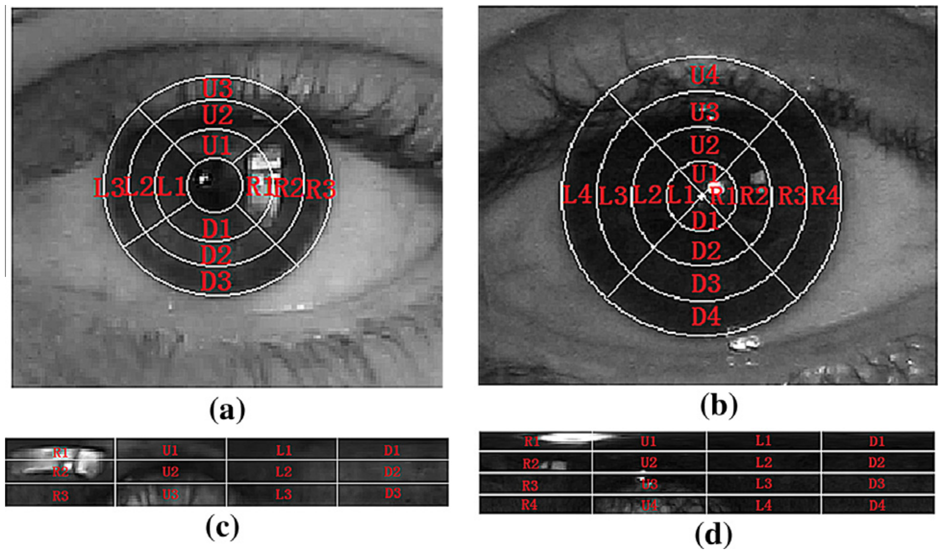

Fig. 3. Examples of iris division. (a) Division of AS-Iris, (b) normalization of (a), (c) division of IAS-Iris, and (d) normalization of (c).

feature set F_{WP}. $y_i = -1$, if x_i is generated from intra-class match. Otherwise, $y_i = -1$. Then the classifier for noisy iris recognition $H(x)$ could be obtained by the algorithm described above.

In fact, dissimilarity of each comparison is what we concerned in NICE:II. And "dissimilarity" in Adaboost is indicated by $\sum_{t=1}^{t=T}\alpha_t h_t(x)$. $\sum_{t=1}^{t=T}\alpha_t h_t(x) \in [-1,1]$. We normalize it by $S(x) = 0.5* \left(1-\sum_{t=1}^{t=T}\alpha_t h_t(x)\right)$, then $S(x) \in [0,1]$. Obviously, the smaller the $S(x)$ is, the more probable x is the result of intra-class comparison. On the contrary, the larger the $S(x)$ is, the more probable x is the result of inter-class comparison.

In this paper, two different classifiers are learned by Adaboost for recognition: Adaboost_{AS} for AS-Irises and Adaboost_{IAS} for IAS-Irises.

2.5. Recognition process

The flow chart of recognition process of the proposed method is illustrated in Fig. 4. Firstly, both iris images are segmented. Then, whether the irises are AS-Irises or IAS-Irises is determined by Err. With this judgment, we use two different strategies for recognition: (1) AS-Irises are normalized by rubber sheet. Moreover, feature set is generated and combined with Adaboost_{AS} to obtain dissimilarity. (2) IAS-Irises are normalized by simplified rubber sheet. Afterward, feature set is constructed and Adaboost_{IAS} is used to obtain dissimilarity.

2.6. Decidability

ROC (Receiver Operating Characteristic) curve is a widely used evaluation method for iris recognition (Li et al., 2004). Decidability is another evaluation index for iris recognition system (Daugman, 2001, 2004). Here we employ decidability to evaluate the performance of proposed iris recognition approach.

The index of decidability d' is calculated as follows:

$$d' = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{\sigma_1^2+\sigma_2^2}{2}}} \tag{7}$$

where μ_1, σ_1 are the means and standard deviations of dissimilarities of intra-class, while μ_2, σ_2 are that of inter-class.

d' indicates how well the two distributions are separated. Generally, the higher d' is, the better recognition performance is.

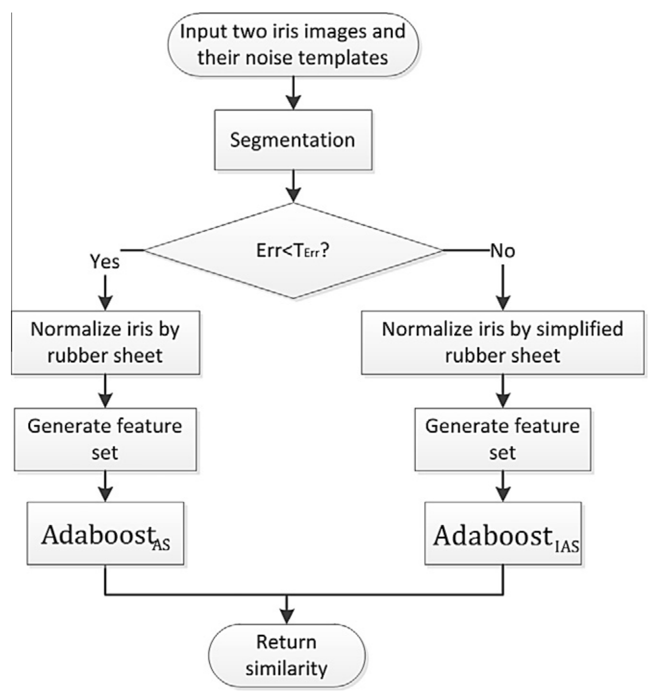

Fig. 4. Flow chart of recognition process of propose method.

3. Experiments and performance

The training database is composed of 1000 noisy iris images in NICE:II. We select 810 images from the training database to carry out experiments. These 810 iris images are used to train both Adaboost_{AS} and Adaboost_{IAS}. The details and results of experiments are described in this section.

3.1. Adaboost_{AS} classifier for AS-Irises

The 810 accurately segmented irises are used to train Adaboost_{AS} classifier. Firstly, irises are normalized by rubber sheet which is given in formula (2.1) and (2.2). Then, irises are divided with $M = 3$, $N = 4$. The amount of Gabor directions $L = 8$. So the feature set F_{WP}^{AS} is composed of 104 HDs. Finally, we choose 2325 intra-class and 2075 inter-class matches to train Adaboost$_{AS}$ classifier.

Fig. 5 shows the decidability of Adaboost$_{AS}$ classifier with an increasing dimension of selected features. The curve indicates that the classifier performs better with more features selected. Considering the computational complexity, we select the 40 most discriminative features to construct Adaboost$_{AS}$ classifier. Fig. 6 shows the distribution of dissimilarity of intra-class and inter-class comparison of Adaboost$_{AS}$ classifier. The dissimilarity distribution of intra-classes matches has a mean of $\mu_1 = 0.3124$ and standard deviation $\sigma_1 = 0.1529$, while that of inter-classes matches has a mean of $\mu_2 = 0.6030$ and standard deviation $\sigma_2 = 0.0953$. The decidability of Adaboost$_{AS}$ classifier is 2.2808.

The four most discriminative features of Adaboost$_{AS}$ are listed in Table 1. Obviously, Gabor feature of the whole iris is the most discriminative. Besides this, representations of D2, D3 and L3 are excellently discriminative. In fact, D2, D3 and L3 are less affected by noises than the other patches according to observation. So it is reasonable that the representations of these patches are better for recognition than the other features.

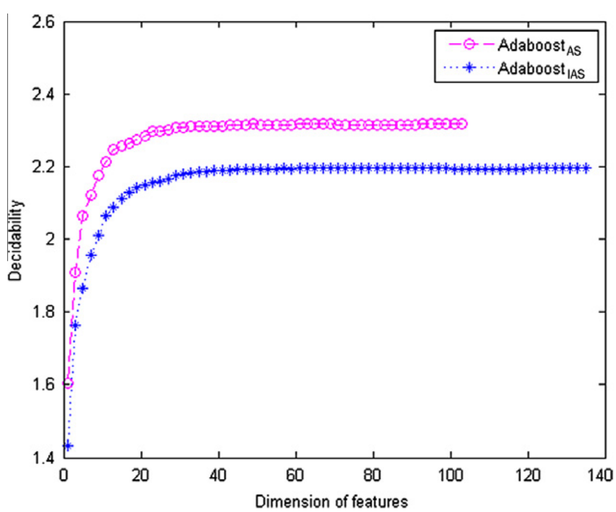

Fig. 5. Decidability curve with an increasing dimension of feature.

Table 1
The four most discriminative features selected by Adaboost$_{AS}$.

Rank of feature	Region	Orientation of Gabor
1	Whole	$\theta = 0$
2	D2	$\theta = 7\pi/8$
3	D3	$\theta = 0$
4	L3	$\theta = 7\pi/8$

3.2. Adaboost$_{IAS}$ classifier for IAS-Irises

For the recognition of IAS-Irises, Adaboost$_{IAS}$ is trained. The training of Adaboost$_{IAS}$ classifier is also based on the 810 segmented irises. But the training process is different from that of Adaboost$_{AS}$ at two points: (1) normalization method: IAS-Irises are normalized by simplified rubber sheet which corresponds to formula (3.1) and (3.2), not rubber sheet and (2) amount of patches (M,N): IAS-Irises are divided with $M = 4$, $N = 4$, not $M = 3$, $N = 4$.

These differences lead to different feature sets in training process. With the amount of Gabor directions $L = 8$, there are 136 HDs in feature set F_{WP}^{IAS}. We select 2325 intra-class and 2075 inter-class matches to train Adaboost$_{IAS}$ classifier.

The decidability curve for Adaboost$_{IAS}$ is shown in Fig. 5. The figure reports a fact: with the same amount of best features, Adaboost$_{AS}$ is better than Adaboost$_{IAS}$. This is consistent with the common sense. Although the performance of Adaboost$_{IAS}$ is not as good as that of Adaboost$_{AS}$ in the figure, it is still very important for noisy iris recognition. As we have mentioned before, noisy iris segmentation is quite challenging. Some of irises could not be segmented accurately (IAS-Irises). While Adaboost$_{IAS}$ classifier is especially designed to recognize IAS-Irises. With Adaboost$_{IAS}$, the performance of noisy iris recognition has been reinforced a lot.

Here we select 40 most discriminative features for Adaboost$_{IAS}$ classifier. Fig. 7 shows the distribution of dissimilarity of intra-class and inter-class comparisons of Adaboost$_{IAS}$ classifier. The dissimilarity distribution of intra-classes matches has a mean of $\mu_1 = 0.3346$ and standard deviation $\sigma_1 = 0.1394$, while that of inter-classes matches has a mean of $\mu_2 = 0.5949$ and standard deviation $\sigma_2 = 0.0932$. The decidability of Adaboost$_{IAS}$ classifier is 2.1950.

The best four features Adaboost$_{IAS}$ classifier selected are listed in Table 2. In this table, D3 appears 2 times which indicates D3 is the most discriminative region for recognition. The feature of the

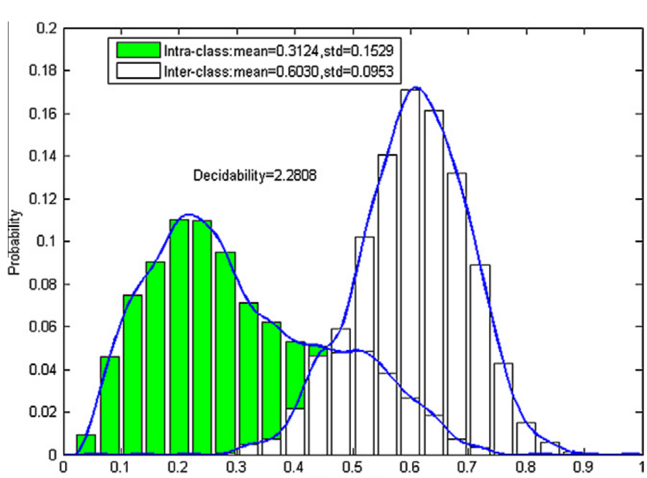

Fig. 6. Distribution of dissimilarity of Adaboost$_{AS}$ on the selected 810 images from NICE:II training database.

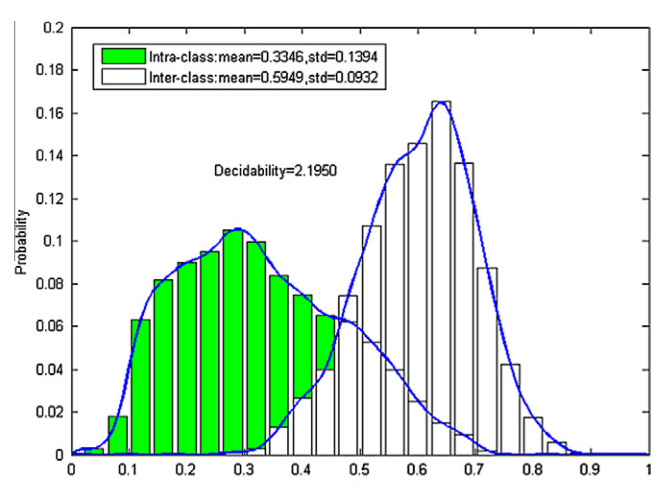

Fig. 7. Distribution of dissimilarity of Adaboost$_{IAS}$ on the selected 810 images from NICE:II training database.

Table 2
The 4 most discriminative features selected by $\text{Adaboost}_{\text{IAS}}$.

Rank of feature	Region	Orientation of Gabor
1	D3	$\theta = 0$
2	Whole	$\theta = 0$
3	D3	$\theta = \pi/4$
4	L4	$\theta = 3\pi/4$

whole iris is still very important for recognition and takes up the second place. In addition, the representation of L4 is also a good classifier.

In fact, D3 and L3 are less affected by noises than the other patches according to observation. So representations of these patches are discriminative.

4. Conclusion

In this paper, a noisy iris recognition method is proposed. The method provides a framework which combines regional Gabor feature with Adaboost algorithm for noisy iris recognition. With this framework, two different recognition strategies are designed according to the accuracy of pupil segmentations.

The proposed method has been validated in NICE:II contest. It was ranked 2nd among all of the 67 participants from 29 different countries/districts.

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