Boosting Ordinal Features for Accurate and Fast Iris Recognition

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Abstract

In this paper, we present a novel iris recognition method based on learned ordinal features.Firstly, taking full advantages of the properties of iris textures, a new iris representation method based on regional ordinal measure encoding is presented, which provides an over-complete iris feature set for learning. Secondly, a novel Similarity Oriented Boosting (SOBoost) algorithm is proposed to train an efficient and stable classifier with a small set of features. Compared with Adaboost, SOBoost is advantageous in that it operates on similarity oriented training samples, and therefore provides a better way for boosting strong classifiers. Finally, the well-known cascade architecture is adopted to reorganize the learned SOBoost classifier into a 'cascade', by which the searching ability of iris recognition towards large-scale deployments is greatly enhanced. Extensive experiments on two challenging iris image databases demonstrate that the proposed method achieves state-of-the-art iris recognition accuracy and speed. In addition, SOBoost outperforms Adaboost (Gentle-Adaboost, JS-Adaboost, etc.) in terms of both accuracy and generalization capability across different iris databases.

1. Introduction

In this work, we are interested in introducing a novel machine learning algorithm named Similarity Oriented Boosting for efficient feature selection and classifier design. In particular, we will demonstrate the efficiency of the SOBoost framework on ordinal measure based iris recognition.

As depicted in Fig. 1, the human iris is the annular part between the black pupil and white sclera. It displays rich texture determined by many distinctive minutes like furrows, rings, scripts, *etc.* Iris is commonly thought to be highly discriminative between eyes and stable over individuals' lifetime, which makes it particularly useful for personal identification [5, 10].

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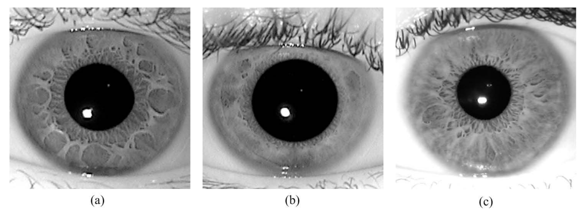

Figure 1. Example iris images, illustrating the uniqueness, angular self-similarity and radial distribution properties of iris textures.

Although various features (Zero-Crossings [3], Gabor [4], DCT [6], *etc.*) have been proposed, what are the intrinsic features for iris representation remains unrevealed. Recently, ordinal measures (OM) are suggested to be effective for iris representation [14]. In [14], Gaussian based ordinal filters are used to encode the iris texture, and encouraging performance is achieved. However, there are too many parameters for tuning in ordinal image analysis and how to build an optimal classifier of ordinal iris features is still an open problem.

Another problem challenging iris recognition is its large scale deployment. In state-of-the-art iris recognition systems, the probe iris image has to be matched with all the templates stored in a database, with all the iris features computed. This matching procedure is time-consuming, especially when the iris database grows into national scale. Therefore, how to speed up the matching procedure is in urgent need. However, this respect of iris recognition has not been adequately addressed by the research community.

Adaboost is a recently developed machine learning algorithm that can select a small set of the most discriminative features from a candidate feature pool, and seems to be a good choice to select the best ordinal features. However, two serious limitations of Adaboost are noticed in practice. First, Adaboost is developed in terms of purely statistical optimization principles (*i.e.* maximum likelihood [7]) without considering the physical meaning within the train-

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ing samples. This makes Adaboost tend to be over-fitting especially when large training set is unpractical. Besides, Adaboost is usually used for boosting weak classifiers that are moderately accurate. This, while having received great success in object detection, limits its application to object recognition where strong classifiers are more common. Therefore, more efficient learning method is desired in order to boost strong classifiers (*e.g*. those based on ordinal features) for iris recognition.

The objective of this work is to develop an efficient machine learning algorithm to select the most discriminative ordinal features, and combine them in an effective way for accurate and fast iris recognition. The rest of the paper is organized as follows: In Section 2, we introduce a new iris representation method based on regional ordinal features. In Section 3, the novel Similarity Oriented Boosting algorithm is described. SOBoost's advantages over Adaboost are also discussed. In Section 4, experimental results are presented and discussed, with the cascade architecture introduced for speeding up the matching procedure. Finally, the conclusions are given in Section 5.

2. Regional OM-based Iris Representation

2.1. Ordinal Measures

Ordinal features come from a simple and straightforward concept that we often use [11]. For example, the absolute intensity associated with an image can vary due to various imaging conditions; however, the ordinal relationships between neighboring image regions present some stability to such changes and reflect the intrinsic natures of the image. For this sake, an ordinal feature qualitatively encodes the ordinal relationship between two dissociated image regions with binary bits, see Fig. 2 for an intuitive understanding.

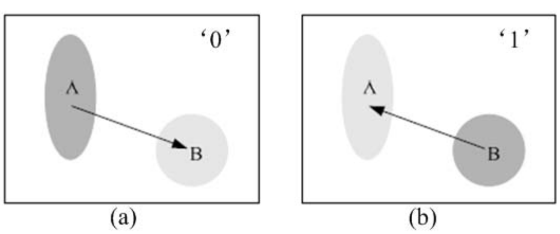

Figure 2. Ordinal measure of relationship between two dissociated image regions. (a) Region A is darker than B, *i.e*. coded with '0'; (b) Region A is brighter than B, *i.e*. coded with '1'.

Three typical ordinal filters used by Sun *et al*. [14] are shown in Fig. 3(a)-(c). Like differential filters, an ordinal filter also consists of excitatory and inhibitory lobes. Usually, there are four types of parameters in ordinal filters for tuning.

- the number of lobes (or Gaussian kernels) n.
- the scale parameters σ of each Gaussian lobe.
- the inter-lobe distance d between the centers of two lobes.
- the orientation θ (*i.e*. the angle between the line joining the centers of two lobes and the horizontal line, $\theta \in (0, 2\pi)$).

Ordinal measure encoding is in fact convolving the image with an ordinal filter and then encode the resulted image with binary bits as illustrated in Fig. 3.

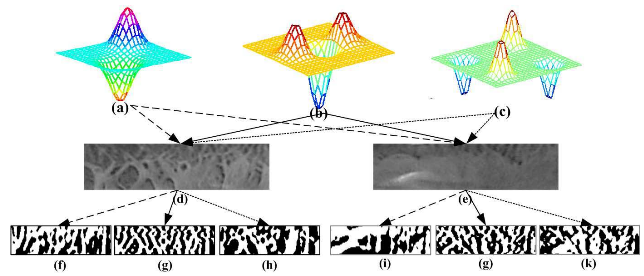

Figure 3. Ordinal filters and ordinal measure encoding. (a)-(c): three typical ordinal filters. (d)-(e): Two sub-regions cropped from different irises. (f)-(k): the resultant OM codes.

Ordinal filters present several advantages compared with other filters such as Gabor and Log-Gabor. First, they are separable since the Gaussian kernels are separable, which ensures their computational efficiency. Second, they are qualitative rather than quantitative. This, along with the Gaussian smoothing effect, makes them robust to various noise and intra-class variations (*e.g*. monotonic image transformations). Finally, different configurations of ordinal filters can be easily constructed by tuning the topology and shape of Gaussian kernels. Hence, they are flexible enough to represent different local structures of different complexity. These advantages make ordinal filters useful for iris representation.Further details of ordinal measures can be found in [14].

2.2. Iris Division

The iris texture presents several desirable properties. For example, the texture patterns are different from iris to iris. Even within an iris, the scale of the iris micro-structures varies a lot along the radius. Usually the larger the radius is, the bigger the iris micro-structures will be (see Fig. 4(a)). What is more, although different angular regions remain discriminative, their texture patterns display a certain degree of consistence/correlation as shown in Fig. 4(b). This implies that it might be possible to achieve similar recognition accuracy while only using parts of the angular regions. These properties suggest dividing the iris into multiple regions as shown in Fig. 4(c) and (d) (Note Fig. 4 is just an illustration of iris division. Many more overlapped sub-regions are obtained in practical application in order to completely represent the whole iris image.). We can see that each sub-region contains a texture pattern with a different scale and orientation.

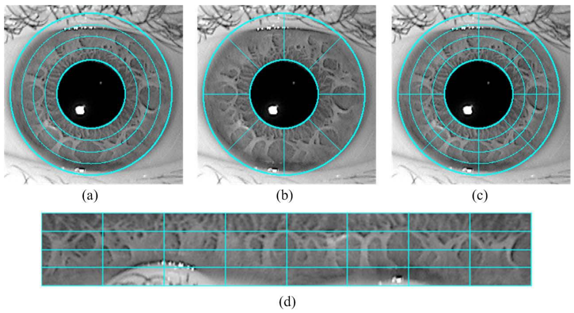

Figure 4. A possible division of the iris image.

2.3. Regional OM Feature Pool

In order to efficiently represent each sub-region, plenty of ordinal filters with varying parameters are designed and calculated on each of them. A large pool of regional ordinal features is therefore generated (Suppose we have L sub-regions and K ordinal filters on each sub-region, then there will be $L \times K$ regional ordinal features in total). Definitely, this feature pool must contain much redundant information because of the redundancy between different ordinal filters as well as that between different sub-regions. To learn the most discriminative regional ordinal features from the redundant feature pool, we proposed the following similarity oriented boosting algorithm.

3. Similarity Oriented Boosting

SOBoost has two distinctive characteristics. First, it is similarity oriented, which means it is driven by the following ***Similarity Rule:*** The higher the similarity score is between two images, the more confidently they come from the same class.

Second, SOBoost aims to boost strong classifiers, and therefore is useful for object recognition. In our experiments, some regional ordinal features can even achieve as low as 2% equal error rate (EER).

3.1. Similarity Oriented Training Samples

Similarity rule requires training samples with similarity meaning. Difference images are adopted to generate such samples. A difference image is calculated between two iris images, which is intra/positive class if the two iris images are of the same person, or inter/negative class if not. Since the features (or hypotheses in boosting language) are ordinal measures, hamming distance is used as the measure of difference. The smaller the hamming distance is, the more similar the image pair is.

By adapting the hamming distance-based difference images, the multi-class classification problem is converted to a much simpler binary one. More importantly, the training samples 'happen' to gain a concrete physical meaning—similarity. We will see that the concept of similarity oriented training samples forms the main building block for SOBoost.

3.2. Technical Details of SOBoost

Given that $\{x_i, y_i\}_{i=1}^N, (x \in R^d, y \in \{+1, -1\})$ is N labeled training samples with associated weights $\{w(x_i)\}_{i=1}^N$; $\Phi = \{\phi_m(\cdot) : R^d \to R\}_{m=1}^M$ is a candidate feature pool of x; $P_w^+(\phi_m(x))$, $P_w^-(\phi_m(x))$ are the positive and negative probability distributions of $\phi_m(x)$ on the weighted training set (see Fig. 7(a)), our goal is to automatically learn a small set of the most discriminative features $\{\phi_t\}_{t=1}^T$ from the feature pool, and construct an ensemble classifier:

$$H(x) = \text{sign}\left(\sum_{t=1}^{T} h_t(\phi_t(x))\right) \tag{1}$$

where $h_t(s) : R \to R$ is a component classifier that can output a 'confidence' of x being a positive when $\phi_t(x)$ equals s. In our cases, x is a difference image (*i.e.* an iris image pair) and $\{\phi_m(x)\}_{m=1}^M$ are the *similarity scores* of the candidate regional ordinal features on the image pair.

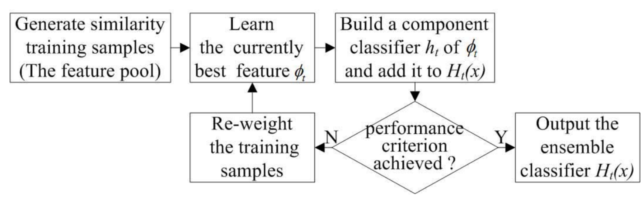

Figure 5. Flowchart of the similarity oriented boosting algorithm.

The flowchart of SOBoost is depicted in Fig. 5. It begins with generating training samples. After that, SOBoost repeatedly learns the component classifiers $h_t(\phi_t(\cdot))$ on the weighted versions of the training samples until the performance criterion is satisfied. Clearly, there are three key modules involved in SOBoost: the weak learner, the component classifier and the re-weighting function.

(1) The Weak Learner The weak learner is essentially the criterion for choosing the best feature on the weighted training set. AUC (the Area Under the ROC Curve) offers a good measure for comparing different features.

$$AUC = \int_0^1 FRR \, dFAR \tag{2}$$

where (FAR, FRR) is a point on the ROC curve. AUC corresponds to the summed error rate of a considered classifier, and therefore seems to be a good candidate for the weak learner. However, a drawback of AUC is that it gives equal weights to different FAR levels, whereas in our particular biometric application we concern more on low FAR points since a false accept is more dangerous than a false reject. Therefore, we suggest using $Log\text{-}AUC$ instead of the original AUC.

$$Log\text{-}AUC = \int_{0^+}^{1} FRR\, d\log(FAR) = \int_{0^+}^{1} \frac{FRR}{FAR}\, dFAR \quad (3)$$

$Log\text{-}AUC$ assigns higher weights on low FAR points of the ROC curve and hence the weak learner can give more preference on features with less false accepting danger. The best feature is then selected by:

$$\phi_t = \arg\min_{\phi\in\Phi} Log\text{-}AUC \quad (4)$$

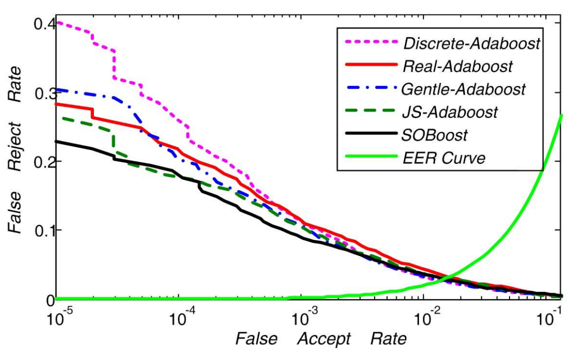

Figure 6. The ROCs of the best features selected by $Log\text{-}AUC$ (denoted by SOBoost) and several Adaboost weak learners.

Fig. 6 shows the ROC curves of the best features selected by $Log\text{-}AUC$ and several famous Adaboost weak learners during one single example feature selection round. We can see that the feature selected by $Log\text{-}AUC$ is the best of all, which promises better recognition performance.

(2) The Component Classifier The component classifier h_t outputs a confidence score of x being a positive based on ϕ_t. According to the similarity rule, a natural requirement of h_t should be: $h_t(\phi_t(x_1)) > h_t(\phi_t(x_2))$, if $\phi_t(x_1) > \phi_t(x_2)$. For this sake, we suggest to construct the component classifier using sigmoid function based on the bidirectional cumulative distributions of ϕ_t.

$$h_t(\phi_t) = 2\,\mathrm{sigmf}(C_w^+(\phi_t) - C_w^-(\phi_t), \alpha, 0) - 1 \quad (5)$$

where $\mathrm{sigmf}(x,\alpha,c) = \frac{1}{1+\exp(-\alpha(x-c))}$ is a sigmoid function with α the slop constant and c the center position, and $C_w^+(\phi_t)$, $C_w^-(\phi_t)$ are the bidirectional cumulative distributions of the positive and negative samples defined as follows

$$C_w^+(\phi_t) = \int_{-\infty}^{\phi_t} P_w^+(\phi_t) d\phi_t$$
$$C_w^-(\phi_t) = \int_{\phi_t}^{\infty} P_w^-(\phi_t) d\phi_t \quad (6)$$

As illustrated in Fig. 7 (c) and (d), Eq. 5 is advantageous because it is tolerant to outlines (*e.g.* pints B and C), which benefits greatly from the cumulative distributions. The sigmoid function is adopted for its smooth output and its flexibility when tuning α. Other monotonically increasing functions satisfying the similarity rule can also be tried.

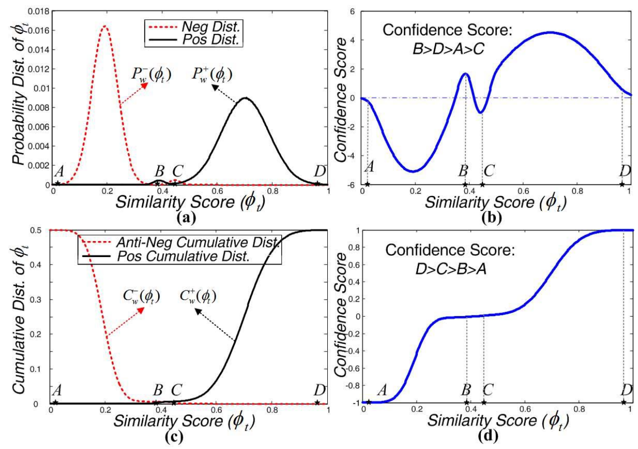

Figure 7. A comparison of the component classifiers of Adaboost and SOBoost. (a) The probability distributions of an example ϕ_t (Similar or even more complicated distributions can often be confronted during boosting especially when some hard samples gain high weights.); (b) The component classifier constructed by Adaboost (see Table 1); (c) The bidirectional cumulative distributions of ϕ_t; (d) The component classifier constructed by Eq. 5 of SOBoost.

(3) The re-weighting function An important idea under boosting is re-weighting. A distribution over the training samples is maintained and updated in such a way that the subsequent component classifier can concentrate on the hard samples by giving higher weights to the samples that are wrongly classified by previous classifier. Obviously, the more rapidly the weights are updated, the faster the learning procedure will converge. However, a too fast convergence can result in over-fitting to the training set. For tradeoff, we suggest the conservative sigmoid function as the reweighting function:

$$w_{t+1}(x_i) = \frac{w_t(x_i)\,\mathrm{sigmf}(-y_i h_t(\phi_t(x_i)), \beta, 0)}{Z_t} \quad (7)$$

where Z_t is a normalization factor (chosen so that $\{w_{t+1}(x_i)\}_{i=1}^N$ will be a distribution). Sigmoid function is preferred for that we can freely control the speed of weight updating by adjusting β.

3.3. The Relation between Adaboost and SOBoost

Although Adaboost and SOBoost share the same framework as shown in Fig. 5, several fundamental differences exist between them. For example, Adaboost's component

Algorithms	Adaboost (*e.g.* Real-Adaboost [7])	SOBoost
Training samples	⋆ The original feature value ⋆ Treated as a random variable ⋆ Lack of physical meaning	⋆ The similarity of corresponding feature values ⋆ Treated as similarity scores ⋆ Have a physical meaning–similarity
Weak learner	$\phi_t = \arg\min_{\phi\in\Phi} 2\sum_{j=1}^{N}\sqrt{P_w^+(j)\,P_w^-(j)}$ ⋆ Minimize the exponential cost function [7]	$\phi_t = \arg\min_{\phi\in\Phi} Log\text{-}AUC$ ⋆ Directly minimize the summed error rate
Component classifier	$h_t(\phi_t) = 0.5\ln(P_w^+(\phi_t)/P_w^-(\phi_t))$ ⋆ Based on probability distributions ⋆ Sensitive to noise ⋆ Maximum likelihood; conflict with similarity rule	$h_t(\phi_t) = 2\,\mathrm{sigmf}(C_w^+(\phi_t) - C_w^-(\phi_t), \alpha, 0) - 1$ ⋆ Based on bidirectional cumulative distributions ⋆ Tolerant to noise ⋆ Satisfy similarity rule; flexible by tuning α
Re-weight function	$w_{t+1}(x_i) \leftarrow w_t(x_i)\exp(-y_i h_t(\phi_t(x_i)))$ ⋆ Aggressive	$w_{t+1}(x_i) \leftarrow w_t(x_i)\,\mathrm{sigmf}(-y_i h_t(\phi_t(x_i)), \beta, 0)$ ⋆ Conservative; flexible by tuning β

Table 1. A comparison between Adaboost and SOBoost

classifier (see Table 1) is only optimal in maximum likelihood viewpoint [13], which conflicts the similarity rule: as shown in Fig. 7(b), the sorted confidence of points A, B, C and D given by Adaboost classifier is $B > D > A > C$. However, regarding the inherent similarity meaning of ϕ_t, we can definitely say that the correct order should be $D > C > B > A$. SOBoost corrects this 'error' by constructing its component classifier with monotonically increasing functions instead of Bayesian classifier, and hence satisfies the similarity rule, see Fig. 7(d). The insight is that the statistical meaning of the training samples should be subordinate to their physical meaning. Other differences between Adaboost and SOBoost are listed in Table 1. These differences make SOBoost superior to Adaboost.

4. Experiments

Experiments are carried out to evaluate the efficiency of the proposed SOBoost algorithm on the application of regional OM based iris recognition. Two iris image databases are adopted: CASIA-IrisV3-Lamp and ICE V1.0.

Both iris databases are challenging. CASIA-IrisV3-Lamp [1] contains 16213 iris images from 819 eyes. It was collected in an indoor environment with illumination change, and contains many poor images with heavy occlusion, poor contrast, pupil deformation, *etc*. To the best of our knowledge, this is the largest iris database in public domain. ICE V1.0 [2, 12] iris database includes two subsets: ICE-Left and ICE-Right. ICE-Left contains 1528 iris images from 120 left eyes while ICE-Right contains 1425 iris images from 124 right eyes. Some of its images are of poor quality due to defocus, occlusion and oblique view-angle. This database was also adopted by ICE2005 for iris recognition evaluation [2].

It is interesting to compare SOBoost with Adaboost. Therefore, four well-known Adaboost algorithms (Discrete-Adaboost [15], Real-Adaboost [13], Gentle-Adaboost [7] and JS-Adaboost [9]) are also implemented and tested in the same experiments.

4.1. Training a SOBoost Classifier

6000 iris images from the CASIA-IrisV3-Lamp iris database are selected as the training set (denoted by *CASIA-Train*). The remaining iris images serve as the test set (denoted by *CASIA-Test*), and there is no overlap between *CASIA-Train* and *CASIA-Test* in terms of subjects. After preprocessing, the normalized iris image is divided into 224 overlapped sub-regions with size 16*64. On each sub-region 708 multi-scale ordinal features are extracted. Therefore, 158592 candidate regional OM features are extracted in total, providing an overcomplete iris representation. As

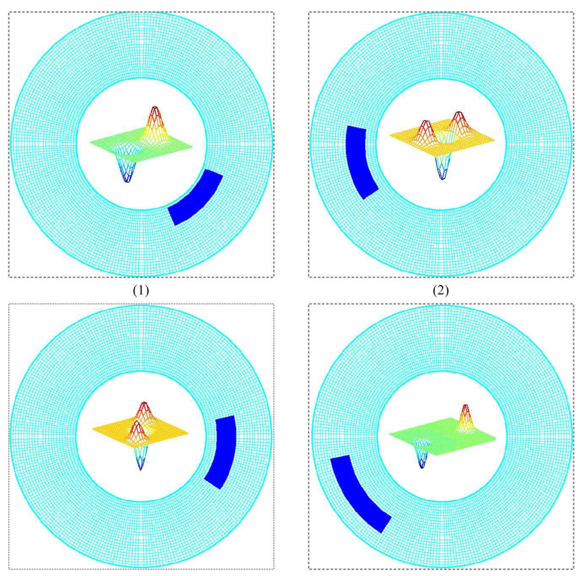

Figure 8. The first four sub-regions and the corresponding ordinal filters selected by SOBoost.

described in Section 3.1, hamming distance based difference image is calculated between two regional OM features to serve as the similarity oriented training sample. For each candidate regional OM feature 56538 intra/positive and 185440 inter/negative samples are obtained based on which a SOBoost classifier is learned.

The learned SOBoost classifier consists of 24 regional OM features. Compared with hundreds or even thousands of features as reported in [9, 11, 15], we can conclude that the classifiers (based on single regional OM feature) used in our experiments are indeed much stronger. Furthermore, we can also conclude that: (a) Ordinal measure is a powerful tool for iris representation; and (b) SOBoost works well with strong classifiers.

The first four sub-regions learned by SOBoost are shown in Fig. 8. It implies that the regions close to the pupil and between $(135^\circ \leftrightarrow 240^\circ)$ and $(-60^\circ \leftrightarrow 45^\circ)$ are more discriminative than other regions, this is no surprise since these regions are less possibly occluded by eyelids and usually have richer textures. Meanwhile, different ordinal filters are selected on different sub-regions, which demonstrates the success of applying multi-scale analysis on different iris sub-regions. Finally, we can see that horizontal ordinal filters are preferred which suggest angular direction may convey more discriminative information.

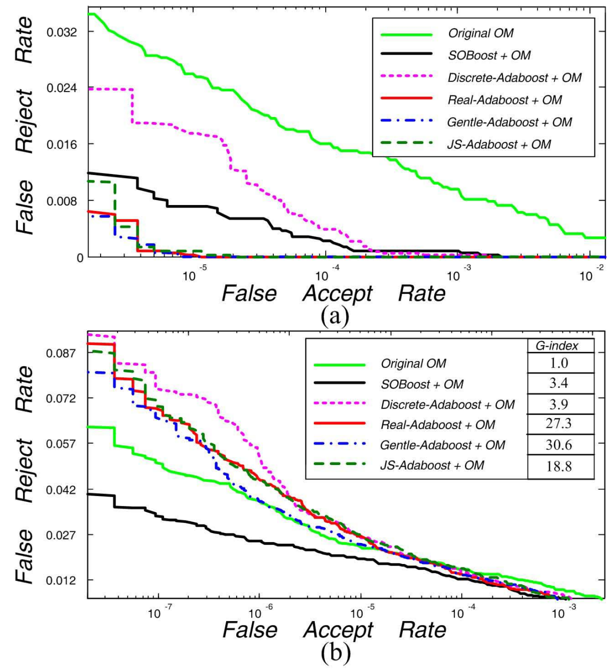

Figure 9. Generalization capability of SOBoost and Adaboost on CASIA-IrisV3-Lamp iris database. (a): *ROC* curves on *CASIA-Train*. (b) *ROC* curves and *G-indexes* on *CASIA-Test*.

4.2. Iris Recognition Accuracy

In the first experiment, we evaluate the efficiency of SOBoost on ordinal features. The *ROC* curves on *CASIA-Test* are shown in Fig. 9(b). We can see that the recognition accuracy is significantly improved by SOBoost compared with the original OM method [14], which clearly demonstrates the efficiency of SOBoost. Moreover, the encouraging performance on *CASIA-Test* implies that the learned SOBoost classifier shows high tolerance to occlusion noticing the large amount of occluded iris images in CASIA-IrisV3-Lamp iris database. This benefits greatly from the novel region based iris representation strategy. Since SOBoost always tries to learn the most discriminative regions, the regions with possible noise (*e.g*. eyelid/eyelash occlusions) will be discarded.

In the second experiment, we compare the generalization capability of SOBoost and Adaboost. To give a quantitative evaluation, we define a new measure called *Generalization Index* (*G-index* for short). *G-index* is calculated as follows:

$$G\text{-}index = \frac{Log\text{-}AUC_{Test}}{Log\text{-}AUC_{Train}} \tag{8}$$

G-index measures a method's performance variation on the training and testing set, and the smaller the better.

The *ROC* curves obtained by SOBoost, Gentle-Adaboost, JS-Adaboost, *etc*. on *CASIA-Train* and *CASIA-Test* are depicted in Fig. 9(a) and (b) respectively. The corresponding *G-index* values (normalized by the *G-index* of the original OM method) are listed in the legend of Fig. 9(b). We observe that all boosting methods achieve impressive training performance (much better than the original OM method), especially Real-Adaboost and Gentle-Adaboost. That is not surprising regarding boosting as a supervised learning method. However, on *CASIA-Test* the performance of Adaboost decreases dramatically while SOBoost still keeps an encouraging result, which implies that the generalization capability of SOBoost outperforms its Adaboost counterparts. This is also confirmed by the *G-Indexes* in Fig. 9(b), *i.e*. the *G-index* of SOBoost is significantly smaller than those of Adaboost variants.

So far, the efficiency and generalization capability of SOBoost is only demonstrated on CASIA-IrisV3-Lamp iris database, which is not of much interest since both the training and testing set are from the same database. To further evaluate it over a different database, the learned SOBoost classifier is tested on ICE V1.0 iris database. The *ROC* curves on ICE-Left are shown in Fig. 10(a). We can see that SOBoost again achieves better performance than its Adaboost counterparts. To our knowledge, this is one of the best results on this database in the literature. The top three results released by ICE2005 are shown in Fig. 10(b) for reference. It shows that our SOBoost classifier achieves comparable or even better results compared with the top three results of ICE2005.

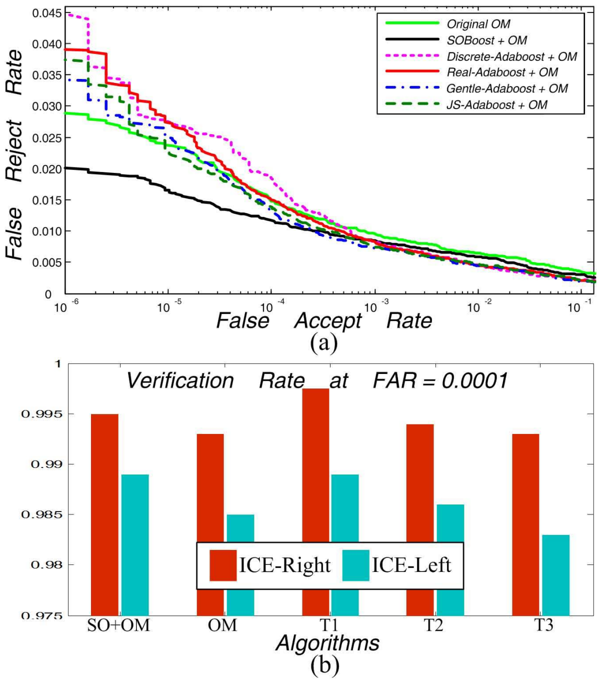

Figure 10. (a): The ROC curves of SOBoost and Adaboost on ICE-Left iris database. (b): Comparison with three results (denoted by T1-T3) of ICE2005.

4.3. Iris Recognition Speed

Although each component classifier of $H(x)$ in Eq. 1 is learned optimally, they are simply linearly combined. This is not efficient for rapid template matching since all the component classifiers have to be calculated in order to reject an imposter matching attempt as shown in Fig. 11(a). To tackle this problem, we propose to use the cascade architecture [8, 15] to reorganize $H(x)$ into s stage classifiers:

$$H(x) = \sum_{t=1}^{T_1} h_t + \sum_{t=T_1+1}^{T_1+T_2} h_t + ... + \sum_{t=T-T_s+1}^{T} h_t \tag{9}$$

As illustrated in Fig 11(b), each matching attempt is processed by a sequence of stage classifiers, and if any stage

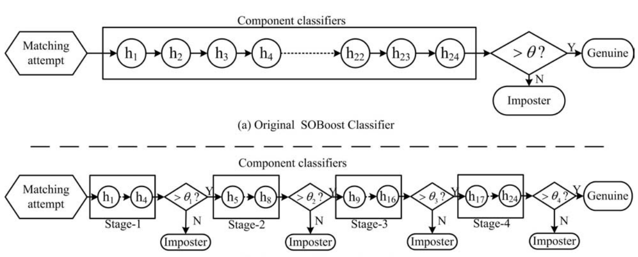

Figure 11. A comparison between the architecture of the original SOBoost classifier and the cascaded SOBoost classifier.

classifier rejects it, no further process is performed. Such a cascaded SOBoost classifier allows a majority of imposter matching attempts to be quickly rejected with fewer component classifiers, while spending more computation on promising genuine matching attempts. Consequently, the matching speed is expected to be greatly accelerated. Suppose:

- T is the total number of component classifiers in $H(x)$.
- c_0 is the computation cost of each component classifier.
- $P_i, i = 1, ..., s$ is the percentage of the imposter inputs passing previous stages but are rejected by the ith stage, determined by θ_i in Fig. 11.
- $T_i, i = 1, ..., s$ is the number of component classifiers in stage i, and $\sum_1^s T_i = T$.

Then, the computation cost of the original SOBoost classifier will be $C_{original} = Tc_0 = 24c_0$. On the contrary, the cost of the cascade classifier will be

$$C_{cascade} = c_0 \sum_{i=1}^{s} T_i P_i \Big(\prod_{j=1}^{i-1} (1 - P_j) \Big) \tag{10}$$

Constructing a cascade is in fact to determine T_i and P_i (or equally θ_i). In our experiments, T equals 24 and s is set to 4. $T_1 - T_4$ are set to 4, 4, 8 and 8. $\theta_1 \sim \theta_4$ are adjusted so that the obtained cascade classifier has comparable performance as the original SOBoost classifier. Under this setting, $P_1 \sim P_4$ are 0.75, 0.68, 0.813 and 1.0 respectively in ICE-Left iris database. As a result, the matching speed is, according to Eq. 10, greatly accelerated ($C_{cascade} = 4.32c_0$, about 4.56 times faster than the original SOBoost classifier), while having noticeable influence on the recognition accuracy.

4.4. Discussions

Three things contribute to the superiority of the proposed iris recognition method. The first one comes from the efficient regional ordinal feature based iris representation. Dividing the iris into overlapped sub-regions takes full advantages of the properties of iris textures, and paves the way for individual analysis of different iris regions. On the other hand, ordinal filters provide a powerful tool for representing the rich iris texture within each sub-region. Moreover, the optimally learned sub-regions effectively avoid the corruption of the whole iris code by localized noise like eyelids, eyelashes and specular reflections.

The second more important contributor is the novel similarity oriented boosting algorithm. SOBoost learns the most efficient regional ordinal features and the corresponding component classifiers for iris recognition. As we know, boosting is a margin maximizing learning method. However, a margin based analysis by Schapire and Singer [13] suggests that it might be a bad idea to boost in a too aggressive mode. For this sake, SOBoost performs more conservatively. For instance, it operates on similarity oriented training samples, which for the first time breaks through Adaboost's dependence on purely statistical optimization. Based on this, SOBoost constructs its component classifiers with monotonically increasing functions, which not only satisfies the similarity rule but also makes it less sensitive to noise. Moreover, considering the strong classifiers SOBoost has to boost, a ROC-based weak learner is obviously more natural and more effective. Finally, the less aggressive and more flexible sigmoid re-weighting function allows better trade-off between the convergence speed and stability. All these desirable conservative properties guarantee SOBoost's efficiency and generalization capability.

The third contributor is the introduction of the cascade architecture to the learned SOBoost classifier. The 'cascade' accelerates the matching speed of iris recognition by rejecting most imposters in early stages with fewer component classifiers, and hence greatly enhances iris recognition's searching ability towards large-scale deployments.

5. Conclusions

In this paper, we have presented a novel iris recognition method based on regional ordinal encoding and SOBoost learning. The main contributions are summarized as follows: (1) Taking advantages of the properties of iris textures, a novel iris representation method based on regional ordinal features is proposed, resulting in an overcomplete iris feature set for learning. (2) A novel learning algorithm called Similarity Oriented Boosting is developed to train an efficient and stable iris classifier with fewer regional ordinal features.(3) The cascade architecture is applied to the learned SOBoost classifier, which greatly enhances its searching ability in large scale deployments.

Experimental results on two challenging iris image databases show that the proposed method achieves state-of-the-art iris recognition accuracy, while being computationally much more efficient. Furthermore, SOBoost outperforms Adaboost in terms of both accuracy and generalization capability. In our future work, we will investigate the application of SOBoost on other iris features and even other object recognition tasks.

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