ROBUST EYELID, EYELASH AND SHADOW LOCALIZATION FOR IRIS RECOGNITION

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ABSTRACT

Eyelids, eyelashes and shadows are three major challenges for effective iris segmentation, which have not been adequately addressed in the current literature. In this paper, we present a novel method to localize each of them. First, a novel coarse-line to fine-parabola eyelid fitting scheme is developed for accurate and fast eyelid localization. Then, a smart prediction model is established to determine an appropriate threshold for eyelash and shadow detection. Experimental results on the challenging CASIA-IrisV3-Lamp iris image database demonstrate that the proposed method outperforms state-of-the-art methods in both accuracy and speed.

Index Terms— Eyelid localization, eyelash detection, iris segmentation, iris recognition, biometrics

1. INTRODUCTION

Iris segmentation is an essential module in iris recognition because it defines the effective region used for feature extraction, and therefore is directly related to the recognition accuracy. A particularly important issue involved in iris segmentation is the localization of eyelids, eyelashes and shadows (EES). EES localization is important because the iris is almost always partially occluded by eyelids, eyelashes and shadows (see Fig. 1 for example images), which will increase the danger of false acceptance and false rejection if not properly excluded.

However, efficient EES localization is difficult. First, the shape irregularity of eyelids makes accurate eyelid localization challenging. Second, the variation of the intensity and amount of eyelashes and shadows (ES) in individual iris images often makes it hard to determine a proper threshold for ES detection. Although EES occlusion can be partially avoided by excluding a predefined EES region, this is insufficient and will inevitably cause loss in recognition accuracy. Therefore, an efficient EES localization method is highly desirable.

So far, only a few researchers have paid attention on EES localization. Daugman [1] used the so-called integrodifferential operator to fit the eyelids with an arc model. Wildes [2] developed an edge detection plus Hough transforms framework for eyelid localization. Both methods provided many insightful ideas for subsequent iris segmentation researchers. More recently, Liu [3] et al. proposed to fit the eyelid by two straight lines, which, however, trades accuracy for simplicity. Regarding the eyelash detection, Kong and Zhang [4] developed three predefined criteria for eyelash detection. Kang and Park [5] proposed to detect eyelashes based on focus assessment. And Daugman [6] proposed a statistical inference method for eyelash detection. To the best of our knowledge, shadows are not considered by most of iris segmentation methods.

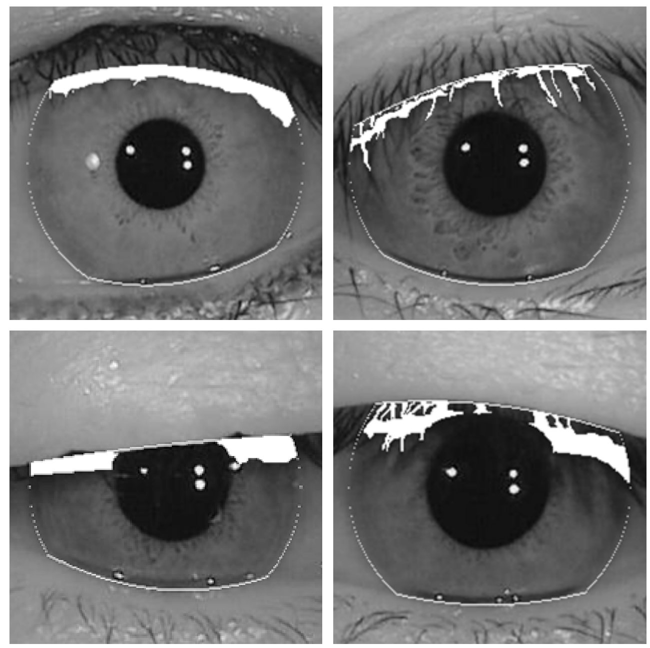


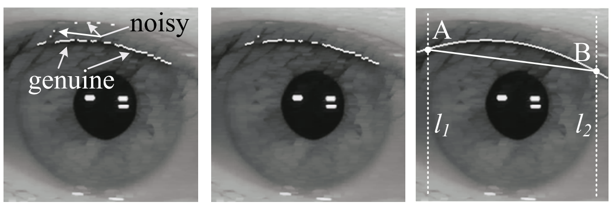
Fig. 1. Successful EES localization results by the proposed method on various challenging iris images.

Although impressive localization results have been obtained by the above methods, accurate and fast EES localization is still an open problem. In this paper, we present a novel algorithm, aiming at fast and accurate eyelid, eyelash and shadow localization. The basic approach incorporates two major contributions. The first one is a novel coarse-line to fine-parabola eyelid fitting scheme based on a learned eyelid curvature model; and the second one is a smart prediction model for determining an appropriate threshold for eyelash and shadow detection. Our experimental results indicate that the proposed method achieves state-of-the-art localization accuracy and speed, and brings a significant improvement in iris recognition accuracy.

The remainder of this paper is organized as follows. In Section 2, the novel coarse-line to fine-parabola eyelid fitting scheme is presented. In Section 3, the smart prediction model for eyelash and shadow detection is described. The experimental results are given in Section 4 prior to the conclusions in Section 5.

2. EYELID LOCALIZATION

Two things make effective eyelid localization difficult. One is the eyelash occlusion, and the other is the shape irregularity of eyelids. In our earlier work [7], we have proposed a method based on a 1-D rank filter to tackle the eyelashes. The idea is that the eyelashes are mostly vertical thin and dark lines, and therefore can be weakened or even eliminated by a 1-D horizontal rank filter. After rank filtering, edge detection is performed on the result iris image along vertical direction. Only one edge point is reserved in each column so that most noisy edge points can be avoided. As a result, a raw eyelid edge map E_{raw} is obtained as illustrated in Fig. 2(a).



(a) (b) (c)

Fig. 2. An illustration of eyelid localization. (a) The raw eyelid edge map obtained by [7]. (b) The result of curvature noise elimination. (c) The result of parabolic curve fitting.

However, E_{raw} often contains several noisy points as labeled in Fig. 2(a). Usually, there is no high reliable method to eliminate such noise due to the shape irregularity of eyelids. In this work, a so-called eyelid curvature model is statistically established to tackle this problem. The insight is that although the shapes of eyelids vary considerably from image to image, they possess a common arc structure. That is, if we join the two intersection points (e.g. points A and B in Fig. 2(c)) of the upper eyelid and the two vertical lines bounding the iris (l_1 and l_2 in Fig. 2(c)) with a straight line, all the genuine eyelid points should be above this line. And generally the closer the point is to the center, the farther it is above this line. Clearly, if we can accurately estimate this arc structure and subtract it from the raw eyelid E_{raw}, the result should resemble a straight line, which can be easily fitted with, for example, simple line Hough transforms. For this sake, the upper and lower eyelid curvature models (E_{upper}, and E_{lower}) are statistically established by manually labeling 1000 iris images from the CASIA-IrisV3-Lamp iris image database [8]. The learned models are depicted in Fig. 3(a).

Once the eyelid curvature models are established, the upper eyelid is localized as follows:

1. Calculate a raw eyelid edge map. Filter the iris image with a 1-D horizontal rank filter, and then perform vertical edge detection. An example is depicted in Fig. 2(a) and re-plotted in Fig. 3(b) (Note that only one edge point is reserved along each column).
2. Subtract E_{upper} from the detected E_{raw}. As mentioned above, the result of $E_{raw} - E_{upper}$ should resemble a straight line as shown in Fig. 3(b).
3. Fit $E_{raw} - E_{upper}$ with line Hough transforms. Although inaccurate it is, the line fitting provides cues for noise elimination. For instance, only the points that are in accordance with the best fitting line are reserved as genuine eyelid points, while other points are eliminated, see Fig. 2(b) and Fig. 3(b). we call this noise elimination strategy curvature noise elimination (CNE).

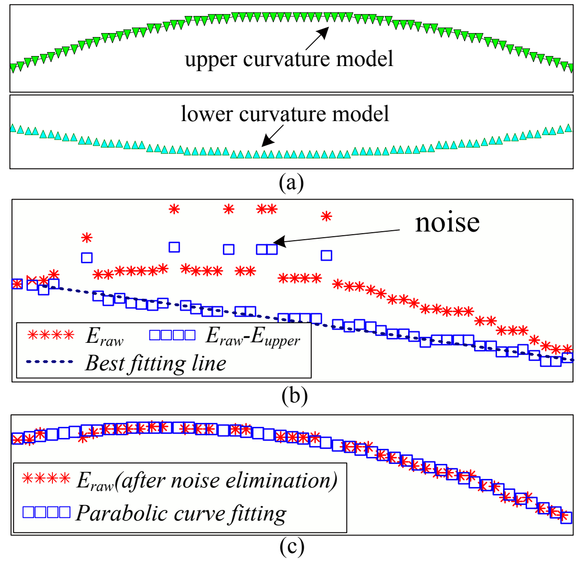


Fig. 3. The mechanics of coarse-line to fine-parabola eyelid fitting. (a)The learned eyelid curvature models. (b)Curvature noise elimination after line fitting on E_{raw}-$E_{upmodel}$. (c)The parabolic curve fitting on E_{raw} after noise elimination.

4. Fit the remaining points of E_{raw} with a parabolic curve, see Fig. 2(c) and Fig. 3(c) for an example.

Consequently, the shape irregularity is efficiently addressed by this coarse-line to fine-parabola eyelid fitting scheme. Here, CNE is useful because it improves the localization accuracy than direct parabolic curve fitting on E_{raw} by eliminating noisy edge points.

A similar approach is used to locate the lower eyelid, with another lower eyelid curvature model shown in Fig. 3(a).

3. EYELASH AND SHADOW DETECTION

Eyelashes and shadows (ES) are another source of occlusion that challenges iris segmentation. The basic idea of our solution is to extract an appropriate threshold for ES detection via a statistically established prediction model.

The most visible property of ES is that they are generally darker than their backgrounds (eyelids or iris), a straightforward detection strategy is therefore thresholding. However, usually it is hard to get a proper threshold due to the variation of the intensity and amount of ES between individual iris images. Inspired by the work of Daugman [6], we try to get a proper threshold by analyzing the intensity distributions of different iris regions. As shown in Fig. 4(a), our approach begins with dividing the candidate iris region into two parts: ES_{free} and $ES_{candidate}$. Then, the intensity histograms of both regions are respectively calculated (e.g. the ones imposed on the upper-left corner of Fig. 4(b)). Clearly, if $ES_{candidate}$ region is occluded by eyelashes and shadows, its histogram should be different from that of ES_{free} region. Furthermore, the more occlusion, the more difference between them. Therefore, we can predict the amount of the ES occlusion according to the level of difference between the two histograms. And considering that eyelashes and shadows are usually the darkest points in the candidate iris region, we can easily get a proper detection threshold.

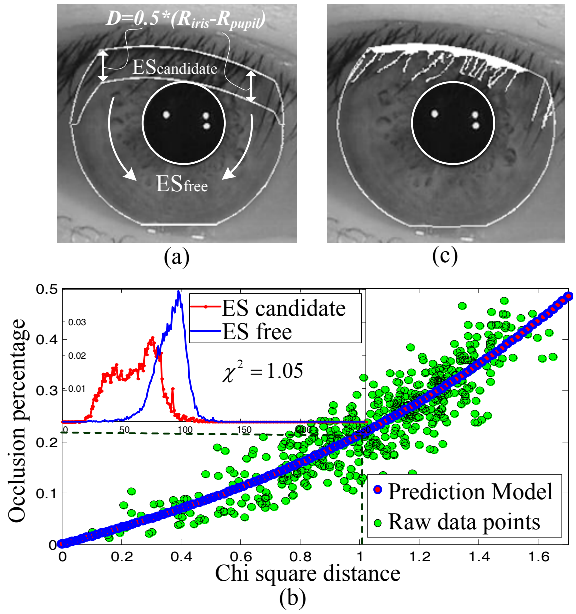


Fig. 4. (a) Adaptive iris division. (b)The prediction model for ES detection. (c)The ES detection result of (a).

Figure 4(b) shows the relationship between the amount of ES occlusion and the difference level between histograms of ES_{free} and $ES_{candidate}$ (estimated on CASIA-IrisV3-Lamp image database). χ^2 distance is adopted to measure the difference between two considered histograms h_1 and h_2 as follows:

$$\chi^2 = \sum_i \frac{(h_{1i} - h_{2i})^2}{h_{1i} + h_{2i}} \tag{1}$$

The solid line in Fig. 4(b) is the prediction model learned by fitting these raw data points with a cubic polynomial curve. According to this prediction model, we can get an appropriate threshold for ES detection. For example, if the χ^2 distance of the histograms of ES_{free} and $ES_{candidate}$ is 1.05, we can say that the amount of the ES occlusion is about 22%. Accordingly, we set the detection threshold to the intensity up to which the sum of the histogram of $ES_{candidate}$ is above 22%. Thus, an adaptive ES detection threshold is obtained, which results in an impressive detection result as shown in Fig. 4(c).

Finally, we further refine the detection result by checking the connectivity of the candidate points to the upper eyelid. The idea is that most eyelashes and shadows appear near the upper eyelid [4]. This refinement is necessary because it relaxes the burden of selecting the detection threshold. It allows us to not spend too much effort trying to find an optimal threshold but just a moderately good and loose one.

Compared with Daguman's method [6], our method is advantageous because: (a) a more refined division of the candidate iris region is used as depicted in Fig 4(a); (b) the prediction model is more efficient in determining an appropriate ES detection threshold; and (c) the refinement further guarantees the accuracy of ES detection.

4. EXPERIMENTS

Experiments are carried out on CASIA-IrisV3-Lamp iris image database [8] to evaluate the efficiency of the proposed method. This database is preferred because it contains many images with heavy occlusions due to eyelids, eyelashes and shadows. To the best of our knowledge, it is also the largest iris database in the public domain (16213 iris images from 819 eyes).

It is interesting to compare our method (denoted by $EES_{proposed}$) with other EES localization methods, so Daugman's methods [1, 6] (denoted by $EES_{Daugman}$), Wildes's edge detection plus Hough transforms method [2] (denoted by EES_{Wildes}) and Liu's method [3] (denoted by EES_{Liu}) are also implemented and tested for comparison.

4.1. Accuracy Illustrations

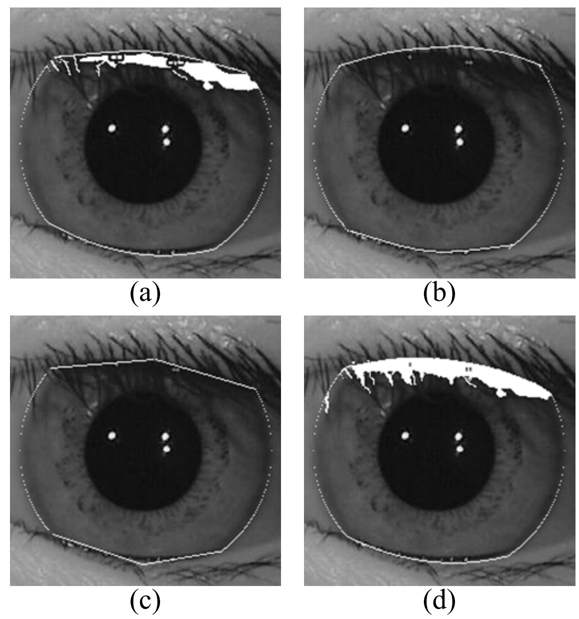


Fig. 5. Localization results by (a) $EES_{Daugman}$, (b) EES_{Wildes}, (c) EES_{Liu} and (d) $EES_{Proposed}$ respectively.

Figure 5 shows the localization results of an example iris image by different EES localization methods. We can see that $EES_{Proposed}$ obtains more accurate eyelid localization result than EES_{Liu}. That is because EES_{Liu} uses only two simple lines to fit the eyelid while $EES_{Proposed}$ use more refined parabolic curve fitting. $EES_{Proposed}$ also slightly outperforms $EES_{Daugman}$ and EES_{Wildes}. This is because the integrodifferential operator in $EES_{Daugman}$ tends to be sensitive to local intensity change, while the Hough transforms in EES_{Wildes} are brittle to noisy edge points. These drawbacks often lead to local optima while localizing the eyelids. In contrast, under the proposed eyelid localization framework, the 1-D rank filter removes most of the eyelash noise and the curvature noise elimination scheme deals with the shape irregularity very well, which together guarantee the localization efficiency.

In terms of the accuracy of eyelash and shadow detection, we can observe that $EES_{Proposed}$ achieves better results than $EES_{Daugman}$. This can be attributed to the efficient prediction model in determining the threshold for eyelash and shadow detection. Finally, shadow detection, for the first time, acts as an independent module in iris segmentation, which enables more precise labeling of the invalid iris region for subsequent encoding and matching modules.

More segmentation results of $EES_{Proposed}$ on several other challenging iris images are shown in Fig. 1, which clearly demonstrates the accuracy and robustness of our method to typical iris noise in practical applications.

4.2. Performance Evaluation

In this subsection, we demonstrate the efficiency of the proposed method via iris recognition accuracy and its execution speed. Intuitively, the more accurate the localization is, the higher the recognition accuracy will be. In our experiments ordinal measure (OM) filters are adopted to encode the iris texture [9]. Accordingly, Hamming Distance (HD) is adopted as the measure of dissimilarity between two considered OM codes $codeA$ and $codeB$:

$$\text{HD} = \frac{\|(codeA \bigotimes codeB) \bigcap maskA \bigcap maskB\|}{\|maskA \bigcap maskB\|} \qquad (2)$$

where $maskA$ and $maskB$ are the masks of $codeA$ and $codeB$ respectively. A mask signifies whether any iris region is occluded by eyelids, eyelashes and shadows, so it reflects the EES localization results. HD is therefore a fractional measure of dissimilarity after EES regions are discounted.

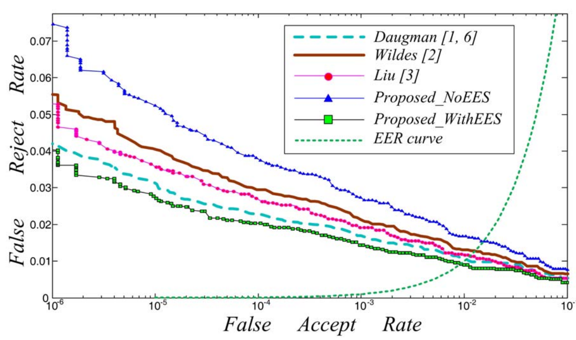


Fig. 6. ROC curves on CASIA-IrisV3-Lamp iris database.

The ROC curves of several EES localization methods on CASIA-IrisV3-Lamp iris image database are shown in Fig. 6. Note that in order to measure the effect of the EES localization on the recognition performance, the results without EES localization (i.e. without a mask in Eq. 2) is also compared in the same experiments, and is denoted by $Proposed_{NoEES}$ (while the results with EES localization is denoted with $Proposed_{WithEES}$). The computation cost, the equal error rate (EER), and the discriminative index (d') of each algorithm are also listed in Table 1 for comparison.

From Fig. 6 and Table 1, we can see that: (1) EES localization brings a significant improvement on the iris recognition performance (e.g. EES detection brings 21.2% improvement on d'), which confirms that the EES localization is an essential step in iris recognition. (2) The proposed method outperforms other EES localization methods in both accuracy and speed. $EES_{proposed}$ obtains the highest accuracy scores (smallest EER and largest d'), while its computation cost is much lower than others. From these results we can conclude that the proposed method is efficient in EES localization and is useful for iris recognition.

Table 1. Performance on CASIA-IrisV3-Lamp iris image Database

	Speed (ms)	**EER(%)**	**d'**
Daugman [1, 6]	16	1.08	4.45
Wildes [2]	31	1.29	4.05
Liu [3]	22	1.14	4.11
Proposed_NoEES	–	1.49	3.78
Proposed_WithEES	11	0.92	4.58

5. CONCLUSIONS

In this paper, we have presented an accurate and fast method for eyelid, eyelash and shadow localization. Our method has made two major contributions. The first one is a coarse-line to fine-parabola curve fitting scheme for accurate eyelid localization. The second one is a novel prediction model for determining a proper threshold for eyelash and shadow detection. Experimental results show that the proposed method achieves state-of-the-art localization performance in both accuracy and speed, and brings a significant improvement in iris recognition accuracy.

6. ACKNOWLEDGE

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