COMPARISON OF EYELID AND EYELASH DETECTION ALGORITHMS FOR PERFORMANCE IMPROVEMENT OF IRIS RECOGNITION

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ABSTRACT

Eyelids and eyelashes occluding the iris region are noise factors that degrade the performance of iris recognition. If they are incorrectly classified as the iris region, the false iris pattern information will increase, decreasing the recognition rate. Thus, reliable detection of eyelids and eyelashes is required to improve the performance of iris recognition. The objective of this paper is to present a research direction for reduction of noise factors based on analysis and performance comparison of existing eyelid and eyelash detection algorithms. With CASIA version 3 database we compare six existing eyelid and eyelash detection algorithms and analyze the characteristics and performance of each algorithm. The performance of each algorithm is evaluated in terms of different performance measures such as the decidability, the equal error rate, and the detection error trade-off curve.

Index Terms— iris recognition, eyelid detection, eyelash detection

1. INTRODUCTION

Iris recognition authenticates and recognizes persons using the unique iris pattern information. It has a higher accuracy rate than other biometric recognition methods such as face recognition, fingerprint recognition, voice recognition, and hand geometry, noting that an iris has much pattern information and is invariable through a lifetime [1]–[3]. Thus, iris recognition is in the limelight of security applications.

Current iris recognition systems use iris images taken under the constrained conditions, where a high accuracy rate is guaranteed. However, these constrained conditions in image acquisition are inconvenient for users and restrict the scope of the applications. If the unconstrained iris images are used, the performance of iris recognition will be degraded considerably due to noise factors such as eyelids, eyelashes, and reflections [4]. Thus, accurate and reliable detection and restoration of the occluded region caused by these noise factors is an important problem.

The objective of this paper is to present a research direction for reduction of noise factors based on analysis and performance comparison of existing eyelid and eyelash detection methods. We compare six existing eyelid and eyelash detection algorithms for analyzing the characteristics and performance of each algorithm.

The rest of the paper is organized as follows. Section 2 describes the iris recognition step and various methods applied to this step. Sections 3 and 4 present the eyelid and eyelash detection algorithms, respectively. Experimental results with CASIA version 3 database are presented and discussed in Section 5. Finally, conclusions are given in Section 6.

2. IRIS RECOGNITION

A typical iris recognition method consists of five steps: image acquisition, segmentation, normalization, feature encoding, and feature matching. Fig. 1 shows overall processes of iris recognition.

An eye image is captured by a digital camera in an image acquisition step. In a segmentation step, iris and pupil boundaries are detected for segmenting an iris region. Typical iris segmentation methods include Duagman's integro-differential operator [1] and edge detection using the circular Hough transform [2].

In a normalization step, the segmented iris region is resampled to the fixed-size rectangular image to compensate for the different size of each iris input image for reliable feature matching. A typical normalization method uses a Duagman's rubber sheet model [5].

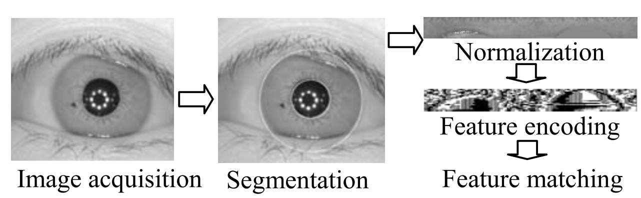
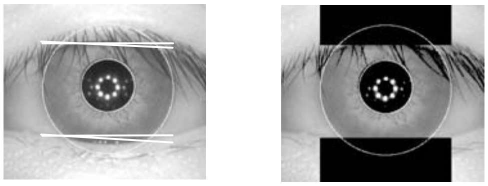


Fig. 1. Overall processes of iris recognition.



(a) (b)

Fig. 2. Eyelid detection using Masek's algorithm. (a) Lines approximated to upper and lower eyelid boundaries, (b) Detected eyelid region.

In a feature encoding step, a template representing each iris pattern information is created using wavelet encoding, Gabor filter, log-Gabor filter, or zero-crossing. Created templates are compared using the Hamming or Euclidean distance and then the similarity values are evaluated.

Eyelid and eyelash detection using Masek's [6], Bachoo and Tapamo's [7], and Kang and Park's [8] algorithms are performed after the segmentation step. Whereas Zhang *et al.*'s [9], Huang *et al.*'s [10], and Xu *et al.*'s [11] algorithms are processed after a normalization step.

These algorithms are classified into two classes: block-based detection and pixel-based detection. Xu *et al.*'s, and Bachoo and Tapamo's algorithms are block-based while the other algorithms are pixel-based. Eyelash detection algorithms are also classified by whether or not the occlusion region is restored. Zhang *et al.*'s and Huang *et al.*'s algorithms restore the detected eyelash whereas the other algorithms do not consider the eyelash region in feature matching.

3. EYELID DETECTION ALGORITHMS

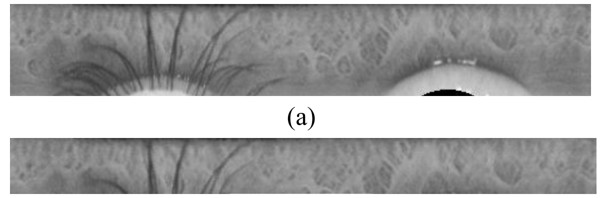
Masek separated the eyelid and iris region by horizontal lines [6]. Lines approximated to upper and lower eyelid boundaries are detected by the line Hough transform, and then the intersections between the detected lines and boundary of an iris region extracted in the segmentation step are found. Horizontal lines crossing the point closest to the pupil of the intersections are used for separating the eyelid and iris region. Fig. 2 shows the eyelid detection process using Masek's algorithm.

Kang and Park isolated the eyelid region using the parabolic Hough transform [8]. The parabolic arc approximated to the eyelid boundary is expressed as

$$((x-h)\sin\theta+(y-k)\cos\theta)^2 = a((x-h)\sin\theta-(y-k)\cos\theta) \quad (1)$$

where a represents the curvature of a parabolic arc, (h,k) signifies the peak coordinate of a parabolic arc, and θ denotes the angle of rotation.

The line Hough transform has less parameters and thus requires less computation time than the parabolic one. However, the line Hough transform has greater chances of missing the iris pattern information.



(a)

(b)

Fig. 3. Eyelid removal process. (a) 512×80 resampled iris image (before removing the eyelid), (b) Iris image consisting of 48 rows of pixels nearest to the pupil (Zhang *et al.*'s [9] and Huang *et al.*'s [10] algorithms, after removing the eyelid).

Fig. 4. Eyelid/eyelash models (Xu *et al.*'s algorithm [11]).

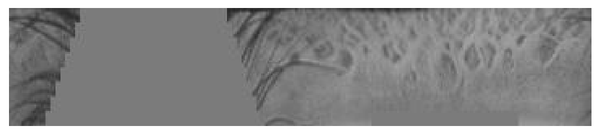


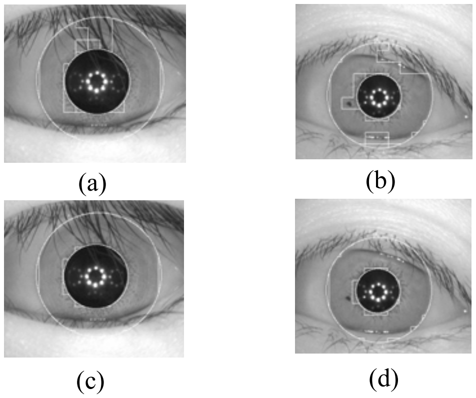
Fig. 5. Resampled image giving incorrect eyelash detection (Xu *et al.*'s algorithm [11]).

For reducing the effect caused by eyelid occlusion, Zhang *et al.* [9]'s and Huang *et al.* [10]'s algorithms use only the region of the normalized image near the pupil. These algorithms are simpler than Masek's algorithm, however the chances of missing the iris pattern information and using incorrect information are greater. Fig. 3(a) shows the resampled iris image before removing the eyelid and Fig. 3(b) shows the eyelid removal process using Zhang *et al.*'s and Huang *et al.*'s algorithms.

Xu *et al.* divided the upper and lower eyelid candidate regions into eight sub-blocks and chose the eyelid/eyelash model based on the maximum deviation of each sub-block [11]. Fig. 4 shows the eyelid/eyelash models defining the region occluded by eyelids and eyelashes. This algorithm detects the reflection near the eyelid because the reflection makes the deviation larger. However, if the occlusion region is wider than the eyelid/eyelash model, then incorrect iris patterns are used for feature matching, yielding incorrect eyelash detection as shown in Fig. 5.

Bachoo and Tapamo [7] divided the candidate region containing an iris region into sub-blocks, and then classified each sub-block based on feature clustering, K-means clustering, or fuzzy C-means clustering. Fig. 6 shows the eyelid and eyelash detection result using Bachoo and Tapamo's algorithm. The feature of each sub-block F is defined as

$$F = \sum_{i,j=1}^{G} p_{\theta,d}(i,j)\left(\frac{i}{j}\right) \quad (2)$$



(a) (b)

(c) (d)

Fig. 6. Detected eyelid and eyelash regions using Bachoo and Tapamo's algorithm [7]. (a) Fuzzy C-means clustering (Eye 1), (b) Fuzzy C-means clustering (Eye 2), (c) K-means clustering (Eye 1), (d) K-means clustering.

where $p_{\theta,d}(i,j)$ represents the (*i,j*) element of the gray level co-occurrence matrix that signifies the joint probability of the gray level pair *i* and *j*, with the pixel pair separated by *d* pixels along the given direction θ, and G denotes the number of gray levels.

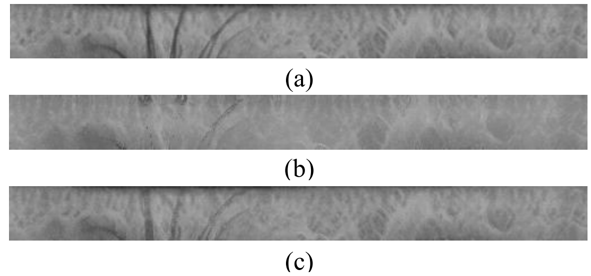
Figs. 6(a) and 6(b) show the detected eyelid/eyelash regions using fuzzy C-means clustering for Eye 1 and Eye 2, respectively. Figs. 6(c) and 6(d) show the detected eyelid/eyelash regions using K-means clustering for Eye 1 and Eye 2, respectively. Fig. 6 shows that the eyelid/eyelash detection algorithm using fuzzy C-means clustering detects the eyelid/eyelash region better than the algorithm using K-means clustering.

4. EYELASH DETECTION ALGORITHMS

In general, the gray level of the eyelash region is lower than that of the iris region. Based on this characteristic, Masek detected the pixels that have the gray levels lower than the threshold that is selected experimentally. This algorithm is simple but sensitive to the change of illumination.

An eyelash region has a large gradient value because of the large gray level difference between eyelash and iris regions. The region containing many eyelashes has a large variation in gradient direction. Zhang *et al*. extracted the eyelash candidate region based on these characteristics. In the candidate region, eyelashes are detected and restored by a nonlinear conditional directional filter. The filter uses the one-dimensional (1-D) median filtering along the gradient direction which is perpendicular to the eyelash direction. Then, if the difference between a filtered value and original pixel's gray level is larger than the threshold, the gray level at the current pixel is replaced by a filtered value.

Huang *et al*.'s algorithm detected the eyelash using the edge information extracted by a phase congruency, which is invariant to the change of illumination. The detected eyelash region is restored by a simple inpainting technique using the four pixels nearest to the block containing the eyelash region. Fig. 7(a) shows the resampled iris image without eyelash removal. Figs. 7(b) and 7(c) show the eyelash detection and restoration results using Zhang *et al*.'s and Huang *et al*.'s algorithms, respectively. From Fig. 7, it is noted that Zhang *et al*.'s algorithm has a better eyelash restoration performance than Huang *et al*.'s algorithm.

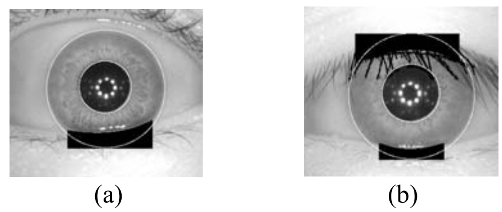


(a)

(b)

(c)

Fig. 7. Eyelash detection and restoration. (a) Image without eyelash removal, (b) Eyelash removed image using Zhang *et al*.'s algorithm [9], (c) Eyelash removed image using Huang *et al*.'s algorithm [10].



(a) (b)

Fig. 8. Detected eyelid and eyelash regions using Kang and Park's algorithm [8]. (a) Eye 1, (b) Eye 2.

Kang and Park measured the focus score of an iris image using a 5×5 convolution kernel. Using the focus score, they decided the threshold of local variance and sizes of the local window and convolution kernel for detecting the eyelash. In their algorithm, eyelashes were classified into separable eyelashes and multiple eyelashes. The region containing many multiple eyelashes has the low gray level and high variance. Using these characteristics, the local window is applied at the point connected to eyelid or eyelash to detect the multiple eyelashes. For detecting the separable eyelashes, horizontal and vertical direction convolution kernels are applied at the point connected to eyelid or eyelash. If ten successive checking points meet the conditions based on the mean and variance of gray level, then these points are detected as separable eyelash. Fig. 8 shows the detected eyelid and eyelash region using Kang and Park's algorithm.

5. EXPERIMENTAL RESULTS AND DISCUSSIONS

We use the CASIA version 3 database [12] for a performance comparison of six eyelid and eyelash detection algorithms. CASIA version 3 database contains 22501 iris images acquired from more than 700 different people and captured in variable environment.

TABLE I
DECIDABILITY AND EER

	Masek	Zhang *et al.*	Huang *et al.*	Xu *et al.*	Bachoo and Tapamo	Kang and Park
d	3.7846	3.8185	3.7907	3.5671	3.6443	4.0768
EER (%)	4.58	3.70	3.79	5.88	5.16	3.37

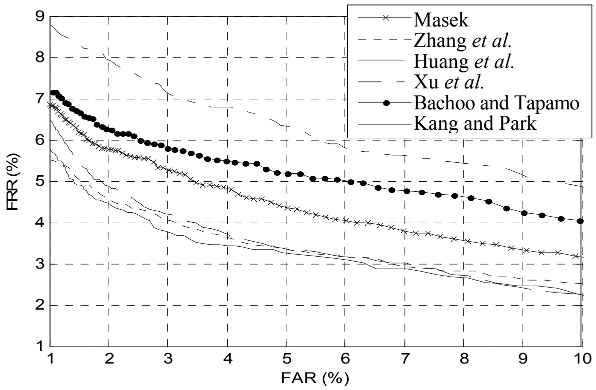


Fig. 9. DET curves.

In experiments, six existing algorithms are considered: Masek's, Zhang *et al.*'s, Huang *et al.*'s, Xu *et al.*'s, Bachoo and Tapamo's, and Kang and Park's algorithms. For an unbiased comparison, the same recognition method is applied to each of the eyelid and eyelash detection methods. The circular Hough transform is used in the segmentation step, a 1-D Gabor filter is employed for feature encoding, and the Hamming distance is used for feature matching.

The performance of each algorithm is evaluated in terms of different performance measures such as the decidability, the equal error rate (EER), and the detection error trade-off (DET) curve.

Decidability d is defined as

$$d = |\mu_S - \mu_D| / \sqrt{(\sigma_S^2 + \sigma_D^2)/2} \qquad (3)$$

where μ_S and μ_D are the means of Hamming distances for intra-class and inter-class, respectively. σ_S and σ_D are the standard deviations of Hamming distances for intra-class and inter-class, respectively.

Table I shows the decidability and EER of each algorithm. Fig. 9 shows the DET curves that represent the false reject rate (FRR) in terms of the false accept rate (FAR) for each algorithm. The FAR is the probability that an unauthorized object is identified by a system whereas the FRR is the probability that an authorized object is incorrectly rejected.

Based on these performance measures, Kang and Park's algorithm shows the best performance among six algorithms. Because the parabolic arc that Kang and Park used for detecting the eyelid is more similar to the eyelid shape than those used in other algorithms. Thus, the chance of missing the iris pattern information is small. They also considered the focus of an iris image when they detected the eyelash, so their algorithm is less sensitive to the blur degree. Zhang *et al.*'s and Huang *et al.*'s algorithms not only detected the eyelash, but also restored the eyelash. Thus, this approach shows the good performance in spite of that their eyelid detection algorithm has the lower accuracy than other algorithms.

Xu *et al.*'s and Bachoo and Tapamo's methods do not give good performance because they detected the eyelid and eyelash by a sub-block unit. Six algorithms have the common drawbacks that the parameters and threshold values used in each algorithm are selected experimentally, which are sensitive to image acquisition condition.

6. CONCLUSIONS

We compare six existing eyelid and eyelash detection algorithms for performance comparison of iris recognition. The parabolic Hough transform gives the best performance for detecting the eyelid among six algorithms. Eyelash detection implemented by a pixel unit gives better performance than that by a sub-block unit. Considering the focus of an iris image and restoring the detected eyelash improves the performance of iris recognition. The future research will focus on the development of an iris segmentation method as well as the eyelid and eyelash detection methods.

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