

EYELASH REMOVAL METHOD FOR HUMAN IRIS RECOGNITION

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ABSTRACT

A novel eyelash removal method for preprocessing of human iris images in a human iris recognition system is presented. The method filters each occluded pixel along an axis perpendicular to the eyelash direction, and accepts the filtered value if it changes by more than a certain threshold. This allows partially occluded regions of the iris to be included in iris coding which would previously have been excluded. The method is applied with three iris coding algorithms on an extended 308 class CASIA database and large improvements are shown in the matching performance of two methods, with a modest improvement in the third.

Index Terms—Iris Recognition, Eyelash Removal

1. INTRODUCTION

Iris recognition is gaining acceptance as a robust biometric for high security and large-scale applications [1-3]. As with other pattern recognition systems, a typical iris recognition system includes iris capture, image pre-processing, feature extraction and matching. While early work has focused primarily on feature extraction with great success [4-7], the preprocessing task has received less attention. However, the performance of a system is greatly influenced by the quality of captured images. Amongst the various factors that could affect the quality of iris images, one of the most commonly encountered is eyelash occlusion [8], which can degrade iris images either during enrolment or verification. Examples of iris images with eyelash occlusion are shown in Figure 1. Such strong ‘eyelash textures’ obscure the real iris texture, and hence interfere seriously with the recognition capability of any recognition system. Reducing the influence of the eyelash on recognition is therefore an important problem.

Early efforts to mitigate the effects of eyelash tried to ignore parts of the iris to avoid eyelash contamination [6, 9]. Later some researchers tried to detect and mask the eyelash pixels from the image [8]. Zhang et. al. [8] classified the eyelashes into two categories, separable and multiple. They then used an edge detector to find separable eyelashes, and recognized multiple eyelashes by intensity variance. Daugman [5] detects eyelashes using wavelet demodulation and masks them in iris coding. Both of these methods locate the eyelash pixels in the image and exclude the iris code bits

generated from these pixels. Although these two methods successfully detect and mask eyelashes, the improvements in system performance are quite modest. In this work we have developed a method for removing eyelashes and restoring the underlying iris texture as much as possible.

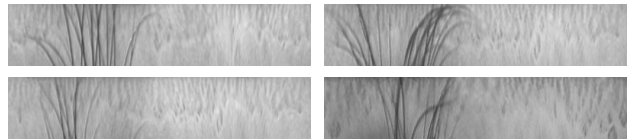


Figure 1. Iris images occluded by eyelashes.

In this work, we recreate iris pixels occluded by eyelashes using information from their non-occluded neighbours. Briefly, for every pixel in the iris image, we first decide if the pixel is in an area contaminated by eyelashes, and if so we determine the direction of the eyelash. We then filter the image locally along a direction perpendicular to the eyelash because we have the best chance of finding uncontaminated pixels along this direction. To avoid incorrectly filtering non-eyelash pixels, no pixel is altered unless the change in that pixel exceeds a certain threshold. Two well known algorithms (Daugman[5] and Tan[6]) and our own method [9] have been tested on an extended 308 class CASIA database and encouraging improvement are shown. The preferred metric for iris recognition performance is the Equal Error Rate (EER), which is the False Acceptance Rate (FAR) and False Rejection Rate (FRR) where they become equal. Our proposed eyelash removal method reduces the EER by a factor of six for both the Tan and Monro algorithms, but Daugman’s is improved only slightly.

This paper is organized as follows. Section 2 presents a detailed description of the proposed eyelash removal method. Experimental details with results are then given in Section 3. Finally, conclusions are drawn in Section 4.

2. EYELASH REMOVAL

Our work is done using images from the CASIA database, resampled into a rectangular 512 x 80 image. For processing we use the 48 rows of pixels nearest the pupil, which are at the top in Figure 1. Figure 2 summarizes the proposed eyelash removal algorithm based on nonlinear conditional directional filtering.

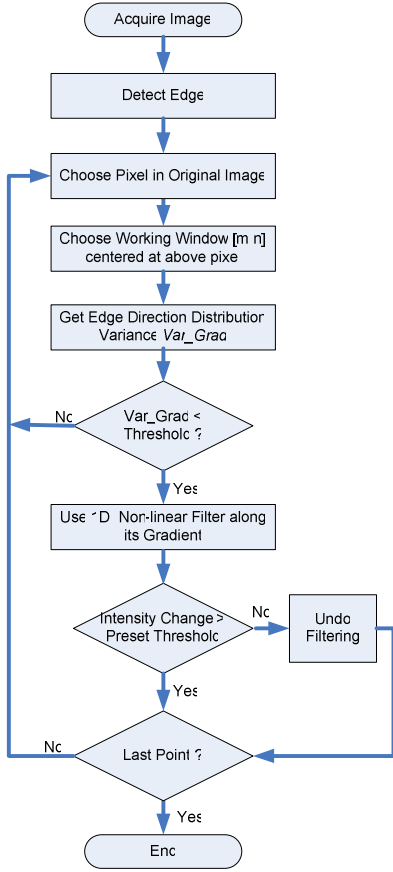


Figure 2. Proposed eyelash removal method

2.1. Edge Detection

An eyelash causes a discontinuity along its edges, so to detect an eyelash and estimate its direction, a 3 x 3 Sobel edge filter is applied to the normalized image, Figure 3.

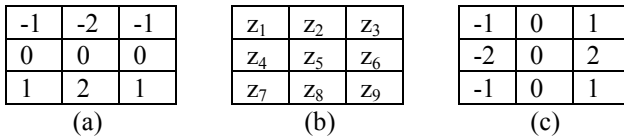


Figure 3. Sobel Edge Filter

(a) X Derivative (b) Image Region (c) Y Derivative

For every pixel, the estimated gradients in the X and Y directions are $[G_x, G_y]$ and the magnitude of the gradient at the center point of the mask, called $Grad$, are computed:

$$G_x = (z_7 + 2z_8 + z_9) - (z_1 + 2z_2 + z_3)$$

$$G_y = (z_3 + 2z_6 + z_9) - (z_1 + 2z_4 + z_7)$$

$$Grad = (G_x^2 + G_y^2)^{1/2}$$

The local gradient direction (perpendicular to the edge) is:

$$\theta = \arctan(G_y/G_x)$$

2.2. Eyelash Area Decision

To decide if a pixel is occluded, we define a window of size $[m \ n]$ centred at the pixel and compute a gradient direction variance over those r pixels for which $Grad > 15$:

$$Var_Grad = \frac{1}{r-1} \sum_{i=1}^r (\theta_i - \bar{\theta})^2$$

If the gradient direction has a small variance, a strong edge is indicated, as can be seen in Figure 4, and this pixel is classified as being affected by eyelash.

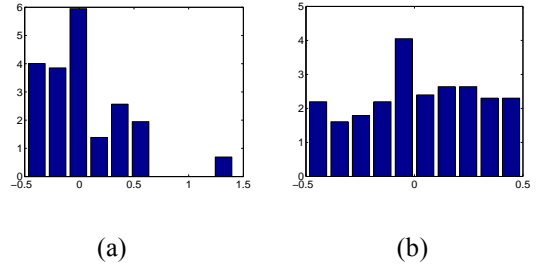


Figure 4. Gradient Direction Distribution
(a) Eyelash Area (b) Non-eyelash Area

2.3. Non-linear Filtering

For each pixel classified as an eyelash pixel, a 1D median filter of length L is applied along the direction θ , to estimate the value of the image with the eyelash removed. In general the direction does not pass exactly through pixels, so the median filter is applied to values equally spaced by the distance between actual pixels, which are calculated using bilinear interpolation of the four nearest pixels.

Not every pixel in the eyelash window is occluded by eyelash, so we only change the intensity if the intensity difference exceeds a threshold related to the total variance of the image. Specifically we compute

$$Recover = Diff - k * Var(Image)$$

$Diff$ is the difference in intensity between the filtered and unfiltered pixel and $Var(Image)$ is the intensity variance of the whole (unfiltered) image. K is the parameter used to tune the threshold. If $Recover$ is positive, the pixel is replaced by the filtered value, otherwise the filter is not applied.

2.4. Visual Results

Figures 5 and 6 show the effect of the eyelash removal method on normalized human iris images with and without filtering. It is seen that visually the filter has little effect on an image with no eyelid occlusion, while in the occluded case the eyelashes are replaced by pixels representative of underlying iris texture. It is not perfect; the positions of the eyelashes are visible.

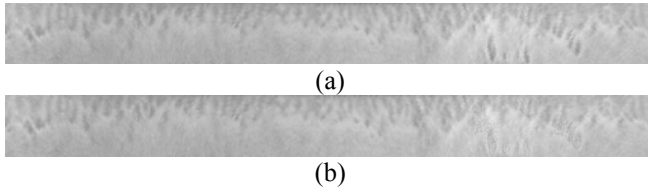


Figure 5. (a) Image without eyelash occlusion; (b) The effect of the eyelash removal filter.

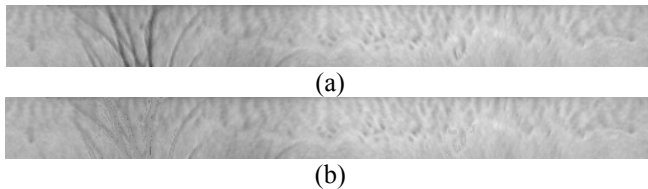


Figure 6. (a) Image affected by eyelash; (b) The effect of the eyelash removal filter.

3. EVALUATION IN IRIS RECOGNITION SYSTEMS

3.1. Experimental Environment

We test the effect of the eyelash removal filter by applying it to images from the CASIA iris database, comprising 2156 images from 308 classes (eyes). Three images from each class are coded and registered in a database and the remainder are used to match against them.

The parameters of the filtering process are tuned using the Monroe Iris Transform (MIT) [9]. Because 100% Correct Recognition Rate (CRR) is achieved on this data before the eyelash removal was applied, we tune the filter for minimum Equal Error Rate (EER).

m	8	12	16	24
EER(10^{-3})	1.72	0.53	0.26	0.40

(a)

n	8	16	32	64
EER(10^{-3})	0.93	3.44	0.26	3.17

(b)

l	9	17	33	65
EER(10^{-3})	3.17	0.39	0.26	1.06

(c)

Var Grad	0.01	0.2	0.5	1
EER(10^{-3})	0.40	0.26	0.26	0.26

(d)

k	0.1	0.2	0.3	0.4
EER(10^{-3})	0.40	0.40	0.26	0.40

(e)

Table 1. Parameter Tuning

3.2. Parameter Tuning

There are five parameters affecting the performance of the proposed directional filter: Window_Size [m n], 1D median filter length L, normalized edge point gradient direction variance Var_Grad, and intensity change k. Experimentally the best parameters are

$$[m \ n \ L \ Var_Grad \ k] = [16 \ 32 \ 33 \ 0.5 \ 0.3]$$

Table 1 shows some EER results by varying each of the parameters in turn around this chosen operating point. It is seen that the performance is quite sensitive to all parameter settings except *Var_Grad*.

3.2. Results on the MIT

With the Monroe algorithm, the CRR remains 100% after eyelash removal. However the EER is reduced significantly, from 1.59×10^{-3} to 2.6×10^{-4} , almost six times smaller than before the eyelash removal. Figure 7 shows the Receiver Operating Characteristic (ROC) before and after eyelash removal. This is obtained by altering the weighted Hamming distance threshold to achieve a desired FAR. [9]. Without eyelash removal there is one False Rejection at a FAR of about 10^{-2} .

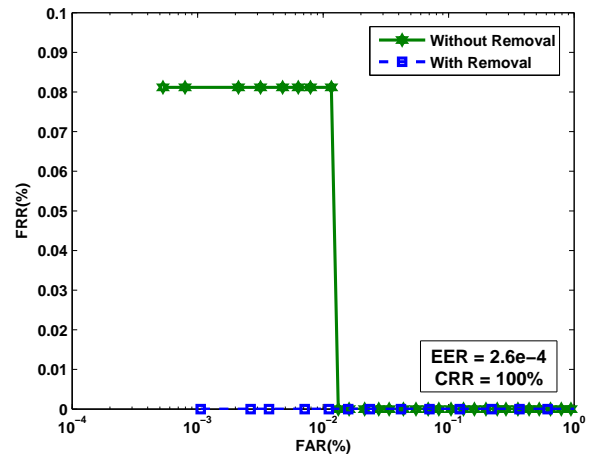
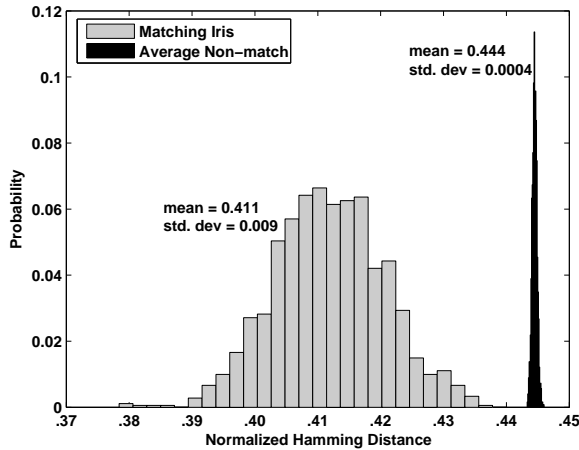


Figure 7. ROC Curves with the Monroe iris coding method, with and without eyelash removal.

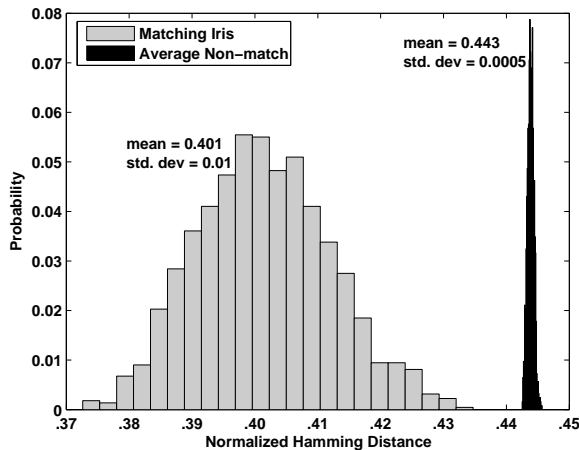
In evaluating performance, comparison between stored images and test images can be divided into matching and non-matching categories and the Hamming distances displayed for each. If these sets are well separated, the system will work well on verification and recognition. The EER of an iris recognition system is the probability at which the two distributions intersect. A decidability index d is often used to measure the separation of two distributions:

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

Where μ_1 and μ_2 are the means of the distributions and σ_1 and σ_2 are their standard deviations. Figure 8 shows that the matching distribution is shifted towards lower Hamming distances, as would be expected, and the decidability shifts from 5.2638 to 5.6594, indicating an improvement in the performance of the system, which could also be seen from inspection of the two distributions.



(a) Distribution without eyelash removal ($d=5.2638$)



(b) Distribution after eyelash removal ($d=5.6594$)

Figure 8. Effect of eyelash removal on Monroe's method

3.3. Results on the methods of Daugman and Tan

Among the many iris coding systems, those of Daugman [5] and Tan [6] are among the best known and the most competitive with our work. Daugman's algorithm uses phase variation derived from Gabor filtering within images [5], and Tan proposed a local sharp intensity based method

after wavelet decomposition [6]. With the methods of Daugman and Tan applied to the CASIA images both with and without our eyelash filtering, we obtained the results given in Table 2.

	Daugman	Tan	Monro
Unfiltered	6.91	3.13	1.59
Filtered	6.61	0.53	0.26

Table 2. EER Comparisons ($\times 10^{-3}$)

4. CONCLUSIONS

The eyelash removal method proposed in this work has achieved a significant improvement in the matching performance of two of the three iris recognition methods tested. By detecting the direction of an occluding eyelash, we are able to replace affected pixels by intensity values that reproduce local image texture well enough to allow the region to be included in the coding of an iris. The results suggest that the performance of any system would benefit from the use of similar methods.

5. ACKNOWLEDGMENTS

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6. REFERENCES

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