Accurate Iris Segmentation Based on Novel Reflection and Eyelash Detection Model

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ABSTRACT

In this paper, we propose a novel noise detection model for accurate segmentation of an iris. Eyelash, eyelid and reflection are three main noises. Eyelid had been solved by traditional eye model; however, eyelash and reflection do not been regarded. To determinate a pixel in an eyelash, our model follows the three criterions: 1) separable eyelash condition, 2) non-informative condition and 3) connective criterion. The first and second condition handle separable and multiple eyelashes respectively. The last criterion avoids misclassification of strong iris texture as a single and separable eyelash. For reflection, strong reflection points are detected by a threshold and the weak reflection points around the strong points are determined by connective criterion and statistical test. A number of images are selected to evaluate the accuracy and necessity of our noise detection model and the results are encouraging.

1. INTRODUCTION

Automatic personal identification using iris, iris diagnosis (iridology) and determination of human ocular torsion are three applications that require accuracy segment iris [1-2, 7]. It is widely accepted that iris is modeled by two circles for pupil and limbus (outer boundary of an iris), and two parabolas for upper and lower eyelids. This model has been used in several areas including iris recognition, eye tracking and animation [1, 4-6]. However, eyelash and reflection detection does not been considered. If the eyelashes or reflection were considered as part of iris, for automatic personal identification, the accuracy would be reduced. This problem is especially serious for small eye person with dense eyelashes or huge area of reflection because the percentage of classifying noise as iris is large.

In the present paper, we develop a noise detection model for accurate iris segmentation, which is divided into two parts, eyelash detection model and reflection detection model. Eyelash detection model relies on three criterions: 1) separable eyelash condition, 2) non-informative condition and 3) connective criterion. Separable eyelash and multiple eyelashes are handled by the first and second condition respectively. The last criterion avoids misclassification of strong iris texture as a single and separable eyelash. Reflection detection model based on two tests. The first test recognizes the strong reflection and the second test classifies the weak reflection around the strong reflection.

In this paper, the traditional iris model is reviewed in section 2 and our eyelash and reflection detection models are discussed in Section 3 and 4 respectively. Experimental results are demonstrated in Section 5. Finally, conclusions are given in Section 6.

2. TRADITIONAL MODEL

Generally, an eye would be modeled by two circles, pupil and limbus, and two parabolas, upper and lower eyelids. The circles can be defined as,

$$(x-x_i)^2+(y-y_i)^2=r_i^2, \qquad (1)$$

where (x_i, y_i) is the center and r_i is its radius ($i = p, l$; p – pupil and l – limbus). The two parabolas have the following general form,

$$(-(x-h_j)\sin q_j+(y-k_j)\cos q_j)^2=a_j((x-h_j)\cos q_j+(y-k_j)\sin q_j), \qquad (2)$$

where a_j (< 0) controls the curvature of a parabola, (h_j,k_j) is the vertex of the parabola and q_j is the principle angle between x-axis and principle axis of the parabola ($j = m, n$; m – upper eyelids and n – lower eyelids).

Fitting the contours of pupil, limbus, upper and lower eyelids can be divided into two steps. First, an image would be convoluted by a lowpass filter, such as a two-dimensional Gaussian. Then, a gradient operator, $(\nabla \equiv (\partial/\partial x\ \partial/\partial y)$, is imposed to select the edge points. Mathematically, it can be represented by $|\nabla G(x,y) * f(x,y)|$, where $G(x, y)$ is a two-dimensional lowerpass filter and $f(x, y)$ is a raw image. If any point in the magnitude of the image intensity gradient is greater than a certain threshold, it is considered as an edge point. Hough transform can be applied to find out the three parameters, (x_p, y_p, r_p) [3]. Fig. 1 shows an eye which is implemented this traditional segmentation technique. Similar techniques are able to determinate the parameters in the parabolas.

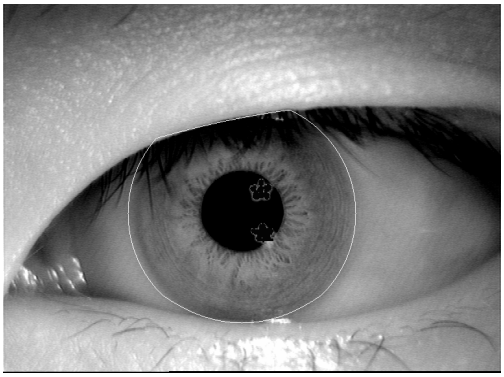


Fig. 1 Illustration of traditional iris segmentation technique

3. EYELASH DETECTION

There are two types of eyelashes in our eyelash detection model (see Fig. 2). One is a separable eyelash that can be distinguished from other eyelashes. Another is multiple eyelash type. It is defined that a lot of eyelashes overlap in a small area so they are impossible to separate.

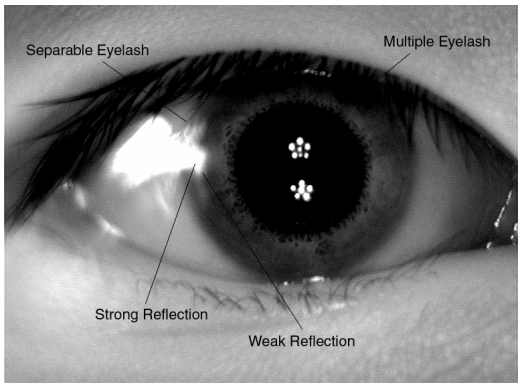


Fig.2 Demonstration of the two types of eyelashes and reflections

Separable Eyelash Condition

A real part of a Gabar filter captures the separable eyelash such a 1-D Gabor filter in the spatial domain has the following general form,

$$G(x,u,s) = \exp\{x^2/2s^2\}\cos(2pux) , \qquad (3)$$

where u is the frequency of the sinusoidal wave, and s is the standard derivation of the Gaussian envelope. The convolution of a separable eyelash with $G(x,u,s)$ would be very small. Thus, if a resultant point is smaller than a threshold, it is noted that this point belongs to an eyelash. Mathematically, it can be represented by

$$f(x) * G(x,u,s) < K_1 , \qquad (4)$$

where K_1 is a pre-defined threshold and $*$ represents convolution.

Non-Informative Condition

This condition manages multiple eyelashes. When a lot of eyelashes overlap in a small area, the variance of intensity is very small. Thus, if the variance of intensity in a small window is smaller a threshold, the center of the window is considered as a point in an eyelash. This criterion is described below,

$$\frac{\sum_{i=-N}^{N}\sum_{j=-N}^{N}(f(x+i,y+j)-M)^2}{(2N+1)^2-1} < K_2 , \qquad (5)$$

where M is mean of intensity in a small window, $(2N+1)$ is the size of the window and K_2 is a threshold. In the following experiments, the window size is 5 by 5.

Connective Criterion

In order to provide more robust and high accuracy detection method, the connective property avoids misclassification from the previous criterions. Each point in an eyelash should connect to another point in an eyelash or to an eyelid. If any point fulfills one of the two previous criterions, its neighbor pixels require to check whether they belong to an eyelash or eyelid. If none of the neighbor pixels has been classified as a point in an eyelid or in eyelashes, it does not consider as a pixel in an eyelash.

4. REFLECTION DETECTION MODEL

We roughly give two definitions for strong and weak reflection (see Fig. 2). A pixel belongs to strong reflection which intensity is large than a certain threshold. Weak reflection is a transition from strong reflection to iris. Mathematically, strong reflection is recognized by the following inequality,

$$f(x,y)<K_3, \qquad (6)$$

where $f(x,y)$ is the intensity of a image at point (x,y) and K_3 is a threshold which is 180 in our following experiments.

According to our discovery, intensity of an iris image is close to a normal distribution. A cumulative distribution of an iris image and a cumulative normal distribution is shown in Fig. 3. Strictly speaking, according to Kolmogorov – Smirnov goodness of test, the intensity of an iris does not follow normal distribution [8]. Since it is close to normal distribution, we still propose to impose statistical to determinate weak reflection points. The statistical test is based on the inequality,

$$m+a s<f(x,y), \qquad (7)$$

where m and s are mean and standard deviation of the distribution of intensity of an iris, α is parameter to control false type I and type II error. If any point around strong reflection and satisfy equation 7, it will be noted as a weak reflection point. According to Eq. 7, we need to estimate m and s; generally m and s are approximated by

sample mean, $\overline{X}$ and sample standard deviation *S*. $\overline{X}$ and *S* are computed from the general formulae,

$$\overline{X} = \frac{\sum_{(x,y)\in P} f(x,y)}{N_P}, \quad (8)$$

$$S = \sqrt{\frac{\sum_{(x,y)\in P} f^2(x,y) - N_p \overline{X}^2}{N_p - 1}}, \quad (9)$$

where *P* represents a set of pixels which belong to iris and do not influence by any noise such as eyelash, reflection and N_p is number of pixels in set *P*.

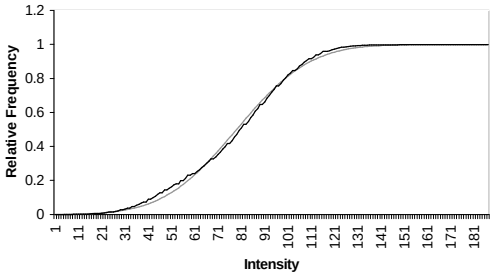


Fig. 3 Comparison between cumulative distribution of a normal distribution and a cumulative distribution of intensity of an iris image. The gray and black curves represent the normal and iris's distribution respectively. Their means and standard deviations are same.

Originally we want to detect weak reflection points. Then, we formulate the problem to a statistical test. To perform the test, we need to estimate the mean and standard deviation by $\overline{X}$ and *S*. In order compute accurate $\overline{X}$ and *S*, we need construct a set *P*. Actually the set *P* is originally what we want. Our formulation looks like to form a close loop. In fact, it can be solved by iterative approach. The steps briefly describe below:

1) Set $P=P_j$ and $j=0$. P_j is a set of pixels which do not belong to eyelash, strong reflection and eyelid. Based on Eq. 8 and 9 to compute, $\overline{X}_j$ and S_j. Let Q_j be a set of pixels which all of them belong to strong reflection.
2) According to Eq. 7, test all pixels in set P_j which connected any pixel in set Q_j. If a pixel, *x*, satisfies Eq 7, it is removed from set P_j and is inserted to set Q_j. Update the $\overline{X}_j$, S_j and N_j bases on the following equations,

$$N_{jnew} = N_j - 1, \quad (10)$$

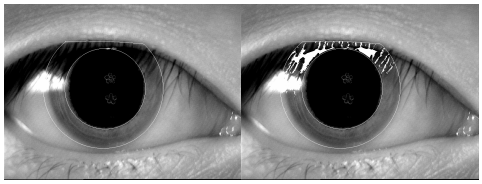
$$\overline{X}_{jnew} = \frac{\overline{X}_j N_j - x}{N_{jnew}}, \quad (11)$$

$$S_{jnew} = \sqrt{\frac{N_{jnew}(S_j^2 - \overline{X}_{jnew}^2) + N_j \overline{X}_j^2 - x^2}{N_{jnew} - 1}}, \quad (12)$$

3) If none of pixels is removed from P_j in step 2, set $P=P_j$ and exit the loop. Otherwise, repeat step 2.

5. EXPERIMENTAL RESULT

Many different irises have been selected to test the proposed model. Fig 4 is a typical example. Fig. Fig. 4(a) and Fig. 4(b) give the segmentation result using traditional model without and with proposed noise detection model respectively. The white region in Fig. 4(b) is masked as eyelashes detected and reflection by our model. Comparing Fig. 4(a) and Fig. 4(b), a lot of eyelash and reflection points remain inside the segmented area in Fig. 4(a) but in Fig. 4(b), almost all the eyelash and reflection point are recognized by the proposed model. The result image demonstrates the effective and accuracy of our model.



(a) (b)

Fig. 3 Different segmented results from traditional model with and without proposed model (a) Result from traditional model, (b) Result using proposed model.

Detection Error Test

In the last two experiments, we concentrate to test the eyelash detection model. This experiment investigates the accuracy of proposed model. Seven images are captured from the same person with different percentages of eyelashes to cover her iris. The experimental result shows in Table 1. The percentages of eyelashes to cover her iris and detection error show in column 2 and 3 respectively. Two images, number 1 and 2, do not have any eyelashes which will be treat as a reference point in next experiment; other of them have different percentage of eyelashes. The detection errors mentioned in last column. The maximum detection error in the testing images is 4%. In this small database, our model is accuracy.

Table 1: Percentages of eyelashes cover the iris and detection error.

Image No	Percentages of eyelashes Covers iris	Detection Error
1	0%	0%
2	0%	0%
3	15%	2%
4	18%	2%
5	21%	2%
6	21%	4%
7	22%	3%

Identification Test

The purpose of this test is to investigate the effect of propose model for iris recognition. We have

developed an iris recognition system to test our model. It is divided in four parts and briefly describes below:

1) Segmentation — Detect and segment the iris.
2) Normalization — Normalize the light effect and size of iris.
3) Feature Extraction — Texture information is captured by 12 2-D Gobar filters with different set of parameters. The filtered images are decomposed to a lot of small regions. The mean of texture energy in each small region is considered as feature. It is defined as,

$$E_{kR} = \frac{\sum_{(x,y)\in R} I_k[x,y]^2}{n_R}, \quad (13)$$

where I_k is a filtered image, R is a small region and n_R is number of pixels in a small region.

4) Matching —The matching score of two different images are defined as,

$$S_{ij} = \sum_{R\in A} \left| E_{iR} - E_{jR} \right|, \quad (14)$$

where i, j are represented two irises, A is a set of all small region.

In this experiment, same set of images is tested. All the images are compared with first image since it does not have any eyelashes.

The traditional iris segmentation technique is applied in step 1 and the matching scores are displayed in Table 2, column 2. The matching score S_{12} is a reference point. Even though two images do not have any eyelashes, their matching score is not zero. According to Table 1, column 2 and Table 2, column 2, the matching scores increase with respect to the percentages of eyelashes covering iris. The last column of Table 2 are the matching scores which generated by using proposed model in step 1. The matching score is stable about 0.06 no matter how to increase the percentages of eyelashes covering iris. One special case, S_{17} with proposed detection model is less than half of S_{17} only using traditional model. The experimental results demonstrate that our detection model is necessary for iris recognition.

Table 2: Summary of recognition score from traditional iris segment model with and without our proposed detection model.

Different match up	Matching Score based on Traditional iris segment model	Matching Score with Proposed Detection Model
S_{12}	0.050	0.050
S_{13}	0.076	0.064
S_{14}	0.077	0.060
S_{15}	0.090	0.062
S_{16}	0.098	0.061
S_{17}	0.095	0.043

6. CONCLUSION

A novel noise detection model has been developed and reported in this paper, which concentrates on eyelash and reflection detection. Eyelash classification bases on three conditions for, separable eyelash, non-informative condition and connective condition and reflection detection relies on a threshold and iterative statistical test. A number of images are selected to evaluate the accuracy and necessity of our eyelash detection model and the results are encouraging.

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