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Accurate Iris Segmentation Method for Non-Cooperative Iris Recognition System

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Abstract: Problem statement: Iris segmentation is one of the most important steps in iris recognition system and determines the accuracy of matching. Most segmentation methods in the literature assumed that the inner and outer boundaries of the iris were circular. Hence, they focus on determining model parameters that best fit these hypotheses. This is a source of error, since the iris boundaries were not exactly circles. **Approach:** In this study we proposed an accurate iris segmentation method that employs Chan-Vese active contour method to extract the iris from his surrounding structures. **Results:** The proposed method was implemented and tested on the challenging UBIRIS database the results indicated the efficacy of the proposed method. **Conclusion:** The experimental results showed that the proposed method localized the iris area probably even when the eyelids occlude same part of iris.

Key words: Iris segmentation, adaboost detection, Chan-Vese active contours

INTRODUCTION

With the increasing demands of security in our daily life, the systems for person recognition based on biometric features have broad applications in both commercial and security areas. As a promising topic of biometric, iris has distinct advantages. Since the degree of freedom of iris textures is extremely high, the probability of finding two identical irises is close to zero, therefore, the iris recognition systems are very reliable and could be used in most secure places (Boles and Boashash, 1998; Camus and Wildes, 2002; Daugman, 1993).

Iris segmentation is to locate the valid part of the iris for iris biometrics (Daugman, 2007), including finding the pupillary and limbic boundaries of the iris, localizing its upper and lower eyelids if they occlude and detecting and excluding any superimposed occlusions of eyelashes, shadows or reflections. Each algorithm of iris recognition system begins with iris segmentation. It is reported that most failures to match in iris recognition system result from inaccurate iris segmentation (Ma *et al*., 2004).

However, several challenges are noted in practical iris segmentation. For example, iris is often partially occluded by eyelids, eyelashes and specular reflections. In the present study, we consider a non-cooperative technique where the user has no active participation in the image-capture process (Proenc and Alexandre, 2006).

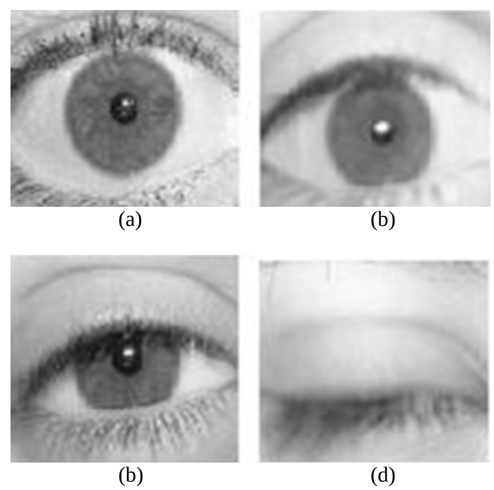

Fig. 1: Non-cooperative iris images: (a) good quality image, (b) poor iris image, (c) iris occlusion by eyelids and (d) close eye

Obviously, these image-capture conditions tend to acquire images with more heterogeneous characteristics regarding focus, contrast, brightness, reflections and eyelid or eyelashes obstruction parameters. Figure 1 shows some example of non-cooperative iris images.

Related work:

Daugman's method: The best known and thoroughly examined iris segmentation method is Daugman

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(2001) method. Daugman (2001) introduced a circular edge detection operator for iris localization, as follows:

$$\max(_{r,x0,y0})\,|\,G_\sigma(r) * \frac{\partial}{\partial r}\oint_{r,x0,y0}\frac{I(x,y)}{2\pi r}ds\,| \qquad (1)$$

The operator search over the image domain (x,y) for the maximum in the blurred derivative with respect to increasing radius r, of the normalized contour integral of I(x,y) along a circular arc ds of radius r and center (x_0, y_0). The symbol * donates convolution and G(r) is a Gaussian filter used as a smoothing function. It is obvious that the results are inner and outer boundaries of iris. First, the inner boundary is localized, due to the significant contrast between iris and pupil regions. Then, outer boundary is detected, using the same operator with different radius and parameters.

Hough transform: Wildes (1997); Kong and Zhang (2001) and Ma *et al*. (2004) use Hough transform to localize irises. It uses the gradient-based Hough transform to decide the two circular boundaries of an iris. It includes two steps. First a binary edge map is generated by using a Gaussian filter. Then, votes in a circular Hough space are analyzed to estimate the three parameters of one circle (x_0, y_0 , r). A Hough space is defined as:

$$H\,(x_0,y_0,r) = \sum_i H(x_i, y_i, x_0, y_0, r) \qquad (2)$$

Where:

(x_i, y_i) = is an edge pixel and

$$H(x_i, y_i, x_0, y_0, r) = \begin{cases} 1 \text{ if } (x_i, y_i) \text{ is on the circle } (x_0, y_0, r) \\ 0 \text{ otherwise} \end{cases}$$

The location (x_0, y_0 ,r) with the maximum value of H (x_0, y_0 ,r) is chosen as the parameter vector for the strongest circular boundary.

Other segmentation methods: Other researchers use methods similar to the described segmentation methods. Tisse *et al*. (2002) proposed a segmentation method based on Integro-differential and the Hough transform. Huang *et al*. (2003) proceeded to iris segmentation by simple filtering, edge detection and Hough transform. (Proenc and Alexandre, 2006) proposed a preprocessing method which applies the fuzzy k-means clustering algorithm on the position and intensity feature vector of the iris image flowed by Hough transform. Our previous study (Yahya and Nordin, 2008), proposed iris segmentation by direct least squares fitting of ellipses.

Having analyzed the accuracy of above mentioned methods, we can state the following remarks and drawbacks:

- Usually, the inner and outer boundaries are detected by circle fitting techniques. This is a source of error, since the iris boundaries are not exactly circles
- In almost all of these methods, inner and outer boundaries, eyelashes and eyelid are detected in different steps

Considering these remarks, we propose a new iris segmentation methodology faithfully detecting and modeling those boundaries whatever their shapes based on active contour method.

METERIALS AND METHODS

Overview: The general idea of proposed algorithm and its main processing steps are illustrate in Fig. 2. The procedure of iris segmentation in the eye image starts from loading the image from a file and finding reflections. Next the input eye image is preprocessed by filling in the segmented reflections based on image inpainting technique. Then the Adaboost-Cascade Detector is adopted to detect the iris region in the eye image and to determine that the eye is not closed. Next, the Chan-Vese active contours method is applied to find the inner and outer boundaries of iris.

Removing specular reflection: Usually, specular reflection appears as the brightest area in the iris image and almost has maximal intensity values. However, specular reflections are a major cause of errors in iris recognition systems because of the fact that the affected iris pixels cannot be used for recognition. In this case, these bright spots are a cause of segmentation error as high texture values are assigned to the pixels surrounding these points which are in turn segmented as eyelashes. In this study we adopt an image imprinting technique to remove the sepecular reflection form the input image. Figure 3 gives an example of reflection removable.

Adaboost-cascade iris detector: After reflection removable we applied the Adaboost-cascade detector technique (Chan and Vese, 2001) based on iris detection our objective is to identify the iris and determine its position, forth more, we performed the initialize image for active contour.

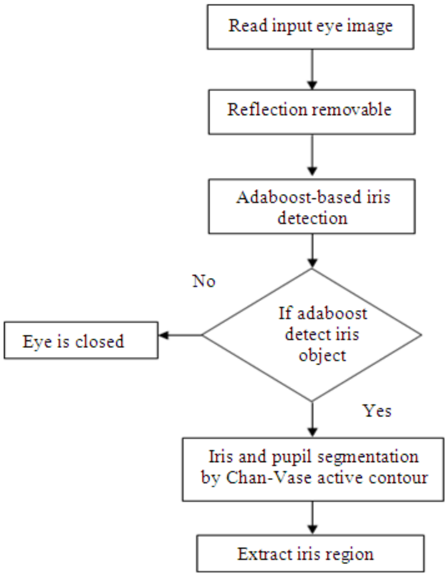
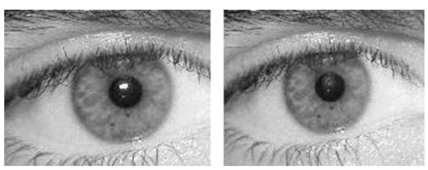


Fig. 2: Overall procedure of the new proposed method

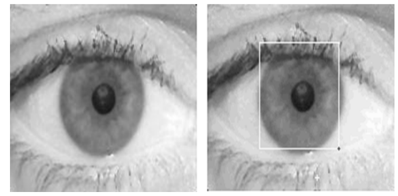


(a) (b)

Fig. 3: Illustration of reflection removal, (a) original image, (b) the iris image after specular reflection removable

The adaptive boosting (AdaBoost) is an algorithm that constructs a strong classifier by coupling the weak classifiers (Friedman *et al*., 2000). This algorithm takes a lot of time to learn weak classifiers, but it has advantages such as fast detection speed and good classification performance (Viola and Jones, 2004). In the training stage of the Adaboost-cascade iris detector, 2228 positive samples and 2000 negative images are collected to serve as the training set. Here, each positive sample is a re-sampled region of interest of the iris image with a size of 20*20, while negative samples can be any non-iris Images. Figure 4 gives an example of Adaboos-based iris detection.

Chan-Vese active contours model: The technique of active contours has become quite popular for a variety of applications, particularly image segmentation and motion tracking, during the last decade. This methodology is based upon the utilization of deformable contours which conform to various object shapes and motions.



(a) (b)

Fig. 4: An example of Adaboost-based iris detection: Iris image, (b) result of Adaboost detection

The Chan-Vese Active Contour Model was proposed by Chan and Vese (2001) using the Momford-Shah segmentation model (Mumford and Shah, 1989; Mumford and Shah, 1985), the model moves deformable contours minimizing an energy function instead of searching edges.

Let the evolving curve C in Ω be the boundary of an open subject ω of Ω (i.e., $\omega \subset \Omega$ and $C = \partial \omega$). The region inside C is represented by ω and $\Omega \backslash \bar{\omega}$ denotes the region outside C. The basic idea of the Chan-Vese model is as follows: Assume that the image u_n is formed by two approximately piecewise-constant regions with intensities u_n^i and u_n^o. Further, assume that the object to be detected is represented by the region with intensity u_n^i. Let C denote its boundary. Thus, we have $u_o \approx u_n^o$ outside C and u0 $\approx u_n^i$ inside C. Consider an energy function

$$E = F1(C) + F2(C) \tag{3}$$

Where:

$$F1(C) = \int_{\text{inside } C} u_0(x,y) - C1^2 dxdy \tag{4}$$

$$F2(C) = \int_{\text{outside} C} u_o(x,y) - C2^2 dxdy \tag{5}$$

Here C is on the boundary of the object, i.e., it is the fittest curve C, the energy function gets the minimum.

$$E_{min} = \inf(F1(C) + F2(C) \approx 0 \approx F1(C_0) + F2(C_0) \tag{6}$$

Obviously:

$F1(C) > 0$ and $F2(C) \approx 0$ C outside the object
$F1(C) \approx 0$ and $F2(C) > 0$ C inside the object
$F1(C) > 0$ and $F2 > 0$ C both inside and outside the object
$F1(C) \approx 0$ and $F2(C) \approx 0$ Con the boundary of the object

(a) (b) (c) (d)

Fig. 5: Example of all possible cases in the position of the curve

Figure 5 gives an explanation of Chan-Vese Model. The energy function gets the minimum only when the curve is on the boundary of the object. Minimizing the energy function and adding some regularizing terms, Chan and Vese (2001) proposed the energy function $F(C, C_1, C_2)$ defined by:

$$\begin{aligned} F(C, C_1, C_2) = {} & \mu.\text{Lengh}(C) + \nu.\text{Area}(\text{inside}(C)) \\ & + \lambda_1 \int_{\text{inside}(C)} \left|\mu_0(x, y) - C_1 dxdy \right. \\ & \int_{\text{outside}(C)} \mu_0(x, y) - C2 \left| dxdy \right. \end{aligned} \quad (7)$$

where, μ, ν, λ_1 and λ_2 are fixed parameters, $\mu > 0, v > 0, \lambda_{>0} \text{and} \lambda_2 > 0$.

One important feature of Chan-Vese active contours model is their ability to detect objects with edges that are not necessarily defined by gradient or with smooth boundaries and its initial contour can be placed anywhere in the image and robust to noise.

RESULTS

We perform experiments to measure the effectiveness of the proposed method. It is detailed as follows.

Dataset: The performance of the proposed method is evaluated on the UBIRIS eye image database. The UBIRIS (Proenc and Alexandre, 2005) database was built during September 2004. It comprised 1877 images captured from 241 persons in two distinct sessions: 1214 images in the first and 663 in the second. The images with size 600×800 pixels were saved in JPEG format with lossless compression. The images in the database are classified with respect to three parameters (‘Focus’, ‘Reflections’ and ‘Visible Iris’) in a three value scale (‘Good’, ‘Average’ and ‘Bad’). This classification was obtained manually and the results were: Focus (Good = 73.83%, Average = 17.53%, Bad = 8.63%), reflections (Good = 58.87%, Average = 36.78%, Bad = 4.34%) and visible iris (Good = 36.73%, Average = 47.83%, Bad = 5.44%).

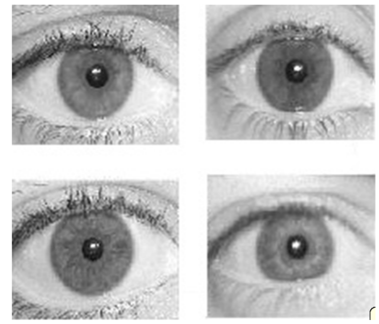
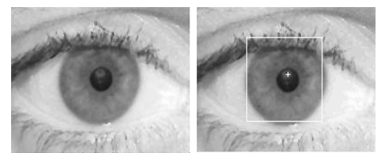


Fig. 6: Sample UBIRIS images



(a) (b)

Fig. 7: Illustration of iris detection and estimated center, (a) original image, (b) result of iris detection where the reticle denotes the estimated of the iris center and the square is an indicator of the size of the iris

The iris test images for the study are chosen from the UBIRIS database because the images are taken under non-cooperative environment. Figure 6 shows some sample images from UBIRIS dataset.

Estimation of iris center: We calculate the approximate center of iris based of iris detection method. Using this technique, the initial point for active contour is performed around the approximate center, as it is shown in Fig. 7.

Iris segmentation: After estimating the center of the iris, the contour initialized around the iris center and continues to move minimizing the energy function until the energy function gets the minimum (only when the curve is on the iris boundary in our case).

Figure 8 shows the result of applying the proposed method to some irises with boundaries partly occluded by eyelashes and eyelids. As it can be seen in this Fig. 8, iris locations have been found correctly.

Performance evaluation: Here, we demonstrate the efficiency and usefulness of the proposed methods via iris recognition accuracy. During the test, each iris image in the considered test database is segmented by three techniques proposed method; Integro-differential operator (Daugman, 2001) and Hough transform (Wildes, 1997).

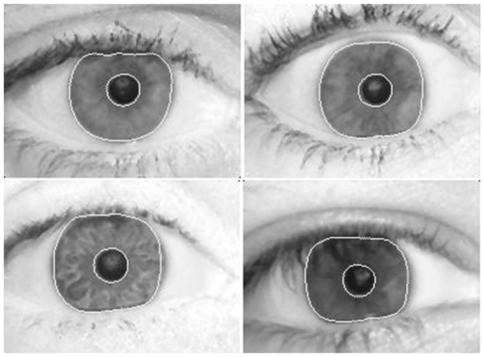


Fig. 8: Example of iris segmentation using the proposed method

Table 1: Comparison of previous methods and proposed

Methods	ERR
Integro-differential operator (Daugman, 2001)	16.8635
Hough transforms (Wildes, 1997)	33.8226
Proposed	5.5068

After segmentation, the iris images are processed with identical unwrapping and encoding modules. In our experiments 1-D log polar Gabor transform (Vatsa *et al.*, 2008) is adopted to encode the iris texture. Accordingly, Hamming Distance (HD) is adopted as the metric of dissimilarity between two considered codes code A and code B.

The performance of iris recognition is estimated with the Equal Error Rate (EER). The lower the EER value, the higher is the performance of the iris recognition. From Table 1, we can see the performance of the proposed method is much better than Integro-differential operator and Hough transform. It obtains the highest recognition rate (smallest EER).

DISCUSSION

From the Table 1, it is clear that the proposed method achieved the lower EER for the non-cooperative dataset UBIRIS. Upon analyzing the performance, it was found that, the iris outer boundary is often partly occluded by eyelids, and the iris inner boundary may be partly occluded by reflections from illumination. This is the reason for false matching when eyelids areas are taken is the iris region. The proposed method based on active contour method prove an excellent way to detect the iris boundaries.

CONCLUSION

In this study, an accurate iris segmentation method for non-cooperative iris images has been proposed, which uses AdaBoost iris detector to excluded non-iris image before further processing so that unnecessary computation is avoided. In addition, a rough iris center is extracted in iris images, which provides important cues for contour initialized. Also, the proposed method uses the Chan-Vese model to detect the inner and outer boundaries of iris. Experimental results on the UBIRIS non-cooperative dataset clearly indicate that the proposed method localize the iris area probably even when the eyelids occlude same part of iris.

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