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A New Technique for Iris Localization in Iris Recognition Systems

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Abstract: Iris localization is one of the most important steps in iris recognition system and determines the accuracy of matching. In this study, an efficient technique for iris localization is proposed. First, the direct least square fitting of ellipse is used to detect the inner boundaries of iris. Then the integro-differential operator is used to detect the outer boundaries of iris. Experimental results show that the technique has a good performance, which improve the speed and accuracy on iris localization.

Key words: Iris localization, least square fitting of ellipse, integro-differential operator

INTRODUCTION

The use of biometric systems has been increasingly encouraged by both government and private entities in order to replace or improve traditional security systems. The identification systems using unique factors of human irises play an important role in this field. In comparison with other biometrics, iris recognition systems have many 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; Ma *et al*., 2002). One of the most important steps in iris recognition systems is iris localization, which is related to the detection of the exact location and contour of the iris in an image. Obviously, the performance of the identification system is closely related to the precision of the iris localization step (Daugman, 1993, 2001). The previous iris segmentation approaches assume that the boundary of pupil is a circle. However, according to present observation, circle cannot model this boundary accurately. To improve the quality of segmentation, this study proposes a new method based on direct least square fitting of ellipse to locate the inner boundaries of iris. The new algorithm compute fast and has higher locating accuracy. Figure 1 shows original eye image.

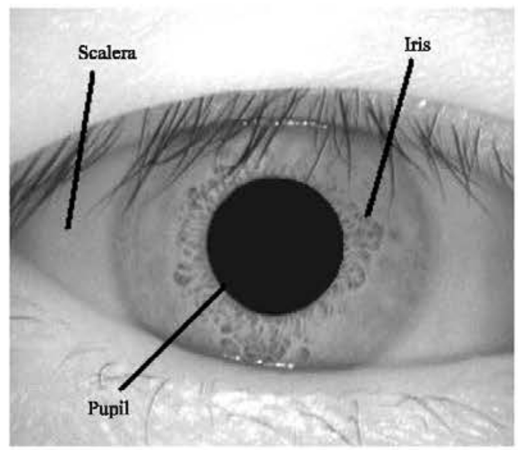

Fig. 1: Sample original eye image

RELATED WORKS IN IRIS LOCALIZATION

Daugman's algorithm: Daugman (1993) introduced a circular edge detection operator for iris localization, as follows:

$$\max_{(r,x_0,y_0)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right| \quad (1)$$

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.* (2002) use Hough transform to localize

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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:

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

Where:

(x_i,y_i) = An edge pixel

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

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. Boles and Boashah (1998) and Lim *et al*. (2001) mainly focused on the iris image representation and feature matching without introducing a new method for segmentation.

Considering the above mentioned methods, we can state the following remarks:

- Usually, the inner boundaries are detected by circle fitting techniques. This is a source of error, since the inner boundaries are not exactly circles
- In noisy situations, the outer boundary of iris does not have sharp edges

In this study, we introduce method based on direct least squares fitting of ellipse to detect the inner boundary of iris. Theoretically, the ellipse model also fits a circular shape. To show the necessity of ellipse fitting for real iris images, Fig. 2 shows an example image from CASIA (Institute of Automation Chinese Academy of Sciences) iris database, localized by different methods. The results in Fig. 2a were obtained using a circle model to fit by Hough transform. It is obvious that a circle does not fit the pupil/iris boundary well. The result in Fig. 2b uses direct ellipse fitting and the boundary is fitted precisely.

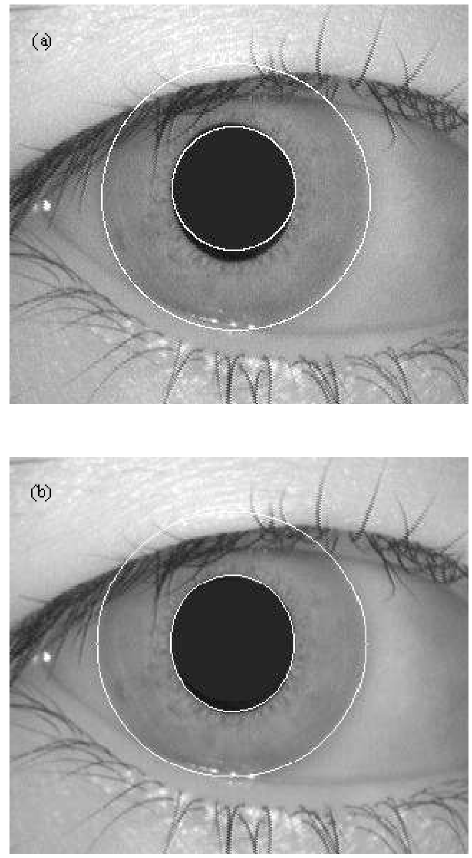


Fig. 2: Iris localization using; (a) circle Hough transform and (b) direct ellipse fitting

DIRECT LEAST SQUARES FITTING OF ELLIPSES

Direct Least Squares fitting of ellipses was proposed by Fitzgibbon *et al*. (1999). The proposed method combines several advantages:

- It is ellipse-specific, so that even bad data will always return an ellipse
- It can be solved naturally by a generalized Eigensystem
- It is extremely robust, efficient and easy to implement
- The method works on segmented data (that means all data points are assumed to belong to one ellipse)

An ellipse is a special case of a general conic which can be described by an implicit second order polynomial;

$$F(x,y) = ax^2+bxy+cy^2+dx+ey+f = 0 \quad (3)$$

with an ellipse-specific constraint;

$$b^2\text{-}4ac<0 \quad (4)$$

where, a, b, c, d, e and f are coefficients of the ellipse and (x,y) are coordinates of points lying on it. The polynomial F(x,y) is called the algebraic distance of the point (x,y) to the given conic. By introducing vectors:

$$a = [a,b,c,d,e,f\,]^T \quad (5)$$

$$x = [x^2,xy,y^2,x,y,1]^T \quad (6)$$

where, T is the transpose of the vector. It can be rewritten to the vector form:

$$F_a(x) = x \cdot a = 0 \quad (7)$$

The fitting of a general conic to a set of points (x_i,y_i); i = 1…..N may be approached (Haralick and Shapiro, 1993) by minimizing the sum of squared algebraic distances of the points to the conic which is represented by coefficients a:

$$\min_a \sum_{i=1}^{N} F(x_i, y_i)^2 = \min_a \sum_{i=1}^{N} (F_a(x_i))^2 \quad (8)$$

$$= \min_a \sum_{i=1}^{N} (x_i \cdot a)^2 \quad (9)$$

The problem (Eq. 9) can be solved directly by the standard least squares approach, but the result of such fitting is a general conic and it needs not to be an ellipse. To ensure an ellipse-specificity of the solution, the appropriate constraint, Eq. 4, has to be considered. That means after getting a, we should insure whether the parameters of a satisfy the Eq. 4.

However, this constrained problem is difficult to solve (Fitzgibbon *et al*., 1999). This problem can be solved by scaling the constraint Eq. 4. Since η.a represent the same conics as a for every real number $\eta \neq 0$, we can scale the a to appropriate scaling and change the inequality constraint Eq. 4 to equality constraint;

$$4ac\text{-}\,b^2 = 1 \quad (10)$$

and we can rewrite the ellipse-specific fitting to the following:

$$\min_a \|Da\|^2 \text{ subject to } a^TCa = 1 \quad (11)$$

where, D is a matrix of size N×6 defined as follow:

$$D = \begin{pmatrix} x_1^2 & x_1y_1 & y_1^2 & x_1 & y_1 & 1 \\ : & : & : & : & : & : \\ x_i^2 & x_iy_i & y_i^2 & x_i & y_i & 1 \\ : & : & : & : & : & : \\ x_N^2 & x_Ny_N & y_N^2 & x_N & y_N & 1 \end{pmatrix} \quad (12)$$

represents Eq. 9 and C is constraint matrix of size 6×6.

$$C = \begin{pmatrix} 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad (13)$$

represents Eq. 10. Equation 11 can be easily solved by a quadratically constrained least squares minimization as proposed by Gander (1980). By applying the lagrange multipliers we get the following conditions for the optimal solution a:

$$\begin{aligned} Sa &= \lambda Ca \\ a^TCa &= 1 \end{aligned} \quad (14)$$

where, S is the scatter matrix of the size 6×6, $S = D^TD$

$$S = \begin{pmatrix} S_{x^4} & S_{x^3y} & S_{x^2y^2} & S_{x^3} & S_{x^2y} & S_{x^2} \\ S_{x^3y} & S_{x^2y^2} & S_{xy^3} & S_{x^2y} & S_{xy^2} & S_{xy} \\ S_{x^2y^2} & S_{xy^3} & S_{y^4} & S_{xy^2} & S_{y^3} & S_{y^2} \\ S_{x3} & S_{x^2y} & S_{xy^2} & S_{x^2} & S_{xy} & S_x \\ S_{x^2y} & S_{xy^2} & S_{y^3} & S_{xy} & S_{y^2} & S_y \\ S_{x^2} & S_{xy} & S_{y^2} & S_x & S_y & S_1 \end{pmatrix} \quad (15)$$

where, S denotes the sum of:

$$S_{x^ay^b} = \sum_{i=1}^{N} x_i^a y_i^b \quad (16)$$

After that, the Eq. 14 is solved by using generalized eigenvectors. The result is six real solutions (λ_j,a_j), but due to Eq. 14 and 15:

$$\|Da\|^2 = a^TD^TDa = a^TSa = \lambda a^TCa = \lambda \quad (17)$$

The eigenvector a_k will be chosen corresponding to the minimal positive eigenvalue λ_k.

Finally, after a proper scaling to ensure $a_k^T C a_k = 1$, we get a solution of the minimization problem (11) which represents the best-fit ellipse for the given set of points. The result of the algorithm is an ellipse with the following measurements.

- The length of the short axis of the ellipse
- The length of the long axis of the ellipse
- The orientation in radians of the ellipse
- The center of the ellipse (x,y)

ALGORITHM STAGES

Iris inner localization: In order to get the pupil area, we should choose a reasonable threshold value. The pupil's regions intensity value are smaller then other region's in the whole eye image, so we analyze the histogram of the original eye image and chose the threshold value. Then we convert the original iris image to the binary image.

For the purpose of clearing operation the following morphological operations are used:

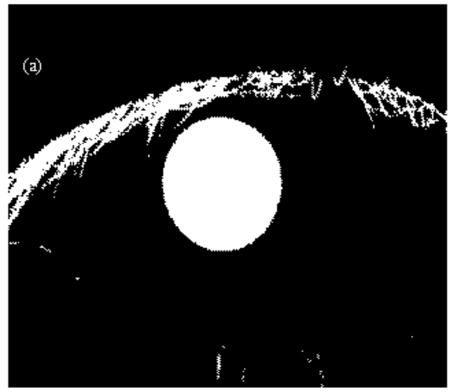
- Morphological opening for clearing out small elements which are present in thresholded image (i.e., eyelashes, eye makeup and others)
- Closing for removing reftections from pupil area (if present); The results are shown in Fig. 3a and b

Then we removed the interior' pixels (foreground pixels that have no background neighbors). Finally, we applied the direct least squares fitting of ellipse to get the ellipse parameters.

Iris onter localization: For outer bounder estimation (iris-scale), histogram equalization is used to enhance the intensity level in the eye image. Next, Daugman's integro-differential operators (Daugman, 1993) is applied. This method found to be efficient and effective in CASIA iris image. Figure 4 shows the detected iuner and outer boundary of an iris.

EXPERIMENTAL RESULTS

We measured the performance of the proposed algorithm with CASIA database (The Institute of Automation, Chinese Academy of Sciences, http://ulpr.ia.ac.cn/english/irds/irisdatabase.htm, accessed on 25.12.2007). The CASIA database contains 756 iris image at (340×280) pixels from 180 eyes of 80 subject. The experiments are done in Matlab on a PC with 1.7 MHz CPU and 1 Gb physical memory.



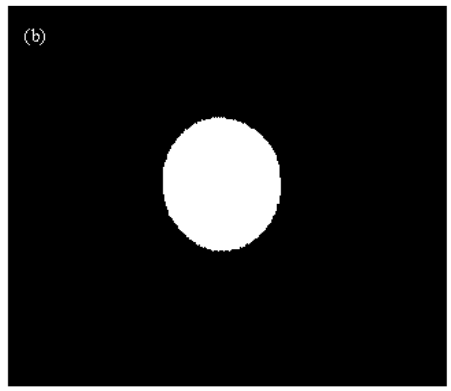


Fig. 3: (a) Binary image and (b) pupil region in binarized image

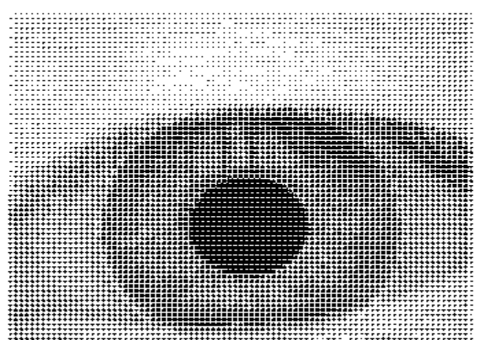


Fig. 4: Sample iris after localization

The proposed direct least squares fitting of ellipse proves its ability to detect inner boundary of the iris. It is estimated 100% success of pupil detection for CASIA database.

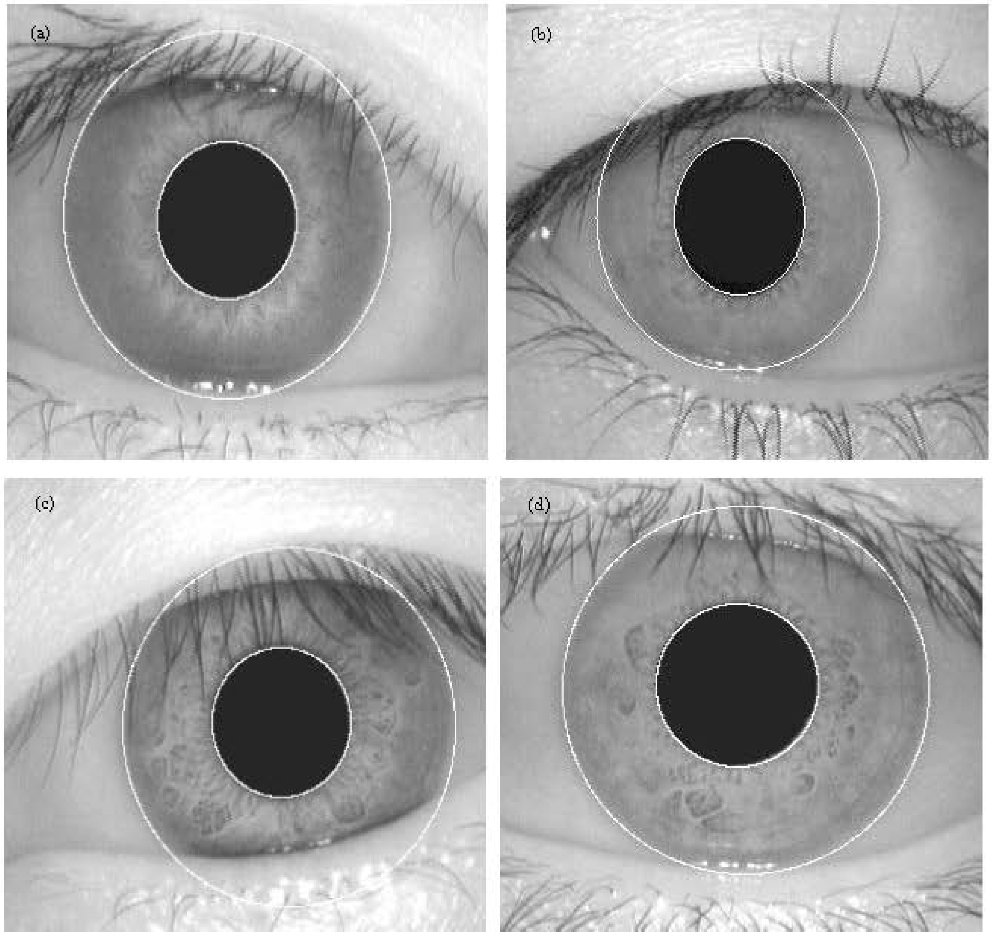


Fig. 5a-d: Examples localization iris images from CASIA database

On the other hand, integro-differential operator works properly on CASIA iris database for outer iris detection. However, the failure may occur due to low contrast, eyelids and eyelashes occlusion. The probability of failure on outer iris detection is around 2% in CASIA iris database and the whole process takes 1.2 second with non-optimize code.

Figure 5a-d shows examples localization images from CASIA database.

CONCLUSION

In this study, we proposed a new method for iris localization in iris recognition system, which improves in accuracy and efficiency. Our images are from CASIA database which, is the largest iris database in the word. In our experiment we use 756 images to process and the result of this image are ideal.

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