Optica Applicata, Vol. XXXIX, No. 2, 2009

Efficient iris segmentation method with support vector domain description

RONGNIAN TANG[1, 2*], JIUQIANG HAN[2], XINMAN ZHANG[2]

[1]Hainan University, School of Mechanical and Electronic Engineering, Baodao Xincun, Danzhou 571737, P.R. China

[2]Xi'an Jiaotong University, School of Electronics and Information Engineering, 28 Xianning West Rd, Xi'an 710049, P.R. China

[*]Corresponding author: Rongnian.Tang@gmail.com

With the aim to improve the performance of iris segmentation method to process images with heterogeneous characteristics, the authors introduce a new method inspired by the support vector domain description (SVDD). A local geometric moment function is used to extract shape features of the iris borders. Then, these features are fed into the trained SVDD classifier for borders recognition followed by the application of Hough transform to solve circumference parameters of iris. The performance of the proposed method and the most cited methods, Daugman's method and Wilders' method, had been tested on the UBIRIS database. Compared with the two existing methods, our proposal is not only comparable to them when the iris image has good quality, but has better segmentation performance in the case of poor quality images. The experimental results show that the method proposed does have a higher robustness and is less dependent on the quality of raw iris image.

Keywords: iris segmentation, local geometric moment, support vector domain description (SVDD), border recognition.

1. Introduction

With the increasing emphasis on security, the technology of biometrics has been extensively used to identify an individual by both government and private entities [1]. Biometrics aims to accurately identify each individual using various physiological or behavioral characteristics [2], and will replace traditional security systems in the future. Recently, iris recognition comes into focus in this area.

The human iris, an annular part between the pupil (the black central area in the eye) and sclera (the white area in the eye) as shown in Fig. 1, provides many interlacing minute characteristics such as furrows, freckles, crypts and coronas which

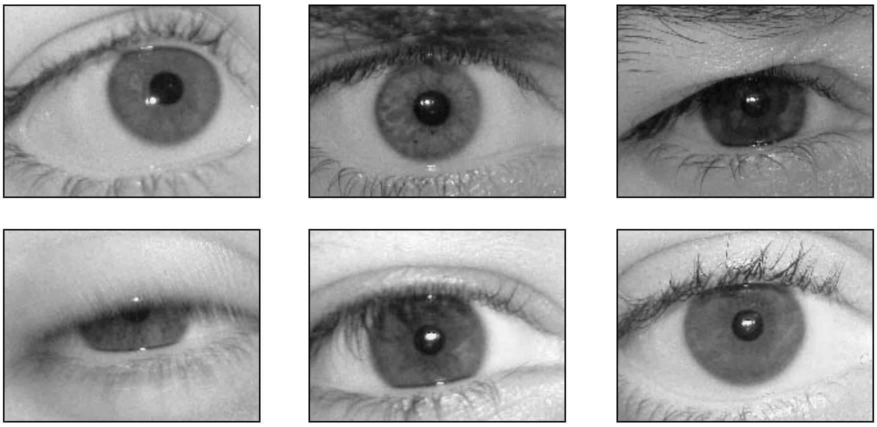

Fig. 1. Sample of iris image.

are used to identify an individual. The suitability of iris as an exceptionally accurate biometric derives from the following: *i*) the texture of iris is highly stable over a person's lifetime; *ii*) iris is an internal organ that is externally visible as well; *iii*) the irises of two eyes of an individual or identical twins are completely independent and uncorrelated; *iv*) iris has rich physical structure and can provide lots of data. So, the iris recognition has some advantages, including high reliability, uniqueness and noninvasiveness. However, despite the safer and quicker access, some critical problems persist and significant work needs to be done before mass-scale deployment on national and international levels can be achieved [3]. Many issues, including system robustness, speed of enrolment and recognition, the accuracy and robustness of iris image segmentation in various environments, *etc.*, remain to be addressed.

In practice, the condition of the environment and that of the lab is not always satisfactory. So, the captured images always have heterogeneous characteristics, being unclear, unfocused or obscured by eyelashes. All this not only disturbs the performance of the existing segmentation methods, but has direct negative effect on the iris recognition system. To improve the robustness of iris segmentation is a challenging task now.

The aim of this paper is to develop a new iris segmentation method which has higher robustness and is computationally efficient and less time-consuming. We first present our intuitive observations about the characteristics of the iris, and then introduce a new segmentation method inspired by the support vector data description (SVDD). Finally, a series of experiments are performed in order to evaluate the method proposed.

The remainder of this paper is organized as follows. Section 2 reviews related work in the area. Section 3 provides detailed descriptions of the theory and steps of the method proposed. The experimental results and discussion are presented in

Section 4. Finally, in Section 5, we draw conclusions and give suggestion for future work.

2. Related work

Much valuable work on iris segmentation was done in the past. In 1987, Flom and Safir discovered that iris morphology would keep stabilization throughout the whole human life, and developed the first relevant method [4]. In 1993, DAUGMAN [5] proposed one of the most famous iris recognition methods, constructed on the basis of modern iris recognition, and proved scientifically the feasibility of iris recognition. For segmentation, DAUGMAN [5–7] introduced an integrodifferential operator to find the inner and outer borders of the iris. The operator searches over the image domain for the maximum in the partial derivative with respect to increasing radius, of the normalized contour integral along a circular arc of radius and centre coordinates.

In 1997, WILDES [8] proposed the iris segmentation method relying on the binary edge-map operation and the Hough transform. The raw image of the iris is converted into a binary edge-map via gradient-based edge detection, then the iris is segmented by Hough transform. In a similar manner, MA *et al.* [9] roughly determine the iris region in advance, and then use the Canny edge detection operator and Hough transform to exactly segment iris.

Like in Daugman's method, CAMUS and WILDES [10] proposed another integrodifferential operator, a component-goodness-of-fit operator, in the polar coordinate system that searched over a three-dimensional space, and the parameters of iris borders were obtained as the equation maximized.

Assuming prior segmentation of iris inner border, DU *et al.* [11] proposed a method to detect the iris outer border. They found the parameters of iris outer border in polar coordinates with the largest horizontal edge resultant from Sobel filtering.

MIRA and MAYER [12] solved this problem with morphological operators. They applied threshold, closing and opening operators to detect the borders of the iris.

Based on the assumption that iris is not a perfect circle, MIYAZAWA *et al.* [13] developed elliptic model to simulate iris shape, and determined iris parameters throughout maximizing the absolute difference of contour summation, of pixel values along the ellipse.

PROENÇA and ALEXANDRE [14] proposed a new iris segmentation method that consists in selecting three discrete features followed by the application of a fuzzy--clustering algorithm.

From the existed literature, we can conclude two major strategies for iris segmentation: one construct the iris edge-map, and the other maximize the specific equations. Both of them are dependent on the specific image characteristics, brightness and contrast, as well as the existence of noise factors (reflections, eyelids and eyelashes, and so on). So, the methods in both classes show perfect performance for high quality iris image, but their performance is seriously degraded when the iris image includes some heterogeneous characteristics.

3. Proposed method

We can see from the iris images that the iris borders are always obscured by eyelashes and eyelids, and it is very difficult to segment the iris and to remove the noise factors only depending on the intensity or brightness of image. Obviously, it is not enough to separate the pixels belonging to the iris from the obscuring element. For a more accurate and robust iris segmentation method, it is inevitable to restrain the noise factors from a new viewpoint as well as find the borders of iris.

In fact, iris borders have regular shape as well as the gradient of the borders. Both them are totally different from that of the obscuring element such as eyelashes and eyelid. Intuitively, if we can extract these features and segment the iris by recognizing corresponding borders, then we will obtain a new method with characteristics and noise factors being less dependent on particular image. Based on this idea, our segmentation method is given in the block diagram of Fig. 2 (with outer border segmentation as an example). The essential point is to make the edge-map less dependent on the specific image characteristics. A SVDD classifier is introduced to construct it.

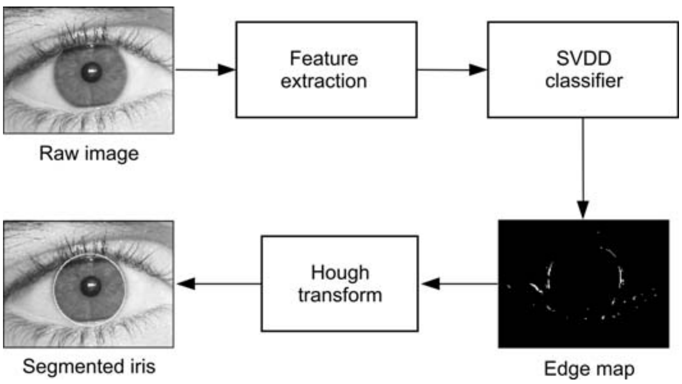

Fig. 2. Block diagram of the method proposed.

The proposed method begins with the feature extraction where feature vectors are extracted for each image pixel. Then SVDD classifier is applied to recognize the edge of iris borders. Finally, the Hough transform is used to complete the circumference detection task.

3.1. Feature extraction

Image moment theory was used to extract the features in our method. It has been widely used in various areas of computer vision and image processing. Calculating moment values, geometric information of an object can be captured easily. Local geometric moment function measures the image characteristics of a pixel neighborhood, and adapts to capture the shape property of iris outer border.

$$w_{pq}(x, y) = \sum_{i=-N}^{N} \sum_{j=-N}^{N} i^p j^q f(x+i, y+j) \tag{1}$$

where, w_{pq} is the local geometric moment, N is the width of windows, $f(x, y)$ is the gray-level value of image.

Besides moment values, the gradient of a pixel is also to be considered. And our feature vector is composed of thirteen discrete components, that is,

$$\mathbf{v_i} = \{g_1, \dots, g_9, w_{10}, w_{01}, w_{20}, w_{02}\} \tag{2}$$

where g_i is the gradient of a 3×3 neighborhood centered as an image pixel, w_{10}, w_{01}, w_{20} and w_{02} are the first order and second order local geometric moments.

In applications, the moment values are obtained using existing masks derived from Eq. (1), and this can efficiently reduce the execution time of the moment function.

3.2. SVDD classifier

The identification of the iris inner and outer borders can be seen as a data domain description problem, with the only need being to obtain a description of iris borders. This description should cover the class of inner or outer borders, and ideally should reject all other possible objects in iris space.

TAX and DUIN [15, 16] proposed a method for data domain description called support vector domain description (SVDD) inspired by support vector machine (SVM) [17], and it was used for novelty outlier detection. The basic concept of SVDD is to describe a class of data by finding a sphere with minimum volume which contains this class of the data. The radius and center are obtained from the support vector which is the results of SVDD training. The data is accepted when its distance from the sphere center is smaller than the radius. Just like SVM, SVDD also becomes more flexible by using different kernels, which in turn induces more accurate description.

The SVDD algorithm makes us realize that we can only use sample of iris borders to train SVDD classifier for inner border or outer border. The SVDD classifier can recognize the iris borders according to the description obtained. We can extend SVDD to our SVDD classifier as below.

Consider a set of instance-label pairs (x_i, y_i), $i = 1, 2, \dots, N$, the samples of which form the same category, where $x_i \in R^n$ and

$$y_i = +1, \qquad i = 1, \dots, N \tag{3}$$

We construct a hypersphere for these samples, then we can get the following quadratic optimization problem:

$$\min\left\{R^2 + C\sum_{i=1}^{N}\xi_i\right\} \tag{4}$$

subject to the constraints

$$y_i\left\|\Phi(x_i) - a\right\|^2 \le R^2 + \xi_i, \qquad \xi_i \ge 0, \qquad i = 1, ..., N \tag{5}$$

where C determines the tradeoff between the volume of the hypersphere and the number of outliers. We introduce the Lagrange multipliers $\alpha_i > 0$ and $\lambda_i > 0$, and get the Lagrangian

$$L = R^2 + C\sum_{i=1}^{N}\xi_i - \sum_{i=1}^{N}\alpha_i\left(R^2 + \xi_i - y_i\left\|\Phi(x_i) - a\right\|^2\right) - \sum_{i=1}^{N}\lambda_i\xi_i \tag{6}$$

Using the Karush–Kuhn–Tucker (KKT) condition, the optimal solution of this optimization problem can be obtained. The kernel trick is used to avoid treating the high-dimensional feature space explicitly. However, as noted in [15, 16], polynomial kernels do not yield tight representations of the clusters, while Gaussian kernels work very well. Then we can design the iris border SVDD classifier

$$f(x) = \operatorname{sgn}\left[R^2 - 1 + 2\sum_i \alpha_i y_i K(x, x_i) - \sum_{i,j}\alpha_i\alpha_j y_i y_j K(x_i, x_j)\right] \tag{7}$$

$$R^2 = \frac{1}{k}\sum_k\left[1 - 2\sum_i \alpha_i K(x_k, x_i) + \sum_{i,j}\alpha_i\alpha_j K(x_i, x_j)\right] \tag{8}$$

where x_k represents support vector and k is the number of support vector.

To test a feature vector, the distance to the center of the sphere has to be calculated. With this SVDD classifier, a pixel i is accepted as the iris inner or outer border if its feature vector $\mathbf{v_i}$ makes $f(\mathbf{v}) > 0$. Figure 3 is an example of outer border segmentation, and the outer border recognized through our SVDD classifier is shown in Fig. 3**b**. Obviously, the majority of iris border can be recognized by the SVDD classifier. We can also see that the SVDD classifier has excellent capacity to suppress the obscuring element. From our edge-map, we can also see that our SVDD classifier has excellent capacity for suppressing the obscuring element.

3.3. Hough transform

As with Wlides' method, Hough transform is used to solve the performance of iris border. However, the Hough transform is more computationally efficient in our method because if hardly has redundancy pixels in the edge-map. From Fig. 3**c**, we can see

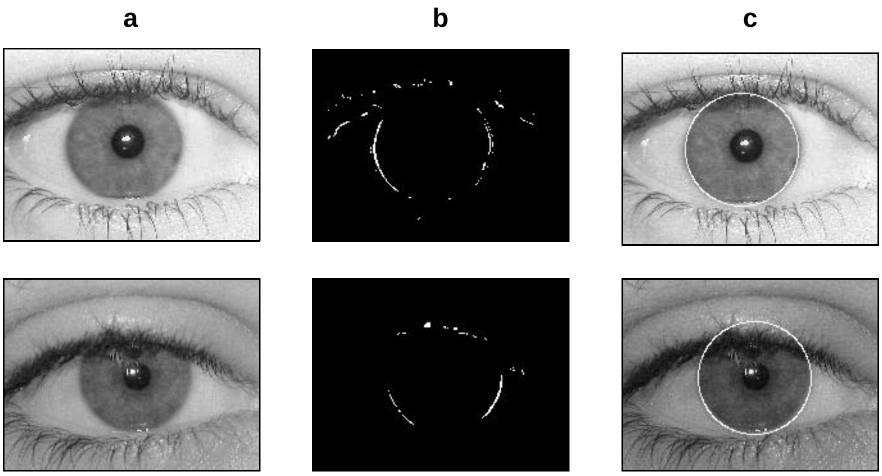

Fig. 3. Example of outer border segmentation.

that the result of Hough transform is accurate and reasonable, and the outer border is segmented properly.

4. Experiments

A series of experiments were designed to test the performance of our method by comparing it to the two most cited methods of Daguman and Wildes. The experiments were conducted on a PC with Celeron 2.6GHz processor, 192MB RAM, and Matlab 7.0 platform.

4.1. Experimental database

UBIRIS database is used in our experiment because it contains lots of images with several types of noise and can simulate the noncooperative environment [18]. The UBIRIS database contains 1877 images which belong to two distinct sessions: 1214 images in the first and 663 in the second one. Table 1 contains the statistical information [14].

4.2. Experiment results

In our experiment, segmentation results are seen as correct when the circumference parameters corresponding to the inner and outer borders almost fall exactly into

Table 1. UBIRIS database statistics.

Quality	Session 1 (%: good, average, bad)	Session 2 (%: good, average, bad)
Focus	(82.94, 13.67, 3.78)	(69.68, 19.45, 10.85)
Reflections area	(94.56, 2.80, 2.63)	(24.13, 38.61, 37.25)
Visible iris area	(89.29, 7.16, 3.45)	(22.32, 69.07, 8.59)

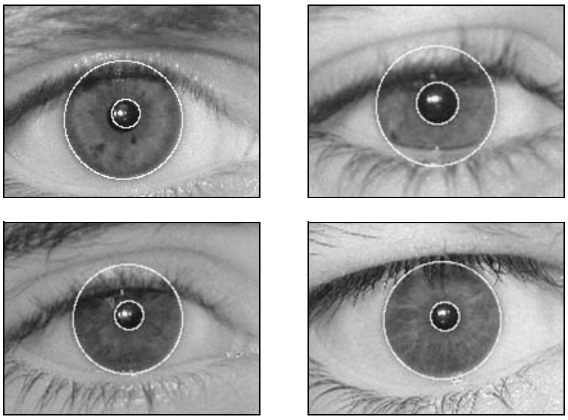

Fig. 4. Segmentation result obtained by our method.

T a b l e 2. Iris segmentation results (CR – correct ratio, T – computation time).

	Session 1		Session 2	
Method	CR [%]	T [s]	CR [%]	T [s]
Daugman	94.87	3.86	90.92	5.02
Wildes	95.66	5.12	90.12	6.84
Proposed	95.51	3.59	94.88	3.97

the respective borders, as we can see in Fig. 4. Or else, the result is considered as unsuccessful segmentation.

In the experiment, the segmentation performance is mainly analyzed by means of two main parameters: correct ratio and average computation time. Here, the existing methods are implemented according to the published papers [5–8]. All of the experimental data are presented in Tab. 2. The first column identifies the method, the second and third specify the correct ratio and averaged computation time of images from the first UBIRIS session, and the fourth and fifth contain the correct ratio and averaged computation time of images from the second UBIRIS session.

From Table 2, we can observe that the proposed method is clearly less dependent on image conditions and correct ratio degradation of the first and second session images was just about 0.63%, which presents the smallest degradation in the presence of noise factors. Although the correct ratio of our method is slightly less than that of Wildes' method of the first session, it should be noticed that our method presented the best results, 94.88%, of the second session. Otherwise, we can see that our method requires the shortest time spending whether the quality of images is good or not. All of the data clearly show that the method proposed is satisfactory and can well deal with images in various conditions.

The results from Daugman's method show that its performance is reasonable of the first image sessions. It can reach 94.87% at 3.86 s. However, the relevant results become clearly degraded as the image quality changes. The correct ratio degradation is 3.95% and the degradation time is 1.16 s. Compared with our method, Daugman's method presents weaker robustness for image quality changing.

Wildes' method gave the best results in absolute terms, having 95.66% correct ratio of the first session images. However, the performance of Wildes' method is degraded seriously as the image quality decreases. Its correct ratio degraded by more than 5% and the time expenditure increased to 1.72 s. These data are totally worse than those of Daugman's method and the method proposed.

From Table 2, we can see that all the methods experience degradation when the image quality changes. But, it is obvious that our method has stronger robustness and satisfactory performance.

5. Conclusions

We analyzed some of the most cited traditional methods in the iris segmentation literature. Performing the experiments on the UBIRIS database, we proved their weak robustness which was induced by their dependence on the specific image-capture conditions.

We proposed a new iris segmentation method which considers the idea of border recognition based on our SVDD classifier. Experimental results showed the encouraging performance of our method in correct ratio, execution time and robustness. Such performance evaluation and comparison not only verify the validity of our observation and understanding of the characteristics of the iris but also provides help for further research.

Acknowledgements – The authors would like to thank Dr. Hugo Pedro Proença (Universidade da Beira Interior, Portugal) and Dr. Luís A. Alexandre (Universidade da Beira Interior, Portugal) for their hard work on the UBIRIS iris image database. The work was supported by a grant from the National Natural Science Foundation of China (No. 60602025), the Ph.D. Programs Foundation of Ministry of Education of China (No. 20050698025).

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Received May 3, 2008