An Incremental Method for Accurate Iris Segmentation

Peihua Li, Xiaomin Liu
School of Computer Science and Technology, Heilongjiang University
Harbin, Hei Long Jiang Province, 150080, China
peihualj@hotmail.com

Abstract

The paper presents an incremental method for accurate iris segmentation. Firstly, observing the characteristics of iris images, we search for a square region that contains pupil within or nearby which a specular highlight lies. Means and standard deviations of both pupil and specular highlight are employed for detection of such a square, and Integral Images are used to accelerate the detection procedure. Next Canny edge detection followed by Hough transform are used for accurate localization of pupillary boundary. Secondly, by seeking points with maximum gradient along two line segments radiating from pupil center, the radius of outer, limbic boundary can be coarsely determined. According to the rough radius, two annulus sectors are found out within which limbic boundary is finely localized by Canny edge detection plus Hough transform as well. The incremental technique reduces region for edge detection and parameter space for Hough transform, facilitating accurate and fast iris segmentation. Experiments on publicly available UBIRIS database show that the proposed method has encouraging performance.

1. Introduction

With an increasing emphasis on security nowadays, biometric technologies are becoming much more important than ever. In particular, iris recognition in recent years receives growing interests. In contrast to other biometrics technologies, such as fingerprint, face or voice recognition, iris recognition has several distinct advantages [3]: iris pattern of an individual is unique and consistently stable, it is noninvasive and enjoys very high recognition rate, among others.

Accurate iris segmentation is an important, prerequisite step for a successful iris recognition system. Two well-known iris segmentation approaches are attributed to Daugman [3] and Wildes [9] respectively. In his pioneering paper [3], Daugman developed integro-differential operator to find cicular pupil and limbus boundaries. It can be interpreted as a circular edge detector, which searches, in a smoothed image by Gaussian filter, the parameters of a circular boundary along which the integral derivative is maximal. Wildes proposes a two-stage iris segmentation method [9]: a gradient based binary edge map is first constructed from the intensity image, and next the inner and outer boundaries are detected via Hough transform.

Daugman's and Wildes' methods are very influential and dominate the basic ideas for iris segmentation. However, as pointed out by Wildes [9], both methods are likely to get poor results if more clutter is involved or the subjects are less cooperative. Modern biometrics recognition systems are required to need as little cooperation of the subject as possible and thus should be able to deal with heterogeneous characteristics of iris images. Proença et al. [7] introduced unsupervised clustering algorithms to segment the original intensity image and then a method similar to Wildes' is applied. That method has proven to be robust in the presence of heterogeneous and noisy images. Liu et al. [5] proposed an improved iris segmentation method, which concerns localizing inner then outer boundaries, reducing edge points that are not on the boundaries of pupil and limbus, and improving Hough transform etc. In [4], Huang et al. developed a method where edge and region information are combined and noise is also removed. Other related techniques are omitted here, and a comprehensive review is referred to [1].

Despite diverse algorithms proposed, accurate and robust iris segmentation still remains to be far from perfectly resolved, especially in challenging conditions. We contribute to this field by proposing an incremental method, which uses idea of focus of attention: first pupillary and then limbic boundaries, in each stage, raw localization is followed by fine positioning. The reason we first localizing inner boundary is that the pupil together with specular highlight have approximately uniform gray-levels, and are spatially adjacent. The incre-

978-1-4244-2175-6/08/$25.00 ©2008 IEEE

mental strategy facilitates accurate edge detection involved and also decrease parameter spaces of Hough transform. This idea leads to a new method for a progressive, accurate iris segmentation approach.

The remainder of this paper is organized as follows. Section 2 details the proposed method. Experimental results are provided in Section 3. And finally section 4 gives conclusion.

2. The proposed method

Our iris segmentation approach mainly consists of two steps: 1) roughly locating a square region that contains pupil, followed by Canny edge detection plus Hough transform for accurate pupillary boundary localization; 2) roughly localizing two annulus sectors in which limbic boundary is finely positioned.

2.1. Localizing pupillary boundary

In an iris image, a pupil region and a specular highlight region have approximately uniform low and high gray-levels respectively, and one neighbors the other. The means and standard deviations (STDs) of both regions are compactly distributed. Some iris images are chosen from UBIRIS database [6] and their statistics are learned. Figures 1(a), 1(b), 1(c) and 1(d) show respectively the histograms of the mean and standard deviation (STD) of pupil regions, and those of specular highlights. We can determine the ranges of means and STDs of pupil and specular highlight, denoted respectively as $[Tl_{PM}, Th_{PM}]$, $[Tl_{PV}, Th_{PV}]$, $[Tl_{HM}, Th_{HM}]$ and $[Tl_{HV}, Th_{HV}]$. Take the mean of pupil as an example, using a univariate Gaussian $G(\mu, \sigma)$ to fit its distribution, we can select $Tl_{PM} = \mu - 4\sigma$ and $Th_{PM} = \mu + 4\sigma$.

For the purpose of rough localization of pupil, we start to scan the whole iris image using varying-size squares, searching for a set of candidate regions $Sp = \{sp_1, sp_2, ..., sp_n\}$ that may contain pupil, as shown in Figure 2(a), whose means and STDs are in the intervals $[Tl_{PM}, Th_{PM}]$ and $[Tl_{PV}, Th_{PV}]$. For each of the candidate regions, we scan further to look for possible existence of a sub-region with much smaller size, whose means and STDs are respectively in the intervals $[Tl_{HM}, Th_{HM}]$ and $[Tl_{HV}, Th_{HV}]$. The regions that do not satisfy this criterion are eliminated from the set Sp, and we hence obtain a much smaller subset Sh of Sp in which each contains a specular highlight. Please refer to Figure 2(b) for the set Sh. Finally the position of these candidate regions is averaged to get a final square, as shown in 2(c), which is enlarged 50% in size to obtain the raw region that contains pupil.

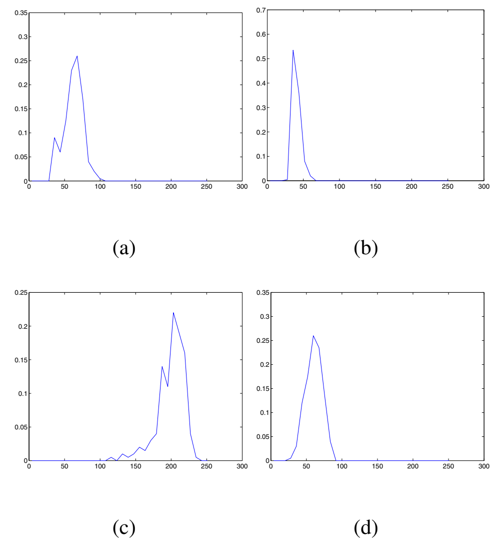


Figure 1: Statistics of pupil and specular highlight. Top row: histograms of pupil mean (a) and STD (b). Bottom row: histograms of mean (c) and STD (d) specular highlight.

It is obvious when searching for the set Sp and then Sh, we need to calculate the mean and STD of every square under consideration, which has high computational cost. Fortunately, by the concept of Integral Images [8], we can leverage greatly the computational load. We construct the Integral Images of mean and variance in one pass of the original iris image, through which the mean and variance (and thus standard deviation) can be computed by four array references respectively. In addition, we can further restrict the searching scales of both "pupil square" and "specular highlight square". As a result of these strategies the rough localization process is time efficient.

It is straightforward to locate the inner circle that describes pupillary boundary accurately after getting the rough location of the pupil. First, Canny edge detection [2] is used to generate an edge map of the sub-image that contains pupil. Then Hough transform is applied to the edge map for obtaining the parameters of the inner circle. Figures 2(d) and 2(e) give respectively edge map of the sub-image and fine localization of the pupil.

2.2. Locating limbic boundary

On the basis of the inner circle center, we can estimate roughly the outer circle radius along two line segments slightly below the horizontal line, as shown in Figure 3(a). Figure 3(b) plots a 1D signal filtered with Gaussian along the right line segment. After the 1D signal is filtered, the first derivative of the filtered signal

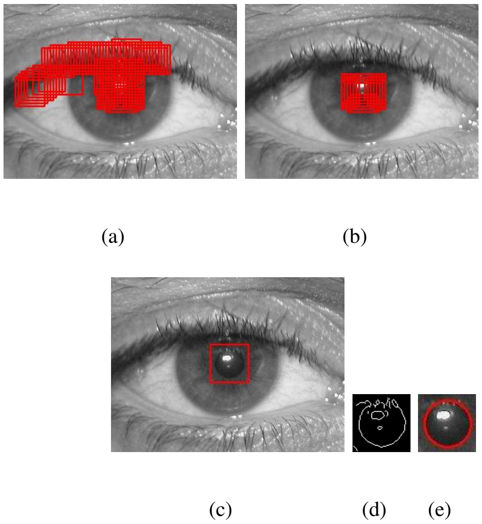


Figure 2: Pupillary boundary localization. Top row: the set Sp (a) and Sh (b). Bottom row: the final square containing pupil (c), edge map (d) after Canny edge detection and inner circle (e) after Hough transform.

is computed discretely with central difference, as illustrated in Figure 3(c). It can be clearly seen that the point with the maximum derivative is on the limbic boundary.

The crude radius R of the outer circle is adopted as an average of those obtained from the left and right line segments. Subsequently two symmetric annulus sectors are determined ranging within the interval $[-26.5°, 45°]$, $[135°, 206.5°]$, with the inner radius $0.8R$ and outer radius $1.2R$ respectively. Canny edge detection plus Hough transform are applied to both annulus sectors. In this way, we avoid possible occlusions of eyelids or eyelashes, besides, Canny edge detector is more accurate constrained in these annulus sectors. Note that only vertical edge is considered. The two annulus sectors and the edge detection results are respectively shown in Figures 3(d) and 3(e).

As we have already obtained the center and radius of pupil, it is possible to restrict both the center and radius of outer circle characterizing limbic boundary to small ranges. This can greatly reduce computational cost of Hough transform. An example of iris segmentation can be seen in Figure 3(f).

3. Experiments

Among some Iris databases public available, UBIRIS database [6] is employed in which iris images have much more heterogeneous characteristics involving large illumination changes, bad focus, severe image noises etc. UBIRIS database consists of two sessions, in which session 1 comprises 1214 iris images, and session 2 is more challenging, comprising 663 images.

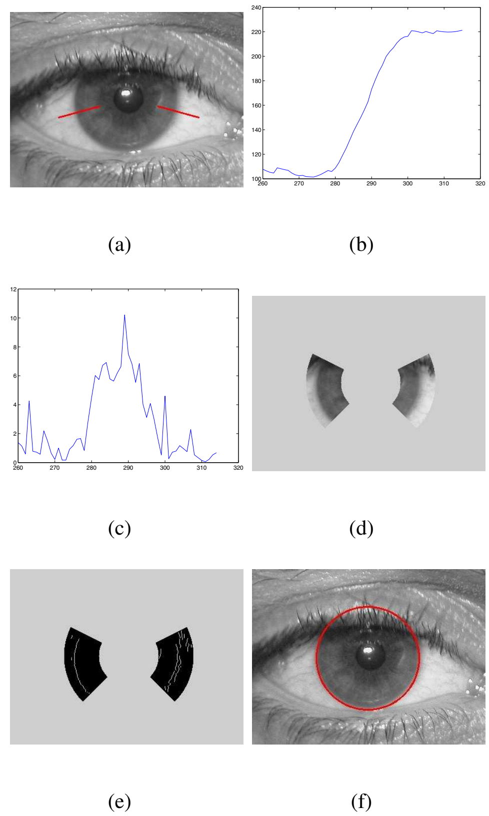


Figure 3: Limbic boundary localization. Top row: the left and right line segments (a) and filtered 1D signal (b) along the right one. Middle row: gradient of 1D signal (c) and the annulus sectors (d). Bottom row: edge map (e) and outer circle (f).

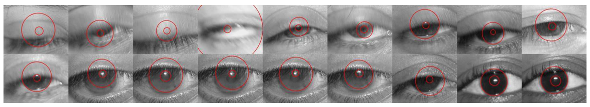
200 iris images selected from Session 1 are used for training to obtain the ranges of means and STDs of pupil and specular highlight, and the remaining 1014 images are used for testing. Note that the parameters learned are applied directly to Session 2 without any adjustment.

For the purpose of comparison, Wildes' algorithm is implemented with Matlab and tested in this database. Cases of segmentation failure are determined visually. Table 1 lists accurate rates of iris segmentation using both algorithms.

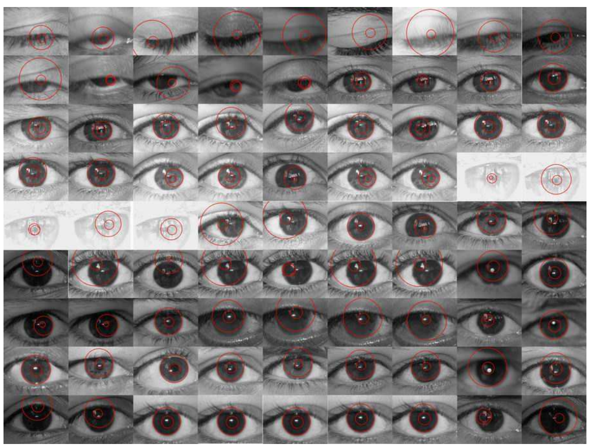
Table 1: Accurate rate of iris segmentation

Method	Session 1	Session 2	Time (s)
Proposed	98.13%	87.48%	0.65 (C++)
Wildes	86.64%	73.26%	3.60 (Matlab)

The failure of Wildes' method is mainly because it is difficult to determine appropriate threshold when edge detection is done in the whole iris image. There are roughly three reasons accounting for failure of our approach: one is that the eyes are completely or almost completely closed; the second is poor quality of images due to illumination change, bad focus or noise; and the third is inaccurate rough localization of pupillary boundary. Figures 4(a) and 4(b) show respectively results (18 out of 19) of inaccurate iris segmentation in session 1, and those (81 out of 83) in session 2.



(a) Inaccurate iris segmentation in Session 1



(b) Inaccurate iris segmentation in Session 2

Figure 4: Inaccurate segmentation in UBIRIS database

To testify the robustness of the proposed method to ranges learned, as discussed in section 2.1, we enlarge all the four intervals by 20%, and run the program again. Table 2 shows results, from which we can see when enlarging the ranges, accurate rate decreases slightly, less than 1% in Session 1 and less than 0.5% in Session 2.

Table 2: Accurate rate *vs* ranges of mean and STD

Interval	Session 1	Session 2	Time (s)
Original	98.13%	87.48%	0.65 (C++)
Enlarge 20%	97.40%	87.16%	0.67 (C++)

4. Conclusion

The paper proposed an incremental iris segmentation method. According to mean and STD of pupil and specular highlight and their spatial relationship, pupil position is crudely localized, followed by Canny edge detection and Hough transform for accurate positioning of iris boundary. After that, we roughly determine two annulus sectors which contain parts of iris boundary. In these two annulus sections we perform similar edge detection plus Hough transform for fine localization. The strategy of incremental focus of attention from rawness to fineness not only reduces computations, but also make localization more accurate. Experiments on UBIRIS database show encouraging results. Future research is to develop methods for localizing eyelids and for eliminating eyelashes.

Acknowledgements

The work was supported by the National Natural Science Foundation of China under Grant 60673110 and Natural Science Foundation of Heilongjiang Province (F200512), supported in part by Program for New Century Excellent Talents of Heilongjiang Province (1153-NCET-002), Sci. & Tech. Research Project of Educational Bureau of Heilongjiang Province (1151G033), the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry and Ministry of Personnel of China, Sci. and Tech. Innovation Research Project (2006RFLXG030) of Harbin Sci. & Tech. Bureau.

References

[1] K. W. Bowyer, K. Hollingsworth, and P. J. Flynn. Image understanding for iris biometrics: a survey. *Computer Vision and Image Understanding*, 2008, to appear.

[2] J. Canny. A computational approach to edge detection. *IEEE Trans. Pattern Anal. Mach. Intell.*, 8(6):679–698, 1986.

[3] J. G. Daugman. High confidence visual recognition of persons by a test of statistical independence. *IEEE Trans. Pattern Anal. Mach. Intell*, 15(11):1148–1160, 1993.

[4] J. Huang, Y. Wang, T. Tan, and J. Cui. A new iris segmentation method for recognition. In *Int. Conf. on Pattern Recognition*, pages 554–557, 2004.

[5] X. Liu, K. Bowyer, and P. Flynn. Experiments with an improved iris segmentation algorithm. In *IEEE Workshop on Automatic Identification Advanced Technologies (AutoID)*, pages 118–123, 2005.

[6] H. Proença and L. A. Alexandre. UBIRIS: A noisy iris image database. *Int. Conf. on Image Analysis and Processing (ICIAP)*, pages 970–977, 2005.

[7] H. Proença and L. A. Alexandre. Iris segmentation methodology for non-cooperative recognition. *IEE Proc.-Vision, Image and Signal Processing*, 153(2):199–205, 2006.

[8] P. Viola and M. Jones. Rapid object detection using a boosted cascade of simple features. In *Int. Conf. on Computer Vision and Pattern Recognition*, pages 511–518, 2001.

[9] R. P. Wildes. Iris recognition:an emerging biometric technology. *Proc. IEEE*, 85(9):1348–1363, 1997.