Detecting Iris Lacunae Based on Gaussian Filter

Bo Shen, Yong Xu, Guangming Lu, David Zhang

Bio-computing Research Center, Dept. of Computer Science, Harbin Institute of Technology Shenzhen Graduate School, China

Abstract

Lacunae is a typical sign of iris, and the detection of lacunae is of great importance in automatic iris diagnosis. In this paper, we first introduce the lacunae detection in iris images. Although current literature has a variety of edge detection algorithms, they do not always lead to acceptable results in extracting various features in an image. Lacunae usually have poor local contrast and the application of existing edge detection algorithms yield results which are not satisfactory. Thus, we proposed a lacunae detecting approach based on Gaussian filters, which is robust to noise. When the Gaussian filter in the vertical orientation is implemented to normalized iris image, the time complexity of this approach is reduced considerably. Experimental results show the validity of this approach.

Keywords: *Iridology, Gaussian filter, lacunae detection*

1. Introduction

As an organ of human body, iris plays an important role not only in identity identification, but also in medical diagnosis. In the west, iridology has a history more than one hundred years, and it has become a more completed system. Iridology is a technology to diagnose diseases by investigating iris and is the study of the patterns and markings in the iris. Iridology involves the use of an optic microscope to analyze the color and markings of the iris to determine patient health. It is harmless, non-invasive, applies no radiation or medicines, and is painless, quick and inexpensive. Before the human organ shows symptoms of illness, the iris can appear some signs to predict the illness. According to the iridology, the iris can reflect the healthy state of the human organs [1, 2, 3].

In traditional iris diagnosis, the doctor firstly uses a microscope and a slit lamp to examine the patient's iris, and then identifies symptoms on the basis of professional knowledge, finally makes a handwritten record of the examination. Obviously, this process has some faults. The slit lamp is tiring for the eyes of both doctor and patient. And the examination and identification are very subjective and dependent on the experience of the doctors. In order to deal with these problems, we can use the digital image processing and pattern recognition technologies to implement an automated iris diagnosis system.

There are six pathological signs in iridology [2]: crypt, lacunae, spots, lines, color and density. Through analyzing the changes of the texture and the color of an individual iris, we can know the health status of the person. In this paper, we study the lacunae pathological feature of iris from structural pattern, and proposed an effective method based on Gaussian filter to detect lacunae in iris image.

As an important sign of iris, lacunae is the symptoms of chronic disease. For example, chronic nephritis will result in the appearance of lacunae in the adrenal gland region of iris; when a person caught a cough or chronic bronchitis, the lacunae would appeared in the lung region of iris; if a person is suffering from waist pain, there would be lacunae pass through the waist region on his iris. The deeper the lacunae color is, the more toxins are accumulated, and the blood circulation of the corresponding organ will slower, which may cause brain dysfunction. The toxins of lacunae are from intestines, which is caused by long period of digestion and excretion function disorders. Therefore, the research on iris lacunae detection is an important technique of automatic iris diagnosis.

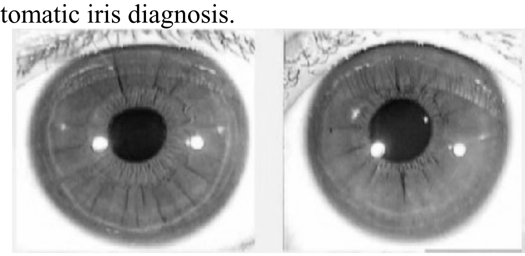


Figure 1. Iris lacuna signs

In iridology, lacunae extend outward from inner boundary to outer boundary of iris, and is likely to appear in the whole iris area [2]. Figure 1. shows some lacunae in iris image, which have poor local contrast. Traditional edge extraction methods have often extracted the image edge using an operator such as that of Robert, Prewitt and canny

[8, 9, 10]. But the texture of the iris is too complicated to be divided, so these operators are unsuitable for lacunae detection. In this paper, we will use Gaussian filters proposed in [4] to model iris lacunae and name this lacunae detecting approach as LDoG.

2. Lacunae Detection

By observing the cross-sections of iris lacunae, we found that they are Gaussian-shaped lines. Fig 3 shows some cross-sections of the iris lacunae. Based on this observation, the matched filter proposed in [4,5] can be used to detect lacunae. The matched filter is defined as

$$g_\phi(x,y) = -\exp\left(-\frac{x'^2}{2\delta_x^2}\right) - m, \quad for\ |x'| \le 3\delta_x, |y'| \le L/2 \tag{1}$$

$$x' = x\cos\phi + y\sin\phi \tag{2}$$

$$y' = -x\sin\phi + y\cos\phi \tag{3}$$

where ϕ is the filter direction, δ is standard deviation of Gaussian, m is the mean value of the filter, L is the length of the filter in y direction which is set according to experience, and the filter is truncated at $|x'| \le 3\delta_x$, $|y'| \le L/2$ in [4]. So this filter can be regarded as Gaussian filter in x direction.

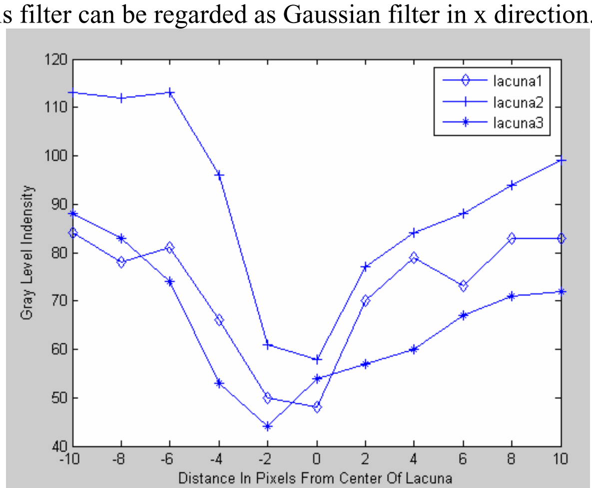


Figure 2. Cross-section of iris lacunae

Since lacunae is likely to appear in any direction, different templates in all possible orientations are necessary. According to experience, the proposed scheme with 12 templates was necessary in order to achieve high performance. However, the enhancement of performance is along with a sacrifice in speed.

In iris recognition , Daugman [7] projects the original iris in a Cartesian coordinate system into a doubly dimensionless pseudo-polar coordinate system to normalize irises of different size to the same size. Similar to this scheme, we counterclockwise unwrap the iris ring to a rectangular block with a fixed size. Such unwrapping can be denoted as:

$$I_n(X,Y) = I_o(x,y) \tag{6}$$

$$\begin{cases} x = x_p + r\cos\theta \\ y = y_p + r\sin\theta \end{cases} \tag{7}$$

$$r = Y(r_i - r_p)/M + r_p \tag{8}$$

$$\theta = 2\pi X / N \tag{9}$$

where I_n is a $M \times N$ (128×512 in our experiments) normalized image; (x_p, y_p) is the coordinates of the inner boundary center in the original image I_0; r_p and r_i are the radii of the inner and outer boundary.

The normalization not only reduces to a certain extent the iris distortion caused by pupil movement but also simplifies subsequent processing. Since Iris lacunae travel radially outward from inner edge like solar radial, lacunae become perpendicular to the x-axis in polar coordinate image. Fig. 4(b) shows the result of iris normalization.

Now, apply the Gaussian filter in y direction to the normalized image, we can get the gradient image shown in Fig. 4(c). Then use a threshold, T_p, to convert this original image into a binary image as shown in Figure. 4(f). Mathematically, this transformation can be represented as

$$B(x,y) = 1 \quad if\ O(x,y) * g_{\pi/2}(x,y) \ge T_p \tag{4}$$

$$B(x,y) = 0 \quad if\ O(x,y) * g_{\pi/2}(x,y) < T_p \tag{5}$$

where $B(x,y)$ and $O(x,y)$ are the binary image and the normalized image, respectively; $g_{\pi/2}(x,y)$ is the matched filter in y direction, and "*" represents an operator of convolution.

As shown in Fig. 4(d), the lacunae in binary image are too thick to be described, so the lacunae need to be converted into 1-pixel width lines. Here, we introduce an approach based on the thinning algorithm proposed in [5] to thin binary image.

p_8	p_1	p_2
p_7	p_0	p_3
p_6	p_5	p_4

Figure 3. Neighborhood arrangement used by the thinning algorithm

The thinning algorithm includes the following 2 steps:

Step 1: Flag the point that satisfy the conditions:

$$((2 \le N(p_0) \le 6)\ \&\&(T(p_0)=1)$$
$$\&\&(p_1 \cdot p_3 \cdot p_7 = 0)\ \&\&(p_1 \cdot p_5 \cdot p_7 = 0))$$
$$\|((T(p_0)=2)\ \&\&(p_1 \cdot p_7 = 1)\ \&\&(p_3 = 0)\ \&\&(p_5 = 0)\ \&\&(p_8 = 0))$$
$$\|((T(p_0)=2)\ \&\&(p_5 \cdot p_7 = 1)\ \&\&(p_1 = 0)\ \&\&(p_3 = 0)\ \&\&(p_6 = 0))$$

where $N(p_0)$ is the number of non-zero neighbor points of p_0, $T(p_0)$ is the changing times of the values of the sequence $p_1 p_2 \cdots p_8 p_1$. After all the points of whole image are flagged, delete all the flagged points.

Step 2: Flag the points that satisfy the condition:

$$((2 \le N(p_0) \le 6)\ \&\&(T(p_0)=1)$$
$$\&\&(p_1 \cdot p_3 \cdot p_5 = 0)\ \&\&(p_3 \cdot p_5 \cdot p_7 = 0)$$
$$\|\ ((T(p_0)=2)\ \&\&(p_3 \cdot p_5 = 1)\ \&\&(p_1 = 0)\ \&\&(p_4 = 0)\ \&\&(p_7 = 0))$$
$$\|\ ((T(p_0)=2)\ \&\&(p_1 \cdot p_3 = 1)\ \&\&(p_2 = 0)\ \&\&(p_5 = 0)\ \&\&(p_7 = 0))$$

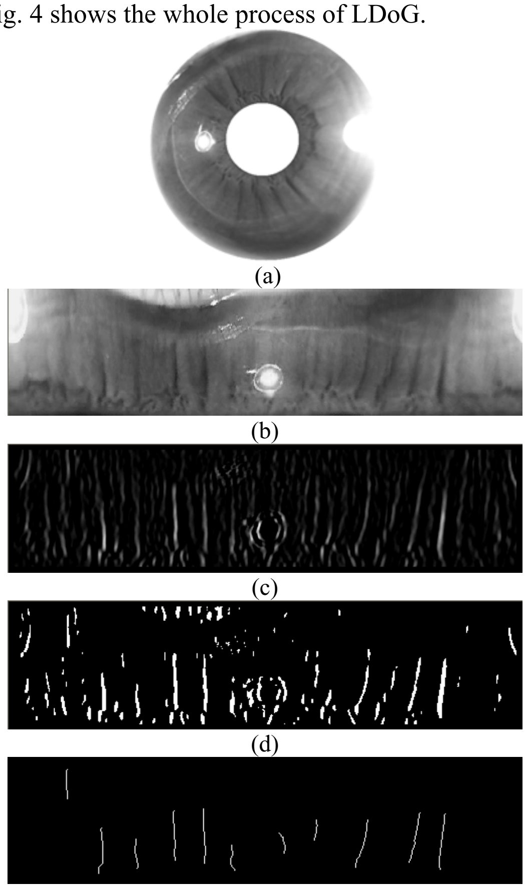
After all the points of whole image are flagged, delete all the flagged points.

Repeat the two steps above until there is no flagged point. We can get 1-pixel width lacunae by eliminating isolated points and short profiles.

To sum up, the LDoG include the following 4 steps:

(1) Normalize iris image;
(2) Filter normalized iris image using Gaussian filter in vertical orientation;
(3) Binarize filtered image;
(4) Thin binarized image and eliminate useless profiles.

Fig. 4 shows the whole process of LDoG.



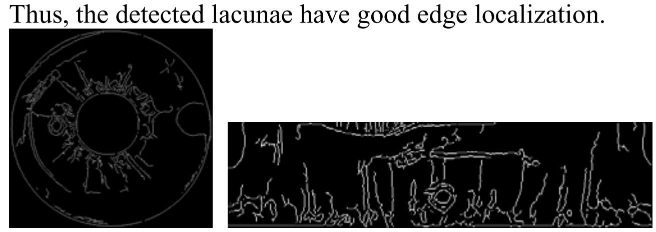
(a) (b) (c) (d) (e)

Figure 4. The process of LDoG; (a)Original iris image; (b) Normalized image; (c) Result of Gaussian filter in vertical orientation; (d) Binarized image; (e) Thinned image.

3. Experiments

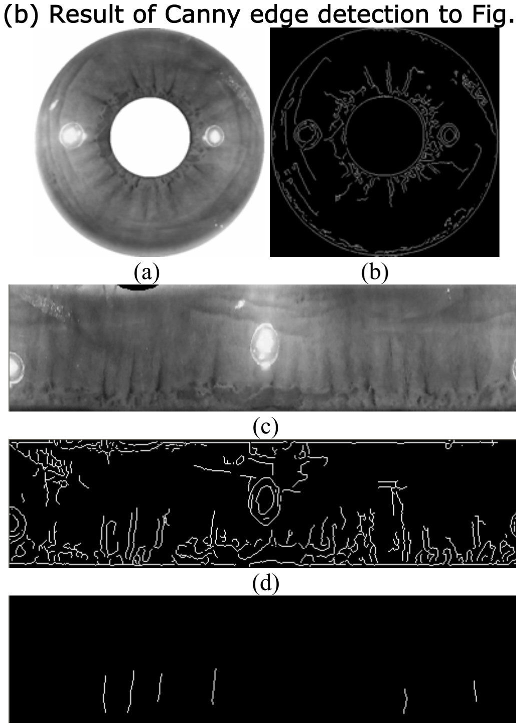
An original iris image is given in Fig. 4(a), and the result of the application of LDoG is given in Fig. 4(e). For this case, we choose $\delta_x = 2$ and $L = 9$. The original image was smoothed by a 5×5 mean filter to reduce the effect of spurious noise. The Canny operator [10] were also applied to the same image, and the corresponding filtered images are given in Fig.5. Comparing these two filtered images, we may conclude that the given algorithm achieves significant improvement compared to Canny based algorithm in detecting iris lacunae.

Fig. 6(a) represents another iris image, and Fig. 6(b, d) is the results of applying the Canny operator. It may be noticed here that, unlike Canny operator where all kinds of edges are detected, the proposed algorithm reduces the noise and only extracts the lacunae skeleton. It is readily seen that the proposed algorithm perform effectively in detecting lacunae even when the local contrast is quite low. Convolution with a Gaussian window does not displace the second-order zero-crossings of the original intensity data [4]. Thus, the detected lacunae have good edge localization.



(a) (b)

Figure 5. (a) Result of Canny edge detection to Fig.4 (a); (b) Result of Canny edge detection to Fig.4 (b).



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

Figure 6. Two different algorithms are applied to the same iris image; (a) Original iris image; (b) Result of Canny edge detection to (a); (c) Normalized iris image; (d) Result of Canny edge detection; (e) Result of LDoG.

It was mentioned earlier that the parameter L was chosen to be equal to 9 pixels which correspond to about 160 pm. Ideally, one would like to have a larger value of L which would further reduce the noise [4]. $L = 9$ at the working level of magnification was experimentally found to be a good choice as it performs well for detecting iris lacunae.

In Fig.7, four different templates were used in the proposed scheme to search for directional components along all possible orientations. The performance of the proposed scheme with 12 templates, using integer valued kernels, was better than that of 12 templates. Higher precision can be achieved by performing convolutions in floating point hardware or software, with a sacrifice in speed. Thus, in order to reduce the time complexity, we implement Gaussian filter along vertical direction on normalized image.

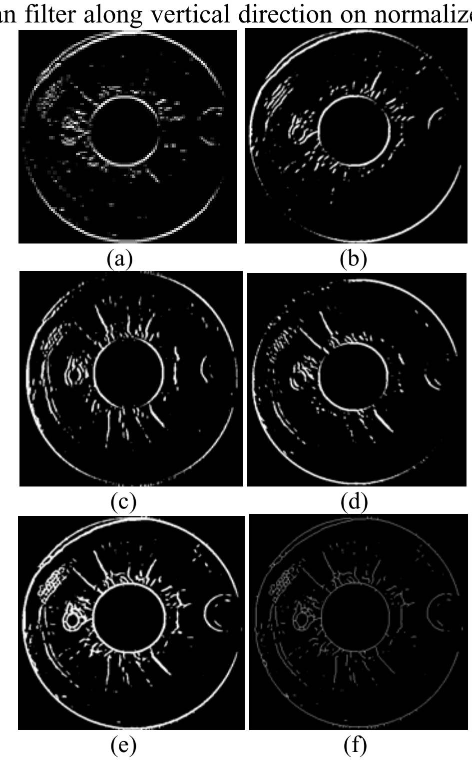


Figure 7. Result of filtering with Gaussian filters in 4 orientations; (a) 0° orientation; (b) 45° orientation; (c) 90° orientation; (d) 135° orientation; (e) Combination of (a)~(d); (f) Thinned image of (e).

Table 1. The comparison of computing time

Image No.	1	2	3	4	5
t_n (ms)	3006	3015	3047	2984	3015
t_o (ms)	254	269	269	253	301

In Table 1, t_n represents the time of detecting lacunae in normalized image, t_o represents the time of detecting lacunae in original image and the image No. is the No. of iris images chosen randomly from iris image database. According to the comparison, time was saved considerably when this approach implemented in normalized images.

4. Conclusion

We proposed an iris lacunae pathological feature detecting algorithm based on Gaussian filter. This approach reduces noise of image and regularizes the ill-posed problem of differentiation. Time complexity is reduced sharply when Gaussian filter is implemented in normalized image. Our experiments validated that it achieves high accuracy than the method based on Canny Operator.

5. Acknowledgements

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6. References

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