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An Iris Image Quality Assessment Method Based on Laplacian of Gaussian Operation

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Abstract

Iris image quality assessment is an important part of iris recognition system because the qualities of iris images would largely influence the recognition results. In this paper, we analyze and compare several representative quality assessment methods, and then propose an effective method based on Laplacian of Gaussian operator for iris image assessment. Through computer simulations of several typical algorithms on our iris image database, SJTU-IDB, the proposed method is shown superior to the compared quality assessment methods.

1. Introduction

In recent years, the increasing security demand has led to a rapid development of personal identification based on iris recognition. As a recognition object, iris has many advantages [1]. For example, its pattern variability among different persons is enormous. Besides, it is stable over time, relatively insensitive to angle of illumination, and the changes in viewing angle cause only affine transformations.

Before iris recognition, an important step is iris image quality assessment. This is because existing iris recognition algorithms with good performance [1, 3] are all based on certain quality images. But not all the iris images obtained from sensor devices have good quality.

There are several classical methods for iris image quality assessment. Daugman [1] measured the energy of high frequency components in the Fourier power spectrum to evaluate the focus of the images. Zhang et al. [2] analyzed the sharpness of pupil and iris boundary for the same purpose. Ma et al. [3] defined a quality descriptor according to three classes, namely, out-of-focus images, motion blurred images and severely occluded images of eyelids and eyelashes. Zhu et al. [4] proposed a quantitative quality measure using discrete wavelet decomposition.

In this paper, a novel iris quality assessment method is proposed, which is based on Laplacian of Gussian operators. The method is conceptually simple but effective, and avoids iris image segmentation, which is time-consuming and unpractical in real-time acquisition.

The rest of this paper is organized as follows. In Section 2, several representative methods for image quality assessment are discussed. In section 3, a new algorithm is proposed. Experimental results and discussions are given in Section 4. And conclusions are drawn in Section 5.

2. Representative Methods

In this section, we will give a brief introduction to several representative methods to assess iris image quality, and discuss their advantages and disadvantages.

2.1. Convolution kernel method

Daugman pointed out that optical defocus can be fully described as a phenomenon in the 2-D Fourier domain [1]. Defocus is equivalent to multiplying the 2-D Fourier transform of a perfectly focused image with the 2-D Fourier transform of the "defocusing" Gaussian operator. The spectral analysis of the defocus suggests that an effective way to estimate the quality of focus is to measure its total power in the 2-D Fourier domain at higher spatial frequencies.

In order to reduce the computational complexity of the Fourier transform, Daugman proposed an 8×8 convolution kernel to extract the high frequency of an image. The convolution kernel is shown in Figure 1. The weights mean that the sum of the central 4×4 pixels can be tripled and then subtracted the outer 48 pixels. The convolution results are squared and accumulated by selecting every fourth rows and fourth column as Parseval's theorem:

$$\iint |I(x,y)|^2 dxdy = \iint |F(u,v)|^2 dudv \qquad (1)$$

Similarly, Wei et al. [5] proposed a 5×5 convolution kernel as shown in Figure 2. Compared with Daugman's 8×8 convolution kernel that can be seen as a band pass filter, the 5×5 convolution kernel is also like a band pass filter and can select higher frequencies. What is more, the 5×5 kernel is computationally more efficient than the 8×8 kernel.

-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	+3	+3	+3	+3	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1

Figure 1 The 8×8 convolution kernel

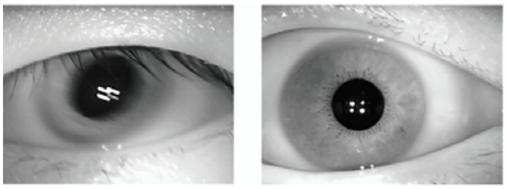
-1	-1	-1	-1	-1
-1	+2	+2	+2	-1
-1	+2	0	+2	-1
-1	+2	+2	+2	-1
-1	-1	-1	-1	-1

Figure 2 The 5×5 convolution kernel

The two methods are simple and executable. However, both of them may falsely regard certain defocused images as the clear ones, which will give wrong results in iris image assessment. For example, we pick up a defocused image shown in figure 3(a) and a clear image shown in figure 3(b) from our database, SJTU-IDB. The convolution results of the two images are shown in Table 1, respectively using Daugman's algorithm, Wei's algorithm and our proposed algorithm (will be introduced in section

3).

According to the principle that larger convolution result indicates a clearer image, Figure 3(a) should be clearer than Figure 3(b) in the evaluations of Daugman's method and Wei's method. However, the fact is opposite, confirmed by our subjective observation.



(a) (b)

Figure 3 (a) A defocused image. (b) A clear image

Table 1 The convolution results of the images in Figure3 with Dauguman's, Wei's, and the proposed method respectively.

	Image in Figure 3(a)	Image in Figure 3(b)
Daugman's 8×8 kernel	167.00	156.98
Wei's 5×5 kernel	37.21	36.01
The proposed method	17.28	18.12

2.2. Sharpness of boundary method

Zhang et al.[4] used the sharpness of pupil and iris boundary for measuring the degree of focus of iris images. They first computed the median pixel value in a portion of the pupil (Mp) and a portion of the iris (Mi)and then computed the magnitude of gradients at the pupil and iris boundaries (gradient). The sharpness measure operator is:

$$\frac{1}{w} = \frac{gradient}{Mi - Mp} \quad (2)$$

which evaluates how sharp the boundary is. The value is maximum at the best focused image and decreases as the degree of defocus increases.

Sharpness is a good measure to assess the degree of focus. However, this method has to estimate the location of the center of the pupil, the radius of the pupil and the radius of the iris at first. So the method depends on the accuracy of pupil localization algorithms. In addition, generally, the quality of an iris image should be evaluated in real time. Thus, another problem we should consider is the time-consuming aspect of the pupil localization algorithms.

2.3. Frequency components method

Ma et al. [3] used the energy of low, middle and high frequency components in Fourier power spectrum to evaluate an iris image's quality. They defined a descriptor as:

$$D = [(F_1 + F_2 + F_3), \frac{F_2}{F_1 + F_3}] \quad, (\mathrm{i} = 1, 2, 3) \quad (3)$$

$$F_i = \iint_{\Omega} |F(u,v)| \, du dv$$

$$\Omega = \left\{ u,v \middle| f_1^i < \sqrt{u^2+v^2} < f_1^i \right\}$$

where F_1, F_2, F_3 are the power of low, middle and high frequency components respectively, and f_1^i and f_2^i are the range of the corresponding frequency components. After computing the quality descriptor of each image, they used SVM method to characterize the distribution boundary of the quality descriptor between low quality images and clear images.

This method fully considers the middle and high frequency components of iris images which determine the clearness of iris texture. However, three pairs of frequency f_1^i and f_2^i (I = 1, 2, 3) should be carefully chosen by plenty of experiments on test data set. In addition, for avoiding the complexity of the fast Fourier transform, Ma's method [3] used two iris subregions. So the iris region must be located at first. Then the same problems aroused, i.e. the method greatly depends on the algorithms of pupil and iris location.

2.4. Other related method

The methods of iris image quality assessment based on wavelet decomposition [6, 7, 8] have been fully developed in recent years. The wavelet transform obtains a smooth representation in both space and frequency domains with flexible window sizes which are varying up to a scale factor. Thus most methods related with wavelet decomposition are based on localized quality assessment. This can simplify the computation of wavelet transform and is simulated to human visual systems. But one drawback of the methods is also their dependence on the segmentation performance of iris regions. The local quality would be contaminated by non-iris regions when segmentation of iris fails.

3. Laplacian of Gaussian Operator

The disadvantages of the methods mentioned above mainly lie in the following three aspects:

1. high False Acceptance Rate and False Rejection Rate;
2.great dependence on pupil and iris location algorithms;
3. complex computation and time consume.

In practical applications, the method of iris image quality assessment should be accurate and fast. So we propose a simple but effective algorithm, in which Laplacian of Gaussian (LoG) operator is used to evaluate the qualities of the iris images.

The Laplacian is a 2-D isotropic measure of the second spatial derivative of an image [9]. The Laplacian of an image highlights regions of rapid intensity change and is often used for edge detection. The Laplacian L(x,y) of an image with pixel intensity values I(x,y) is given as follows:

$$\cdot\ L(x,y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2} \quad (4)$$

Because it is approximating a second derivative measurement on image, it is very sensitive to noise. To reduce its sensitivity to noise, the Laplacian is often applied to an image that first has been smoothed by a Gaussian smoothing filter. We call this combined filter Laplacian of Gaussian filter. The 2-D LoG (Laplacian of Gaussian) function centered on zero and with Gaussian standard deviation σ has the form:

$$LoG(x,y) = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2+y^2}{2\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (5)$$

where σ is the Gaussian standard deviation.

Since the image is represented as a set of discrete pixels, we have to find a discrete convolution kernel that can approximate the Laplacian operator. Set different values of the Gaussian σ, we can get different LoG operators. For example, if we set σ = 1.4, we get a LoG operator as shown in Figure 4. In order to simplify the computation, we choose a 3×3 Laplace operator. Two commonly used 3×3 kernels are shown in Figure 5.

0	1	1	2	2	2	1	1	0
1	2	4	5	5	5	4	2	1
1	4	5	3	0	3	5	4	1
2	5	3	-12	-24	-12	3	5	2
2	5	0	-24	-40	-24	0	5	2
2	5	3	-12	-24	-12	3	5	2
1	4	5	3	0	3	5	4	1
1	2	4	5	5	5	4	2	1
0	1	1	2	2	2	1	1	0

Figure 4 Discrete approximation to LoG (σ=1.4)

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$$\begin{array}{|c|c|c|}\hline 0 & -1 & 0 \\ \hline -1 & 4 & -1 \\ \hline 0 & -1 & 0 \\ \hline \end{array} \qquad \begin{array}{|c|c|c|}\hline -1 & -1 & -1 \\ \hline -1 & 8 & -1 \\ \hline -1 & -1 & -1 \\ \hline \end{array}$$

(a) (b)

Figure 5 Two commonly used Laplace Operators

In our experiment, we found the operator in figure 5(b) had good performance for iris image quality assessment. So we adopt this 3×3 operator to convolute each iris image. The larger the convolution result of an image is, the clearer the image.

4. Experimental Results

4.1 Iris image database

SJTU-IDB database is a standard iris image database developed by our lab at Shanghai Jiao Tong University. The SJTU-IDB database contains 8400 grayscale eye images collected from 420 persons. Each person was captured 10 images per eye. The image size is 320×240.

To evaluate the performance of the proposed method, we constructed a training dataset and a testing dataset from the SJTU-IDB database. The training dataset contained 870 images with good quality and 133 images with bad quality (defocused or motion blurred). The testing dataset contained 1227 images with good quality and 159 images with bad quality.

4.2 Training and testing

First, we used our proposed method to assess each image with good quality in the training dataset and got the total score of each image. The total score is the convolution result of an image with the 3×3 convolution kernel shown as figure 5(b). The score distribution diagram is drawn in Figure 6(a). From the diagram, we can easily distinguish the good quality images from the poor quality images. Therefore we set the threshold θ_{LoG} for distinguishing the two kinds of images: θ_{LoG} = 15.5. If the score of an image is above the threshold θ_{LoG}, the image is thought to be a good quality image. Otherwise, it is considered a poor quality image.

Then we used our proposed method to assess the images in the testing dataset. The score distribution of testing dataset is shown in Figure 7(a). The result is pretty good. By the threshold θ_{LoG}, 1226 out of 1227 good quality images in the testing dataset passed the evaluation, and 156 out of 159 poor quality images were rejected. The False Acceptance Rate (FAR) and False Rejection Rate (FRR) of our algorithm are also shown in the Table 2.

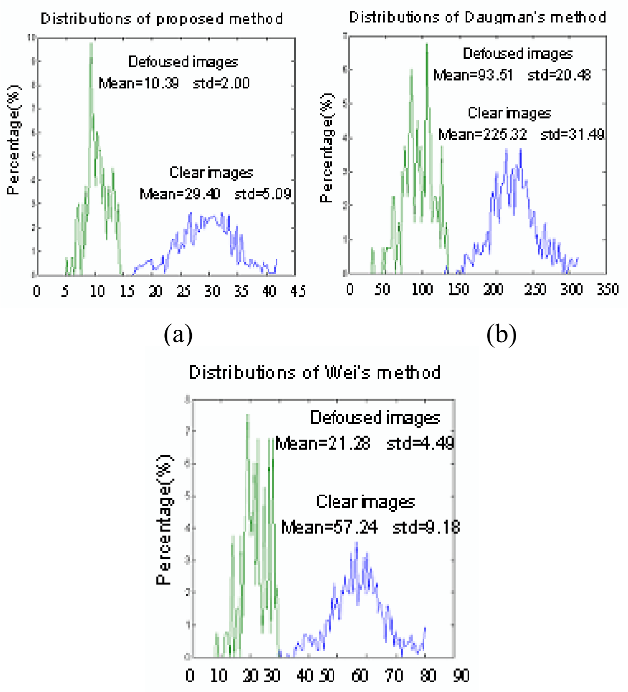

Figure 6 (a) Score Distribution of the training dataset with the proposed algorithm. (b) Score Distribution of the training dataset with the Daugman's algorithm. (c) Score Distribution of the training dataset with the Wei's algorithm.

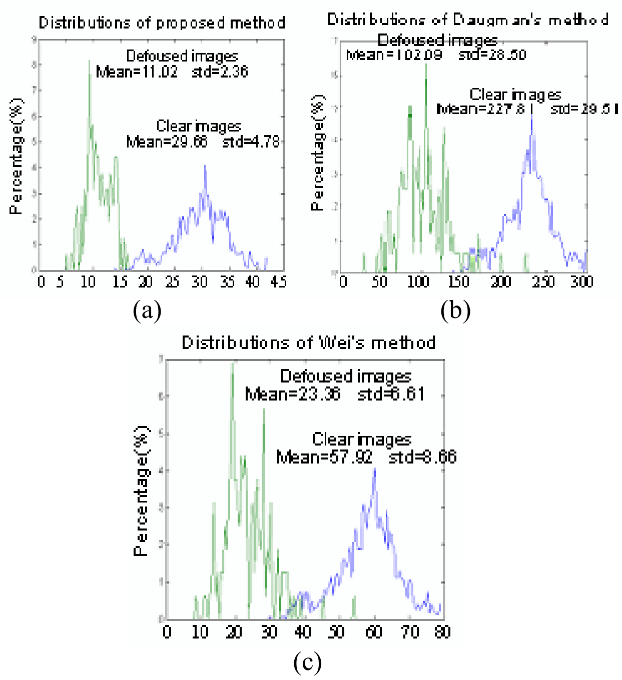

Figure 7 (a) Score Distribution of the test dataset with the proposed algorithm. (b) Score Distribution of the test dataset with the Daugman's algorithm. (c) Score Distribution of the test dataset with the Wei's algorithm.

To make a comparison with other algorithms, we used Dauguman's algorithm [1] and Wei's algorithm [5], two typical algorithms for iris image quality assessment. By their score distributions of the training dataset (seen in Figure 6(b) and Figure 6(c)), we set the threshold for Dauguman's algorithm $\theta_{Dau} = 150$ and the threshold for Wei's algorithm $\theta_{Wei} = 35.5$. Their score distributions of the training dataset are shown in Figure 7(b) and Figure 7(c). And their FAR and FRR for the testing dataset are shown in Table 2. Obviously, from Figure 7 and Table 2 we can see the proposed algorithm works best.

Table 2 FAR and FRR of three algorithms

	Proposed algorithm	Daugman's algorithm	Wei's algorithm
FAR	1.89%	5.03%	3.14%
FRR	0.08%	0.33%	0.57%

4.3 Speed

We also compared the three algorithms in terms of speed. The training and testing experiments were implemented using Matlab 7.1 on a Pentium IV 1.5GHz processor with 512MB RAM. All of the Matlab codes used in these experiments were optimized. The averaged execution time for the training and testing of the three algorithms are shown in Table 3. Clearly, the proposed algorithm is the fastest.

Table 3 The averaged execution time of the three algorithms

	Training time on average (s.)		**Testing time on average (s.)**	
The number of images	870 good images	133 poor images	1227 good images	159 poor images
Proposed	0.0151	0.0154	0.0155	0.01850
Wei's	0.0260	0.0276	0.0274	0.0332
Daugman's	0.1703	0.2098	0.1787	0.2478

4.4 Discussions

Some discussions can be given based on the above experimental results.

1.The proposed algorithm deals with the whole image, avoiding the location and segmentation of the pupil and iris. The execution time of the algorithm is suitable for a real-time recognition system.

2.The proposed algorithm is effective for the defocused and motion blurred images, but it is ineffective for the occluded images of eyelids and eyelashes. Since the occluded images are common when capturing iris images, our future work will focus on how to improve our algorithm to effectively reject the occluded images.

3.The FAR of the proposed algorithm is mainly caused by the images in half-clear status, such as slightly movement blur of pupil, which is not common in capturing of iris images. We can adjust the threshold to get a satisfied FAR and a tradeoff between FAR and FRR. Details will be given in our future work.

4. The proposed operator is one of the simplest Laplace Operators. Our future work will concentrate on how to set the Gaussian σ and get the LoG operator which is an optimal convolution kernel adapted to the different situations.

5 Conclusions

Iris image quality assessment plays an important role in iris recognition system. In this paper, we first analyzed several typical image quality assessment methods, and then proposed an efficient method based on Laplacian of Gaussian operator. Using our SJTU-IDB iris image database, we gave a comparison between our proposed method and several representative methods. The results illustrated the encouraging performance of the proposed method in terms of accuracy and speed.

Acknowledgements

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