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A Robust Coarse-to-Fine Method for Pupil Localization in Non-ideal Eye Images

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Abstract

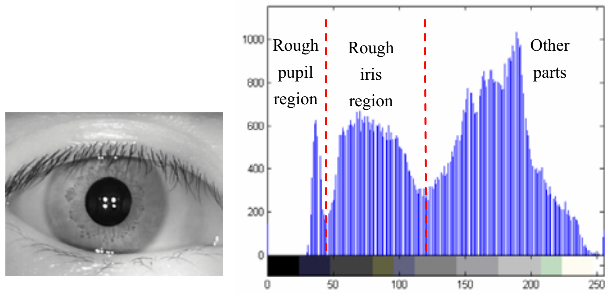
Pupil localization is a very important preprocessing step in many machine vision applications. Accurate and robust pupil localization especially in non-ideal eye images (such as images with defocusing, motion blur, occlusion etc.) is a challenging task. In this paper, a detailed method to solve this problem is proposed. This method is implemented in three main steps: first, segment the rough pupil region based on Gaussian Mixture Model according to the gray level distribution of eye image; then modify the rough segmentation result using morphological method to minimize the influence of some disturbing factors; last step is to estimate the pupil parameters based on minimizing the least square error. The proposed method is first tested on CASIA iris image dataset, and then on our self-captured iris dataset which with more varieties. Experiments show that the proposed method can perform well for non-ideal eye images of various qualities.

1 Introductions

Pupil localization is a very important preprocessing step in machine vision applications, such as iris recognition, pupil tracking [1], ocular torsion measurement [2], pupil size estimation [3], pupillometry [4], point of gaze extraction [5], iris registration in eye surgery etc. No matter what application it serves, the performance of pupil localization will have great impact on the subsequent processing. So it is of importance to find an accurate, robust and fast pupil localization method theoretically and practically.

Pupil localization is traditionally based on the gray level distribution of the eye image (i.e., the pixels in pupil area have approximately the same gray level and are darker than other parts of the eye) and its circle-like shape, as shown in Fig.1. Gray level thresholding, circular Hough transform [6], Integro-differential operator [7] and deformable contour model (snakes) [8] are the most widely used pupil localization methods. They all achieve good performances in ideal eye images.

Gray level thresholding is the simplest segmentation process. Mode method is usually applied to select the threshold as a minimum histogram value between two local maxima. It is computationally inexpensive and fast. But it cannot get a desirable result in the case of uneven illumination or dense eyelashes (because the eyelashes are of similar grayscale value to pupil). The Circular Hough transform and Integro-differential operator are mostly guided by gradient information. They are computational demanding. Deformable contour model is dependent too much on the initial parameters. Moreover it is easy to be trapped in local minima, especially in non-ideal eye images.



(a) (b)

Figure 1. Eye Image Histogram
(a) An ideal eye image; (b) gray level distribution

But in real applications, the eye images are not necessary to be ideal; there exist many disturbing factors, such as eyelashes and eyelids occlusion, illumination artifacts, motion blur, defocusing, makeup etc. In this paper, we proposed a three-step procedure means to correctly and robustly localize the pupil in non-ideal eye images.

2 The Proposed Method

The whole procedure of the proposed pupil localization method is divided into three main steps:
(1) Rough segmentation of pupil region
(2) Modification of rough segmentation
(3) Fitting the pupil region to a circle

2.1 Rough Segmentation of Pupil Region

Thresholding method hardly segments the correct and complete pupil from the eye image because both the restriction of the global thresholding method and the non-ideal eye image itself. But if appropriate threshold is selected and some restrictions are made, the rough pupil region can still be utmostly detected. Then other techniques can be applied on this result to further make a fine localization.

According to the property of the eye image, the gray-level distribution of an ideal eye image can be modeled as a sum of three Gaussian distributions, (i.e. the

Gaussian Mixture Model), which can be seen explicitly in Figure.1 (b).

In the case of the non-ideal eye images, shown as Figure.2(a), the histogram of eye image is first smoothed with a mean filter, and then fitted with three weighted Gaussian distributions.

$$H_{GMM}(x)=\sum_{k=1}^{3}\alpha_k G_k\left(x\mid\mu_k,\sigma_k\right)$$

Variable x represents the gray level values from the image gray level histogram; and $G_k\left(x\mid\mu_k,\sigma_k\right)$ denotes the Gaussian function; $\left(\mu_k,\sigma_k\right)$ is the parameters of the k_{th} Gaussian; α_k is the weight for each Gaussian; $\alpha_k>0$ and $\sum_{k=1}^{3}\alpha_k=1$.

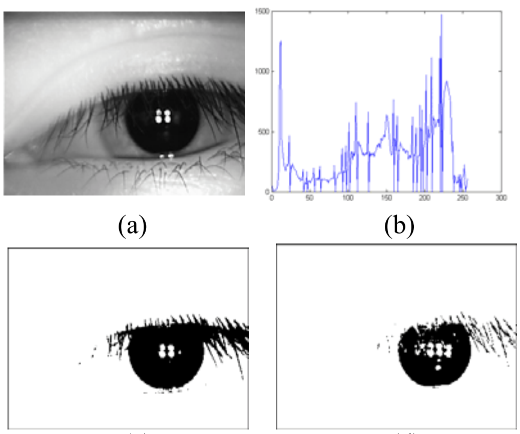
The parameters of every Gaussian component are iteratively estimated using Expectation Maximization method (EM) [9] with the following iterative equations:

$$\omega_{nk}=\frac{\alpha_k^{old} f_k\left(x_n\mid\mu_k,\sigma_k\right)}{\sum_{k=1}^{3}\alpha_k^{old} f_k\left(x_n\mid\mu_k,\sigma_k\right)}$$

$$\alpha_k^{new}=\frac{1}{N}\sum_{n=1}^{N}\omega_{nk}\ ,\qquad \mu_k^{new}=\frac{\sum_{n=1}^{N}\omega_{nk}x_n}{\sum_{n=1}^{N}\omega_{nk}}$$

$$\sigma_k^{new}=\frac{\sum_{n=1}^{N}\omega_{nk}\left(x_n-\mu_k^{new}\right)\left(x_n-\mu_k^{new}\right)^{\mathrm{T}}}{\sum_{n=1}^{N}\omega_{nk}}$$

Then the threshold is set as the closest gray level corresponding to the minimum probability between the maxima of the first two Gaussian distributions, which will result in minimum error segmentation.

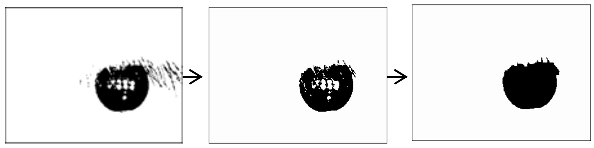


(a) (b) (c) (d)

Figure 2. Rough Segmentation of Pupil Region
(a) Original image; (b) Gray level distribution; (c) result of mode method; (d) result of rough segmentation

2.2 Modification of Rough Segmentation

Because global thresholding method is sensitive to the interferential factors such as uneven illumination, blur, occlusion etc, totally correct and complete segmentation of pupil usually cannot be achieved in the first processing step. As can be seen in Figure.2 (d), though the pupil region is detected, the result still involves some eyelashes and illumination artifacts. Morphological method (shown in Figure.3) is applied to modify the rough segmentation result before the estimation of pupil parameters.



(a) (b) (c)

Figure 3. Modification of rough segmentation
(a) Rough pupil region; (b) Find the biggest connective area and apply open operation to erase eyelashes;
(c) Perform close operation to fill illumination artifacts;

2.3 Fitting the Pupil Region to a Circle

The pupil can be approximated by a circle according to its physiological shape property. Though the rough pupil region is segmented after the first two processing steps, it is usually not complete or still leaves some eyelashes adhere to the pupil region. Therefore, if projection is used to determine the parameters of the pupil circle, localization error will occur.

In this paper we determine the circle parameters (center parameter (x,y), and radius R by minimizing the least square error [10]. The square error J is:

$$J=\sum\omega_i\left[\left(x_i-x_0\right)^2+\left(y_i-y_0\right)^2-R^2\right]^2$$

where the summation is over all edge points $\left(x_i,y_i\right)$ by differentiating J with respect to x_0, y_0 and R. Then x_0, y_0 and R are iteratively given by:

$$x_0=\frac{B_yC_x-B_xC_y}{A_xB_y-A_yB_x}\ ,\qquad y_0=\frac{A_yC_x-A_xC_y}{A_yB_x-A_xB_y}$$

$$R^2=\frac{1}{W}\sum\omega_i\left[\left(x_i-x_0\right)^2+\left(y_i-y_0\right)^2\right]$$

where:

$$W=\sum\omega_i\ ,\qquad \bar{x}=\frac{1}{W}\sum\omega_i x_i\ ,\qquad \bar{y}=\frac{1}{W}\sum\omega_i y_i$$

$$A_x=\sum\omega_i\left(x_i-\bar{x}\right)x_i\ ,\qquad B_x=\sum\omega_i\left(x_i-\bar{x}\right)y_i\ ,$$

$$C_x=\frac{1}{2}\sum\omega_i\left(x_i-\bar{x}\right)\left(x_i^2+y_i^2\right)$$

$$A_y=\sum\omega_i\left(y_i-\bar{y}\right)x_i\ ,\qquad B_y=\sum\omega_i\left(y_i-\bar{y}\right)y_i$$

$$C_y=\frac{1}{2}\sum\omega_i\left(y_i-\bar{y}\right)\left(x_i^2+y_i^2\right)$$

The initial values of the weights ω_i are all set to 1; other variables are initially set to 0. The procedure of fitting and weighing is executed ten times. The localization result is shown in Figure.4.

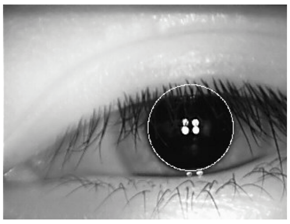
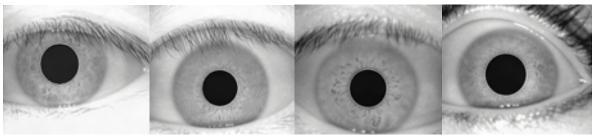


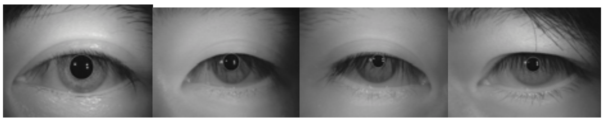
Figure 4. The pupil localization result

3 Experiments

We test our procedure first on the CASIA eye images dataset [11]. The images in the previous version of this dataset are somewhat 'ideal' because they have been modified to remove the illumination artifacts; and few images have the occlusion or blur problem. Some samples are shown in Figure.5 (a). The correct localization rate on this set is 100%. The images in the second version of CASIA are captured with remote device, so the images extend a larger area and easy to be influenced by external illuminations, some samples are shown in Figure.5 (b). The correct localization rate on this set is 95.2%.



(a)



(b)

Figure 5. CASIA eye images
(a) Previous version; (b) Second version

In order to further test the performance of our proposed method, we also do experiments on the eye images which we practically collected using the capture device for iris recognition. To test the robustness of the proposed method, we haven't put much restriction when capturing, so this dataset has more variety and not so 'ideal' as other datasets.

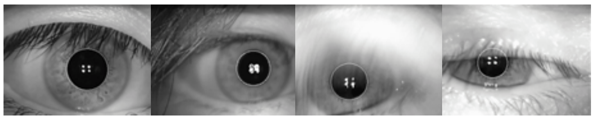
First the traditional pupil localization method is re-implemented, i.e. use mode method to select threshold and projection to determine the circle parameters. Then our proposed pupil localization procedure is employed. Moreover, we test the performance when the first step in our method is changed to simple threshold, and also when the second step (modification of rough segmentation) is dropped from the proposed procedure. The localization results are shown in Table.1. The propose method get a higher correct rate than the traditional method.

Some localization results of non-ideal eye images are shown in Figure.6 to indicate the robustness of the proposed method. Some failed samples are also shown in Figure.7.

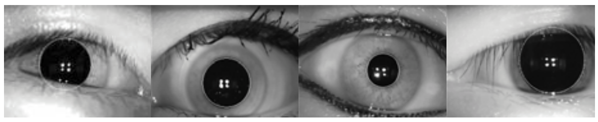
Table 1. Experiences on SJTU-IDB

	Image number	Localization method	Correct rate
Image set 1*1	5320	Integro -Differential	72.9%
		Thresholding only	62.7%
		Our proposed method	87.2%
Image set 2*2	4531	Integro -Differential	87.0%
		Thresholding only	70.2%
		Our proposed method	98.9%
		Modification 1*3	83.3%
		Modification 2*4	84.9%

*1 Image set 1: all images in SJTU-IDB
*2 Image set 2: images after some low-quality samples are excluded from SJTU-IDB
*3 Modification 1: the first step change to simple threshold, other steps are same as our proposed method.
*4 Modification 2: drop the second step (Modification of rough segmentation) from our proposed method, other steps are same.

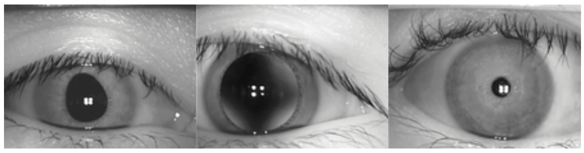


(a) (b) (c) (d)

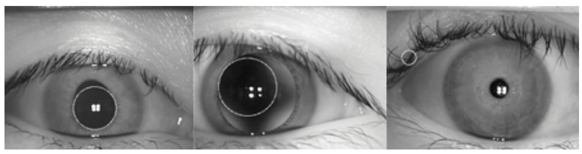


(e) (f) (g) (h)

Figure.6. Localization Results of Non-ideal Images
(a) average eye image; (b) defocus image; (c) motion blur; (d)(e) occlusion; (f)(g) makeup eye images; (h) big pupil (by mydriatic when surgery)



(a)



(b)

Figure.7. Some Failed Samples
(a) Original samples; (b) their localization results

In this paper, we only take into consideration of the single frame of eye image. If video sequences of eye movements are employed, accurate localization of pupil will be more challenging. This is part of our future work.

4 Conclusion

In this paper, a detailed method of pupil localization in non-ideal eye image is proposed. This method is implemented in three main steps: first segment the rough pupil region based on GMM and EM; then modify the rough segmentation using morphological method to minimize the influence of eyelids, eyelashes and illumination artifacts; last estimate the parameters of pupil based on minimizing the least square error. The proposed method is first tested on CASIA iris image dataset, and then on our self-captured iris dataset that with more variety. Experiments show that the proposed method can perform well for non-ideal eye images of various qualities.

Acknowledgements

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