An Automatic Eye Detection Method for Gray Intensity Facial Images

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Abstract

Eyes are the most salient and stable features in the human face, and hence automatic extraction or detection of eyes is often considered as the most important step in many applications, such as face identification and recognition. This paper presents a method for eye detection of still grayscale images. The method is based on two facts: eye regions exhibit unpredictable local intensity, therefore entropy in eye regions is high and the center of eye (iris) is too dark circle (low intensity) compared to the neighboring regions. A score based on the entropy of eye and darkness of iris is used to detect eye center coordinates. Experimental results on two databases; namely, FERET with variations in views and BioID with variations in gaze directions and uncontrolled conditions show that the proposed method is robust against gaze direction, variations in views and variety of illumination. It can achieve a correct detection rate of 97.8% and 94.3% on a set containing 2500 images of FERET and BioID databases respectively. Moreover, in the cases with glasses and severe conditions, the performance is still acceptable.

Keywords: *Eye detection, Iris detection, Facial features extraction, Face detection, Entropy.*

1. Introduction

Automatic face recognition has attracted significant attention in image analysis and understanding, computer vision, pattern recognition, security system, and credit-card verification for decades [1,2]. Several face recognition systems are based on basic facial features such as eyes, nose and mouth, and their spatial relationship. For most 2D and 3D recognition algorithms, it is critical that faces be aligned before being compared. Typically, alignment begins with the detection of facial features. Statistical-based face recognition systems such as eigenface [3] or independent component analysis method [4] use eye corners for alignment. Also, in order for face recognition algorithms-based on geometric, that use the overall geometrical configuration of the facial features, to work well, facial features should be detected before any other processing can take place [5].

Among these facial features, eyes remain the most important one because they can be considered salient and relatively stable features on the face in comparison with other facial features. So detection of eyes will be the first step in a face recognition system. On the other hand, some works consider that the positions of other facial features can be estimated using the eye positions [6]. A brief review of existing eye detection methods is given in the next section.

The rest of this paper is organized as follows. A brief review on existing eye detection methods is presented in Section 2. The proposed method for detection of the center of two eyes is introduced in Section 3. Experimental results are reported in Section 4 and finally, the conclusions and future research are given in Section 5.

2. Brief review on the existing eye detection methods

Detection of the human eye is a very difficult task because the contrast of the eye is very poor. Eye detection is divided into two categories; eye contour detection [7], [9] and eye position detection [3], [6]. This paper focuses on the second type; i.e., eye position detection, as most algorithms for eye contour detection such as those are based on the deformable template [6] require the detection of eye positions to initialize eye templates. Thus, eye position detection is important not only for face recognition but also for eye contour detection.

Several eye detection methods have been developed in the last ten years. Deformable template [10], [11] is the popular method in locating the human eye. In this method, an eye model is first designed and the eye position can be obtained through a recursive process. However, this method is feasible only if the initial position of the eye model is placed near the actual eye position. Moreover, deformable template suffers from two other limitations.

First, it is computation expensive. Second, the weight factors for energy terms are determined manually. Improper selection of the weight factors yields unexpected results. Lam and Yan [12] extended Yuille's work [11] by introducing the concept of eye corners, which proved to be effective in reducing the processing time.

In the template matching aspect, Ryu and Oh [13] propose an algorithm based on eigenfeatures and neural networks for the extraction of eyes using rectangular fitting from gray-level face images. The advantage is that it does not need a large training set by taking advantage of eigenfeatures and sliding window. However, their algorithm can fail on the face images with glasses or beard. It was tested on a small set of 180 images only from ORL database and its best performance is 91.7% and 85.5% for left and right eye respectively. Pentland *et al*. [6] use the eigenspace method to detect the eyes. The eigenspace method shows better eye detection performance than a simple template matching method since training samples cover different eye variations in appearance, orientation and lighting conditions. But, its detection performance is largely dependent on the choice of training images. Another drawback is that, it requires the training and test images to be normalized in size and orientation.

Hough transform is also widely used eye detection method. It is based on the shape feature of an iris and often works on binary valley or edge maps and it does not require an image of a specific person's eye for the eye model. The shortcoming of this approach is that its performance depends on the threshold values selected for the binarization of valley or edge maps and it is difficult to detect the circle corresponding to the iris unless the likely region of occurrence of the iris is narrowed down, since the iris is smaller than the face. Using Hough transform and deformable template technique, Chow and Li [14] propose a method of detecting the likely iris region. First, a valley image is given, consisting of the difference between the original image in gray scale and an image to which the closing operation of gray-scale morphology is applied to the original image. Then, the valley region is detected by binarizing the valley image. The succeeding components of the valley image are approximated by rectangles. Then, two rectangles corresponding to the eyes are selected by using their positional relationship. Unfortunately, correct selection of the two rectangles requires that the left and right eyes be in separate rectangles, that the whole of each eye be enclosed by a single rectangle, and that each eye and eyebrow be in a separate rectangle. Therefore, it is difficult to determine the threshold value for binarization of the valley image.

Kawaguchi and Rizon [15] detect the iris using the intensity and the edge information. Their method first detects the face region in the image, and then extracts intensity valleys from the face region. Next, it extracts iris candidates from the valleys using the feature template and the separability filter. Finally, using cost function, a pair of iris candidates corresponding to the irises is selected. The costs are computed by using Hough transform, separability filter and template matching. To evaluate the validity of their method, they use images from two databases; the Bern and AR database. The method achieves a correct iris detection rate of 95.3% for 150 Bern face images and 96.8% for 63 AR images. But they do not explain how to automatically detect the light dot in the iris.

Besides these three classical approaches, recently other eye detection methods have been proposed. In [16], a method is proposed for eye detection that uses iris geometries to determine the region candidates which possibly contain the eye, and then the symmetry for selecting the couple of eyes. Ehsan *et al*. [17] present a rotation-invariant facial feature detection system based on combining the Gabor wavelet and the entropy measure. One advantage of their method is that it can be trained for any individual facial feature using a small set of sample images.

Song *et al.* [18] use the binary edge images and intensity information to detect eyes. Their method consists of three steps: first extraction of binary edge images (BEIs) from the grayscale face image based on multi-resolution wavelet transform, second extraction of eye regions and segments from BEIs, and third eye localization based on light dots and intensity information. A correct eye detection rate of 98.7% and 96.6% may be achieved on 150 Bern and 564 AR images, respectively. Though this high detection rate, this method depends basically on different types of thresholds on different database. So the method is neither simple nor applicable.

Choi and Kim [19] propose an eye detection method using the Modified Census Transform (MCT)-based pattern correlation. The method detects two eyes by the MCT-based AdaBoost eye detector over the eye regions. To reduce the falsely detected eyes due to the limited detection capability of the eye detector, they propose a method for eye verification that employs the MCT-based pattern correlation map. They verify whether the detected eye patch is eye or non-eye depending on the existence of a noticeable peak. When one eye is correctly detected and the other eye is falsely detected, the method can correct the falsely detected eye using the peak position of the correlation map of the correctly detected eye. The method achieves detection rate of 98.7% and 98.8% on the Bern and AR-564 databases, respectively.

Zhou and Geng [20] extend the idea of the integral projection function (IPF) and variance projection function (VPF) [7] to the generalized projection function (GPF) and showed with experimental results that the hybrid projection function (HPF), a special case of GPF, is better than VPF and IPF for eye detection. Although the detection rate of this method on BioID database is 94.81%, it basically requires that each eye should be in a separated window. This depends on detection of the rough eye position which is not trivial process. On the other hand, Peng et al. [21] combine the two existing techniques feature based method and template based method to overcome their shortcomings. The method firstly makes use of feature based methods to detect two rough regions of eye. The precise locations of iris centers are then detected by performing template matching in these two regions. When it is tested on 227 images from ORL face database without glasses, it gives 95.2% detection rate. In spite of considerable amount of previous work on the subject, detection of eye features will remains a challenging problem and there is still a long way to go before the methods become really mature [22,23].

3. The proposed method

3.1 Entropy

Suppose that there exists a set of events S = $\{x_1, x_1, \ldots x_n\}$, with the probability of occurrence of each event $p(x_i) = p_i$. These probabilities, $P = \{p_1, p_2, \ldots, p_n\}$ are such that each $p_i \geq 0$, and the probability distribution function (PDF) satisfies that $\sum_{i=1}^{n} p_i = 1$. For measuring the uncertainty and unpredictability of a set of events S, Shannon introduced an important concept which is the entropy in the form

$$H(S) = H(p_1, p_2, \ldots, p_n) = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{1}$$

A good measure for uncertainty should have some properties; continuous, a strictly convex function, which reaches a maximum value when all probabilities are equal, and maximized in a uniform probability distribution context. Because entropy satisfies these properties, we chose it to measure the uncertainty of eye region. The Shannon entropy can be computed for an image, where the probabilities of the gray level distributions are considered in the Eq. (1). A probability distribution of gray values can be estimated by counting the number of times each gray value occurs in the image or sub-image and dividing those numbers by the total number of occurrences. An image consisting of a single intensity will have a low entropy value; it contains very little information.

In this paper, the entropy is used to detect facial feature points such as eyes. In the eye regions the PDF (probability distribution function) of gray scale intensities is flatter, which indicates that pixel values are highly unpredictable and this corresponds to high entropy. On the other hand, in the other regions the PDF is peaked, which means that most of these pixels are highly predictable and hence entropy is low. To show this point clearly, six different regions of the top half of the face and their corresponding PDF (An intensity histogram in this paper) are depicted in Fig. 1. The two eyes regions (windows) (b) and (f) exhibit unpredictable local intensity indicating that flatter of PDF and hence entropy is high, while in the other areas such as (c) or (d) the PDF is peaked and therefore low entropy. From Fig. 1, one can note that entropy value of eye regions (b) and (f) is 6.986 and 6.8538 while entropy value of other regions (c) and (d) is 5.3617 and 4.998 respectively. This fact can be used to detect the facial feature such as eyes.

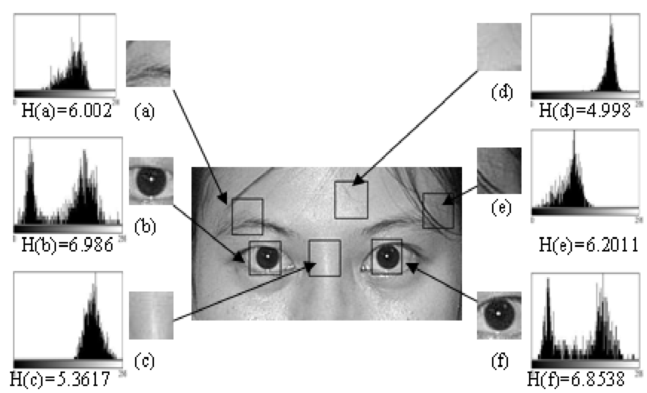


Fig. 1: The PDF and entropy value of six different regions of eye area.

3.2 Iris detection

The eye features include eye center (pupil or iris), eye corners and eyelid contours. This work will focus on eye center detection or iris detection. To detect the eye center (iris), the above fact of unpredictable gray intensity in small window of size *w* x *h* pixel around iris and the fact that the iris is dark will be used. The flowchart of the proposed method is shown in Fig. 2. First, the face region is extracted from the input gray scale image by applying the Boosted Cascade Face Detector due to Viola and Jones [24]. This algorithm utilizes a boosting method known as AdaBoost to select and combine a set of features, which can discriminate between face and non-face image regions. The detector is run over a test image and image window with the highest face score calculated by summing the classifier scores from each level of the cascade deemed to be the location of the face in the image. Second the top part of detected face is scanned with overleaped small windows of size *w* x *h* pixels (Fig. 2(c)) to find eye region. Therefore the total number of windows will be large (say *M*), for more illustrative a few number of these windows is drawn in Fig. 2(c), calculate entropy value for each window using Eq. (1), the highest entropy value windows should be around the iris because as mentioned in section 3.1 in this area the variation of pixels is high so the entropy will also be high. Then, we chose only *n* windows that have highest entropy value from all these *M* windows and exclude the other windows (*M-n*) as shown in Fig. 2(d).

Entropy alone (Eq. (1)) is not enough to detect iris or the window which contains iris from these chosen *n* highest entropy value because it measures the variation of pixels values in the candidate region not region features. In other words entropy help us to select *n* windows around iris, one of these windows contains the iris (dark circle). So, other cues are required to select only one window *W* from these *n* windows which will be the iris. To do this, entropy and darkness of the iris are combined together. We consider the fact that the iris is circle and dark, and calculate the sum of intensity pixel value in a circle of radius *r* around the center of each window *W* (i.e., the center of this circle is the center of the window). Based on the entropy value and this sum of intensity pixel value, a total score is given to each window. This score is as follow

$$T_{score} = H_{score} + C_{score} \tag{2}$$

where T_{score} is the total score of each window, H_{score} entropy score, and C_{score} is the score of iris darkness;

$$H_{score} = \frac{Entropy(W_i)}{\sum_{i=1}^{n} Entropy(W_i)}, \quad \text{and}$$
$$C_{score} = 1 - \frac{Darkness(W_i)}{\sum_{i=1}^{n} Darkness(W_i)} \tag{3}$$

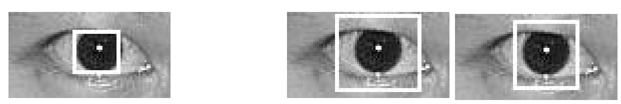
where *Entropy* (W_i) and *Darkness* (W_i) are calculated for each window W_i, (i =1,…, n) using Eq. (1) for *Entropy* (W_i) while *Darkness* (W_i) is calculated in a circle of radius *r* around the center of a window using sum of intensity pixels value. Finally, according to Eq. (2), the eye region is the window that has the highest total score T_{score}, this window contains the iris as shown in Fig. 2(e). The center of the selected window is the required point (see Fig. 2(f)).

In some cases, few highest entropy value windows are away from the iris, may be at eyebrow or near the edge of scanned area as shown in Fig. 1 (a,e), but these regions are not circle or dark around the center, only iris is circle and dark (Fig. 1(b,f)) which means that darkness and circle is a unique feature for the window that contains the iris among all the other windows. So the idea here is to select the window which has high entropy value and is dark around the center. According to that, these windows do not affect too much on the performance of the proposed method.

Eq. (2) can be considered as open research problem, now this method guarantees that 99% of highest entropy value windows are around iris of eye (Fig. 2(d)). In this work, darkness of iris cue is used in Eq. (2) to guide for the correct window; other cues may outperform our darkness cues. The most advantage of the proposed method is that, it is simple and can be implemented easy because it dose not require complicated pattern matching or a predefined threshold.

3.3 Selecting of window size

Choosing the width and height of windows is important. Fig. 3 shows two examples for selecting the size of window. If the width and height are chosen as in case (a) the role of entropy in Eq. 2 will disappear, because in this case there is not any kind of variation in intensity but only dark pixels. On the other hand case (b) will guarantee the intensity variation and hence high entropy value.



(a) Bad window size (b) Good window size

Fig. 3: Examples of selecting window size.

A Geometric eye model is used to optimize window size as shown in Fig. 4, the eye region width *d* is considered to be equal ¼ of face width. Then 2*r*=*d*/3, where *r* is radius of iris. Therefore the width *w* and height *h* of the window can be determine using the formula,

$$w = 2r + \Delta x, \text{ and } \quad h = 2r + \Delta y \tag{4}$$

As this model is not 100% accurate and we need to avoid window size of case (a) in Fig. 4 (a), small value Δx, $\Delta y \geq 1$ is added to the formula. For example, in this work we use faces of size 128x128 pixels, therefore eye width *d*=128/4= 32, then the iris radius 2*r* =32/3 ≈ 10.7. So we empirically choose Δx =3.3 and

$\Delta y = 1.3$. In this way, the window size is adapted to 14 x 12 pixels, with overlap or shifted 2 pixels in horizontal and vertical directions, and radius of circle to 5, while the number of windows which have highest entropy value n is chosen to be 50 windows.

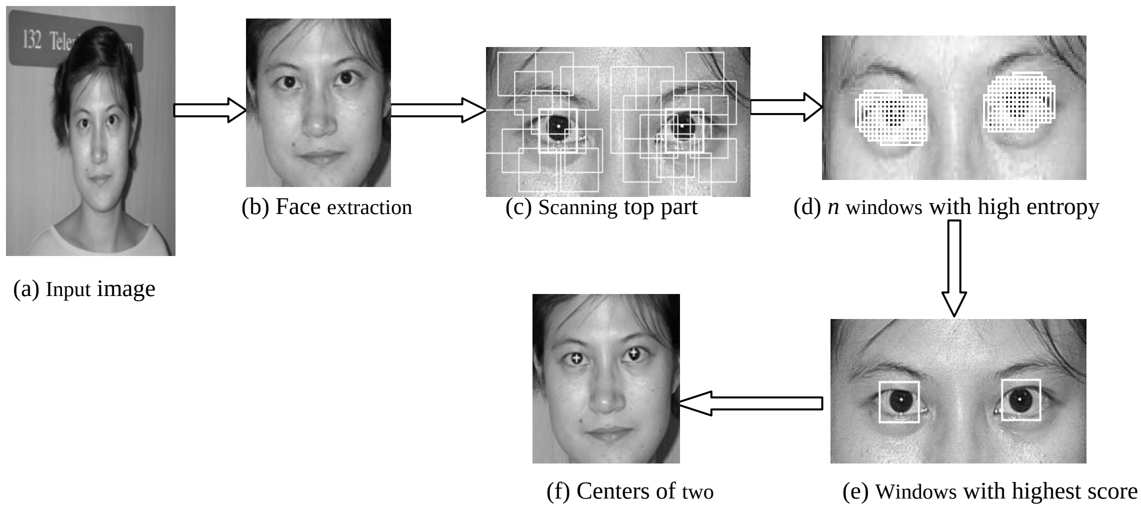


Fig. 2: Flowchart of the proposed eye detection method.

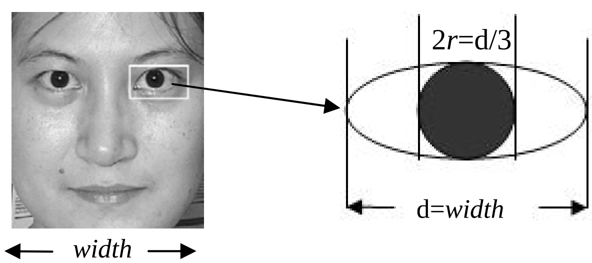


Fig. 4: Geometric eye model.

4. Experimental results

4.1 Data sets

The proposed method is basically tested on two face databases. One is a subset of the FERET database [25] and the other is the BioID face database [26]. A subset of 2500 face images (**fa**, **hl**, **hr**, **fb**) was randomly selected from the FERET database. Where **fa** is regular frontal image, **hl** half left- head turned about 67.5 degrees left, **hr** half right-head turned about 67.5 degrees right, and **fb** alternative frontal image, taken shortly after the corresponding **fa** image. Images in this database are color of 256 x 384 pixels, and before used they are converted to 8-bit gray level images. The images primarily contain an individual's head, neck and shoulder. There are nearly no complex background in these images.

The BioID face database is also a head-and-shoulder image face database. However, it stresses “real world” conditions. Sample images from BioID database are shown in Fig. 5. The BioID face database features a large variety of illumination and face size. Background of images in the face database is very complex. The images were recorded during several sessions at different places. The database consists of 1521 frontal view gray level images of 23 different test persons with a resolution of 384×286 pixel.

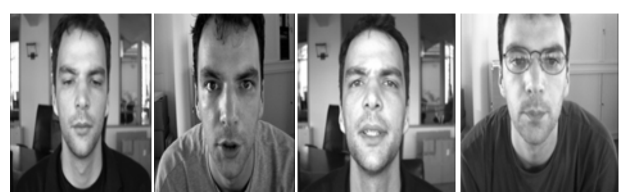


Fig. 5: Sample images of BioID database with complex background.

4.2 Evaluation criterion of the results

To quantitatively assess and fairly compare the methods that aim at addressing the eye detection or face localization, algorithms should be tested on the same benchmark dataset according to a standard testing procedure. Unfortunately, such a requirement is seldom satisfied in practice. Moreover, a universal objective measure for evaluating eye detection or face localization methods dose not exist [27]. Although numerous

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algorithms have been developed, most of them have been tested on different datasets in a different manner. In this paper to evaluate the performance of the proposed method, the criterion of [28] is used. The criterion is a *relative error* measure based on the distances between the expected and the estimated eye positions. Let C_l and C_r be the manually (ground-truth) extracted left and right eye positions of a face image, $\tilde{C}_l$ and $\tilde{C}_r$ be the estimated positions by the eye detection method, d_l be the Euclidean distance between C_l and $\tilde{C}_l$, d_r be the Euclidean distance between C_r and $\tilde{C}_r$, and d_{lr} be the Euclidean distance between C_l and C_r. Then the relative error of this detection is defined as

$$Rerr = \frac{\max(d_l, d_r)}{d_{lr}} \tag{5}$$

If *Rerr* < 0.25, the detection is considered to be correct. Notice that *Rerr* =0.25 means the bigger one of d_l and d_r roughly equals half an eye width. Therefore, for a face database comprising *N* images the detection rate is defined as

$$R = \sum_{i=1}^{N} \frac{i}{N} \times 100 \quad , \quad Rerr_{i<0.25} \tag{6}$$

4.3 Results and discussions

This section presents the experimental results of the proposed method. First the method is tested on 2500 images of FERET database; examples of successful detection of this test are shown in Fig. 6. From these results one can note that the method can detected eye center accurately form frontal and non frontal view images even if these images are occluded by glasses. Fig. 7 depicts the distribution function of the relative error against successful detection rate, our method achieves 97.8 % eye detection rate when the relative error is equal to 0.25. Recently, some works [18] consider the criterion *Rerr* < 0.25 is very loose and may not be very suitable when the detected eye positions are used for face normalization, the method gives 96.7% successful detection rate at *Rerr* =0.15, which means that the proposed method is still efficient.
Second the proposed method is tested on BioID database. As mentioned before this database features a large variety of illumination, gaze directions, and face size. Though the large variety of illumination and gaze directions existed in these images, the performance of our method is reasonable; in this case the detection rate is 94.3%. Fig. 8 shows some samples for which this method success to detect the two eyes, the first and second rows show the robustness of this method against gaze direction, while the third and fourth rows show its robustness against variety of illumination. The distribution function of the relative error against successful detection rate for this test is drawn in Fig. 9 (a), one can see that when the relative error *Rerr* = 0.15, the detection rate is 94.1 %.

Fig. 6: Examples of FERET images for which two eyes are correctly detected.

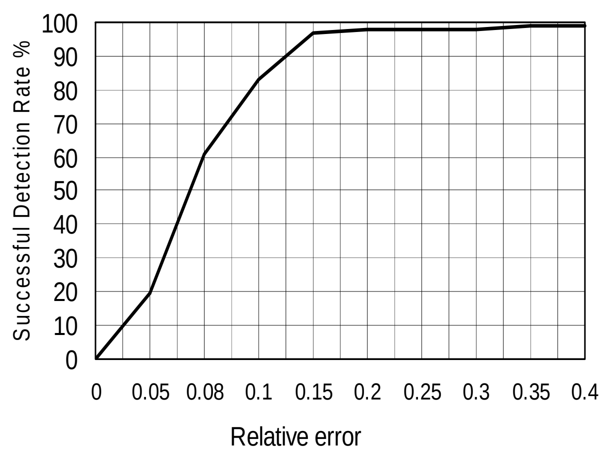

Fig. 7: Relative error versus detection rate for FERET images.

For a thorough quantitative analysis of the performance of the method in the case of images with glasses, 150 images with glasses of BioID are chosen randomly. The detection rate in this case is 92.4 % , which is less than the case where the images are without glasses. It is also shown in Fig. 9 (b) that when relative error *Rerr* is 0.15 the successful detection rate is 89.2 %. This low detection rate is due to the difficulty of these images and reflection of light near to irises. Samples of the successful detected eyes are shown in Fig. 10.

Fig. 8: Examples of BioID images for which two eyes are correctly detected.

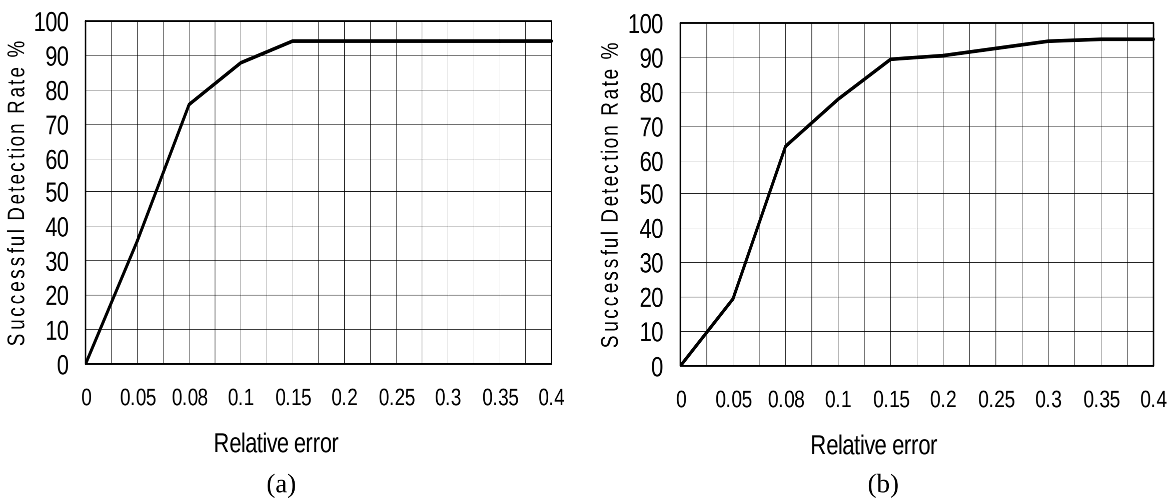

Fig. 9: Relative error versus detection rate for BioID images, (a) without glass, (b) with glass.

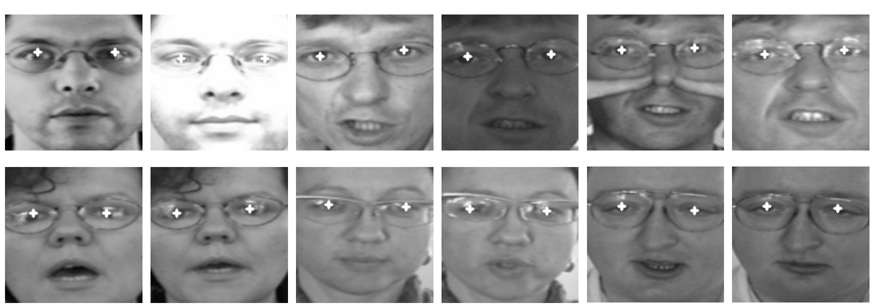

Fig. 10: Examples of BioID images with glass for which two eyes are correctly detected.

The performance of the method on FERET images is better than on BioID images, because the BioID face database is believed to be more difficult than FERET and other commonly used head-and-shoulder face database without complex background. For example, when the same detection method and evaluation criteria were applied to both XM2VTS and BioID face databases, the successful detection rates are 98.4% and 91.8%, respectively [28]. Some examples of the images for which the method failed to correctly detect irises are shown in Fig. 11 and Fig. 12 for FERET and BioID database respectively. The false detection is mainly due to some reasons; shad, eyes are almost closed and therefore the iris is hiding, glisten of glasses on eyes, the frame of glass is black and too wide which in turn can achieve the unique feature of darkness and circle around the center of window and hence guide to wrongly selection of this window, or the image is too dark to discriminate eyes from other parts.

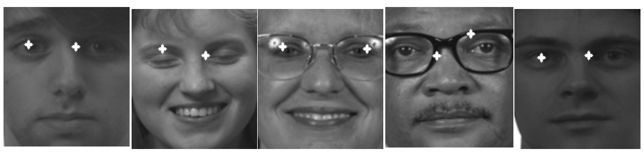

Fig. 11: FERET images for which eyes are wrongly detected.

Fig. 12: BioID images for which eyes are wrongly detected.

In order to verify that the proposed method is still robust if it is used on other different images with different conditions than FERET or BioID images, we tested it on images for persons of Georgia Institute of Technology face database. Each person has 15 images of frontal and/or tilted faces with different facial expressions, lighting conditions and scale. Figure 13 shows that this method works well under various conditions. One image of each person was lost due to the used face detection method and three only (right bottom) of 28 images are failed to detect the irises correctly using our method. The first two are failed to detect correctly because the glass frame covers or hides the iris and the last one the eye is closed so the iris can not be seen clearly.

The contribution of the proposed method to images with severe conditions is also studied separately. For this purpose 260 images with severe conditions such as reflection on the surface of eyeglasses, iris occlusion by eyelid or sleeping, shade, and lighting conditions are collected from different resources. The difficulty in these images leads to hide the iris partially or totally which in turn weaks the role of second part in Eq. 2, since this part measures the darkness of iris in a circle region. Therefore the performance of the method is reduced to 84.2% when the relative error *Rerr* is 0.15. Fig. 14 shows some examples of these severe conditions images for which the proposed method can correctly detect both eyes. The distribution function of the relative error against successful detection rate for this test is drawn in Fig. 15. Generally, because the proposed method depends on darkness of iris (*i.e.*, second part in Eq. 2), we can conclude that in images with severe conditions like reflection on the surface of eyeglasses this method can fail in the cases where the iris is not dark for any reason or totally occluded by glisten of glasses or eyelid. Examples of fail due to these reasons are shown in Fig. 16.

Finally, it is reasonable that high successful detection rate of a certain algorithm should be on a large number of images not on a few number such as 150 Bern database or 63 AR images. Table 1 compares the detection performance of various eye detection methods against the total number of used images to test these methods. Although, these methods worked well they were tested on a small number of database images. It is clear that the proposed method is the only method that gives acceptable detection rate on 4000 images. The average calculation time to detect the two eyes center-point is 30 *ms* on a PC of PIII 1GB, 256 Ram, and OS windows XP.

5. Conclusions

This paper introduced an efficient method to detect the eye's center-point. This method is based on two fact: first eye region exhibit unpredictable local intensity, which means that pixel values are highly unpredictable and this corresponds to high entropy compared to other regions. Second, eyes (iris) are circle and dark. A total score based on the high entropy and darkness of the iris is given to rectangle regions of fixed size, the highest score region is considered to contain the iris. The proposed method is tested on the BioID and a subset of FERET databases. It shows that a correct eye detection rate of 94.3% and 97.8% can be achieved on BioID and FERET, respectively. These two datasets images are combined with other images of different databases to create a set of more than 4000 images and we tested the method on this number of images. It gives average correct eye detection rate of 96.2%. The proposed method along with a robust face detection method can be effectively used in real-time applications because it is very simple and works well under various conditions than other existing eye detection methods.

Fig. 13: Testing the proposed method on two person's images of Georgia Tech face database.

Fig. 14: Examples of images with severe conditions for which eyes are correctly detected.

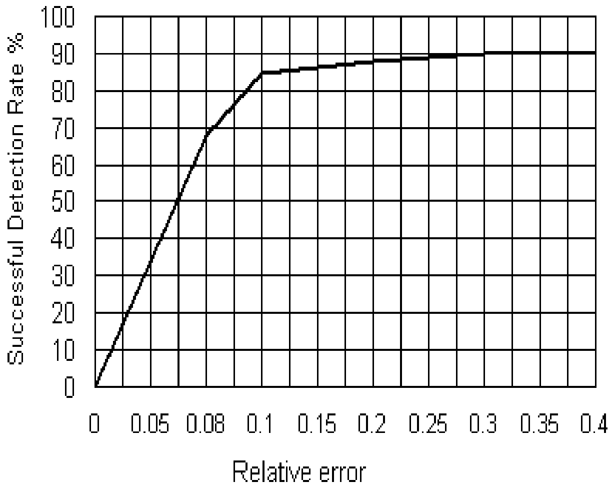

Fig. 15: Relative error versus detection rate for the set of images with severe conditions.

Fig. 16: Examples of images with severe conditions for which eyes are wrongly detected.

Table 1: Comparison of various eye detection methods against number of used images.

Method	Total number of used images	Detection Rate
Proposed method	4000	96.2 %
Zhou and Geng [20]	2093	95.9 %
Choi and Kim [19]	714	98.7 %
Song and Liu [18]	714	97.6 %
Kawaguchi and Rison [15]	564	96.8 %
Peng et al. [21]	227	95.2 %

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