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Eye Detection Using Intensity and Appearance Information

M. Hassaballah
Department of Electrical and Electronic Engineering and Computer Science
Ehime University, 790-8577, Japan.
m.hassaballah@ic.cs.ehime-u.ac.jp

Shun Ido
Department of Electrical and Electronic Engineering and Computer Science
Ehime University, 790-8577, Japan.
ido@cs.ehime-u.ac.jp

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 face identification and recognition. This paper presents a new method for eye detection of still gray scale images. The method is based on two facts; eye regions exhibit unpredictable local intensity, therefore entropy in eye regions is high and the iris of eye is circle and too dark 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 eye detection rate of 97.8% and 94.3% on the FERET and BioID images respectively. Moreover, in the case of glasses the performance is still acceptable.

1. Introduction

Automatic face recognition has attracted significant attention in computer vision and pattern recognition [1]. Several face recognition systems are based on basic facial features, such as eyes, nose and mouth, and their spatial relationship. Among all 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. Detection of the human eye is a very difficult task because the contrast of the eye is not remarkable [2].

Several eye detection methods have been developed in the last ten years. Deformable template [3] is the popular method in locating the human eye. However, this method is feasible only if the initial position of the eye model is placed near the actual eye position. Moreover, deformable template is computation expensive and the weight factors for energy terms are determined manually. Improper selection of the weight factors will yield unexpected results.

Hough transform is also used widely for eye detection. 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. Kawaguchi and Rizon [4] detected the iris using the intensity and the edge information. To evaluate the validity of their method, they used images from two databases; the Bern and AR database. The method achieved a correct iris detection rate of 95.3% for 150 Bern face images and 96.8% for 63 AR images. But they did not explain how to automatically detect the light dot in the iris.

Besides these two classical approaches, recently other eye detection methods have been proposed. Ehsan et al. [5] presented a rotation-invariant facial feature detection system based on combining the Gabor wavelet and the entropy measure. Zhou and Geng [6] extended the idea of the integral projection function (IPF) and variance projection function (VPF) 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. 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. Song et al. [7] use the binary edge images and intensity information to detect eyes. Their method consists of three steps: first extraction of binary edge images based on multi-resolution wavelet transform, second extraction of eye regions and segments, and third eye localization based on light dots and intensity information. A correct eye detection rate of 98.7% and 96.6% can 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.

Eye detection is divided into two types; eye contour detection and eye position detection [8]. This paper focuses on the second type; eye position detection, as most algorithms for eye contour detection such as those are based on the deformable template [9] 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. In this work a new method for eye detection of still gray scale images is introduced. The method is based on entropy of eye regions and the fact that the center of eye is too dark compared to the neighboring regions. A score based on the entropy of eye and darkness of iris is used to detect eye center coordinates.

The rest of this paper is organized as follows. The proposed method for eye's center-point detection is introduced in Section 2. Experimental results are reported in Section 3 and finally the conclusions and future research are given in Section 4.

2. 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 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:

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

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. As an example, Fig. 1 shows six different regions of the top half of the face and their corresponding PDF (An intensity histogram in this work). The two eyes (b,f) exhibit unpredictable local intensity indicating that flatter of PDF and hence entropy is high, while in the other two areas (c,d) the PDF is peaked and therefore low entropy.

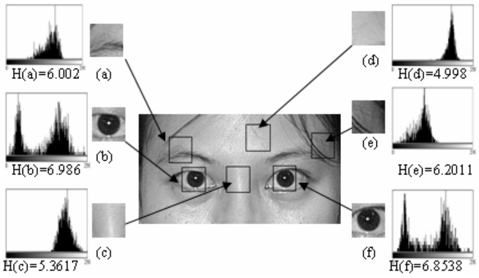

Fig. 1. The PDF and entropy of six different regions of eye area

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, 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 [10]. Second the eye region (in the range from 10% to 50% of face height) is divided into small windows of size w x h pixel (Fig. 2(c)), these windows can overlap for good performance and therefore the total number of windows will be large (say M), calculate entropy value for each window using Eq. (1), the highest entropy value windows should be around the iris because in this area the variation of pixels is high, therefore the entropy will also be high as mentioned above. Then, we chose n windows only that have highest entropy value from all these M windows as shown in Fig. 2(d).

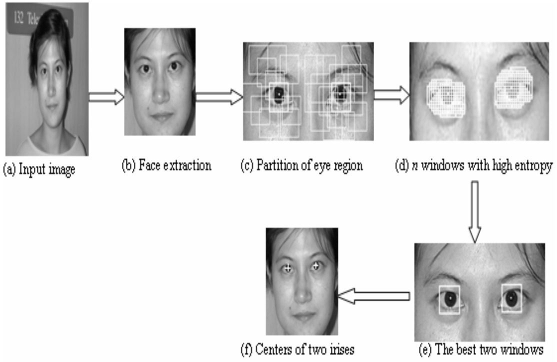
(a) Input image
(b) Face extraction
(c) Partition of eye region
(d) *n* windows with high entropy
(f) Centers of two irises
(e) The best two windows

Fig. 2. Flowchart of the proposed eye detection method

Entropy alone is not enough to detect the window which contains iris from these chosen n highest entropy value, because it measures the variation of pixel values not eye features. 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. In other words, 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:

$$T_{score} = H_{score} + C_{score} \qquad (2)$$

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

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

$$C_{score} = 1 - \frac{Color(W_i)}{\sum_{i=1}^{n} Color(W_i)} \qquad (3)$$

Color (W_i) and *Entropy* (W_i) are calculated for each window W_i, ($i = 1, \ldots, n$) using sum of intensity pixel value and Eq. (1) respectively. Finally, according to Eq. (2), the best window which has highest total score T_{score} is selected; 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 this paper we adopt n to 50 windows, the windows size to 14 x 12 pixels with overlap 2 pixels in horizontal and vertical directions, and radius of circle r to 5. 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 the darkness and circle are unique features for the window which contains the iris among all the 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 an open research problem, now this method guarantees that 99% of highest entropy value windows are around the iris of eye (Fig. 2(d)). In this work, appearance of eye cue (circle and darkness of iris) is used in Eq. (2) to guide for the correct window; other cues may outperform our appearance cue. The great advantage of the proposed method is that it is simple and can be implemented easily because it dose not require complicated pattern matching.

3. Experimental results

3.1. Data sets and Evaluation criterion

To assess the viability of the proposed method, two face databases are used; a subset of 2500 face images of the FERET database [11] and BioID face database [12]. The performance of the proposed method is evaluated on the basis of the criterion of [13]. 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 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:

$$R\,err = \frac{\max(d_l, d_r)}{d_{lr}} \tag{4}$$

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:

$$R = \sum_{i=1}^{N} \frac{i}{N} \times 100 \quad , \quad R\,err_{i<0.25} \tag{5}$$

3.2. 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. 3. From these results one can note that the method is robust for frontal and non frontal view images even if these images are occluded by hairstyle or glasses. Fig. 4 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 [7] consider that 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. Though the large variety of illumination and gaze directions existed in these images, the performance of the method is reasonable; in this case the detection rate is 94.3%. Figure 5 shows some samples for which this method success to detect the two eyes. Also the distribution function of the relative error against successful detection rate for this test is drawn in Fig. 6, it is noted that when the relative error *Rerr* = 0.15, the detection rate is 94.1 %.

For a thorough quantitative analysis of the performance of the proposed method in the case of images with glasses, 150 images with glasses of BioID are chosen randomly. Samples of the successful detected eyes are shown in Fig. 7. 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. 8 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.

Fig. 3. Examples of FERET images for which two eyes are correctly detected

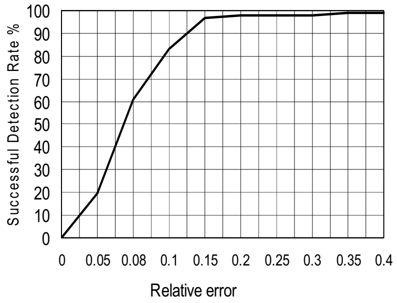

Fig. 4. Relative error versus detection rate for FERET images

Fig. 5. Examples of BioID images for which two eyes are correctly detected

Some examples of the images for which the method failed to correctly detect irises are shown in Fig. 9. 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 or the image is too dark to discriminate eyes from other parts. The advantage of the proposed method is that it is simple and can be implemented easily because it dose not require complicated pattern matching. It works well under various conditions. Moreover in all previous tests, we do not apply any type of preprocessing on the used images and the average calculation time to detect the two eyes center-point is 30 *ms* on a PC of PIII 1.0 GB, 256 RAM, and OS windows XP.

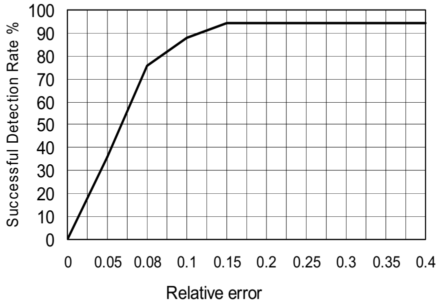

Fig. 6. Relative error versus detection rate for BioID images without glass

Fig.7. Examples of BioID images with glass for which two eyes are correctly detected

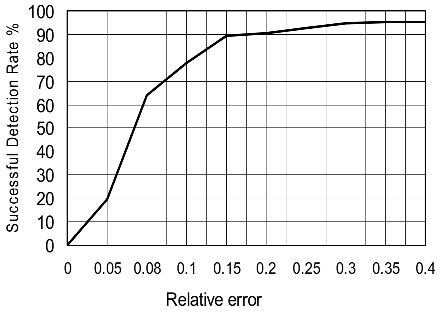

Fig. 8. Relative error versus detection rate for BioID images with glass

Fig. 9. Examples of images for which eyes are wrongly detected

4. Conclusions

This paper introduces an efficient method to detect the eye's center-point. This method is based on two facts; 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, eye (iris) is 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 method is tested on a subset of FERET and BioID databases. It shows that a correct eye detection rate of 97.8% and 94.3% can be achieved on FERET and BioID respectively. 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. Improving performance further for images with severe conditions such as glisten of glasses on eyes or occlusion by eyelid is the main goal of the future work.

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References

[1] X. Tan, S. Chen, Z-H. Zhou, F. Zhang, "Face recognition from a single image per person: A survey," *Pattern Recognition*, Vol. 39, 2006, pp. 1725- 1745.

[2] G.C. Feng, P.C. Yuen, "Variance projection function and its application to eye detection for human face recognition," *Pattern Recognition Letters*, Vol. 19, 1998, pp. 899-906.

[3] A.L. Yuille, P.W. Hallinan, D.S. Cohen, "Feature extraction from faces using deformable templates," *International Journal of Computer Vision*, Vol. 8, No. 2, pp. 99-111, 1992.

[4] T. Kawaguchi, M. Rizon, "Iris detection using intensity and edge information," *Pattern Recognition*, Vol. 36, pp. 549-562, 2003.

[5] F. Ehsan and John S. Zelek, "Rotation-Invariant facial feature detection using gabor wavelet and entropy," *LNCS* 3656, pp. 1040-1047, 2005.

[6] Z-H. Zhou, X. Geng, "Projection functions for eye detection," *Pattern Recognition*, Vol. 37, pp. 1049-1056, 2004.

[7] J. Song, Z. Chi, J. Liu, "A robust eye detection method using combined binary edge and intensity information," *Pattern Recognition*, Vol. 39, pp. 1110-1125, 2006.

[8] K. H. Mohammad, R. Safabakhsha, "Human eye sclera detection and tracking using a modified time-adaptive self-organizing map," *Pattern Recognition*, Vol. 41, No. 8, pp. 2571-2593, 2008.

[9] P. Campadelli, R. Lanzarotti, Fiducial point localization in color images of face foregrounds, *Image and Vision Computing*, Vol. 22, 863-872, 2004.

[10] P. Viola, M. Jones, "Rapid object detection using a boosted cascade of simple features," In Proc. of *IEEE Conference on Computer Vision and Pattern Recognition* (CVPR 2001), Vol. 1, pp. 511-518, 2001.

[11] P.J. Phillips, H. Moon, S. Rizvi, P. Rauss, "The FERET evaluation methodology for face recognition algorithms," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 22, No. 10, pp.1090-1103, 2000. http://www.nist.gov/humanid/colorferet.

[12] R.W. Frischholz, U. Dieckmann, "Bioid: a multimodal biometric identification system," *IEEE Computer*, Vol. 33, pp. 64-68, 2000. http://www.bioid.com/downloads/

[13] O. Jesorsky, K. Kirchberg, R. Frischholz, "Robust face detection using the hausdorff distance," In Proc. of the 3rd *Int. Conference on Audio-and Video-based Biometric Person Authentication*, Sweden, pp. 90-95, 2001.