Eye detection under varying illumination using the retinex theory

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A B S T R A C T

Eye detection plays an important role in face recognition because eyes provide distinctive facial features. However, illumination effects such as heavy shadows and drastic lighting change make it difficult to detect eyes well in facial images. In this paper, we propose a novel framework for illumination invariant eye detection under varying lighting conditions. First, we use adaptive smoothing based on the retinex theory to remove the illumination effects. Second, we perform eye candidate detection using the edge histogram descriptor (EHD) on the illumination normalized-facial images. Third, we employ the support vector machine (SVM) classification for eye verification. Finally, we determine eye positions using eye probability map (EPM). Experimental results on the CMU-PIE, Yale B, and AR face databases demonstrate that the proposed method achieves high detection accuracy and fast computation speed in eye detection.

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1. Introduction

Eye detection is the most important task in face recognition due to the distinctness of eye features in human faces. Thus, accurate eye detection leads to effective face recognition. Moreover, eye detection is the key technology for facial expression recognition, man-machine interaction, and driver fatigue monitoring systems.

1.1. Related work

Up to now, a lot of studies for eye detection have been conducted by researchers [1–20]. Early studies focused on the projection profile analysis to determine eye positions [1,2]. In the studies, the distinct edges in eye patterns were mainly extracted for accurate eye detection. Their results showed that the gray projection-based methods achieved high-speed performance, but were not robust against noise and illumination effects due to the relatively low generalization. The SVM-based methods have been widely used and achieved considerable high accuracies in eye detection [3–6]. The knowledge based method is also another approach to eye detection [7]. It employed the prior information such as outline, color, and position relationship. Park et al. proposed an eye filter considering textural characteristics of eye regions to improve the candidate detection part [8]. That is, the

eye filter was employed for detecting pairs of eye candidate points. In addition, to detect the exact eye position, all pairs of the eye candidates were evaluated by a cost function, which minimized the non-negative matrix factorization (NMF)-based image reconstruction error. Song et al. proposed a novel eye detection method to combine binary edge and intensity information [9]. This method was composed of three main parts: face region extraction, eye region segmentation based on the binary edge image (BEI), and fine eye localization. In this method, BEI could be effectively used for eye region extraction, reflected light-dot detection, and eye segment extraction. Valenti et al. proposed an eye detection method through invariant isocentric patterns. In this method, an isophote based strategy was used to detect the gray gradient circle in eye patterns. The detected isocenters were linearly combined to determine the eye position. Then, mean-shift and machine learning methods were employed to enhance the eye detection accuracy [11].

In actual outdoor scenes, the brightness and direction of lighting change greatly over time. Illumination effects such as heavy shadows and drastic lighting change inevitably occur in facial images. They make it difficult to detect eyes well and thus have detrimental effects on the computer vision systems. Thus, recent studies have focused on the illumination-invariant eye detection [10,16–18]. Tan proposed an eye detection method robust against complex conditions including illumination, pose, expression, and occlusion [10]. In this method, an enhanced pictorial structure model was adopted, and SVM was used to approximate the energy function of the model. Moreover, an illumination normalization strategy was utilized to deal with the

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varying lighting conditions [17,18]. The retinex theory motivated by Land [21] was one of the representative methods for illumination normalization. The theory was based on the physical imaging model, in which an image $I(x,y)$ was regarded as the product $I(x,y) = R(x,y) \cdot L(x,y)$ where $R(x,y)$ was the reflectance and $L(x,y)$ is the illumination at each pixel (x,y). Here, the nature of $L(x,y)$ was determined by the illumination source, whereas $R(x,y)$ was determined by the characteristics of the objects in images. Therefore, the illumination normalization was achieved by estimating the illumination L and then dividing the image I by it. In most retinex methods, the reflectance R was estimated as the ratio of the image I and its smoothed version which served as the estimate of the illumination L. Thus, many smoothing filters to estimate L were proposed, such as single scale retinex (SSR) [22], multi-scale retinex (MSR) [23], self-quotient image (SQI) [24,25], and adaptive smoothing [26]. Although the retinex methods were able to deal with illumination effects and improve eye detection performance, the related studies were relatively small.

1.2. Overview and contributions

In this paper, we propose a novel framework for illumination invariant eye detection under varying lighting conditions based on the retinex theory. As shown in Fig. 1, the proposed eye detection method consists of four main procedures: illumination normalization, eye candidate detection, eye verification, and eye position determination. First, we perform illumination normalization to deal with the illumination effects in facial images. Our illumination normalization is based on the retinex theory, and we employ the adaptive smoothing filter for illumination normalization to preserve features and reduce cast shadows effectively [21,26]. Second, we conduct eye candidate detection on R, i.e., illumination-normalized facial images, for the fast computation. R is somewhat different from ordinary facial images. That is, edges and features in R are somewhat sharpened by the adaptive smoothing filter. Thus, we use the edge histogram descriptor (EHD) considering the characteristics of R for eye candidate detection [27,28]. Third, the eye candidates are verified by SVM using normalized-gray features. In the eye verification, we construct the training database and verify the eye candidates on R, i.e., the illumination normalized-facial images. Finally, we generate an eye probability map (EPM), and determine the eye positions by selecting the two largest maxima of EPM. The eye verification results in different hierarchies are elaborately combined into eye probability map (EPM) using the Gaussian

weighting function. Main contributions of this work are as follows: (1) We design an effective eye detection framework by employing the illumination normalization based on the retinex theory to achieve the high detection accuracy under varying illumination. (2) All procedures of the proposed method are performed on the illumination normalized-facial images unlike previous eye detection methods. That is, the edge histogram descriptor (EHD) of the eye candidate detection is employed to consider the distinctive edge distribution of eye patterns in the illumination normalized-facial images. Also, the features of the SVM verification are extracted on the illumination normalized-facial images. (3) We adopt a coarse-to-fine strategy of eye candidate detection and verification to reduce the computing time for eye detection. Therefore, experimental results show that our method achieves both high detection accuracy and fast computation speed in eye detection.

1.3. Organization

This paper is organized as follows. In Section 2, we introduce the illumination normalization method based on the retinex theory. Eye candidate detection based on EHD is described in Section 3. In Section 4, a brief review on SVM verification is provided. In Section 5, we explain the method of determination of eye positions. In Section 6, experimental results are provided and we conclude this paper in Section 7.

2. Illumination normalization

Based on the retinex theory, the illumination normalization is performed. As shown in Fig. 2, the Retinex algorithm consists of two main steps: estimation and normalization of illumination. We employ adaptive smoothing for the illumination estimation as in [26]. The key idea of adaptive smoothing is to iteratively convolve the input image with the 3×3 averaging mask whose coefficients reflect the discontinuity level of the input image at each point. Since we estimate illumination as a smoothed version of an input image I, the initial value of the estimated illumination should be the same as $I(x,y)$. Then, the estimated illumination $L^{(t+1)}(x,y)$ at the $(t+1)$th iteration is obtained by the following equations:

$$L^{(t+1)}(x,y) = \frac{1}{N^{(t)}(x,y)} \sum_{i=-1}^{1} \sum_{j=-1}^{1} L^{(t)}(x+i,y+j) \cdot w^{(t)}(x+i,y+j) \qquad (1)$$

$$N^{(t)}(x,y) = \sum_{i=-1}^{1} \sum_{j=-1}^{1} w^{(t)}(x+i,y+j) \qquad (2)$$

$$w^{(t)}(x,y) = g(d^{(t)}(x,y)) \qquad (3)$$

Here, $N^{(t)}(x,y)$ in (2) represents a normalizing factor. A mapping function g is a non-negative monotonically decreasing function such that $g(0)=1$ and $g(d^{(t)}(x,y))$ approaches 0 as $d^{(t)}(x,y)$ increases, where $d^{(t)}(x,y)$ represents the amount of discontinuity at each pixel (x,y). For more accurate description of real environments, an additional constraint is addressed that surfaces
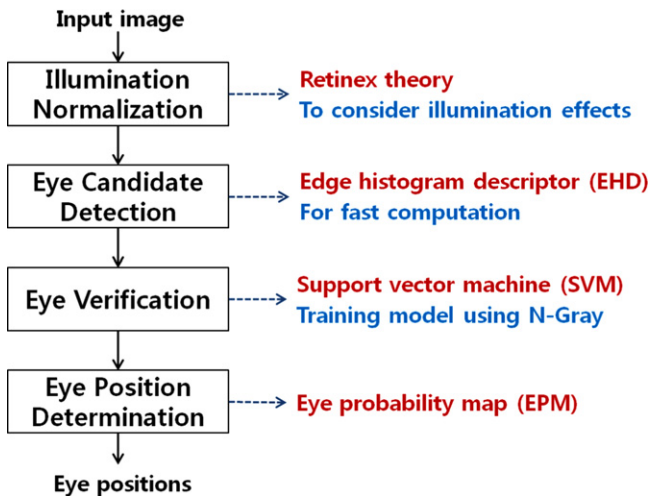

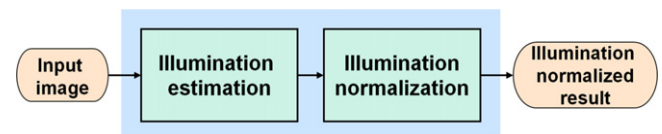Fig. 1. Block diagram of the proposed eye detection method.

Fig. 2. General framework of the retinex algorithm.

cannot affect more light than what is shed on them. Thus, R is restricted to be in the range $R \in [0,1]$. This constraint is called the smoothing constraint [29]. After applying this smoothing constraint, (1) can be rewritten as follows:

$$L'^{(t+1)}(x,y) = \frac{1}{N^{(t)}(x,y)} \sum_{i=-1}^{1} \sum_{j=-1}^{1} L^{(t)}(x+i,y+j) \cdot w^{(t)}(x+i,y+j) \quad (4)$$

$$L^{(t+1)}(x,y) = \max\{L'^{(t+1)}(x,y), L^{(t)}(x,y)\} \quad (5)$$

To distinguish discontinuities and shadows, we combine two different measures such as spatial gradient and local inhomogeneity [26,30]. First, spatial gradient is a common local discontinuity measure in image processing. The spatial gradient of an image $I(x,y)$ at a pixel (x,y) is defined as the first partial derivatives of its image intensity function with respect to x and y:

$$\nabla I(x,y) = [G_x, G_y] = \left[\frac{\partial I(x,y)}{\partial x}, \frac{\partial I(x,y)}{\partial y} \right] \quad (6)$$

where $G_x = I(x+1,y) - I(x-1,y)$ and $G_y = I(x,y+1) - I(x,y-1)$. Thus, the magnitude of the gradient vector in (6) is obtained by

$$\nabla I(x,y) = \sqrt{G_x^2 + G_y^2} \quad (7)$$

Second, local inhomogeneity is used as an alternative discontinuity measure of spatial gradient [26]. This measure provides the degree of uniformity between all the pixels in the small neighborhood and current pixel. Thus, if local inhomogeneity at a pixel (x,y) is large, we can expect that discontinuity occurs at a pixel (x,y). The average of local intensity differences at a pixel (x,y) is as follows:

$$\tau(x,y) = \frac{\sum \sum_{(m,n) \in \Omega} |I(x,y) - I(m,n)|}{\Omega} \quad (8)$$

where Ω is a local neighborhood of the pixel (x,y), and (m,n) indicates the locations of pixels in the neighborhood Ω. We only consider the 3×3 neighborhood of the pixel (x,y). Then, $\tau(x,y)$ at each pixel (x,y) is normalized by

$$\hat{\tau}(x,y) = \frac{\tau(x,y) - \tau_{\min}}{\tau_{\max} - \tau_{\min}} \quad (9)$$

where $\tau_{\max}$ and $\tau_{\min}$ are the maximal and minimal values of τ across the entire facial image, respectively. To emphasize higher values of $\hat{\tau}$ that more likely correspond to cast shadows as in [26,30], a nonlinear transformation is adopted as follows:

$$\hat{\tau}(x,y) = \sin\left(\frac{\pi}{2}\hat{\tau}(x,y)\right), \quad 0 \le \hat{\tau}(x,y) \le 1 \quad (10)$$

To utilize the two discontinuity measures, the proper mapping function g is newly defined using a parameter K by the following equation [26]:

$$g(d,K) = \frac{1}{1 + \sqrt{\frac{d}{K}}} \quad (11)$$

Here, d is the amount of discontinuity and K is a parameter that determines the level of discontinuities which should be preserved. The mapping function g is applied to both spatial gradient and local inhomogeneity as follows:

$$\alpha(x,y) = g(\hat{\tau}(x,y), h) \quad (12)$$

$$\beta(x,y) = g(|\nabla I(x,y)|, S) \quad (13)$$

Here, two parameters, $0 < h < 1$ and $S > 0$, are used to determine the level of discontinuities to be preserved. Thus, the convolution mask $w(x,y)$ of (4) is determined using $\alpha(x,y)$ and $\beta(x,y)$ as follows:

$$w(x,y) = \alpha(x,y) \cdot \beta(x,y) \quad (14)$$

Then, by taking the difference between the input image and the estimated illumination, we get the normalized facial image $R'(x,y)$ as follows:

$$R'(x,y) = \log(I(x,y)+1) - \log(L^{(T)}(x,y)+1) \quad (15)$$

Finally, the illumination normalization result $R(x,y)$ is obtained by normalizing $R'(x,y)$ as follows:

$$R(x,y) = \frac{R'(x,y) - R'_{\min}}{R'_{\max} - R'_{\min}} \quad (16)$$

where $R'_{\max}$ and $R'_{\min}$ are the maximal and minimal values of $R'(x,y)$ across the entire image. The results of illumination normalization are provided in Fig. 3.
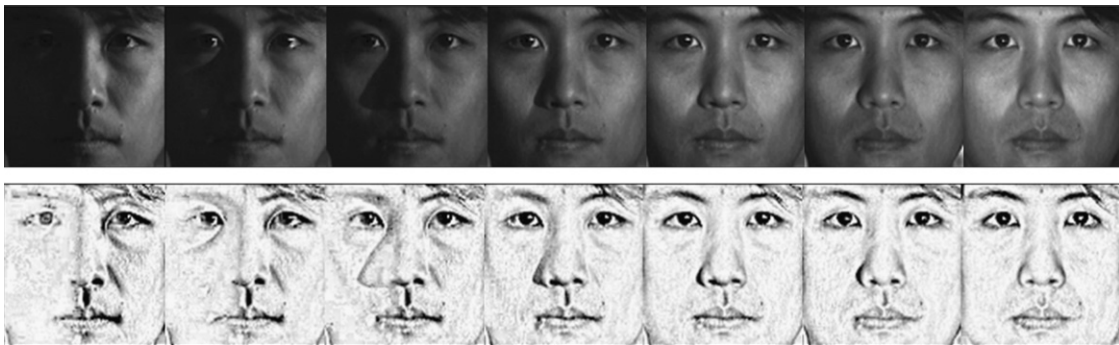

Fig. 3. Some illumination normalization results. Top: original facial images. Bottom: illumination normalization results.

Fig. 4. Five kinds of the computation masks in the edge histogram descriptor (EHD).

3. Eye candidate detection

In MEPG-7, the edge histogram descriptor (EHD) represents the distribution of edges in image with 5 types of edges: vertical, horizontal, 45° diagonal, 135° diagonal, and non-directional edges as shown in Fig. 4. Thus, we get an edge strength direction E_{dir} of edge in image blocks using the EHD as follows [27,28]:

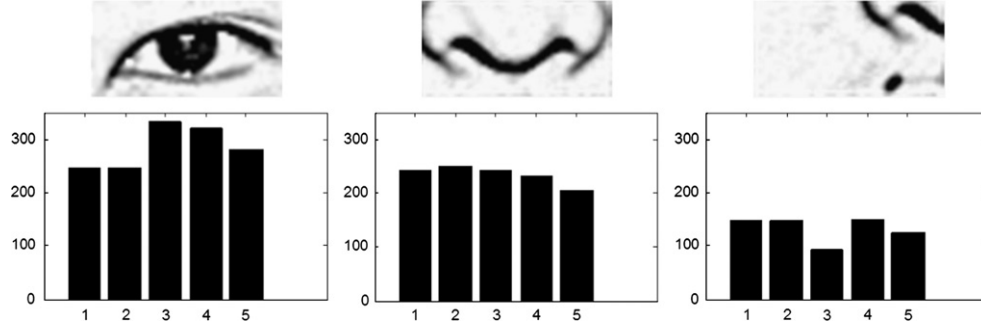$$E_{dir} = \sum_{i=1}^{2} \sum_{j=1}^{2} PIX_{i,j} \cdot M_{i,j} \qquad (17)$$

Fig. 5. EHD of each region in facial images. Left: eye region. Middle: nose region. Right: other region.
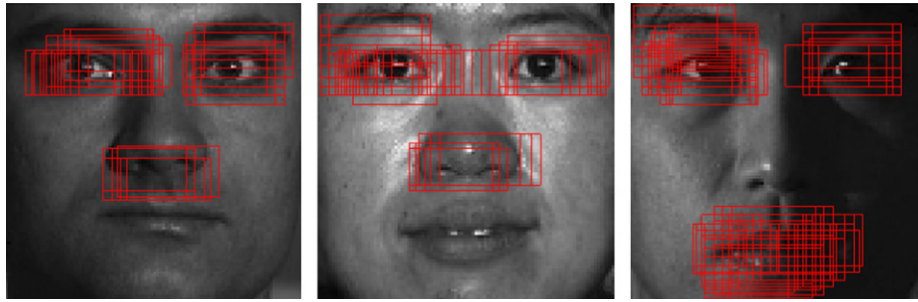

Fig. 6. Some eye candidate detection results using EHD.

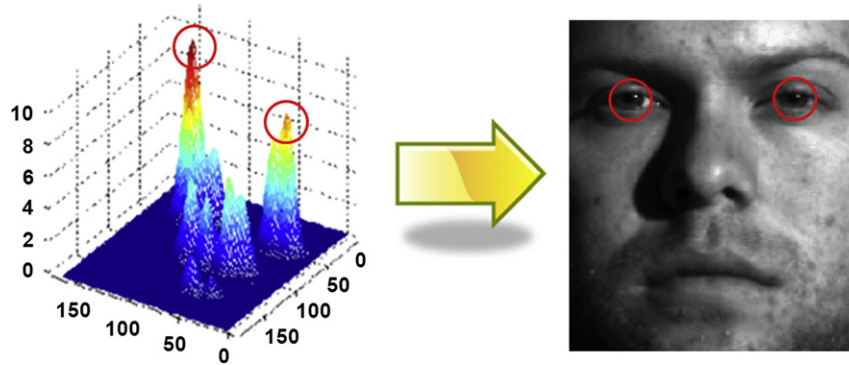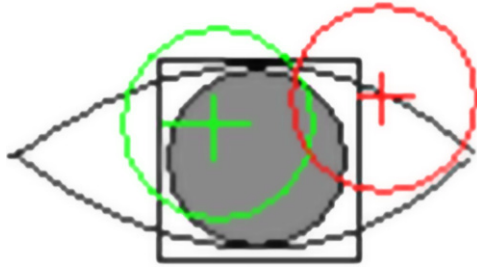Fig. 7. Determination of eye positions. Left: eye probability map (EPM). Right: eye positions. Two largest local maxima in EPM are determined as the positions of eyes, and eyes are localized at red circles. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

Fig. 8. Training data sets. Top: positive samples. Bottom: negative samples.

where $PIX_{i,j}$ is the i-th row and j-th column pixel value in a block; and $M_{i,j}$ is the i-th row and j-th column mask value in the block. This method selects the maximum absolute value of the edge strength. That is, if the value is larger than a given threshold, then we increase the number in the corresponding local histogram bin. The threshold is set to be 20 for illumination normalized image. Thus, we obtain totally 5 bins of edge histogram, which describe the distribution of edges in the block. Fig. 5 shows the EHD of each region in facial images. It is easy to find out that, the eye pattern has a distinct edge histogram from other regions in facial image. Thus, this distinction is used in eye candidate detection. From the figure, it can be observed that the values of EHD bins in eye regions are mainly greater than that in the other regions. That means eye features have more complex edge distribution than the others. Therefore, we use the average of EHD bins as the edge complexity measure of a region. If the average is greater than a given threshold, the region is chosen as an eye candidate. Here, the threshold is set to the average of the edge complexity through the whole image. In the eye candidate detection, a window scanning is performed by 2 pixel overlapping. The window size for scanning

is 10×20. Considering different scale of eye regions, 3 hierarchies are used in scanning. Some candidate detection results are shown in Fig. 6.
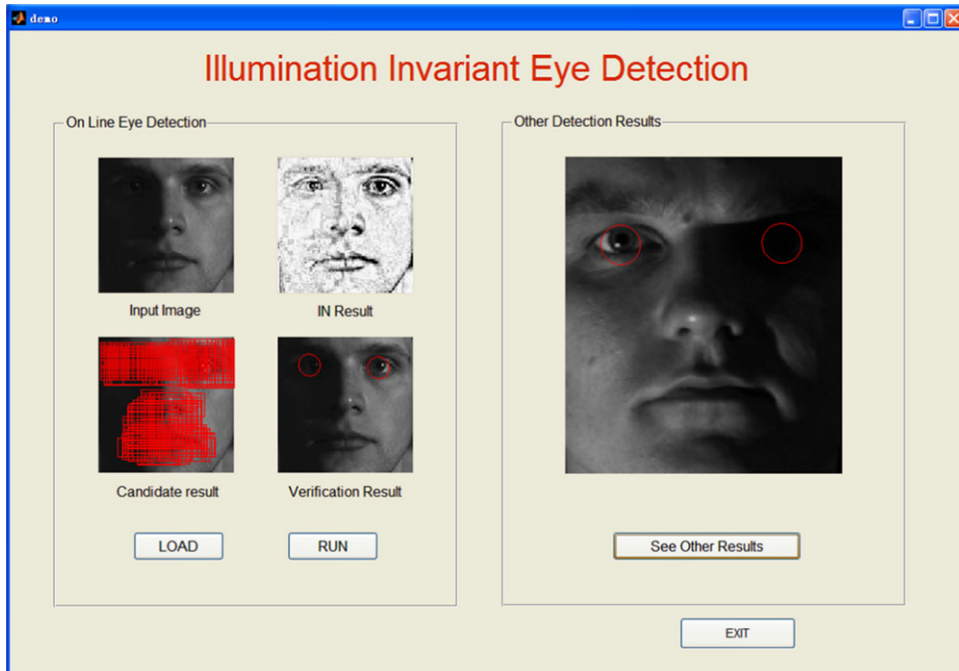
4. Eye verification

After the eye candidate detection, verification is required to get the real eyes from eye candidate detection results. In the eye verification procedure, support vector machine (SVM), one of the powerful tools in pattern classification is used. SVM is a binary classifier introduced by Vapnik [31]. Its main idea is to construct an optimal linear hyper-plane to separate two class samples with the constraint that maximizes the margin between two classes. The decision hyper-plane can be expressed as follows:

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i y_i (\mathbf{x}_i^T \cdot \mathbf{x}) + b \qquad (18)$$

where f is the distance between testing samples and a decision hyper-plane; $\mathbf{x}$ is the input feature vector; α is the Lagrange multiplier; $\mathbf{x}_i$ is the i-th support vector; y_i is the label of the support vector; and N is the number of support vectors. By considering the nonlinear condition, we use a nonlinear kernel to substitute the inner product in (18). Thus, (18) is rewritten as follows:

$$f(\mathbf{x}) = \sum_{i=1}^{N} \alpha_i y_i k(\mathbf{x}_i, \mathbf{x}) + b \qquad (19)$$

where k is a kernel function. We have selected the training data sets for SVM on the illumination-normalized facial images. Then, we get a model for the SVM verification from the training data sets. The distance between testing samples and decision hyper-plane, f, is calculated by (19), and used to determine eye positions.

Fig. 9. The definition for successful detection. The green circle is a successful detection while the red one is a false detection. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

Fig. 10. User interface of the proposed eye detection method. The left window in this figure shows the intermediate results while the right window shows the eye detection results on the test database.

Fig. 11. Eye detection results in facial images. Eyes are localized in the red circles. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

5. Determination of eye positions

It is necessary to determine the real positions of eyes from the verified eye regions. To determine the eye positions, an eye probability map (EPM) is employed [8]. An EPM for the k-th hierarchy, p_k, is the sum of the Gaussian function weighted by $f(\mathbf{x}_k)$ as follows:

$$p_k(x,y) = \sum_{f(\mathbf{x}_k) > 0} f(\mathbf{x}_k) \exp\left(-\frac{(x-\hat{x}_k)^2}{\sigma_k^2} - \frac{(y-\hat{y}_k)^2}{\sigma_k^2}\right) \qquad (20)$$

where $\hat{x}_k$ and $\hat{y}_k$ are x- and y-coordinates at the center pixel in the k-th hierarchy. Then, the EPM for the facial image, p, is the sum of all p_k's, that is $p(x,y) = \sum_k p_k(x,y)$. An example of p is shown in Fig. 7. Two largest local maxima of p are determined as the positions of eyes.

6. Experimental results

Experiments are performed on three publicly available face databases: CMU PIE, Yale B, and AR. The CMU PIE database contains 41 368 images obtained from 68 subjects. We take the frontal face images with 21 different illumination conditions, and thus the total number of face images is 1428 in the CMU PIE database. The Yale B database contains 5760 images taken from 10 subjects under 576 viewing conditions, i.e., 9 poses × 64 illumination conditions. We select 640 face images for 10 subjects representing 64 illumination conditions under the frontal pose. The AR face database includes 26 frontal images for 126 subjects. We select the frontal face images with six different illumination conditions for 120 subjects, and thus the total number of images is 720. Among them, we use 500 images for training as the positive samples, i.e., 1000 positive samples, and the rest for testing. The proposed method is implemented in MATLAB R2010b, and all the experiments are conducted on a PC running Windows XP with Pentium IV CPU (3.19 GHz) and 3 G RAM. Notice that facial images with glasses are not considered to evaluate performance. The training data set is composed of the 1000 positive and 1000 negative samples which are selected from the illumination normalized-facial images in the face databases. In the positive samples, the ground truth of the eye positions are manually selected in the illumination normalized-facial images. Some training samples are shown in Fig. 8. To find the optimal radial basis function (RBF) kernel parameter g and the trade-off C, we conduct 10-fold cross validation on the training data set. The range of g is $[2^{-10}, 2^{-16}]$ while that of C is $[1, 10^4]$. Based on the principle of the highest accuracy and the lowest number of support vector (nSV), we set $g=2^{-12}$ and $C=10$. We train an SVM model using the parameters, and use it for the tests on the illumination normalized-facial images. The predicted detection accuracy of the SVM model is 0.9352. In (19), we use normalized gray-level values as the feature vector. As an evaluation metric, the accuracy measure is used, which indicates the relative frequency of the successfully detected eyes. Here, the successful detection means that the center of detection circle is located at the area of pupil. As shown in Fig. 9, the green circle is a successful detection while the red one is a false detection.

The user interface of the proposed eye detection method is illustrated in Fig. 10. The left window in this figure shows the intermediate results including illumination normalization, eye candidate detection, and SVM verification. The right window shows the eye detection results on the test database. Furthermore, Fig. 11 illustrates some representative results in facial images under varying lighting conditions. In the figure, eyes are localized in red circles. It can be observed that the proposed method achieves demonstrable eye detection results even in facial images with cast shadows and drastic lighting change. The accuracy of our method is listed in Table 1. In the table, the bold numbers represent the best accuracy in each face database. Here, 'IN' means illumination normalization. To verify the superiority of the retinex based illumination normalization, we also evaluate the performance when the illumination normalization is not employed for eye detection. As shown in the table, illumination normalization remarkably improves the eye detection performance. On average, we achieve an increase of over 19.8% by illumination normalization in terms of the detection accuracy. Furthermore, we compare the performance of our method with

some state-of-the art methods such as [8,9,17]. In [17], two illumination normalization methods such as the self-quotient image (SQI) and the fast logarithmic total variation (FLTV) are used, and thus we report both of the evaluation results. It can be observed that our method consistently achieves good detection accuracies in almost all cases. The experimental results show that our method has obvious advantages in accuracy, especially under complex illumination conditions. As shown in Table 2, we provide the average number of false positives in an image by the eye candidate detection (see the second row). Also, we provide its precision based on the prior knowledge that there are a couple of eyes in one facial image (see the third row). As can be seen, the average precision of the eye candidate detection is about 0.72%. Table 3 lists the computation time for eye detection with and without eye candidate detection. As listed in the table, the EHD based candidate detection significantly reduces the computation time for eye detection about average 0.21 s/image (58%). Consequently, we achieve both high detection accuracy and fast computation speed in eye detection by the proposed method. This is caused by the following two reasons: (1) We utilize an illumination normalization method based on the retinex theory to remove undesirable illumination effects such as heavy shadows and drastic lighting change. Thus, our method produces the high detection accuracy under varying illumination. (2) We adopt a coarse-to-fine strategy of eye candidate detection and verification to improve the computation speed of eye detection. It is well-known that the SVM classifier provides good performance, but high computational cost. The EHD based eye candidate detection compensates the weaknesses of the SVM classifier.

Table 1
Detection accuracy (NR: not reported).

Method	CMU-PIE	Yale B	AR
IN+EHD+SVM	**0.9188**	**0.8976**	**1.0000**
EHD+SVM	0.7637	0.5306	0.9497
[8]	NR	NR	0.9860
[9]	NR	NR	0.9680
[17] (SQI)	NR	0.8540	NR
[17] (FLTV)	0.8650	NR	NR

The bold numbers represent the best accuracy in each face database. 'IN' means illumination normalization.

Table 2
The average number of false positives in an image and its precision by the eye candidate detection.

Type	CMU-PIE	Yale B	AR
False positives	263.87	361.36	234.21
Precision	0.0075	0.0055	0.0085

The experiments are performed on a PC running Windows XP with Pentium IV CPU (3.19 GHz) and 3 G RAM using MATLAB R2010b.

Table 3
Computation time for eye detection (unit: s/image).

Database	EHD+SVM	SVM
CMU-PIE	0.1495	0.3471
Yale B	0.1611	0.4006
AR	0.1391	0.3208
Average	0.1499	0.3561

The experiments are performed on a PC running Windows XP with Pentium IV CPU (3.19 GHz) and 3 G RAM using MATLAB R2010b.

7. Conclusion

In this paper, we have proposed a novel framework for illumination invariant eye detection under varying lighting conditions. To achieve the illumination invariant eye detection, the proposed method employs illumination normalization based on the retinex theory, eye candidate detection using EHD, eye verification by SVM, and EPM based eye position determination. Due to the illumination normalization, our method consistently achieves demonstrable results even in extremely ill-conditioned illumination. Moreover, our method greatly improves the computation time because of the eye candidate detection. Experimental results demonstrate the superiority of our method in terms of both effectiveness and efficiency in eye detection. The experimental results and performance comparisons are reported in detail, thereby confirming that the proposed method can be effectively employed for dealing with the eye detection problem.

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