A new iris segmentation method for non-ideal iris images

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Abstract
Many researchers have studied iris recognition techniques in unconstrained environments, where the probability of acquiring non-ideal iris images is very high due to off-angles, noise, blurring and occlusion by eyelashes, eyelids, glasses, and hair. Although there have been many iris segmentation methods, most focus primarily on the accurate detection with iris images which are captured in a closely controlled environment. This paper proposes a new iris segmentation method that can be used to accurately extract iris regions from non-ideal quality iris images. This research has following three novelities compared to previous works; firstly, the proposed method uses AdaBoost eye detection in order to compensate for the iris detection errors caused by the two circular edge detection operations; secondly, it uses a color segmentation technique for detecting obstructions by the ghosting effects of visible light; and thirdly, if there is no extracted corneal specular reflection in the detected pupil and iris regions, the captured iris image is determined as a “closed eye” image.

The proposed method has been tested using the UBIRIS.v2 database via NICE.I (Noisy Iris Challenge Evaluation – Part I) contest. The results show that FP (False Positive) error rate and FN (False Negative) error rate are 1.2% and 27.6%, respectively, from NICE.I report (the 5th highest rank).

1. Introduction
Iris recognition has some advantages over other biometric modalities. For example, most iris patterns are reported to remain unchanged over a life time, and they cannot be easily forged or modified [2–4,11]. In addition, every person has his/her own unique iris pattern with high degrees of freedom. Therefore, many biometric researchers have used iris recognition for high confidence identification and this has led to extensive studies in developing iris recognition techniques in unconstrained environments, where the probability of acquiring non-ideal iris images is very high due to off-angles, noise, blurring and occlusion by eyelashes, eyelids, glasses, and hair. Fig. 1 shows some examples of non-ideal iris images [1] but most of the previous research on iris segmentation has focused on accurate detection with iris images which are captured in closely controlled conditions.

Thus, applying these methods to non-ideal iris images often yields incorrect segmentation results, which deteriorates the recognition accuracy. To accurately segment iris regions for non-ideal iris images, a new method is proposed, which uses AdaBoost eye detection in order to compensate for the iris detection errors caused by two circular edge detection operations. Also, to detect obstructions caused by a ghosting of the visible light, a color segmentation method is adopted. If the corneal specular reflection in the detected pupil and iris regions does not exist, the captured iris image is determined as “closed eye”. In the localized iris region, the eyelids and eyelash regions can also be detected by the proposed method.

2. Description of the proposed method
2.1. Overview
Fig. 2 shows the overall procedure of the proposed method. Because UBIRIS.v2 images are collected with visible light, they include RGB color information as shown in Fig. 1 [1]. Firstly, a RGB color image is transformed into a gray one in order to reduce the processing time and the complexity. For localizing the iris region within the eye image, the inner and outer boundaries of the iris regions are detected by using two circular edge detection (CED) (see step 2 of Fig. 2 and Section 2.2) [8]. However, detection errors due
to noise factors, such as occlusions of the eye due to eyeglasses and hair, are often observed. Therefore, the detected images are divided into two cases, namely “good-detection cases” and “bad-detection cases”, based on the existence of corneal specular reflection (SR). In the “good-detection cases”, the pupil and iris regions are correctly detected, and in the “bad-detection cases”, they are wrongly detected, as shown in Fig. 4(a) and (b).

In general, the corneal SR is produced in the pupil and iris regions by an illuminator, as shown in Fig. 4. Therefore, “good-detected cases” can be discerned from “bad-detected cases” by checking the number of SR points in the detected pupil and iris regions. In [14], Park et al. said that “the gray level of the corneal SR is higher than that of other regions, such as the sclera, pupil and skin, because the reflectance of the corneal surfaces is greater than that of other regions in general”. In view of this fact, the pixels with gray level higher than 250 have been classified as corneal SR points. If the number of SR points is higher than 1 in the detected pupil and iris regions (see step 3 of Fig. 2), it is determined as a “good-detection case”. Otherwise, it is a “bad-detection case”, as shown in Fig. 6, which can be either from incorrect detection, as shown in Fig. 4(b), or “closed eyes”, as shown in Fig. 6. In “the bad-detection cases” an AdaBoost-based eye detection method is used for re-detecting the iris region (see step 4 of Fig. 2 and Section 2.3). As shown in Fig. 5, the iris region can be accurately detected with two CEDs in the eye region, having firstly been detected by the AdaBoost-based method. After that, if the number of SR points is more than 1 in the re-detected pupil and iris regions (see step 6 of Fig. 2), it is determined as a “good-detection case”. Otherwise, as shown in Fig. 6, it is classified as a “closed eye” image (see step 7 of Fig. 2).

Two CEDs are used for detecting the boundaries of the pupil and the iris simultaneously. As shown in Fig. 3, the pupil region has usually lower gray levels compared with other regions, such as the iris and the sclera. In addition, the gray level of the iris region is lower than that of the sclera region. Based on this observation, the pupil and iris regions are detected by using two CEDs, as shown in Eq. (1) [8].

\[
\max_{(x_0,y_0)} \frac{\partial}{\partial r} \left( \int_{-\pi}^{\pi} I(x,y) \left( \frac{5\pi r}{2} \right) ds + \int_{-\pi}^{\pi} I(x,y) \left( \frac{5\pi r}{2} \right) ds \right) + \max_{(x_0,y_0)} \frac{\partial}{\partial r} \left( \int_{-\pi}^{\pi} I(x,y) \left( \frac{\pi}{2} r \right) ds \right)
\]

(1)

where \(r\) and \(r'\) represent the radii of the iris and the pupil, respectively. \((x_0,y_0)\) and \((x_0',y_0)\) represent the center positions of the iris and pupil, respectively. Here, \(r\), \(r'\) and \((x_0',y_0)\) have the searching ranges, respectively, which were determined empirically. \(I(x,y)\) is the gray level of the point on the outer circular boundary of the iris, which is determined by \(r\) and \((x_0,y_0)\). \(I(x,y)\) is the gray level of the point on the circular boundary of the pupil, which is determined by \(r'\) and \((x_0',y_0)\). The pupil and iris boundaries are determined at the position which two integro-differential values between the inner and outer edges are maximized while changing the center positions and the radius values of the pupil and iris boundaries. As shown in Fig. 3, the range of 0 to \(-2\pi\) radians is used for detecting the pupil boundary, but only the range from \(-\frac{\pi}{4}\) to \(\frac{\pi}{4}\) radians and \(-\frac{\pi}{4}\) to \(\frac{\pi}{4}\) radians are for detecting the iris boundary, since it can happen that the upper or lower iris region is occluded by eyelids. Because the discontinuous boundary of SR can cause the detection errors of two CEDs, the discontinuous boundary of SR is removed by using linear interpolation before performing two CEDs. In detail, the points where the gray levels are greater
than 250 are detected as the SR points and these are linearly interpolated by two gray values of the left and right neighboring (non-SR) pixels, which are closest to the SR points. Fig. 4 shows the resultant images in which the pupil and iris are detected by using two CEDs. Fig. 4(a) shows a “good-detection case” in which the pupil and iris are correctly detected, but Fig. 4(b) shows a “bad-detection case” in which they are wrongly detected.

2.3. AdaBoost-based eye detection

As shown in Section 2.1, if there is no corneal SR in the pupil and iris region (see step 3 of Figs. 2 and 5(a)), an AdaBoost-based eye detection algorithm is used for detecting the eye region [7], as shown in Fig. 5(b). The adaptive boosting (AdaBoost) is an algorithm that constructs a strong classifier by coupling the weak classifiers [12]. This algorithm takes a lot of time to learn weak classifiers, but it has advantages such as fast detection speed and good classification performance [6].

As shown in Fig. 5(c), the iris and pupil boundaries are re-detected by using two CEDs in the region of interest detected by the AdaBoost-based method. If a corneal SR does not exist in the pupil and iris region (see step 6 of Figs. 2 and 6(b), (c)) despite the iris detection by AdaBoost and two CEDs, it is determined as a “closed eye” image (see step 7 of Fig. 2).

2.4. Eyelid detection

In order to define an upper eyelid searching area, firstly the two cross points, between the upper eyelid and the outer boundary of the iris, are detected. The cross point is detected based on the discontinuous point which is checked when scanning in the circular direction according to the outer boundary of the iris [9]. Based on the two cross points and the information of the center position and radius of the iris, an upper eyelid searching box is defined.

Next, eyelid candidate points are extracted by using the eyelid detection mask shown in Fig. 7. Because the distinctive eyelid line is smoothed due to the blurred input image, the mask is adaptively selected according to the focus score, which is measured by a $5 \times 5$ mask [10]. Based on the detected eyelid candidate points, the parabolic Hough transform is used to accurately detect the eyelid boundary. By using the parabolic Hough transform and enabling rotation, as shown in Eq. (2), the eyelid lines can be accurately detected in the case of a rotated eye [9].

$$E = (\sin \theta (x - h) + \cos \theta (y - k))^2 - a(\cos \theta (x - h) - \sin \theta (y - k)) = 0 \quad (2)$$

where $x$, $(h,k)$ and $\theta$ represent the curvature, the vertex point of the parabola and the rotational angle, respectively. To reduce the processing time of the Hough transform, the searching dimensions of the four parameters, $x$, $(h,k)$ and $\theta$ are restricted by considering the anthropologic characteristics of the human eye. The lower eyelid is also detected in the same manner. Fig. 8(b) shows an example of eyelid detection using the proposed method.

2.5. Eyelash detection

Fig. 9 shows the overall procedure of the proposed eyelash detection method. For detecting eyelashes, the eyelash candidate region is firstly selected based on the detected pupil, iris and eyelid region, as shown in Eq. (3) [10].

$$W = 2 \times R_i, \ H = R_i$$

$$C_x = (P_x + I_x)/2, \ C_y = (I_y + E_y)/2$$

Fig. 4. The results of pupil and iris detection: (a) good-detection case and (b) bad-detection case.

Fig. 5. An example of AdaBoost-based eye detection: (a) result of two CEDs, (b) result of AdaBoost, and (c) result of two CEDs in the detected range of (b).

Fig. 6. An example of AdaBoost-based eye detection in the case of a “closed eye”: (a) result of two CEDs, (b) result of AdaBoost, and (c) result of two CEDs in the detected range of (b).

Fig. 7. Masks for detecting the eyelid candidate points [9]: (a) mask for an upper eyelid in the case of a focused image, (b) mask for a lower eyelid in the case of a focused image, (c) mask for an upper eyelid in the case of a defocused image, and (d) mask for a lower eyelid in the case of a defocused image.

Fig. 8. An example of eyelid detection: (a) input image and (b) result image of the eyelid detection.
where $W$ and $H$ denote the width of the eyelash candidate region and the height of that region, respectively. $(Cx, Cy), (Px, Py), (Ix, Iy)$ and $(Ex, Ey)$ denote the center position of the candidate region, that of the pupil, that of the iris and the position having the minimum $Y$ value in the detected upper eyelid, respectively. In addition, $R_l$ denotes the radius of the iris. The detected eyelid line is used as the starting position for the eyelash detection. Based on that information, eyelashes (multiple eyelashes and separable eyelashes) are detected in the eyelash candidate region [10].

Similarly to the work of Kong [15,16], eyelashes are classified into two types, as shown in Fig. 10. Separable eyelashes are isolated and easy to be distinguished from other eyelashes. Multiple eyelashes appear overlapped or bunched together [15,16]. The proposed algorithm adopts a local window for detecting multiple eyelashes, and a convolution kernel for detecting separable eyelashes [10].

As mentioned above, the detected upper eyelid position is the starting position for detecting multiple eyelashes, since conventional eyelashes come from the eyelids. From the starting position, the gray mean ($\mu_l$) and variance values ($\sigma_l$) of the local window ($13 \times 13$ pixels) are measured. As eyelashes are usually darker than the iris regions, if eyelashes are contained in the local window, the mean ($\mu_l$) of the gray intensity in the local window is lower than the mean ($\mu_c$) of the whole iris region in Eq. (4). In addition, the standard deviation ($\sigma_l$) of the gray intensity in the local window is high due to the edge between the iris and the eyelashes. So, the following conditions arise.

$$\mu_l < \mu_c, \quad \sigma_l > T_1, \quad I(x,y) \leq \mu_l$$

where $\mu_l$, $\mu_c$ and $\sigma_l$ represent the mean of the gray intensity in the local window, the mean of the entire iris region and the standard deviation of the gray intensity in the local window, respectively. $I(x,y)$ is the gray intensity at the $(x,y)$ position (the center of the window). $T_1$ is the threshold value which was empirically obtained.

To guarantee the interoperability of the proposed algorithm, the optimal threshold ($T_1$) is obtained by using a different open database of CASIA [17] and $T_1$ is fixed for all the images. So, if all conditions of Eq. (4) at the $(x,y)$ position are satisfied, the point is marked as a candidate of multiple eyelashes. As shown in Fig. 9-(4), the procedure of detecting separable eyelashes is performed. The starting positions are the regions of the detected eyelids and multiple eyelashes. From the starting positions, the eyelash-detecting kernels ($K_1$,$K_2$,$K_3$ as shown in Fig. 11) are moved and the $Q$ value is calculated. For every eyelash checking position, $Q$ is calculated by multiplying the image intensity ($I(x,y)$) and the kernel values ($K_1$,$K_2$,$K_3$ as shown in Fig. 11) and then selecting the maximum value. If the measured $Q$, $\mu_l$ and $\sigma_l$ values on the checking point (R position of Fig. 11) do not satisfy the conditions of Eq. (5), the eyelash detection kernel is moved horizontally and the same procedure is repeated.

If these conditions are satisfied less than 10 times, the kernel is moved in order to make the checking point (R) be moved to (S), as illustrated in Fig. 11. When these conditions are satisfied more than 10 times (because eyelashes have the characteristics of continuity), the checked points are determined as separable eyelash regions. So, the conditions are as follows.

$$Q > \sigma_l, \quad \mu_l < \mu_c, \quad \sigma_l > T_2$$

where $\mu_l$ and $\sigma_l$ denote the mean and standard deviations of the gray level in the masked region defined by $K_1$,$K_2$,$K_3$ of Fig. 11. $\mu_c$ denotes the mean of the intensity values in the iris region, and $T_2$ represents the threshold which has been empirically determined. Here, “ten times” is the threshold for determining whether there are eyelashes or not, based on the number of the connected pixels of the eyelash region, which represents the connectivity characteristics of the eyelash. In detail, the condition of Eq. (5) is satisfied more than 10 times with the six kernels ($K_1$, $K_2$,$K_3$ shown in Fig. 11), the proposed method regards the checked points as separable eyelash regions. The optimal threshold of “ten times” has been empirically found, based on the eyelash detection error. To guarantee the interoperability of the proposed algorithm, the threshold is obtained by using a different open database of CASIA [17]. Fig. 12 shows the result of the eyelash detection.

![Fig. 9. Block diagram of the proposed eyelash detection method [10].](image-url)

![Fig. 10. Multiple and separable eyelashes.](image-url)

![Fig. 11. The adaptive convolution kernels for detecting separable eyelashes in focused and blurred images [10]: (a) for detecting eyelashes in the vertical direction and (b) for detecting eyelashes in the horizontal direction.](image-url)
2.6. Color segmentation

As shown in Fig. 2-(10), color segmentation has been performed in order to remove the non-iris area such as ghosting of visible light in the detected iris region. Fig. 13 shows an example of the non-iris area caused by ghosting of visible light.

The ghosted region is produced by visible light reflected from surrounding objects such as windows, etc. This frequently happens in the left or right iris region but rarely happens in the lower iris region. The reason for this is because the reflected light from the ground frequently makes ghosts in the lower iris region, and the amount of light reflected is not great compared to that from other higher objects such as windows, etc. So, the local iris area is selected in the lower iris region in order to obtain the RGB value of the iris pattern, as shown in Fig. 14. In order to select the local iris region, the iris center position \((I_x, I_y)\) and iris radius \(R_i\) are used. The starting position \((X_s, Y_s)\) and the ending position \((X_e, Y_e)\) of the region of Fig. 14 are calculated by the following equation:

\[
X_s = I_x - (R_i/2), \quad Y_s = I_y \\
X_e = I_x + (R_i/2), \quad Y_e = I_y + (2R_i/3)
\]

Because the center and radius of pupil are already known, when extracting the RGB information from the local region, defined by \((X_s, Y_s)\) and \((X_e, Y_e)\), that from pupil region is not used, as shown in Fig. 14. The selected local region has the color information of the iris pattern, as shown in Fig. 15, which is different from that of SR and of the ghost region. Based on this, the non-iris region, such as the ghosting from the iris region, can be discerned. Fig. 15(a) shows the separated red, green and blue channel images of the selected local region. Fig. 15(b) shows the clustering of the extracted RGB color information in the selected local region in the 3 dimensional space. The geometric center of the cluster is calculated, which corresponds to the mean values \((l_R, l_G, l_B)\) from each RGB channel of the selected local region, respectively. Then, the distance between the mean values \((l_R, l_G, l_B)\) and the RGB value of each pixel are calculated, which is extracted in the iris region segmented by the methods of Sections 2.2–2.5. The performances of the Euclidean, Mahalanobis and Cosine distances are compared.

The Euclidean distance does not take into account the correlation of the data set, but the Mahalanobis distance considers it by using the covariance matrix. The Cosine distance measures the angle between two vectors [18] and if the measured distance of a point is greater than a pre-defined threshold, it is considered as a non-iris point. Otherwise, it is considered as a point in the iris region. The optimal threshold has been empirically obtained using the contest training data.

3. Result analysis

The proposed method has been tested using 500 images from the UBIRIS.v2 database [1]. These images were selected for the evaluation in the NICE.I contest [1]. The UBIRIS.v2 database contains ten images in which the user’s eyes are closed and 66 images that were acquired from users with glasses. It also has non-ideal iris images such as off-angles, rotated eyes and blurred images. The image size is 400 × 300 pixels. Fig. 16 shows some examples of the UBIRIS.v2 database.

Fig. 17(b) and (c) show the ground-truth images of the iris regions and the ones detected by the proposed method, respectively. As shown in Fig. 17-(c), the pixels that are classified as non-iris regions appear as white pixels. Oppositely, the noise-free iris regions appear as black pixels.
Fig. 17. Examples of the ground-truth data of the UBIRIS.v2: (a) original images, (b) the ground-truth images provided by NICE.I test, and (c) the resultant images from the proposed method.

Two kinds of classification error rates are measured based on the comparison between the output data of the proposed methods and the ground-truth data. As shown in Eq. (7), the classification error rate \( E_i \) of the input image \( I_i \) is computed as the proportion of correspondently disagreeing pixels between the resulting image \( O(c', r') \) detected by the proposed method and the ground-truth image \( C(c', r') \) \[1\].

\[
E_i = \frac{1}{c \times r} \sum_{c'} \sum_{r'} O(c', r') \otimes X(c', r')
\]  

(7)

where \( c \) and \( r \) are the image width and height, respectively. The E1 error rate is determined by the average of the classification error rates \( E_i \) as shown in the following equation \[1\]:

\[
E1 = \frac{1}{n} \sum_{i} E_i
\]  

(8)

where \( n \) is the total number of images. The value of E1 has the range of \([0, 1]\), representing the accuracy of the iris segmentation. The values “1” and “0” denote the worst value and the best one for the iris segmentation, respectively. As another evaluation criterion, the E2 error rate is used. E2 is determined as the average of the false positive rate (FPR) and the false negative rate (FNR) \[1\]:

\[
E2 = 0.5 \cdot FPR + 0.5 \cdot FNR
\]  

(9)

FPR means the error rate of accepting non-iris pixels such as eyelash or ghosting as iris ones. FNR means the error rate of rejecting the iris pixels as non-iris ones.

Table 1 gives the iris segmentation accuracy evaluated by the NICE.I contest \[1\]. The algorithm submitted to the NICE.I contest uses the Mahalanobis distance for the color segmentation. That is because experimental results have shown that the iris segmentation accuracy using the Mahalanobis distance is better than those of Euclidean and Cosine distances, based on the E1 error rate.

Fig. 18 illustrates some of the images in which the proposed method obtained the highest segmentation errors, which are provided by the NICE.I contest. In Fig. 18(a) and (b), the detection of the lower, upper eyelids and pupil regions failed. In the eyelid detection method, an eyelid searching area is selected by detecting the two cross points between the eyelids and the outer boundary of the irises. However, the cross points are incorrectly detected due to the thick eyelashes and the ghosting region of the iris region in Fig. 18(a) and (b). A pupil detection error occurred due to the discontinuous boundary of the SR region. Although elimination of the SR regions has been attempted by using linear interpolation, as shown in Section 2.2, the SR regions remained in the images after elimination because their gray levels are lower than the pre-determined threshold (250) for the SR elimination.

**Table 1**

<table>
<thead>
<tr>
<th>Error Rate</th>
<th>E1</th>
<th>E2</th>
</tr>
</thead>
<tbody>
<tr>
<td>FPR</td>
<td>2.8</td>
<td>14.4</td>
</tr>
<tr>
<td>FNR</td>
<td>1.2</td>
<td>27.6</td>
</tr>
</tbody>
</table>

Fig. 18. Bad segmentation cases (green region: FP pixels, red region: FN pixels, and black region: true positive pixels).

Fig. 18(a)–(c) contains shaded regions in the upper parts of the iris region. However, the shaded region was not detected by the proposed color segmentation method because the RGB value of the shaded region is similar to the RGB value of the iris region. In Fig. 18(d), there was an eyelid detection error because the cross points were incorrectly detected by the ghosting region of the iris region. The segmentation error of Fig. 18(e) was caused by a pupil detection error that was due to the SR region and the color segmentation error of the shaded region. The eyelid detection error also happened because of the detection error of the two cross points due to thick and dark eyelashes. The causes of segmentation errors in Fig. 18(f) are similar to that of Fig. 18(a). In Fig. 18(g), the RGB values of the shaded area of the upper iris region and the ghosting region are similar to those of the iris region. Therefore, they were not detected by the color segmentation method. In Fig. 18(h), there were detection errors of the lower eyelid, of the pupil and of the ghosting region. Two cross points for the lower eyelid searching area were incorrectly detected due to the ghosting region. The pupil detection error was also caused by the discontinuous boundary of the ghosting region in the iris region. In addition, a part of the ghosting region was not detected because their RGB values were similar to those of the iris region. In Fig. 18(i), the pupil and iris detection errors by two CEDs were caused by the discontinuous frames of the user’s glasses. As mentioned in Section 2.1 and Fig. 2, the proposed method determines “good-detection cases” and “bad-detection cases” by checking the existence of the SR region. However, this detection result has been incorrectly accepted as a “good-detection case” due to the SR of the glasses’
surface in Fig. 18(i). Because the user’s eye is almost closed in Fig. 18(j), most of the iris boundary is hidden by the eyelids and the double (edged) eyelid region is more distinctive than the iris boundary. In Fig. 18(k) and (l), iris and pupil detection errors were caused by SRs and the ghosting regions. In Fig. 18(m), pupil detection error happened due to the discontinuous boundary of the SR. Color segmentation errors also occurred because the colors of local iris region (as shown in Fig. 14) were different from those of other iris regions. The causes of the segmentation errors of Fig. 18(n) are similar to those of Fig. 18(b). The causes of the errors of Fig. 18(o) are similar to those of Fig. 18(h).

Fig. 19 shows examples of good segmentation cases, provided by the NICE.I contest. In general, two CED shows an incorrect localization result of the iris region if the size of iris is small. In such cases, corneal SR does not exist (see step 3 of Fig. 2) and the AdaBoost eye detection method can correctly detect the iris candidate region (see step 4 of Figs. 2 and 5(b)). Then, the operation of the two circular edge detections is performed again in the iris candidate region (see step 5 of Fig. 2) and the correct iris region could be segmented, as shown in Fig. 19. In the iris region, SR and ghosting regions were removed based on the color segmentation.

4. Conclusion

A new iris segmentation method for non-ideal iris images has been proposed, which uses AdaBoost eye detection in order to compensate for the iris detection error caused by two circular edge detection operations. Also, the proposed method uses color segmentation for detecting any obstructions caused by ghosts of the visible light. If there is no extracted corneal specular reflection in the detected pupil and iris regions, the captured iris image is determined as a “closed eye” one. Results show that the E1 and E2 error rates evaluated by the NICE.I contest are 2.8% and 14.4%, respectively. In future works, the proposed enhanced color segmentation scheme will be applied to the iris images which are captured with Near-IR light.

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