Iris Localization with Dual Coarse-to-fine Strategy

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Abstract

Iris-based personal recognition is highly dependent on the accurate iris localization. In this paper, an effective and efficient iris localization algorithm is proposed to overcome the drawback of the traditional localization methods which are time-consuming and sensitive to the occlusion caused by eyelids and eyelashes. The coarse-to-fine strategy is deployed in both the inner boundary localization and the outer boundary localization. In the coarse localization of the inner boundary, the lower contour of the pupil is introduced to estimate the parameters of the pupil since it is stable even when the iris image is seriously occluded. While in the coarse localization of the outer boundary, the average intensity signals on both sides of the pupil are utilized to estimate the parameters of the sclera after the fine localization of the inner boundary. In the fine stage, the Hough transform is adopted to localize both boundaries precisely with the gradient information. Experimental results indicate that the proposed method is more effective and efficient.

1. Introduction

With the increasing requirement for security, it is an urgent and significant task to realize automatic, fast and reliable personal recognition. Among various approaches, iris-based personal recognition [1][2][3][4][5] is referred to as the most promising one because of its high accuracy, good stability and high recognition speed. The iris is an annular part between the pupil (inner boundary) and the sclera (outer boundary). Each boundary can be considered as a circle approximately, but they are not concentric. The iris localization method aims to find the parameters, the centers and the radiiuses, of two boundaries to isolate the annular iris region from the original image. The localization accuracy has great influence on the subsequent feature extraction and classification. Thus, iris localization plays a very important role in iris recognition and has stimulated a great deal of interests in recent years.

There are two classical iris localization methods. One is proposed by Daugman [1][2], who uses an integral differential operator to localize iris; the other is proposed by Wildes [3], who adopts Hough transform to get iris boundaries after edge detection. Both the methods need to search enormously in the three-dimensional parameter space. They impose great computational cost and can not be employed in real-time iris recognition systems.

In order to improve the effectiveness and efficiency of iris localization, the coarse-to-fine localization methods [4][6][7][8] are proposed, which estimate the parameters of boundaries roughly in the coarse stage and then use classical localization methods to search in a smaller range to obtain the precise parameters in the fine stage. These methods perform well when the quality of iris image is good. However, if the image is seriously occluded, the coarse estimated parameters may have great deviations. In addition, most of the methods do not take the coarse localization of the outer boundary into account except for [6], which utilizes projection information to estimate the X-coordinate and the radius of the outer boundary. However, its performance is not good enough if the iris region is small as compared with the whole image.

In this paper, an effective and efficient iris localization algorithm with dual coarse-to-fine strategy is proposed to overcome the drawback mentioned above. We principally improve the iris localization in the following two aspects. First, we use the lower contour of the pupil to estimate the parameters of the inner boundary. It is because the occlusion usually appears at the upper part of the pupil, while the lower part is barely influenced even in a seriously occluded iris image. Second, besides estimating the inner boundary, we also estimate the outer boundary with the average intensity signals on the both sides of the pupil. Finally, we use the Hough transform to localize both boundaries precisely. Experimental results indicate that our methods can give much better performance on the seriously occluded iris images.

The rest of the paper is organized as follows. Section 2 describes the proposed iris localization...
method in detail. Section 3 gives the experimental results and the discussions. Section 4 concludes the whole paper.

2. Iris localization with dual coarse-to-fine strategy

The process of our iris localization algorithm includes two steps, the inner boundary localization and the outer boundary localization. In each step, the coarse-to-fine localization strategy is adopted to obtain the precise parameters of both boundaries effectively and efficiently. In the following paragraphs, we will describe them in detail respectively.

2.1. Inner boundary localization

Since the lower contour of the pupil is barely influenced even in a seriously occluded iris image, it is a better choice for estimating the parameters of the inner boundary.

After binarizing the iris image, we adopt the morphological open operation to reduce the noise and the occlusion. The low contour, denoted as $\zeta$, is computed on the resulted binary image. For the $k$th column, $\zeta(k)$ is the Y-coordinate of the last black pixel. If there is no black pixel in this column, $\zeta(k)=0$. The thick real line in Figure 1(e) shows the lower contour of the Figure 1(d). Besides the exact low contour of the pupil, the obtained $\zeta$ maybe contains some noises introduced by eyelashes and eyelid. Thus, we should find out the part of pupil on $\zeta$ and use it to estimate the parameters of the inner boundary (denoted as $x_p$, $y_p$ and $r_p$). The detail process can be described as follows:

1. Find the nonzero zone corresponding to the pupil on $\zeta$ (see AB in Figure 1(e)). This zone has enough width and its maximum is in the middle part of it.

2. Find the maximum of $\zeta$ in this zone. Denote this point as $D$ and its value as $y_D$.

3. Compute the gradient of $\zeta$. And find the nearest extremum points of the gradient on both sides of $D$ (see E, F in Figure 1(e)), which correspond to the horizontal edge points of the pupil.

4. Estimate $x_p$, $y_p$ and $r_p$ by

$$
\begin{align}
\begin{cases}
x_p &= \text{mean} \{ k \mid k \in EF \land \zeta(k) \geq y_p - 2 \}\newline
y_p &= y_D \newline
r_p &= |EF|/2
\end{cases}
\end{align}
$$

where we using $y_D^2$ instead of $y_D$ in order to avoid the effect of the noise.

Since most of the pupils are near the center of the iris images, we only use the middle part of the image to localize the inner boundary. Furthermore, we down sample the image to speed up the localization process. Figure 1 illustrates the coarse localization process of the inner boundary of the iris.

![Figure 1. Coarse localization process of the inner boundary. (a) Original Image, in which the white rectangle shows the sub-image we selected. (b) Down-sampled sub-Image. (c) Binary image. (d) Binary image after morphological open operation. (e) Lower counter of the pupil. The red-cross in it shows the center of the inner boundary estimated.](image)

The precise parameters of the inner boundary can be obtained by optimizing

$$
\arg \max_{(x_0, y_0, r_0)} \frac{1}{2\pi r_0} \int C G(x, y) \, ds ,
$$

where $G(x, y)$ is the gradient magnitude at the pixel $(x, y)$, and $C$ is the curve described by

$$
(x - x_0)^2 + (y - y_0)^2 - r_0^2 = 0 .
$$

The optimization of (2) can be achieved quickly in the neighborhood of the estimated results obtained from (1), since these results are fairly approximated to the true parameters of the inner boundary.
2.2. Outer boundary localization

The parameters of the outer boundary are denoted as \(x_s, y_s\) and \(r_s\). Since the centers of both boundaries are close to each other, the precise value of \((x_s, y_s)\) can be taken as the estimation of \((x, y)\). Thus, in the stage of the coarse localization of the outer boundary, the only parameter need to be estimated is the radius \(r_s\), which will be obtained with the average intensity signals on both sides of the pupil.

We employ the right-side average signal, denoted as \(S_R\), to demonstrate the coarse localization process. For the pixel \((i, j)\) satisfying \(x_p+1.2 \leq x_i \leq x_p+160\) and \(j \leq y_p\), \(S_R(i)\) equals to the average intensity of its \(5 \times 5\) neighborhood. The left-side average signal, denoted as \(S_L\), can be computed at the symmetrical region.

Before we explain the coarse localization process, the following three facts at the outer boundary should be noticed: there is not sharp edge; the valley is wider than the one caused by single eyelash occlusion; and the gradient is smaller than the one at the place where the occlusion exists. It is never bigger than 30 gray levels, and seldom bigger than 20 gray levels. Thus, we can not detect the position of the outer boundary by simply searching the maximum of the gradient, whereas we can use the width information of the valley and the limitation of the gradient amplitude to reduce the influence of the occlusion. The coarse localization process of the outer boundary is described in detail in the following paragraphs, taking \(S_R\) for instance. \(S_L\) can be processed in the same way after being reversed.

![Figure 2. Coarse localization process of the outer boundary.](image)

First we binarize \(S_R\) with its average and denote the binary signal as \(B_R\). Then find out all the ascent edges of \(B_R\) and get rid of those edges where the widths of the valleys before them are too small. The reserved edges are recorded as \(A_k\). And the outer boundary is close to a certain \(A_k\). For each \(A_k\), detect the first local minimum point of \(S_R\) before it (such as point \(N\) to edge \(A_3\)) and the first local maximum point of \(S_R\) after it (such as point \(N\) to edge \(A_3\)). Compute the gradient of \(S_R\) between these two points with formula (4), and record the point with the largest gradient as one candidate of the outer boundary corresponding to this ascend edge.

\[
G(x) = \frac{1}{3} \sum_{k=1}^{3} [S_R(x+k) - S_R(x-k)]. \tag{4}
\]

Modify the gradient of the candidates as following

\[
G'(x) = \begin{cases} 
G(x) & G(x) < Th_{T} \\
\alpha \times G(x) & Th_{T} \leq G(x) < Th_{L} \\
0 & G(x) \geq Th_{L}
\end{cases}, \tag{5}
\]

where \(Th_{T}=20\), \(Th_{L}=30\) and \(\alpha = Th_{T} / Th_{L}\). Then select the candidate with the largest gradient as the final estimated position of the outer boundary. The parameter \(r_s\) can be estimated by subtracting \(x_p\) from the X-coordinate of this position.

We can get another estimation of \(r_s\) form \(S_L\). If the difference between two estimations is no bigger than 20 pixels, the final estimation of \(r_s\) is the average of these two results. (The difference between \(x_p\) and \(x_s\) is smaller than 10 pixels, so the difference between two estimations should be smaller than 20 pixels). At the same time, the average gradient corresponding to these two candidates is recorded as \(G_o\). Otherwise, select the estimation with bigger gradient as the final estimation, and record the bigger gradient as \(G_o\). \(G_o\) will be used in the fine localization stage to limit the gradient amplitude.

The precise parameters of the outer boundary can be obtained by optimizing a formula similar to (1). The differences are in the definition of \(G(x, y)\) and the integral curve. Here \(G(x, y)\) is computed as following

\[
G(x, y) = \begin{cases} 
\frac{1}{3} \sum_{k=1}^{3} [I(x+k, y) - I(x-k, y)] & x \geq x_p \\
\frac{1}{3} \sum_{k=1}^{3} [I(x+k, y) - I(x-k, y)] & x < x_p
\end{cases}, \tag{6}
\]

where \(I(x, y)\) is the intensity at the pixel \((x, y)\). And then its amplitude is limited beneath \(2G_o\). In other words, set \(G(x, y)=0\) if its absolute value is bigger than \(2G_o\). The influence of the occlusion will be reduced effectively after limiting the gradient amplitude. The integral curve \(C\) is limited at the ranges of \(-45^\circ\sim-45^\circ\) and \(135^\circ\sim225^\circ\) to avoid the interference of eyelids.

3. Experiments and results

To evaluate the performance of the proposed method, we collect 2984 iris images with a special NIR...
(near infrared) senor. The resolution of each image is 640×480. The experiments are performed in Matlab (version 6.5) on a PC with 2.4GHz processor.

Table 1 illustrates the runtimes of the method. Figure 3 displays the localization results of one iris image. For the page limitation, only the central part of the image is displayed.

<table>
<thead>
<tr>
<th>Method</th>
<th>$T_{mean}$ (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coarse localization of the inner boundary</td>
<td>0.0225</td>
</tr>
<tr>
<td>Coarse localization of the outer boundary</td>
<td>0.0494</td>
</tr>
<tr>
<td>The entire localization method</td>
<td>0.3923</td>
</tr>
</tbody>
</table>

Figure 3. The localization result. (a) Coarse localization of the inner boundary. (b) Coarse localization of the outer boundary. (c) Localization using the method proposed in this paper. (d) Localization using the method proposed in [1].

The coarse estimated parameters of the inner boundary are very close to the true values. The maximum difference at each dimension is not bigger than 8 pixels. While the differences between the estimated $r_i$ and the true values are not bigger than 27 pixels. And in 99.13% iris images, the differences are not bigger than 10 pixels. Thus it can be seen that the proposed coarse localization process can reduce the searching range of the fine localization stage efficiently. Figure 1(d) shows the localization using the method proposed in [1]. Since the gradients of the occlusions are much bigger than those of the outer boundary, the localization result biases a little away from the real position. In our method, the influence of the occlusion can be reduced effectively by limiting the gradient amplitude with $G_s$ at the fine localization of the outer boundary. The localization result (see Figure 1(c)) is much better than Figure 1(d).

4. Conclusions

An iris localization algorithm with dual coarse-to-fine strategy is proposed in this paper. It adopts the coarse-to-fine strategy in both the inner boundary localization and the outer boundary localization. In the coarse stage, the lower contour of the pupil is used to estimate the parameters of the inner boundary, while the average intensity signals on both sides of the pupil are used to estimate of the parameters of the outer boundary. In the fine stage, the Hough transform is used to obtain the precise parameters with the gradient information. $G_s$, the gradient at the outer boundary obtained at the coarse stage, is used to limit the gradient amplitude in the fine stage to reduce the influence of the occlusion caused by eyelashes and eyelids. Experimental results indicate that our methods can give much better performance on the seriously occluded iris images and are more effective and efficient.

References


