Non-ideal iris segmentation using anisotropic diffusion

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Abstract: Iris segmentation is critical for iris recognition. In this study, the authors present a circle-based iris segmentation method for non-ideally captured iris by employing anisotropic diffusion. Our proposal consists of two component steps by which interior and exterior boundaries are localised, respectively. To save computational load, Laplace pyramid (LP) method for non-ideally captured iris by employing anisotropic diffusion. Our proposal consists of two component steps by which interior and exterior boundaries are localised, respectively. To save computational load, Laplace pyramid (LP) framework is incorporated into both steps. During the first step, when iris has been decomposed into the coarse level by LP, reflections will be removed by anisotropic diffusion and morphologic operations. In the second step, the authors present the innovated curve evolution to detect exterior boundary. Moreover, order statistical filters are employed to enhance the contrast of iris and sclera. Experimental results depict a high correct ratio of segmentation that is more than 96.90% thereby validating the proposed approach.

1 Introduction

Among the current biometric techniques, iris recognition is often preferred in personal identification and some public security scenarios, because human iris contains highly discriminative and stable texture patterns that distinguishes one person from another [1, 2]. The critical precondition for iris recognition is segmentation, and the detected iris is used as input for subsequent feature extraction and matching procedures. The entire segmentation process has been illustrated in Fig. 1.

Typically, iris region is known as an annulus between pupil and sclera. Based on this knowledge, many researchers have addressed the issue that how to localise both the boundaries. The best well-known integral–differential operator proposed by Daugman [3] is used to search a circle to separate iris clearly from other parts of the imagery and remains in use widely today in commercial applications. Another classical circle-based model is the edge detection-based techniques presented by Wildes [4], where the circular Hough transform is followed by edge detection to localise iris boundary. The above classical approaches and their extensions such as [5–8] are able to achieve encouraging performance when the original iris images are captured in ideal conditions.

However in many real cases, some undesirable conditions in data acquiring process, such as illumination variations, uncooperativeness of persons, unconscious body motions, will degrade quality of iris images. Iris segmentation often suffers from the resulted undesirable disturbances, including reflections, eyelash and eyelid occlusion, and pupil centre deviation. Each of them will make it very difficult to segment true iris region from a non-ideal image. Consequently, non-ideal iris segmentation remains a challenging task. To address such a challenge, Proença and Alexandre [9] designed the fuzzy k-means strategy to cluster the location and intensity features of iris image. However, this approach is difficult to deal with large reflection. Pundlik et al. [10] employed graph cut to segment iris region but edge information was not considered. Active contours were also introduced to the application [11] which inherited the drawback that the parameterised active contour is susceptible to local minima. Zuo and Schmid [12] adopted elliptic model to capture iris boundaries but a heavy computational load is involved. Level set approach was utilised by Santis and Lacoviello [13] to capture pupil’s boundary. Tan et al. [14] presented an iris segmentation algorithm by combining reflection removal, intensity interpolation and a ‘pulling and pushing’ pupil searching methods. In video applications, Sirohey et al. [15] dealt with tracking behaviour of eye by detecting iris region. Other recent literatures include the shape prior model [16], the combination of improved snake model and angular integral projection [17], the variational level set [18], and the image enhancement-based segmentation [19].

In this paper, we propose a novel method to address the interior and exterior boundary localisation. Compared to the traditional ones such as the classical Daugman’s [3] and Wildes’ [4], more component steps are presented in our algorithm to guarantee correct centre and interior
localisation. In interior boundary segmentation, we employ anisotropic diffusion incorporated with morphological operations to remove reflection and eyelash/eyebrow occlusions. Specifically, the diffusion is implemented to smooth iris image to eliminate small-scaled eyelashes and eyebrow, and preserve large-scaled pupil boundary. Such good performance benefits from the intrinsic edge-preserving and scale-smearing properties of anisotropic diffusion derived by partial differential equation (PDE). Moreover, the diffusion is combined with a multi-resolution framework to speed up iris centre detection. In exterior boundary detection, to find ambiguous exterior boundary, we have designed the region-based curve evolution with the aid of order statistical filtering (OSF) regionally. By the means, exterior boundary is extracted exactly. Besides, computation saving is considered embedded in our work for it is critical in commercial applications.

The rest of this paper is organised as follows. In Section 2 we cover the related preliminaries and formulate the anisotropic diffusion. Section 3 illustrates the proposed localisation algorithm for non-ideal iris data. Experiment results and discussions are given in Section 4. Finally, Section 5 concludes the paper and discusses prospective future work.

2 Preliminary of PDE-based anisotropic diffusion

PDE-based anisotropic diffusion is a useful tool in image restoration because of its edge-preserving and scale-smearing properties [20]. The classical formulation of anisotropic diffusion is given by the Perona–Malik (P–M) model in [21], that is

$$\frac{\partial I}{\partial t} = \text{div} (g(\nabla I) \nabla I)$$

where $\nabla I$ denotes gradient of image $I$. The key idea of the formulated PDE is to control the image evolution by a monotonically decreasing function $g(\nabla I)$ with respect to gradient $\nabla I$. Particularly, $g(\nabla I)$ has two forms

$$g(\nabla I) = \exp\left(-\left(\frac{\nabla I}{K}\right)^2\right)$$

or

$$g(\nabla I) = \frac{1}{1 + (\nabla I/K)^2}$$

It is generally thought that gradients of pixels belonging to an edge are larger than those of non-edge pixels in a local region. In this view (2) or (3) guarantees a small diffusion for edge pixels and on the contrary, large diffusion for non-edge ones. That is the reason such diffusion is called anisotropic. An example of the diffusion can be seen in Fig. 2.
Fig. 3  Flowchart of interior boundary localisation of iris in our algorithm

Fig. 4  Flowchart of exterior boundary localisation of iris in our algorithm
3  Proposed anisotropic diffusion-based non-ideal iris segmentation

In iris segmentation, pupil centre localisation is critical for final result. Unfortunately, the result will be worse if reflections or eyelashes/eyebrow occlusions exist. It is observed that the size of eyelashes or eyebrow usually is much smaller than that of pupil. Therefore the anisotropic diffusion with the scale-dependent evolution property provides a practical utility for the non-ideal iris segmentation. Furthermore, to reduce computational load the Laplace multi-resolution framework is incorporated into our proposal. Our iris segmentation algorithm consists of two processes as depicted in Figs. 3 and 4. The first is interior boundary extraction in which the LP decomposition and anisotropic diffusion is employed. In this step we focus on disposing of the occlusions and reflections to guarantee accurate localisation of iris centre and interior boundary.

The second process extracts the exterior boundary by using the innovated region-based curve evolution. Similar to the first step, LP is adopted to accelerate computing. We take advantage of nonlinear OSF regionally to maintain boundary of iris and sclera, meanwhile flatten their internal intensive variations, respectively. By the means our evolved curve convergences to the true exterior boundary. The details of the two-step method are described as follows.

3.1  Interior boundary localisation

The sequential steps of interior boundary localisation in our method are listed as follows. Accordingly in Fig. 3 which has illustrated the entire process, the three substeps, that is anisotropic diffusion, threshold, and binarisation and morphological close operation, are included in the step (S1-2). Besides, mapping pupil region from coarse level of LP to the original scale is performed in the step (S1-3), and remained centroid computing, polar transform, edge detection by Sobel operator and radius computing are performed in the step (S1-4).

3.1.1 (S1-1) Laplace pyramid (LP) decomposition: A straightforward approach to reduce iris data is decomposing an iris image into coarser level by LP [22] or other multi-resolution frameworks. As decomposition level increases step by step, the size of resulted coarse data will decrease exponentially. Here we adopt framing LP in the first step of interior boundary segmentation. For simplicity, more details about LP framework can be seen in the literature [22] and will not be stated in this paper.

3.1.2 (S1-2) Pupil detection with reflections and eyelashes/eyebrow occlusion removal: When iris image has been decomposed into coarse level, the next step is to find pupil region. However it will be difficult if non-ideal iris images contain reflections or eyelashes/eyebrow occlusions. Here we attempt to eliminate them and maintain pupil region. To achieve this goal we design the following path:

1. Anisotropic diffusion: As mentioned in Section 2, anisotropic diffusion is a suitable choice owning to its evolutionary scale-smearing. In our method, the coarse level image obtained by LP will be diffused by P-M equation. Iteration time of the evolution needs to be predefined properly to acquire a good trade-off between occlusions removal and pupil boundary preservation. The diffusion is controlled by (2) or (3) if the parameter \( K \) increases, less iteration time is needed but leads to a similar performance.

2. Threshold: When eyelashes/eyebrow has been diffused, their contrast over other parts will become more distinctive. Also in real cases, iris images captures under some stable circumstances. That means among a database, iris images yield similar statistical distributions. Specifically, because pupil is the dark part, there is a valley in the histogram that separates the pupil from the image. In this condition, a reliable way to segment pupil is to find the valley as the threshold that relies on the probability density function (PDF) of non-ideal iris image.

3. Binarisation and closing operation: When pupil has been detected, internal isolated reflections have to be eliminated. Considering that the size of reflection is much smaller than that of pupils, we use the closing operation, that is, expand the pupil and then erode it, to fill the reflections by darkness.

3.1.3 (S1-3) Mapping pupil region from coarse level into original image: As pupil region has been masked in coarse level, we use nearest interpolation to map this small mask to original level, that is convert a small image to a larger one.

![Flowchart of region-based exterior boundary localisation](image.png)
into a large one. Naturally, mapped mask is dark also, and it will cover real region of pupil that we can compute the pupil’s centroid as the iris centre.

3.1.4 (S1-4) interior boundary detection: In the last step of interior boundary segmentation, we use Sobel operator to find maximum of each column and view them as candidate points of interior boundary of iris in polar-transformed image resulted from previous substeps. Then we record all distances from each maximum point to the pupil’ centre, and form their histogram in which the distance with the maximum probability is the radius. Explicitly, searching pupil’s centre as in (S1-2), founds the algorithm of interior boundary segmentation. As pupil has been modelled as a darkness disk, evidently its centre is the centroid. But eyelashes also form the dark region, therefore it is difficult to separated them from pupil. The feasible way to remove eyelashes is employing P-M evolution, because small-scaled eyelash will be eliminated and on the contrary, large-scaled pupil will be preserved when iris data has been anisotropically diffused. Specifically, by gradient descent method the P-M evolution can be formulated by

\[ I_t = I_{t-1} - a \text{div}(g(|\nabla I_{t-1}|)\nabla I_{t-1}) \]  

(4)

where the parameter \( a \), as \( K \) in (2) or (3), controls the evolution speed and can be assigned experientially. Fig. 1 shows the diffusion where \( a = 0.25 \) and \( g(\cdot) \) is specified by (2). Notably, unnecessary time consuming in diffusion can be avoided by selecting a large \( K \). In fact, if variation of \( K \) or iteration of the formulation (4) is not very large, little will be changed to the diffused effect. That means the P-M evolution is not very sensitive to parameter.

By the diffusion previously mentioned, eyelashes have disappeared but reflections remain. Reflections’ scale is small but still larger and smoother than noise or variations of small-scaled textures. Therefore such highly contrasts are treated as edge information in anisotropic diffusion. That is why we choose morphological operators to eliminate reflections. As eyelashes and reflections have been removed, left dark pupil is the unique dominant pattern over the entire iris image.

Fig. 6 Some experimental results of CASIA-IrisV3-Interval database by our algorithm
3.2 Exterior boundary localisation

Exterior boundary localisation will be described in this subsection. Moreover, its flowchart has been depicted in Fig. 4. Specifically, the operations of polar transform and OSF in Fig. 4 are included in the step (S2-3).

3.2.1 (S2-1) LP decomposition of reflection-removed iris image: In the first step, the resulted image of interior boundary localisation is processed by LP framework. Without reflections, the coarse image is input into subsequent processes directly.

3.2.2 (S2-2) Region selection: By observing real iris data used in our experiment, we find there is eyelid occlusion in most images which will lead to false exterior boundary detection. Since exterior boundary is considered as a circle, in this step we choose a segment within an angular range, in which eyelid occlusions do not exist, to detect the boundary circle. Conveniently selected angular range locates in the top or bottom of iris region.

3.2.3 (S2-3) Polar transform and OSF of selected region: A reliable performance of region-based exterior boundary detection depends on not only grey level of iris and background, but also a distinct edge between them. However, contrast of iris over sclera is not always distinct. For the selected angular region, nonlinear OSF [23] give an efficient contrast enhancing technique. In our algorithm, selected iris region in polar domain is split uniformly into three parts, and each pixel value of the part nearest to iris is replaced by local minimum iteratively. Similarly, in the part farthest to iris it is replaced by local maxima. To protect exterior boundary the middle part is processed by a median filter.

3.2.4 (S2-4) Region-based segmentation: Region-based segmentation in this substep is presented as the simplified curve evolution of active contours. Exterior boundary is initialised as a line near to iris interior boundary, and mean values of the two regions separated by the line are computed. Then the line is pushed far away from interior boundary and also, new both mean values are obtained. If the difference of the previous mean values is smaller than that of the new ones, the line continues to move. Else the previous line is specified as exterior boundary. Actually the purpose of region wise OSF operations previously is significant in global convergence of boundary evolution. More details of this substep have been presented in Fig. 5.

Fig. 7 Some experimental results of MMU1 database by our algorithm
For non-ideal iris data, although searching exterior boundary is not as sophisticated as interior boundary, two issues are still needed to be stressed. One issue is selecting an angular segment in polar domain. In most cases eyelid occludes upper and lower sclera, hence the segment is selected horizontally. In our algorithm the region can be

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**Fig. 8** Some experimental results of UBIRIS 1.0 database by our algorithm

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**Fig. 9** Some experimental results of CASIA-IrisV3-Lamp database by our algorithm
picked up in a simple manner, that is computing the distance from iris centre to the both vertical boundaries of the iris image. Conveniently the larger one is the better choice. The next issue is boundary detection within the patch of polar image. Since there is weak, instead of sharp edge, region-based segmentation scheme achieves a better performance. To reducing computational load, we design a novel technique consisting of two component steps. The first is region-wise OSF recursively as in S2-4. In this way the intensity level of sclera and skin becomes more distinguishable to facilitate subsequent segmentation. The second is a simple curve evolution illustrated in Fig. 5, where difference of the two means values is calculated until such difference stops increasing. According to our assumption, exterior boundary in polar patch is initialised as a line segment and is moved without geometric distortion. As a simplified version of region-based active contour models, the evolution of S2-4 achieves a high speed in global convergence.

4 Experiments

We adopt four non-ideal iris databases, CASIA-IrisV3-Interval and CASIA-IrisV3-Lamp [24], MMU1 [25] and UBIRIS 1.0 [26], to evaluate our segmentation method in exterior and interior boundary localisation. CASIA-IrisV3-Interval and CASIA-IrisV3-Lamp databases are released by Institution of Automation, Chinese Academy of Science. The former database consists of 2903 images with 256 grey levels and 320 × 280 size, and there are 16213 images of 640 × 480 in the latter one. The iris number of MMU1 database is small and it consists of 450 grey images of 320 × 240 size and is provided by Multimedia University, Malaysia. And the UBIRIS 1.0 database, released by Networks and Multimedia group of Universidade de Beira Interior, contains 1885 grey images of 200 × 150. A great number of images in each database have heavy occlusions of eyelash and eyelid, or reflections caused by camera. All experiments are carried out using Matlab 7.0 software on a Pentium 2.4 GHz processor and 2 Gbyte RAM.

4.1 Visual quality of segmentation

Experiment results on the four databases have been shown in Figs. 6–10, where for simplicity only a part of final results of interior and exterior boundary localisation are presented. The CASIA-IrisV3-Interval and CASIA-IrisV3-Lamp databases are popular among researchers in which reflections are caused by digital camera and form a circular-shaped light speckles. The small isolated reflections make themselves evolve little by PDE-based anisotropic methods. A good solution is incorporating morphological close operator to eliminate small-scaled spots. In Fig. 6 speckles have been removed and iris centre is marked by a cross. In process of exterior boundary localisation, we take advantage of region information instead of edge ones, to search true boundary. Results in Figs. 6–9 have been depicted that exterior boundaries are marked by a circle catching the true border.

4.2 Performance in segmentation accuracy (SA)

In our experiments, boundary localisation is evaluated by the SA and averaged processing time. Specifically, we compare three methods in which interior and exterior boundary detection are comprised. It is important that the classical methods of Daugman and Wildes only deal with interior boundary of ideal iris. In our experiment both the methods fails to localise interior boundary of the three non-ideal iris databases as what have been reported in Fig. 10. Therefore to evaluate both methods to our approach equivalently, we combine them with our framework that the substep (S1-2) is replaced by the approach of Daugman or Wildes. All methods are listed as below.
The other aspect of segmentation quality is the efficiency which is evaluated by averaged processing time. Not only interior but exterior boundary is considered and the performance of total time has been in Table 2. Also our method in Section 3.2 for exterior boundary.

In the future, we would like to explore contrast enhancement technology to distinguish iris and complex background, which will make segmentation easier and more robust. Also we like to investigate texture modelling to discern iris, sclera, eyelash and eyelid. Such modelling will help us to achieve a simplified algorithm with less component steps.

## 7 References


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## 5 Conclusions

In this paper, a novel non-ideal iris segmentation method has been proposed. This method composes of two stages: interior and exterior boundary localisation. In the first stage, anisotropic diffusion is utilised to smear small-scaled reflection and maintain large-scaled iris boundary. In this fashion the centre iris is detected by segmenting circle-modelled pupil region, and subsequently interior boundary is localised. During the second stage, we devise a simplified active contour model to detect exterior boundary. Exploiting OSF regionally facilitates a correct convergence of this model. We compare our method to the classical methods of Daugman and Wildes. Experimental results show that our proposal researches to a high correct segmentation ratio and lower averaged time consuming of each iris image.
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