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Iris segmentation for visible wavelength and near infrared eye images

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ABSTRACT

State-of-the-art iris segmentation algorithms exhibit poor performance for non-ideal data, which is mainly because of the noise such as low contrast, non-uniform illumination, reflections, and among others. To address this issue, a robust iris segmentation scheme is proposed that includes the following: First, a set of the Seed-pixels in a preprocessed eye image is marked adaptively. Next, a two-fold scheme based on a Circu-differential accumulator (CDA) and gray statistics is adopted to localize coarse iris region robustly. Notably, the proposed CDA has close resemblance with the Hough transform; however, it consumes relatively less memory and is free from thresholding as well. Similarly, pupillary boundary is localized, which is verified through an intensity test as well. Next, a refine estimate for the limbic boundary is extracted. After that, iris boundaries are regularized using the Fourier series. Finally, the eyelids are localized using a Para-differential accumulator (PDA), and eyelashes and reflections are also localized adaptively in the polar form of iris. Experimental results on the near infrared (NIR) and visible wavelength (VW) iris databases show that the proposed technique outperforms contemporary approaches.

1. Introduction

Biometric technology applies mathematical pattern recognition techniques on the physical/physiological traits of humans in order to recognize individuals [1–4]. Physical traits include retina, iris, fingerprint, DNA, and so on, while behavioral traits include voice, gait, smell, signature, etc. [5–8]. Among these traits, voice, face, and fingerprint have long been in use for the human identification; however, they change with the aging and environmental effects. On the other hand, the iris is non-invasive and remains almost stable over a person's life [1]. It has complex structure that includes corona, freckles, crypts, ridges, furrows, and arching ligaments [1]. Iris biometric technology has potential applications in the health and care, citizen registration, border crossing control, entrance to public buildings, and among others. A typical iris recognition system [1,5,9] comprises image acquisition, iris segmentation, features extraction, and matching and recognition. Among these modules, iris segmentation plays a critical role in maintaining the overall system performance. It is because that it isolates the valid part of iris in an eye image, which all the system subsequent modules strongly rely on. Iris segmentation comprises *Iris localization* that localizes the iris inner (pupillary) and outer (limbic) contours and the *Noise removal* that detects and removes any superimposed noise (e.g., eyelids) in the localized iris.

Commercial iris biometric systems perform well for ideal data that is acquired under controlled environment. For example, a subject (wearing no cosmetics such as eyeglasses/lenses, etc.) stands at a short distance and gazes directly into the camera view. Here, the image quality is maintained via visual/audio feedback. However, if such systems are deployed in less-controlled environment, their performance is badly deteriorated. It is because of their iris segmentation algorithms that are incapable to deal with non-ideal issues, e.g., specular reflections, non-uniform illumination, blurring, rotated-iris (image wherein eye is not oriented horizontally), eyeglasses, cosmetic lenses, eyelashes, and hair. Most commercial iris biometric systems are based on the Daugman [1] and Wildes' [2] approaches. Daugman [1] used an Integro-differential operator (IDO) to localize iris boundaries with a circle approximation, while Wildes [2] used a combination of circular Hough transform (CHT) and gradients to localize iris.

Labati and Scotti [10] proposed an iris segmentation technique for noisy data. It includes localizing coarse iris boundaries using IDO, localizing true boundary points in each of the two linearized strips, and, finally, regularizing iris boundaries via Fourier series. A main drawback of this technique is its computational cost. On average, it takes 3 min to segment an iris, with 98% time consumed by

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IDO, which is because of its inefficient application. Radman et al. [11] proposed an iris segmentation technique for less-controlled data. It includes extracting the coarse pupil center using a circular Gabor filter and localizing pupillary and limbic boundaries within small windows using edge-detecting operators. This technique is tested on relatively good images. However, its coarse pupil localization scheme may be trapped in images where pupil is surrounded by low intensity regions such as eyebrows, eyelashes, and hair. Puhan et al. [12] presented an iris segmentation algorithm for non-ideal data. A similar approach is also present in Refs. [13,14]. First, they develop a spectral image and then binarize it using a row-wise adaptive threshold. The resultant image contains an approximate location of iris. Following that, they localize a kind of partial-limbic boundary. After that, a combination of thresholding- and gradient based techniques is used to extract a binary image containing coarse iris edges. Then, radius and center parameters for circular limbic boundary are extracted using Euclidean distances. A basic flaw herein lies in its pupillary and iris localization tasks that strongly rely on edges present in binary image obtained via an adaptive-based thresholding technique, which may result in absurdity if thresholding parameters are not selected properly. Moreover, it takes 15 s to localize iris in an eye image.

In Ref. [15], authors proposed an iris segmentation technique for noisy data, a similar approach is also present in Ref. [16]. First, to compute an adaptive threshold, they binarize input eye image with a series of thresholds, record the number of binary objects for each case, and finally, select only that non-zero value of a threshold for which minimum objects are found. Next, they binarize input eye image using that threshold, complement resultant image, fill holes, and then compute spectrum image. After that, a pixel with highest gray-level intensity in spectrum image is considered as pupil center. Next, pupil radius is computed by counting the number of pixels between the central and a nearest non-zero pixel. Similarly, to localize limbic boundary, they draw a band of circles centered at pupil center in the preprocessed eye image. Finally, a circle for which the sum of gray values computed on its perimeter is high with respect to the previous circle is considered as the circular limbic boundary. A main flaw in this approach lies in its coarse pupil center extraction. It is because that if pupil in an eye image is surrounded by low intensity regions (e.g., eyebrows), then pupil object in the resultant binary image may not be alone, instead other binary objects (caused by the low intensity regions) may surround it. This technique is incapable to deal with multiple objects present in binary image.

To address the abovementioned issues, this study proposes a robust iris segmentation scheme. It includes preprocessing a gray-level input eye image in order to suppress abrupt gray variations. Next, a two-fold robust strategy based on CDA and gray statistics is adopted to localize coarse iris region reliably in preprocessed image. In a similar way, pupillary boundary is localized. Pupil location is verified through an intensity test. Then, fine limbic boundary is localized, which is followed by boundaries regularization. Finally, eyelids are localized using PDA, and eyelashes and reflections are also marked adaptively.

The remaining of this paper is organized as follows. Section 2 explains the structure and design of the proposed scheme. Experimental results and discussion are elaborated in Section 3, and finally, Section 4 concludes this study.

2. Proposed scheme

Fig. 1 illustrates block diagram of the proposed scheme. It includes *preprocessing*, *iris localization*, and *noise removal*, which are detailed bellow.

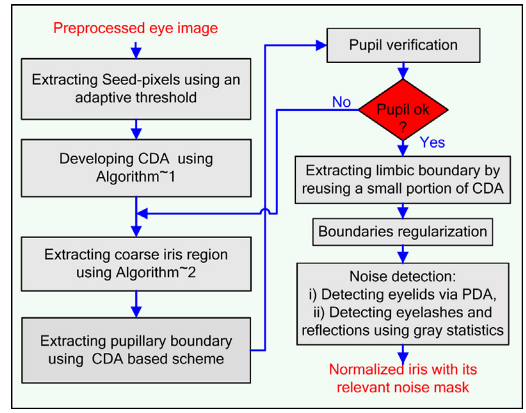

Fig. 1. Block diagram of the proposed iris segmentation scheme.

2.1. Preprocessing

To speed up localization process, first decimate gray-level version $I(x, y)$ of the input eye image by discarding all of its alternate rows and columns, resultant image is $A(x, y)$. It is experimentally found that images in the publically available iris databases are not free from reflections. As reflections generally have higher gray-level intensity, therefore they can interfere in the iris localization task. It is because that they can offer local maxima in an eye image or can produce spurious edge pixels in the relevant edgemap. Besides, it is also experimentally observed that gray-level intensity of pupil in VW images is not consistent; therefore, a simple preprocessing approach (e.g., [3,7]) would result in poor performance. It is because that methods given in [3,7] could affect the gray-level intensity of other unwanted regions such as sclera. Therefore to get rid from reflections, use an effective preprocessing technique as proposed in [6]. It replaces the gray-level intensity of reflections in $A(x, y)$ with a lower gray-level saturated limit [17], which represents the saturated gray-level value of bottom 1% of all gray-values in $A(x, y)$. Fig. 2(a) and (b) shows $A(x, y)$ and the resultant preprocessed image $\Omega(x, y)$, respectively. It is evident that almost all minute details are suppressed in $\Omega(x, y)$, however the coarse details such as the iris- and eyelids contours are significant, which is handy for the iris contours localization.

2.2. Iris localization

Iris localization module localizes the non-circular pupillary and limbic boundaries. It includes Seed-Pixels Extraction, CDA Development, Coarse Iris Region Extraction, Pupillary Boundary Extraction, Pupil Verification, Limbic Boundary Extraction, and Boundaries Regularization. These tasks are explained as follows.

2.2.1. Seed-pixels extraction

It is experimentally observed that gray-level intensity of iris in an eye image is generally less than that of its bright regions (e.g., sclera and skin parts, see Fig. 2(a)). Based on this argument, we use a reliable two-fold scheme (explained in a coming task) that is based on CDA and gray-level statistics to localize the coarse location of iris in $\Omega(x, y)$. However, to seed up the process, only those gray pixels (*Seed-pixels*) in $\Omega(x, y)$ are involved that belong to the iris and/or other dark parts (e.g., hair).

To begin with, adaptively extract *xy*-coordinates $(\bar{X}, \bar{Y})$ of seed-pixels as

$$(\bar{X}, \bar{Y}) = \begin{cases} (x, y), & \text{if } \Omega(x, y) < \phi \\ \text{Ignore}, & \text{otherwise} \end{cases}, \tag{1}$$