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A fusion approach to unconstrained iris recognition

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ABSTRACT

As biometrics has evolved, the iris has remained a preferred trait because its uniqueness, lifetime stability and regular shape contribute to good segmentation and recognition performance. However, commercially deployed systems are characterized by strong acquisition constraints based on active subject cooperation, which is not always achievable or even reasonable for extensive deployment in everyday scenarios. Research on new techniques has been focused on lowering these constraints without significantly impacting performance while increasing system usability, and new approaches have rapidly emerged. Here we propose a novel fusion of different recognition approaches and describe how it can contribute to more reliable noncooperative iris recognition by compensating for degraded images captured in less constrained acquisition setups and protocols under visible wavelengths and varying lighting conditions. The proposed method was tested at the NICE.II (Noisy Iris Challenge Evaluation – Part 2) contest, and its performance was corroborated by a third-place finish.

1. Introduction

The use of the iris as main biometric trait has emerged as one of the most recommended methods due not only to the possibility of noncontact data acquisition and to its circular and planar shape that facilitates detection, segmentation and compensation for off-angle capture but also for its predominately randotypic appearance. Although these factors contribute to high effectiveness in the currently deployed iris-recognition systems, their typical scenarios are quite constrained: subjects stop and stare relatively close to the acquisition device while their eyes are illuminated by a near-infrared light source, enabling the acquisition of high-quality data. As reported in the study conducted by *Aton Origin* for the United Kingdom Passport Service,[1] imaging constraints are a major obstacle for the mass implementation of iris-based biometric systems. Notably, several researchers are currently working on minimizing the constraints associated with this process, in a way often referred to as noncooperative iris recognition, referring to several factors that can make iris images nonideal, such as at-a-distance imagery, on-the-move subjects, and high dynamic lighting variations.

In this study, we stress multiple recognition techniques, each one based on a different rationale and exploiting different properties of the eye region. Furthermore, we show how their fusion can increase the robustness to the degraded data typically captured in unconstrained acquisition setups.

The recognition techniques used in our proposition can be divide in two main categories. In one approach, we use wavelet-based iris-feature-extraction methods, complemented with a zero-crossing representation (Hoyle et al., 2010, 2009) and the analysis of iriscode-matching bit distribution (Santos and Proença, 2010). Complementarily, we expanded the extraction of features to the ocular region outside the iris, as recent studies (Savvides et al., 2010; Miller et al., 2010; Park et al., 2009) have suggested using these data, which appear to be a middle ground between iris and face biometrics and incorporates some advantages of each.

The performance of the fusion method we propose is highlighted by its third-place finish at the NICE.II (Noisy Iris Challenge Evaluation – Part 2), an international contest involving almost seventy participants worldwide.

The remainder of this paper is structured as follows: Section 2 describes the steps for iris-boundary localization and normalization, feature extraction and matching for the different approaches, and how their outputs are joined; Section 3 details the experimental process followed by a discussion of the obtained results; finally, Section 4 states the conclusions.

2. Proposed methodology

This section describes the five steps of our approach: iris-boundary detection, iris normalization, feature extraction, matching and decision ensemble (as schematized in Fig. 1). Furthermore, for feature extraction and matching, five recognition techniques are detailed.

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[1] http://www.ips.gov.uk/cps/rde/xchg/ips_live/hs.xsl/publications.htm.

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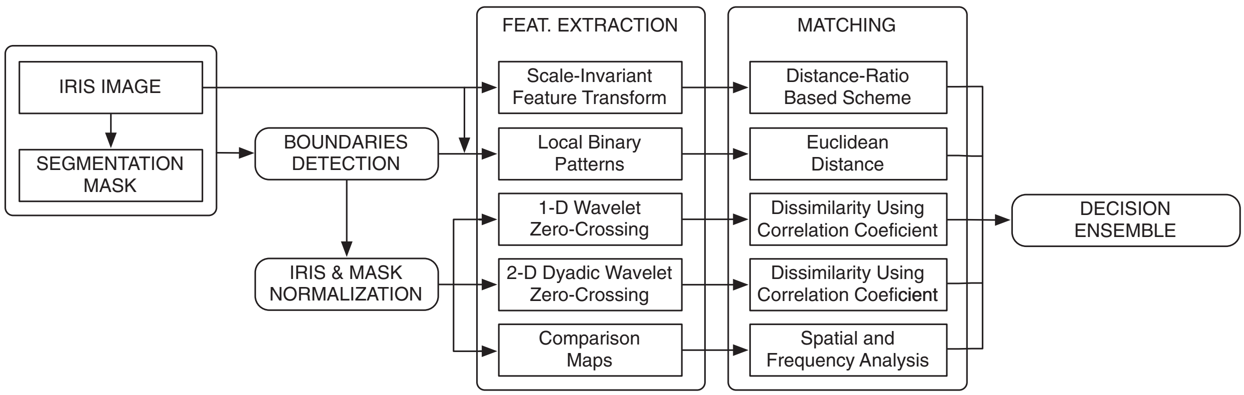


Fig. 1. Proposed methodology.

2.1. Iris boundaries detection

The first task was to locate the circles that best approximate iris and pupil boundaries, a necessity in the majority of methods used for this work. To accomplish this, we utilized a binary mask representing only parts containing iris information, created using the method proposed by Tan et al. (2010), winner of the NICE.I contest.

The steps taken in boundary approximation (Fig. 2(h)) were as follows:

- A contour is extracted from the segmentation mask Fig. 2(b), created with Tan et al. method (Tan et al., 2010). A pixel is part of such contour if it is nonzero, and connected to at least one zero-valued pixel.
- From the contour Fig. 2(c) of the segmentation mask Fig. 2(b), a Hough transform (Ballard, 1981) is applied to obtain the circle best fitting the iris Fig. 2(d).
- Convert the eye image Fig. 2(a) to grayscale and enhance it through histogram equalization Fig. 2(e).
- To the enhanced image Fig. 2(e), a Canny edge detection (Canny, 1986) is applied inside the circular region Fig. 2(f) concentric with the iris and 2/3 its radius, producing the edges shown in subFig. 2(g).
- Finally, a Hough transform is used on the resulting edge map Fig. 2(g) to obtain the circle that best fits the pupil.

Although this method produces good iris-boundary approximations, the estimated pupil limits sometimes diverge from ideal contours (*e.g.* Fig. 3). The main reason for this occurrence is poor lighting conditions when imaging heavily pigmented irises, which results in a low contrast ratio between the iris and the pupil.

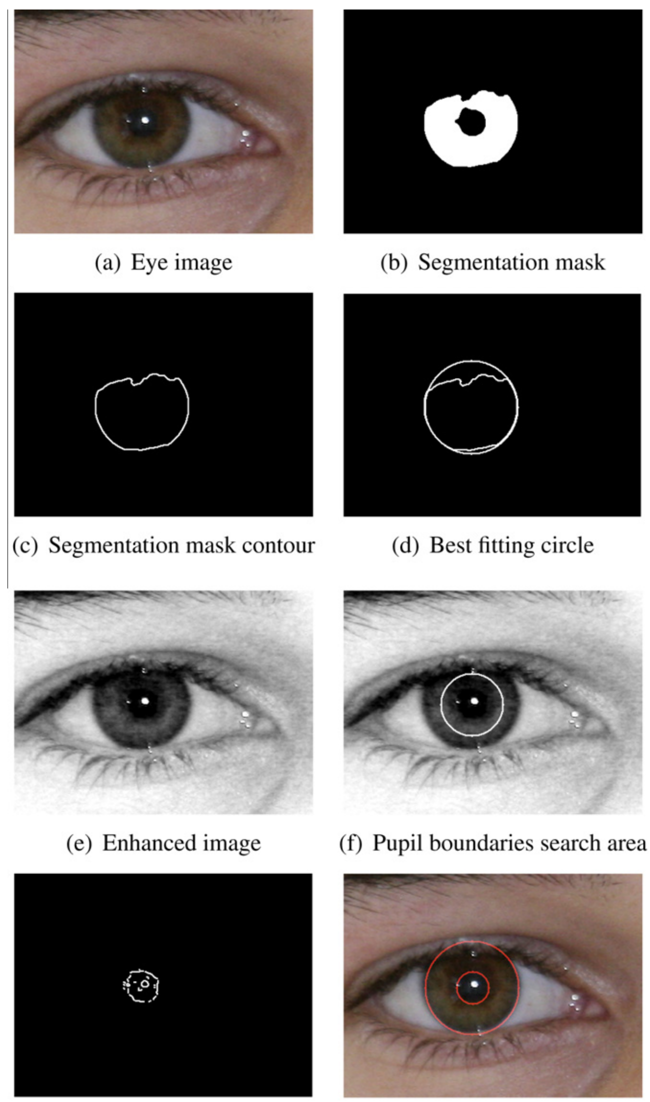
2.2. Iris normalization

The iris-normalization process aims to obtain invariance with respect to size, position and pupil dilatation in the segmented iris region, which is accomplished by assigning each pixel to a pair of real coordinates (r, θ) over the double dimensionless pseudopolar coordinate system. For this purpose, we proceeded with the rubber-sheet model originally proposed by Daugman (2004).

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \tag{1}$$

$$\begin{aligned} x(r,\theta) &= (1-r)x_p(\theta) + r x_s(\theta) \\ y(r,\theta) &= (1-r)y_p(\theta) + r y_s(\theta) \end{aligned} \tag{2}$$

where r and θ denote the radius and the angle, respectively, and $x(r,\theta)$ and $y(r,\theta)$ are defined as linear combinations of both the set of pupillary boundary points $(x_p(\theta), y_p(\theta))$ and the set of limbus boundary points along the outer perimeter of the iris $(x_s(\theta), y_s(\theta))$ bordering the sclera.



(a) Eye image (b) Segmentation mask (c) Segmentation mask contour (d) Best fitting circle (e) Enhanced image (f) Pupil boundaries search area (g) Edge points from the search area (h) Iris and pupil boundaries approximation

Fig. 2. Illustration of the steps taken during the segmentation stage.

Eqs. (1) and (2) give a transformation similar to that depicted in Fig. 4: subfigure (a) is the normalized iris image; subfigure (b)