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Effective elliptic fitting for iris normalization ☆

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ABSTRACT

Having an accurate parametric description of the iris borders is a critical issue for iris recognition systems based on Daugman's rubber sheet normalization. Many methods in the literature use very powerful and effective schemes for iris segmentation but often apply a simple estimator procedure, such as the Hough Transform or Least Square Fitting to get this parametric description. Those fitting methods are very sensitive to the segmentation quality as inaccuracies will provoke large errors in the resulting contour.

In this article we propose an effective way to find optimal parameters for ellipses in order to proceed the normalization. Our method is based on a variational formulation of the well-known Active Contour techniques leading to a compact formulation for elliptic contours. We show improvements compared to an Elliptic Hough Transform and a Direct Least Square Fitting on the following databases: ICE2005, ND-Iris and Casia-Lamp. We also demonstrate that our scheme can be paired effectively with different segmentation algorithms. Significant improvements of the recognition results were obtained when adding our algorithm after the segmentation stage of VASIR and OSIRIS, two open source packages for iris recognition.

1. Introduction

Biometrics studies the identification of people using their intrinsic characteristics. Among the various biometrics studied, the iris texture has shown a highly distinctive capacity to characterize people. It can be captured without contact and is assumed to be very stable over long periods of time (though, this last claim has been challenged in [12]). For these reasons, iris recognition systems have been deployed in several critical applications, such as fast border checking [3,14] or recently in the UIDAI program in India [34].

Most iris recognition systems are based on the earliest works of Daugman [11] and are usually divided into the following main parts: iris acquisition, segmentation, normalization and feature extraction (see Fig. 1) which are set out below.

Acquisition:
The image acquisition is done under Near Infra Red (NIR) illumination, having wavelengths between 700 and 900 nm. At these wavelengths even dark brown irises show a very rich texture which is suitable for recognition. In a standard controlled acquisition scenario, the subject is asked to stand still and look straight at the camera at a short distance. However, recent works tend to relax the acquisition conditions. For example an image can be acquired at a distance [2] or using a visible wavelength [28]. Subjects are also less constrained: they may not look straight at the camera [7] or move during the acquisition [20].

Segmentation:
Given the acquired eye image, the first algorithmic task is the segmentation of the iris, aiming at isolating the iris texture from other elements of the image such as eyelids, shadows or glasses. This segmentation is challenging as the more the acquisition conditions are relaxed, the more degradations have to be handled at this stage.

Normalization:
The texture is mapped into a dimensionless coordinate system to handle variability in the eye image such as pupil dilation. The most common choice for normalization is the rubber sheet model introduced by Daugman in [11]. The iris borders are modeled by two nonconcentric circles and the texture is unwrapped with respect to these circles. Precision is a critical issue at this stage as small errors in the circles' parameters estimation can dramatically decrease the performance of the overall system, as outlined by Proenca in [27].

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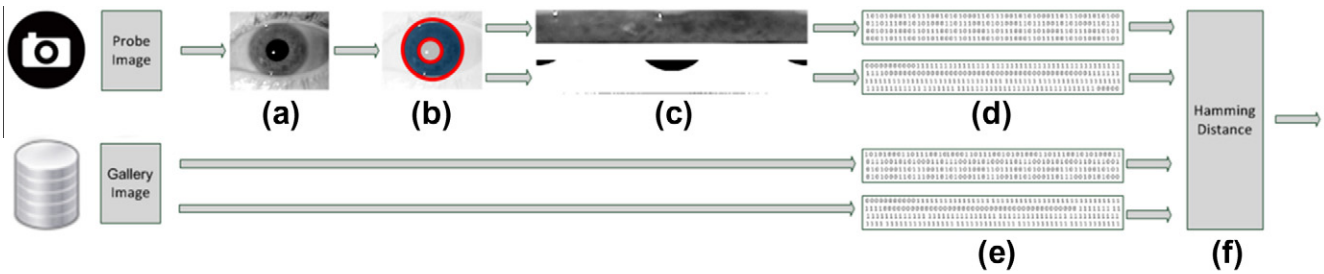

Fig. 1. Complete iris recognition system: The goal is to compare a newly acquired image (probe image) with a reference image (gallery image). (a) Probe image acquired in NIR. (b) Segmented iris texture. (c) Unwrapped iris texture (top) with its segmentation mask (bottom). (d) Binary code characterizing the probe iris. (e) Reference binary code of the gallery image. (f) Comparison of the two iris codes using Hamming distance.

Feature Extraction:
Finally, discriminative iris texture's features are extracted. These features are the basis of the comparison of probe and gallery iris images. The most used features are based on a quantization of Gabor filters' phase. This quantization generates a binary code characterizing the iris. A comparison between irises is made by computing the Hamming distance of the two binary codes.

Degradations resulting from the relaxation of the acquisition conditions affect all stages of the system but in this paper we focus on the normalization stage. In systems deriving from [11], matching is done by aligning the features of specific points from the normalized image, i.e., the rectangular unwrapped texture of the two irises. If the unwrapping is not done properly, the two textures, and therefore, the corresponding points do not correctly align and recognition performance is affected. Consequently, the robustness and precision of the unwrapping is a critical aspect of iris recognition systems.

Iris borders have traditionally been modeled as a pair of circles. The main limitation of this approach is that the circular assumption does not stand for off-angle images or people with a pupil or an iris which is anatomically non circular. To address these shortcomings, more general shapes need to be considered, such as ellipses or general parametric contours.

Ellipses are the intuitive extension of circles, but the two classical operators used to find circles in the iris literature (Daugman's Integrodifferential Operator (IDO) and the Circular Hough Transform (CHT)) do not extend well to ellipses. These operators need the evaluation of an accumulator whose dimension is the number of parameters in the model. Going from 3 parameters for the circle to 5 for the ellipse dramatically increases the computation time, making these operators unsuitable for real-time applications. For this reason, most articles working with ellipses use an elliptic Direct Least Square Fitting (DLS) [13] to fit ellipses onto the iris borders. This method is very fast, but suffers from the usual drawback of least square methods: sensitivity to outliers.

General parametric contours are able to handle any shape for iris borders [10,15,26]. They can achieve very good recognition performance but are strongly dependent on the segmentation stage. Hence, in order to apply them, it is necessary to efficiently distinguish between the pixels belonging to the anatomic borders of the iris and the edges generated by occlusions. If some pixels are misclassified, the resulting contours will be wrongly localized and recognition performance will accordingly be affected.

In this article, our aim is to propose a precise, robust and effective way to fit ellipses on iris borders in order to perform the normalization. Our method, which we have called Elliptic Variational Fitting (EVF) consists in a classical energy-based optimization derived from the Active Contours (AC) formalism. We assume the segmentation can provide a rough location for the iris borders, EVF then morphs these initial contours into ellipses that correctly fit the iris borders. The energy used for the variational optimization is composed of an edge term ensuring that the ellipse relies on areas of strong gradient, a region term based on region competition heuristics [38], such that the ellipse separates regions having different statistical descriptions; finally, a regularization term ensures getting a correct fitting even if few information is available (highly occluded images for example). These energies are classical in the AC literature, but to the best of our knowledge they have not been specifically adapted to elliptic contours. The interesting aspect of this approach is that unlike most fitting methods it does not rely on the segmentation results or on an edge detector. As a consequence our proposed method can even correct some segmentation inaccuracies in addition to giving the suitable contours for normalization.

This paper is organized as follows: Section 2 presents a review of classical segmentation approaches in iris literature and shows how this choice affects the normalization stage. Section 3 presents our novel algorithm to find elliptic contours for normalization. Section 4 briefly exposes our overall recognition system based on B-Snakes for segmentation and standard 2D Gabor wavelets for feature extraction and matching. Section 5 evaluates the performance of our system (presented in Section 4) for different normalization algorithms on reference databases. In this section, we also address specific issues like the evaluation of our contour fitting approach on off-angle images, computation times and improvements obtained on open source software for iris recognition.

2. Related work

Most iris recognition systems rely on Daugman's rubber sheet model for normalization [11]. In this early work the pupil and the iris borders are modeled using two non concentric circles, $\mathcal{C}_p(x_{cp}, y_{cp}, r_p)$ for pupil circle and $\mathcal{C}_i(x_{ci}, y_{ci}, r_i)$ for iris circle with parametrization:

$$\begin{aligned} x_p(\theta) &= x_{cp}(\theta) + r_p\cos(\theta),\\ y_p(\theta) &= y_{cp}(\theta) + r_p\sin(\theta), \end{aligned} \tag{1}$$

$$\begin{aligned} x_i(\theta) &= x_{ci}(\theta) + r_i\cos(\theta),\\ y_i(\theta) &= y_{ci}(\theta) + r_i\sin(\theta), \end{aligned} \tag{2}$$

with $\theta \in [0, 2\pi[$. The formula to unwrap the annular part between the two circles is then:

$$\begin{aligned} x(r,\theta) &= (1-r)x_p(\theta) + r x_i(\theta),\\ y(r,\theta) &= (1-r)y_p(\theta) + r y_i(\theta), \end{aligned} \tag{3}$$

with $r \in [0, 1[$ and $\theta \in [0, 2\pi[$. This model can handle changes in pupil size, however it can not handle problems explained in the