Eyelid Localization for Iris Identification

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Abstract. *This article presents a new eyelid localization algorithm based on a parabolic curve fitting. To deal with eyelashes, low contrast or false detection due to iris texture, we propose a two steps algorithm. First, possible edge candidates are selected by applying edge detection on a restricted area inside the iris. Then, a gradient maximization is applied along every parabola, on a larger area, to refine parameters and select the best one. Experiments have been conducted on a database of 151 iris that have been manually segmented. The performance evaluation is carried out by comparing the segmented images obtained by the proposed method with the manual segmentation. The results are satisfactory in more than 90% of the cases.*

Keywords

Biometric identification, iris analysis, eyelid segmentation, edge selection, curve fitting.

1. Introduction

Biometric is progressively replacing traditional identification methods such as electronic key or password. Among different biometric technologies, iris recognition is considered as the most reliable application [1].

Major difficulties come from the poor quality of the acquired images. They are often blurred, defocused or occulted by eyelids. Several authors propose to analyze the image quality in order to select the best image from an acquisition sequence [2], [3]. However, efficient iris localization is still required, since the whole recognition system depends on the accuracy of this segmentation step.

In particular, the detection of eyelid occlusions is crucial to achieve good recognition rates. But it is a very difficult issue, since eyelashes often hide the eyelid boundaries. Also, the iris and eyelid regions may be difficult to separate, because of a very low contrast or a highly textured iris. Some eyelid localization methods have already been studied in [2], [4], [5], [6], [7], but the segmentation results are generally neither detailed nor quantified.

This paper presents a novel eyelid localization method and focuses on measuring segmentation quality. For that, we define two kinds of errors, sub-segmentation and over-segmentation, by comparing manual and automatic eyelid segmentation on a set of 151 iris images.

The paper is organized as follows: Section 2 describes the global iris recognition system. Section 3 focuses on our new eyelid localization method. Finally, experimental results are presented in Section 4.

2. Global Recognition System

A complete iris recognition system has been already presented in [8], [9]. It is divided in three parts (Fig. 1). The preprocessing part includes the iris segmentation and unwrapping (a). Then a third level wavelet packet decomposition is applied to the unwrapped iris to generate the signature (b). Finally, the recognition process is based on a distance calculation, in order to compare the extracted signature with the ones stored in a reference database (c).

The system is effective and robust to illumination, blurring, optical axis deviation and local defects [9]. But it can be improved by taking into account possible eyelid occlusions.

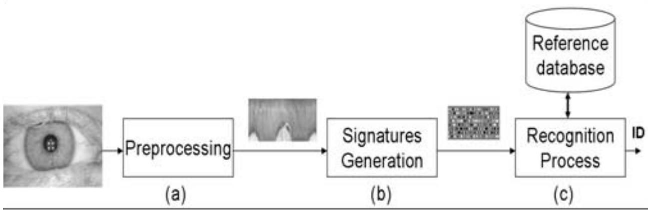

Fig. 1. Global recognition system.

3. Eyelid Localization

3.1 Iris Localization

The iris localization algorithm is performed with a gradient based search method [9]. The pupil is modeled by a circle and the outer iris boundary by an ellipse. Both curves are found by maximizing the mean gradient in the orthogonal direction (Fig. 2.a). Then, the iris region is unwrapped using the polar transform suggested by Daugman [2]. Its size is set to 256x128 pixels (Fig. 2.b).

Up to now, in our system, the occlusions have not been taken into account to generate the signature and have been processed as iris texture. So, the added segmentation step aims at detecting accurately the eyelid boundaries.

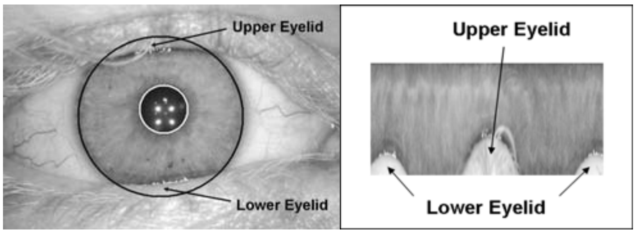

Fig. 2. a) Iris localization b) Unwrapped Iris.

3.2 Eyelid Processing Method

Most of eyelid localization methods presented in the literature model eyelids as parabolic arcs. Daugman uses an integrodifferential operator with arcuate contour integration [2]. Wildes applies a Hough transform for the detection of parabolic arcs [4]. Chen uses a second-order curve fitting applied to the longest connected edge [5].

Eyelids and especially the upper ones are often crossed by eyelashes. Consequently, the eyelid boundary is often cut in several parts, and the longest detected edge does not always correspond to the eyelid boundary. Moreover, the edge detection step is generally to tune the edge detector parameters in order to minimize bad connections, false detections or non detections in all cases.

That is why we propose a new method based on 4 steps: first, boundaries are enhanced by preprocessing. Then, a Canny edge detector [11] is applied on the preprocessed image, in order to get a map of edges. We use a priori information to suppress the ones that cannot correspond to eyelid boundaries. All the others are candidates to eyelid edges, and are fitted with parabolic curve. In the last step, we use a gradient maximization in order to refine the parabola parameters and select the best one.

3.3 Preprocessing

We apply an anisotropic diffusion [10] in order to smooth the iris texture while keeping the eyelid boundaries. Discretized anisotropic diffusion equation is presented as follow:

$$I^{t+1} = I^t + \lambda\left[c_N.\Delta_N I + c_S.\Delta_S I + c_E.\Delta_E I + c_W.\Delta_W I\right] \quad (1)$$

where $0 \leq \lambda \leq 1/4$ for the numerical scheme to be stable t indicates iteration index, Δ indicates the nearest-neighbor differences for each direction N,S,E,W and conduction coefficients c are function of this brightness gradient Δ. We use λ=0.25 and 6 iterations.

The results of the anisotropic diffusion (Fig.3.b) are conform to our goal. Actually, the iris structures are smoothed while eyelid edges are almost not blurred.

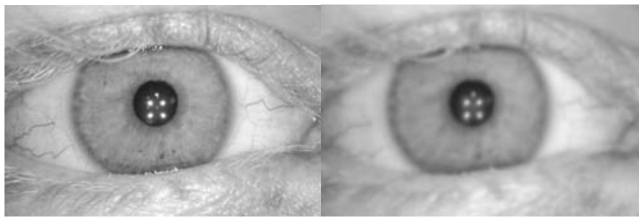

Fig. 3. a) Initial image b) Anisotropic diffusion preprocess.

3.4 Edge Detection

A Canny edge detection is performed on the preprocessed image (Fig. 4.a). The resulting image is binary, and provides a map of eyelid edge candidates.

In order to improve the speed and the robustness of the algorithm, we first restrict the analysis area to the inner iris. We also remove the left and the right parts of the iris in order to avoid connections between eyelids/iris and the iris/sclera boundaries. The remaining edges above the pupil are candidates for the upper eyelid detection, while the ones below the pupil are candidates for the lower eyelid detection (Fig. 4.b).

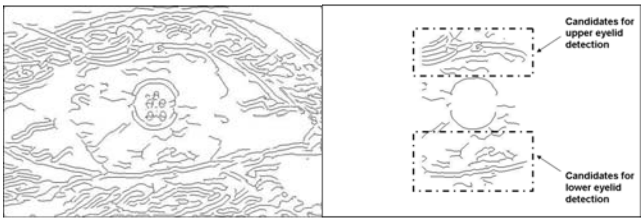

Fig. 4. a) Canny edge detection b) Restricted edge map.

The mean length of all the remaining edges is then computed, and used as threshold to eliminate the smallest ones that come mainly from iris texture.

Every candidate is fitted with a vertically oriented parabolic curve, whose parametric equation is defined by two parameters, the vertex S (Xs, Ys) and the curvature p:

$$\begin{cases} x = Xs + 2pt^2 \\ y = Ys + 2pt \end{cases}, t \in \Re \quad (2)$$

A second selection stage is applied, introducing a priori knowledge about the form of the eyelids, i.e the direction of the parabola. The upper eyelids can be approximated by a parabolic curve whose curvature p is positive. On the contrary, the curvature of the lower eyelid is negative. So, every fitted edge with an incorrect curvature p is automatically eliminated. (Fig. 5).

At the end of this step, the edges that are likely to match the eyelid boundaries have been extracted and modeled by a parabolic curve. Depending on the iris (little or highly textured), around 2 to 30 candidates still remain. We have also observed on many examples that the longest edge is not always the correct one.

The next step aims at refining the parameters of each curve and selects the best one.

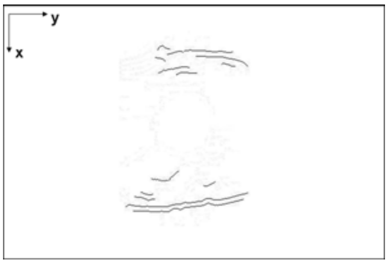

Fig. 5. Final edge candidates.

3.5 Evaluation and Selection

Let us denote by p_i the curvature of the parabola equation for the edge i (2). Each parabolic approximation is refined, by computing the gradient image along the curve for several curvatures.

A new gradient image G is computed from the original image by applying a horizontal sobel operator in order to focus on the horizontal edges. Working on the original image is more suitable than working on the preprocessed one as the eyelid edges are not degraded.

The gradient along the curve is then computed as follows:

$$G^i(p_i) = \frac{1}{N_i}\sum G(x_i, y_i)\,. \tag{3}$$

In this equation, N_i is the length of the edge i. x_i and y_i are the pixel coordinates along the parabolic curve for edge i with the curvature p_i. We limit the analysis in the horizontal direction to twice the iris size. The parameter p_i is refined by calculating the gradient for several curvatures around p_i and maximizing this gradient.

$$G^{(i)} = \max_j G^{(i)}\left(p_j\right), p_j \in \left[0, 2p_i\right]. \tag{4}$$

The final selected edge is the one maximizing this gradient, the method being applied for both upper and lower eyelids. An example is presented in Fig. 6.

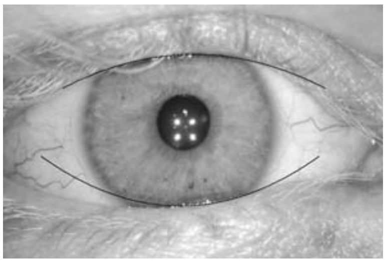

Fig. 6. Eyelids localization result.

4. Experiments and Results

We propose in this section an accurate and quantified performance evaluation of our eyelid localization method.

4.1 Eyelid Testing Set

A set of 151 manually segmented iris is used as benchmark to evaluate the eyelid segmentation method. This set is a part of the ISEP database [9]. All ranges of eyelid occlusions are presented. So, this corresponds to the different cases that a real system might encounter. The set is described in Tab.1.

In it, we define four classes: *null* corresponds to the case with no occlusion. Then, we denote by *small* occlusions witch cover up less than 10% of the iris texture, by *medium* occlusions between 10% and 30% and by *large* occlusions more than 30%. The class distribution is very realistic.

Eyelids/Size	null	small	medium	large
Upper Eyelids	27.15%	15.59%	38.41%	18.55%
Lower Eyelids	30.46%	32.45%	32.45%	4.64%

Tab. 1. Percentage of iris in each class.

4.2 Eyelid Localization Quality

The performance of our eyelid localization method is evaluated on the unwrapped images (section 3.1). Let us consider the binary unwrapped image, where the pixels equal to 1 belong to iris, and the pixels equal to 0 belong to the eyelid. It can be divided in two parts: the central part represents the upper eyelid localization, the side parts represent the lower eyelid localization. These two regions, denoted by P1 and P2 have the same size S (16384 pixels).

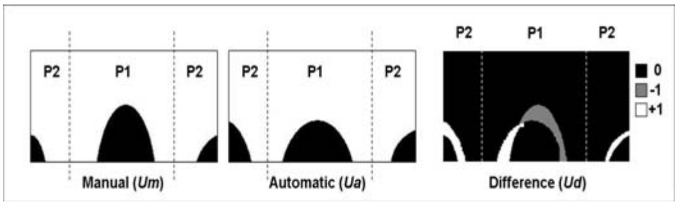

Fig.7. Difference between manual and automatic segmentation.

Using these conventions, we compute the difference between the manually (Um) and the automatically segmented images (Ua). Let us denote by Ud the resulting image. The pixels equal to -1 are pixels classified as iris although they are in the eyelid region (sub-segmentation). Conversely, the pixels equal to +1 are pixels classified as eyelid, although they are in the iris region (over-segmentation). The sub-segmentation error E^p_{sub} and the over-segmentation error E^p_{over} are defined as follows:

$$E^{Pi}_{sub} = \frac{\sum\limits_{(x,y)\in Pi} Ud(x,y) = -1}{S}\,, \tag{5}$$

$$E^{Pi}_{over} = \frac{\sum\limits_{(x,y)\in Pi} Ud(x,y) = +1}{S}\,. \tag{6}$$

From equations (5) and (6), a global error E^{Pi} is given:

$$E^{Pi} = \left|E_{sub}^{Pi}\right| + \left|E_{over}^{Pi}\right|. \quad (7)$$

4.3 Results

Two cumulative distribution functions (Fig. 8) are presented to estimate the performances for the upper and the lower eyelid segmentation. These graphics represent the proportion of images whose global error (Eq. 7) is lower than a given value. These results show that the proposed method is reliable. Indeed, we obtain less than 10% of global error for 90% of the upper eyelids and for 98% of the lower ones. It is worth noting that the maximum global error is less than 13.6% the lower eyelids and less than 18% the upper ones. The system is also very robust to over-segmentation, since non-occulted images (Tab.1) are very well processed.

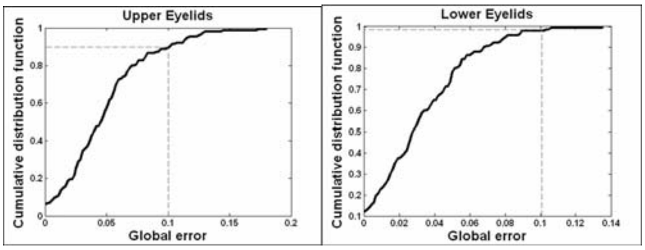

Fig. 8. Upper and lower eyelid cumulative distribution function.

5. Conclusion and Future Work

In this paper, a new eyelid localization algorithm has been proposed. To this end, an edge detection method is performed on a restricted image area, leading to a set of possible boundary candidates. These edges are approximated by parabolic arcs. The parabola curvature of every candidate is refined using a gradient maximization applied on a larger image area. Thus, the final boundaries can be selected and accurately modeled.

The obtained results when compared with manually segmented images show a good reliability of the proposed method. This algorithm will be included in the preprocessing part, and will allow to restrict the signature comparison to the relevant coefficients. We will then study the link between the signature degradation (due to occlusions) and the recognition rates. From this, we will define an identification reliability that will be used in a multimodal system, including face analysis [12].

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