Noncooperative Iris Segmentation

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Abstract

In noncooperative iris recognition one should deal with uncontrolled behavior of the subject as well as uncontrolled lighting conditions. That means eyelids and eyelashes occlusion, non uniform intensities, reflections, imperfect focus, and orientation among the others are to be considered. To cope with this situation a noncooperative iris segmentation algorithm based on numerically stable direct least squares fitting of ellipses model and modified Chan-Vese model (local binary fitting energy) with variational level set formulation is to be proposed. The proposed algorithm is tested using CASIA-IrisV3.

Keywords: *Noncooperative Iris Segmentation, Active Contour Model, Modified Chan-Vese Model, Variational Level Set Formulation.*

1. Introduction

The biometric technology deals with recognizing the identity of individuals based on their unique physical or behavioral characteristics. Physical characteristics as finger print, palm print, hand geometry, and iris patterns and behavioral characteristics as typing pattern, gait, voice, and hand-written signature. The biometrics are used in applications where it is required to establish or confirm the identity of individuals as passenger control in airports, access control in restricted area, border control, database access, and financial services.

The iris pattern has several advantages as stability over time, statistically unique, well protected from the external environment, and impossibility of surgically modifying the iris without unacceptable risk to vision.

The typical stages of iris recognition begin with the iris image acquisition. After that the segmentation of the region correspondent to the iris in detecting the iris inner and outer boundaries at the pupil and sclera, detecting the upper and lower eyelid boundaries if they occlude, and detecting and excluding any superimposed eyelashes or reflections. The iris images are highly affected by their distance and angular position with respect to the camera; moreover, the illumination has a direct impact on the pupil size and causes non linear variations of the iris patterns. To compensate these variations, the iris image is transformed (normalized) into a polar coordinate system where fixed-size rectangular block is produced. The feature extraction process produces a set of numeric values known as the iris signature or the iris template. The comparison between the acquired and the enrolled templates (the enrolled template is stored in database previously once) produces a dissimilarity value used to conclude the identity of the subject.

The emerging needs for a safer and quicker access (building, weapons, and restricted areas) requires noncooperative recognition methods, in which the user has no active participation in the image capture process and is not even aware of the recognition method and also dealing with uncontrolled lighting conditions. This means that we process images with heterogeneous characteristics.

Some segmentation methods [1-3] assume that the inner and the outer boundaries and eyelid boundaries are circular or elliptical. This is a source of error, since the iris boundaries are not exactly circles or ellipses even in cooperative recognition. Daugman [1] applied an integro-differential operator which acts as a circular edge detector to detect the inner and outer boundaries of the iris, while the upper and lower eyelids are also detected using the integro-differential operator by adjusting the contour search from circular to a designed arc. Wildes [2] used an edge detector and a circular Hough transform-based method to segment the iris, while the upper and lower boundaries of the eyelid are approximated using parabolic curves. In [3] noncooperative segmentation method is used where the process begins with the image-feature extraction in which three discrete values are extracted for each image pixel, followed by the application of a clustering algorithm that will classify each pixel and produce the intermediate image. This intermediate image is then used by circular Hough transform-based method.

Recently, several researchers proposed different noncooperative iris segmentation methods based on active contours models [4, 5, 7, 8, 10]. Active contour models are curves that evolve within digital images to recover object boundaries (whatever their shapes are) under the influence of both internal and external forces and user defined constraints. These algorithms have been at the heart of one of the most active and successful research areas in edge detection, image segmentation, shape modeling, and visual tracking. Active contour models are broadly classified as either parametric active contour models (Snakes) or geometric active contour models (level sets). Geometric active contour models have several important advantages over parametric models such as computational simplicity and the ability to change the contour topology during the evolution automatically (e.g., splitting and merging) without requiring an elaborate mechanism to handle such changes. However, this advantage of geometric active contour models turns out to be a liability in applications where the object to be segmented has a known topology that must be preserved.

Geometric active contour models are divided into edge and region based active contour models (the Snake is edge based active contour model). Edge based active contour models depend on large image gradient to stop the curve evolution on the object boundary. Region based active contour models depend on partitioning the image domain by fitting statistical models as the intensity, color, texture, or motion in each of a set of regions and therefore have better performance for the image with weak object boundaries.

In [4, 5, 7] edge based active contour models are used. Daugman [4] used Snake model for detection of the inner and outer boundaries of the iris and to correct the off-axis images, the images are converted into orthographic form by using Fourier-based method and used statistical methods for detecting the eyelashes. In [5], the inner boundary is detected by smoothing the eye image using a 2-D median filter and binarization the smoothed image by certain threshold and then 2-D median filter is applied on the binary image to discard the relatively smaller regions. A circle-fitting procedure is executed on all detected regions. Finally, the circle whose circumference contains the maximum number of black pixels is deemed to be the detected pupil. If reflection is detected in the vicinity of the pupil, it is inpainted. The outer boundary of the iris is detected by level set representation of the geodesic active contour model where the pupil boundary is used to initialize the contour. The contour evolves around a small narrow band [6] to accelerate the evolution process. Important feature of GACs is their ability to handle "splitting and merging" boundaries. This is especially important in the case of iris segmentation (the Snake model has not this feature). But if the iris boundary is weak, the contour evolution may not stop at the desired iris boundary leading to an oversegmentation of the iris. In [7], a level set method with area preserving has been used for determining inner and outer iris boundaries, both performed in one step. The contour initialization is determined by one dimensional derivation in the right horizontal axes from the approximate center of inner boundary of the iris (the approximate center is calculated by intersection of the minimum vertical and horizontal histograms). The one step segmentation approach improves the speed of the whole process in comparison with two–step boundary detection methods. The main difference between [7] and [5] is using an area preserving which make this method is robust in case of the blurred images. But the method which is used in calculating the approximate center of inner boundary of the iris does not give right results in some images because of the noise.

In [8, 10] region based active contour models are used. In [8], a two stages iris segmentation process is proposed. In the first stage, approximation of the inner and outer boundaries of the iris using iterative elliptical fitting model. In the second stage, the approximate inner boundary is used as the initial contour and the contour is evolved by Chan-Vese model (global binary fitting energy) [9] in a narrow band of ±5 pixels. Similarly, the approximate outer boundary is used as the initial contour and the contour is evolved by Chan-Vese model in a narrow band of ±10 pixels. Using the approximate iris boundaries as the initial contours reduces the complexity of curve evolution and is suitable for real-time applications. The eyelids and the eyelashes may be present as noise, the eyelids are isolated by fitting lines to the upper and lower eyelids. A mask based on the detected eyelids and eyelashes is then used to extract the iris without noise. But using iterative algorithm for fitting an ellipse is computationally expensive, also using Chan-Vese model is not suitable for images with intensity inhomogeneity.

Chan-Vese model (region based active contour model) has been successful for images with two regions, each having a distinct mean of pixel intensity where this model assumes that the image consists of statistically homogeneous regions, with intensity in each region being a constant up to certain noise. Since the iris region in the noisy images is not statistically homogeneous, the difficulty due to image inhomogeneity is incorrectly label part of background pixels as the iris, while a significant part of the iris is missing.

The iris segmentation methods in [4, 5, 7, 8] depend on image homogeneity. In [10], also the iris segmentation process is divided into two stages. In the first stage, approximation of the inner and outer boundaries of the iris using a Direct Least Square (DLS)-based elliptical fitting model [11]. In the second stage, the approximate inner boundary is used as the initial contour and the contour is evolved by modified Chan-Vese model (local binary fitting energy) [12] with variational level set formulation [13] in a narrow band of ±10 pixels from outside the approximated inner boundary to remove the effect of reflections. Similarly, the approximate iris boundary is used as the initial contour and the contour is evolved by modified Chan-Vese model with variational level set formulation in a narrow band of ±20 pixels from inside the approximated iris boundary to reduce the effect of the eyelids and the eyelashes. The eyelashes detection technique is deployed. The advantages of [10] are using modified Chan-Vese model which extracts the intensity information in local regions at a controllable scale to solve the problem of image inhomogeneity and using variational level set formulation to speed up the curve evolution and to obtain stable evolution of the level set function. The iris segmentation methods in [5, 7, 8] consume huge computational time for using the traditional level set. But although DLS-based elliptical fitting model is the first non-iterative ellipse-specific fitting and it guarantees an ellipse-specific solution even for scattered or noisy data, in some cases produces wrong results. Our contribution is to attempt solving the previous drawbacks by using numerically stable Direct Least Square fitting of ellipses model [14] to approximate the iris boundary and using modified Chan-Vese model with variational level set formulation.

2. The Proposed Method

The iris segmentation process is divided into two stages. In the first stage we use a numerically stable DLS-based elliptical fitting model to approximate the outer boundary of the iris. In the second stage we use a modified Chan-Vese model to estimate exact outer and inner iris boundaries.

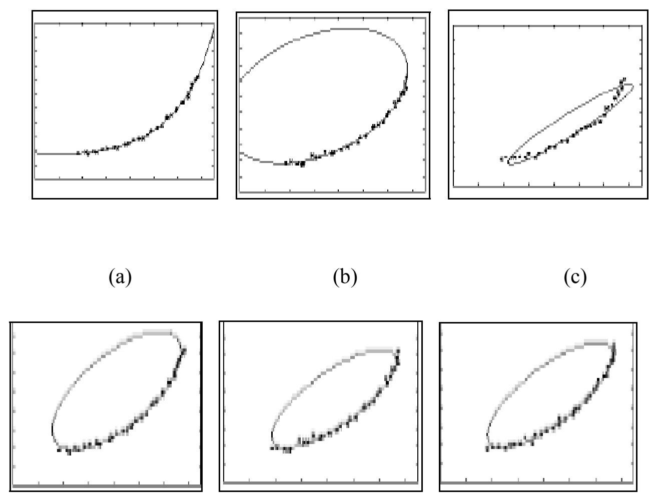
2.1 The Numerically Stable DLS-Based Elliptical Fitting Model

We use a numerically stable DLS-based elliptical fitting model (instead of DLS-based elliptical fitting model as in [10]) to approximate the outer boundary of the iris only through five parameters (p_1, p_2, r_1, r_2, θ) where

(p_1, p_2) are horizontal and vertical coordinates of the outer boundary center,
(r_1, r_2) are the length of the major and minor axes, and
(θ) is the orientation of the ellipse.

These five parameters are used to draw an ellipse which is used as initial contour.

The DLS-based elliptical fitting model is the first non-iterative ellipse-specific fitting and it guarantees an ellipse-specific solution even for scattered or noisy data, but in some cases produces wrong results. These wrong results are eliminated by using a numerically stable DLS-based elliptical fitting model as in "Fig. 1".



(a) (b) (c)

(d) (e) (f)

Fig. 1 (a, b, c) illustrate that DLS-based elliptical fitting model, sometimes produces wrong results, (d, e, f) illustrate that numerically DLS-based elliptical fitting model produces good results on the same data points.

2.2 The Modified Chan-Vese Model

We estimate exactly the outer and inner iris boundaries. The initial contour is evolved using a modified Chan-Vese model in a narrow band of ±20 pixels from outside the approximated outer boundary to inside where the iris region is considered one region and the rest of the image and the superimposed eyelids and eyelashes and reflections are the other region. For each point x Є Ω (where Ω is the image domain), the modified Chan-Vese model (local binary fitting energy E_x^{LBF}) is as Eq. (1)

$$E_{\mathrm{x}}^{LBF}(C, f_1(\mathrm{x}), f_2(\mathrm{x})) = \lambda_1 \int_{in(C)} K(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_1(\mathrm{x})|^2 d\mathrm{y} + \lambda_2 \int_{out(C)} K(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_2(\mathrm{x})|^2 d\mathrm{y} \tag{1}$$

where

C is a contour in the image domain Ω,

f_1(x) and f_2(x) are the values that approximate image intensities inside and outside the closed contour C,

λ_1 and λ_2 are positive constants,

I(y) is the intensity in a local region centered at the point x,

K(x - y) is a weighting function with a localization property where K(x - y) decreases and approaches zero as |x - y| increases (I.e., at the points y away from the center point x) as Eq. (2)

$$K_\sigma(\mathbf{x} - \mathbf{y}) = \frac{1}{(2\pi)^{n/2}\sigma^n} e^{-|\mathbf{x} - \mathbf{y}|^2/2\sigma^2} \tag{2}$$

with a scale parameter σ > 0.
In level set methods, a contour C is represented by the zero level set function Φ. Thus the local binary fitting energy (LBF) in "(1)" can be written as Eq. (3)

$$\begin{aligned} &E_{\mathbf{x}}^{LBF}(\phi, f_1, f_2) \\ &= \lambda_1 \int K_\sigma(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_1(\mathrm{x})|^2 H(\phi(\mathrm{y}))d\mathrm{y} \\ &+\lambda_2 \int K_\sigma(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_2(\mathrm{x})|^2 (1 - H(\phi(\mathrm{y}))d\mathrm{y} \end{aligned} \tag{3}$$

where H is the Heaviside function. Thus, the energy over all the center point x in the image domain Ω is as Eq. (4)

$$\begin{aligned} E^{LBF}(\phi, f_1, f_2) &= \int_\Omega E_{\mathrm{x}}^{LBF} d\mathrm{x} \\ &= \lambda_1 \int[\int K_\sigma(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_1(\mathrm{x})|^2 H(\phi(\mathrm{y}))d\mathrm{y}]d\mathrm{x} \\ &+\lambda_2 \int[\int K_\sigma(\mathrm{x}-\mathrm{y})|I(\mathrm{y}) - f_2(\mathrm{x})|^2 (1 - H(\phi(\mathrm{y}))d\mathrm{y}]d\mathrm{x} \end{aligned} \tag{4}$$

The previous energy is computed from the image data I, so it is called an external energy. Some internal energy terms (as the distance regularizing term $D(\Phi)$ and the length of the zero level contour $L(\Phi)$) are added. Then the total energy function is as Eq. (5)

$$F(\phi, f_1, f_2) = E^{LBF}(\phi, f_1, f_2) + \beta D(\phi) + \nu L(\phi) \tag{5}$$

where β and ν are nonnegative constants.

The term $\beta D(\Phi)$ is to penalize the deviation of the level set function Φ from a signed distance function and therefore completely eliminates the need of the reinitialization procedure which is time consuming in traditional level set methods and therefore significantly larger time step can be used which speeds up the curve evolution and stable evolution of the level set function Φ is produced as Eq. (6)

$$D(\phi) = \int_\Omega \frac{1}{2}(|\nabla\phi(\mathbf{x})| - 1)^2 d\mathbf{x} \tag{6}$$

And the length of the zero level contour to regularize the contour can be defined by Eq. (7)

$$L(\phi) = \int_\Omega \delta(\phi(\mathbf{x}))|\nabla\phi(\mathbf{x})|d\mathbf{x} \tag{7}$$

(a) (b) (c)

(i)

(a) (b) (c)

(ii)

Fig. 2 Illustrates the segmentation process by (i) modified Chan-Vese model (ii) Chan-Vese model. Where (a) original image, (b) the image and the contour, (c) the segmentation.

In our proposed method, we use a single contour instead of two contours [8] and [10]. For using two contours the superimposed reflections on the iris region which are not near the boundaries are not detected as in "Fig. 3".

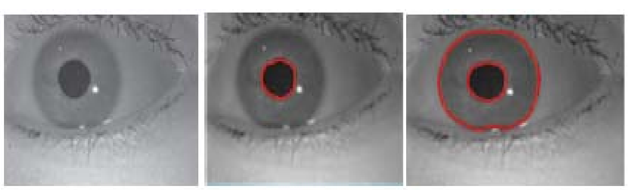


Fig. 3 Illustrates the superimposed reflections on the iris region are not detected.

While using single contour evolves from outside the approximated outer boundary to inside will reduce the effect of eyelids and eyelashes as shown in "Fig. 2". For using a single contour evolves from inside the inner boundary to outside, the contour will detect the pupil boundary and the eyelashes (which have the same intensity) while it can not detect the outer boundary.

3. Experimental Results

3.1 The Database

In our experimentation, we have used CASIA-IrisV3 database [15] which is a noisy database. CASIA-IrisV3 includes three subsets which are labeled as CASIA-IrisV3-Interval, CASIA-IrisV3-Lamp, and CASIA-IrisV3-Twins as in "Fig. 4". CASIA-IrisV3 contains a total of 22051 iris images from more than 700 subjects. All iris images are 8-bit gray level JPEG files, collected under near infrared illumination.

(a) (b) (c)

Fig. 4 (a) image from CASIA-IrisV3-Interval, (b) image from CASIA-IrisV3- Lamp, (c) image from CASIA-IrisV3- Twins.

3.2 Numerically Stable DLS

Numerically stable DLS-based elliptical fitting model is for fitting an ellipse to a set of data points. To determine the data points, we apply circular Hough transform with certain radius. Then applying numerically stable DLS on arc from the resultant circle. The arc interval (in degrees) is 0 - 30.

3.3 The curve evolution parameters

The values of the selected parameters to find the inner and outer boundaries in case of CASIA-IrisV3-Interval are $\sigma = 2$, $\beta = 0.001$, $\nu = 0.2$, $\lambda_1 = 1$, $\lambda_2 = 90$, step size = 90, and the number of iterations = 3 (the maximum number to this database). In case of CASIA- IrisV3-Lamp and CASIA-IrisV3-Twins are $\sigma = 2$, $\beta = 0.001$, $\nu = 0.2$, $\lambda_1 = 1$, $\lambda_2 = 3$, step size = 190, and the number of iterations = 2 (the maximum number).

3.4 Comparison between the proposed method using either Chan-Vese model or modified Chan-Vese model

All the algorithms were implemented in MATLAB 7.0. The 'Time' column from Table 1 contains the average execution time for each of the segmentation tested methods. These time values were obtained by averaging 100 segmentation processes on 100 distinct images.

Table 1 : Contains the average time and segmentation efficiency for each of the segmentation tested methods.

Method	***Time (s)***	***Segmentation Effeciency (%)***

The proposed method using Chan-Vese model	.3	96.7
The proposed method using modified Chan-Vese model	.17	99.02

4. Conclusions

The process of segmenting the iris plays a crucial role in iris recognition systems. This paper presents a noncooperative iris segmentation using numerically stable direct least squares fitting of ellipses model and using modified Chan-Vese model (region based active contour model). The irregular shape of the inner and outer boundaries of the iris was the motivation of using the active contour models where the inner and outer boundaries of the iris are not exactly circular or elliptical. Region based active contour models have better performance for the iris images with weak iris boundaries than edge based active contour models. Also, using local region based active contour model provides a better performance than global region based active contour model when the iris images suffer from intensity inhomogeneity.

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