Shape Analysis of Stroma for Iris Recognition*

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Abstract. In this paper, a new shape analysis approach for iris recognition is proposed. First, the extracted iris images from eye portrait are enhanced by image deblurring filter which computes restoration using FFT-based Tikhonov filter with the identity matrix as the regularization operator. This procedure produces a smooth image in which shape of pigmented fibro vascular tissue known as Stroma is depicted easily. Then, an adaptive filter is defined to extract these shapes. In the next step, shape analysis techniques are applied in order to extract robust features from contour of the shapes such as support functions and radius vectors. These features are invariant under iris localization and mapping. Finally, a feature strip code is defined for every iris image. Introduced algorithm is applied to UBIRIS databank. Experimental results show efficiency of the proposed method by achieving an accuracy of 95.08% on first session of UBIRIS.

Keywords: Biometric Recognition, Stroma, Tikhonov Filter, Shape Analysis.

1 Introduction

Literature of iris recognition is dominated by wavelet methods. First method was proposed by Daugman [1, 2] which used multiscale quadrature wavelets to extract texture phase structure information of the iris. Ma et al. [3–4] adopted a well-known texture analysis method (multichannel Gabor filtering) to capture both global and local details in iris. Wildes et al. [5] with a Laplacian pyramid constructed in four different resolution levels and the normalized correlation for matching designed their system. Tisse et al. [6] combined the original image and Hilbert transform to demodulate the iris texture. 2D Haar wavelet was used by Lim et al. [7] and applied an LVQ neural network for classification. Kumar et al. [8] developed correlation filters to measure the consistency of iris images from the same eye. The correlation filter of each class was designed using the two-dimensional Fourier transforms of training images. Bae et al. [9] projected the iris signals onto a bank of basis vectors derived by independent component analysis and quantized the resulting projection coefficients as features. Gu et al. [10] used a multiorientation features via both spatial

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and frequency domains and a nonsymmetrical SVM to develop their system. They extracted features by variant fractal dimensions and steerable pyramids for orientation information.

Although there exists different feature extraction methods based on wavelet approaches for iris recognition, nevertheless, extra developments are needed to reach highly accurate results in huge size databanks. Besides, most of the approaches are sensitive to iris localization and distortion during iris extraction, where this matter causes in error during template matching. By the definition, other approaches should be considered to extract robust features. Studying the anatomy of iris would assist us to sense it more reliable and obtain more suitable features.

Iris contains two different layers. The thin innermost layer is called the iris pigment epithelium (IPE) and consists of a compact array of opaque cells. The outermost layer is referred to as the iris stroma, which contains more loosely arranged cells, including melanocytes that synthesize the pigment melanin [11]. Iris stroma is the unique characteristic which identifies a person where the following shapes can be considered to process them in the form they appear.

In this paper, we introduce a new method in order to extract the iris stroma shapes in binarized portrait from gray image which is adaptive to light luminance. Gaussian fitting through gray image histogram and detecting threshold boundaries is the essential key for the implemented adaptive filtering. Section 2 reviews the state of art of shape analysis methodology in order to apply it to iris recognition. Nevertheless, Section 3 implements the above method to analyze the unique iris stroma shapes. In Section 4 we set up a feature code for every person's iris, where after all, we apply and evaluate our algorithm to UBIRIS [12] as a databank for classification. Finally, Section 5 concludes the paper.

2 Shape Analysis and Invariant Features

Shape analysis techniques have been of interest in computer vision and intensively developed over the past decades. Shape is a difficult concept, invariant of geometrical transformations such as translation, rotation, size changes and reflection [13]. The normal description of a shape can be defined by functional approach which is explained in Section 2.1.

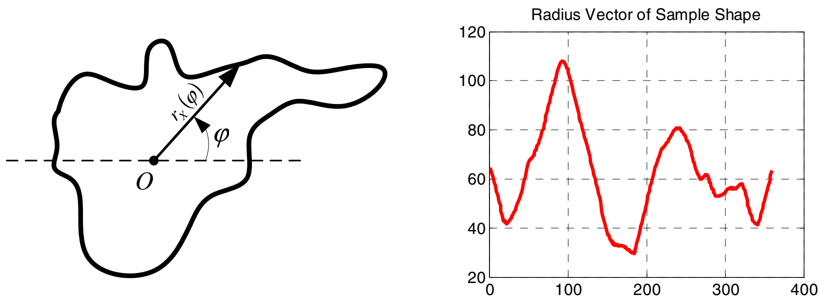
2.1 Functional Approach

The function description of a figure is appropriate for many applications because of its advantages over other methods such as [13]:

- *Effective data reduction:* frequently only a few coefficients of the approximation functions are needed for a rather precise form description, where it causes less computation time in processing the algorithm.
- *A convenient description and intuitive characterization of complex forms:* this leads to considering whole complexity of figure's shape as useful features.

As a functional approach, two distinct features are introduced here to apply them in extracting features from iris images which are *Radius-Vector Functio*n and *Support Function*.

Regarding *radius-vector function*, a reference point O in the interior of the figure X is selected which is called the center of gravity. Next, the appropriate reference line l crossing the reference point O is chosen parallel to the x- or y-axes. The radius-vector function $r_X(\varphi)$ is then the distance from the reference point O.



a b

Fig. 1. a. Figure of a sample shape and definition of radius-vector function **b.** Radius-Vector Function of a sample shape

It is necessary, for polar description, that the figure remains star-shaped with respect to O. This means that there only exists one point of p for every angle. In fact, it is not obligatory to describe a figure in polar coordinates. Here, we used all points of figure as potential features and normalized the radius-vector function. For example, in Fig. 1.b, the number of the points is normalized to 360 points, though this value is completely arbitrary.

It is important to know how Radius-Vector Function depends on geometrical transformations such as *translation, size changes, rotation,* and *reflection*. Above function shows the following features [13]:

1. is invariant under translation: $r_{X+t}(\varphi)=r_X(\varphi)$ where $X+t$ is X translated by a vector t;
2. depends on the size of figure X : $r_{\lambda X}(\varphi)=\lambda r_X(\varphi)$ where λX is the figure X zoomed by a factor λ. Nevertheless, this matter can be solved by normalizing the radius function;
3. is not invariant under reflection;
4. depends on the orientation of the figure X : $r_X(\varphi)=r_Y(\varphi-\alpha)$ where Y is Figure X rotated by an angle α.

The last two seems disadvantages of the radius-vector function. In particular, the fourth argument declares dependency of the function to orientation.

Nevertheless, orientation is not a problem in iris recognition even by mapping the extracted iris from polar to Cartesian coordinates, see Fig. 2, because orientation in polar coordinates is the same as translation in Cartesian coordinates.

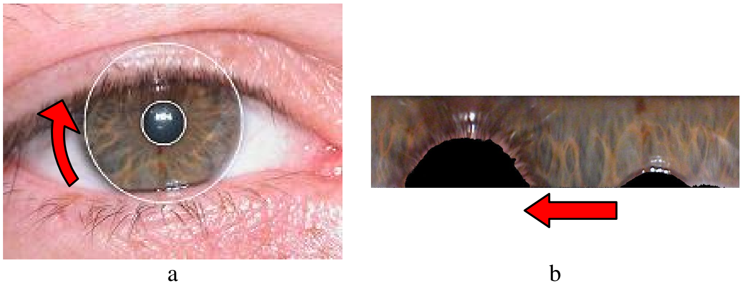


Fig. 2. a. Orientation in polar coordinate **b.** Translation in Cartesian coordinates corresponds to orientation in polar coordinates

Obviously, the third problem, which refers to reflection, will not happen if a distinct definition is introduced for extracting a shape like iris. Usually in iris recognition neither extracted iris nor mapped iris do not reflect the shape, see [15].

The second functional approach to figure description is Support Function. For a figure X, let g_φ be an oriented line through the origin O with direction φ, $0 \le \varphi \le 2\pi$. Let $g_\varphi^\perp$ be the line orthogonal to g_φ so that the figure X lies completely in the half-plane determined by $g_\varphi^\perp$ with $g_\varphi^\perp \cap X \neq \emptyset$, which is opposite to the direction of g_φ. The absolute value of the support function equals to the distance from O to $g_\varphi^\perp$ and the support function $S_X(\varphi)$ is negative if the figure lies behind $g_\varphi^\perp$ as seen from the origin. If O is an element of the figure X, then $S_X(\varphi) \ge 0$ for all φ [13], see Fig. 3.

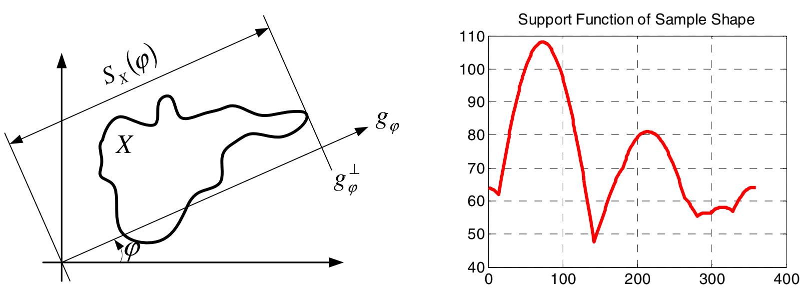


Fig. 3. a. Support Function Description **b.** Support Function of the sample shape

All of the four benefits in the above discussion are appropriate for the support function. This parameter can be calculated as follows:

$$s_X(\varphi) = \max_{0 \le l \le L} \left[x_X(l)\cos(\varphi) + y_X(l)\sin(\varphi) \right] \tag{1}$$

L is the perimeter of figure X and each point $(x_X(l), y_X(l))$ of the contour of X can be defined with a number l. The relation between polar and Cartesian coordinate of the figure thus can be identified by:

$$\begin{aligned} x_X(l) &= r_X(l)\cos(\varphi_l) \\ y_X(l) &= r_X(l)\sin(\varphi_l) \end{aligned} \tag{2}$$

3 Extracting Iris Stroma Shapes

As noted in Section 1, the iris stroma is the outermost layer of iris and has unique characteristic for each individual. It has to be segmented to extract the related features such as radius-vector and support function. Iris stroma is usually a thin layer where by implementing a filter, it should be extracted precisely. Most captured iris images are noisy due to light luminance of camera flash. UBIRIS [12] is databank with dominant noise. The authors of the databank presented a table to discuss the noise factors, see [16]. They introduced the first session of the databank as 11% noisy databank regarding Focus, Reflection-Area and Visible-Iris-Area, simultaneously with 17.06%, 5.4% and 10.71% noise factors. In this paper, we implement an adaptive filter in order to eliminate the above noises.

The portrait of an image consists of two components: a) the amount of source illumination incident on the scene being viewed; and b) the amount of illumination reflected by the objects in the scene [17]. These components are called the Illumination and Reflectance and are denoted by $i(x, y)$ and $r(x, y)$ respectively. Production of the two components called the gray value $f(x, y)$:

$$\begin{aligned} &f(x, y) = i(x, y)r(x, y) \\ &Where:\ 0 \le i(x, y) < \infty \\ &\qquad\quad 0 \le r(x, y) \le 1 \end{aligned} \tag{3}$$

These two components are separable and can be distinguished identically with a logarithmic operation:

$$\log\big(f(x, y)\big) = \underbrace{\log\big(i(x, y)\big)}_{I} + \underbrace{\log\big(r(x, y)\big)}_{R} \tag{4}$$

The amount of R differs from pixel-to-pixel. This value, as shown later, will be adaptively eliminated and only illumination incident I will remain as appropriate value to generate a binary image.

The image smoothed after logarithmic operation in order to distribute focus noise factors along the image. Tikhonov Filter [18] is a suitable tool to denoise the related noise of the images where deblurs an image with identity matrix as the regularization operator known as mask. After deblurring, the high frequency noises of the image removed by a lowpass filter. The whole procedure of the implemented algorithm is shown in Fig. 4. As shown, the image generated by Tikhonov filter is nicely smooth and iris stroma is smoothly depicted.

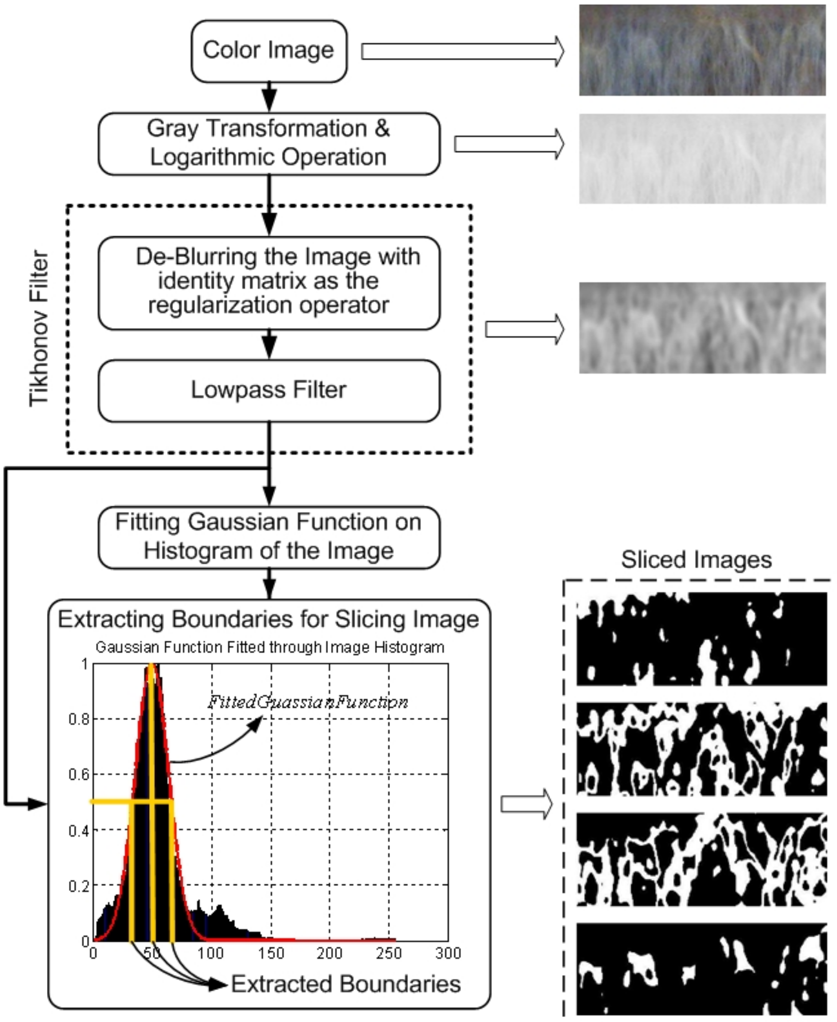


Fig. 4. The implemented algorithm block diagram for extracting iris stroma

After smoothing iris template, we need to extract iris stroma by considering the fact that the reflection noise is not yet removed from the image. A simple method is to binarize image with several distinct thresholds. However, the histogram of incident illumination I is not a fixed distribution. It changes from person to person. This fact causes problem during thresholding the images where in some sample of binarized templates, there exists just tiny shapes which are not suitable for shape analysis. To solve the problem, we proposed an adaptive approach in which the image histogram is fitted by a Gaussian function. This is because almost the entire iris gray levels are clustered around a distinct intensity value which relates to iris stroma. In other words, the variance of the intensity values of the iris image is small.

After fitting a Gaussian function to the image histogram, three threshold boundaries can be extracted. First two, are gotten from intersecting a line parallel to x-axis which bisects the fitted Gaussian function and the third one is considered by middle of the Gaussian. The number of boundaries for binarizing image is completely arbitrary. Here we considered only three boundaries. Four binary images can be generated by the three boundaries. For example, the first binary image is defined by the intensity values between [0, B1] where B1 is the first extracted boundary threshold.

One of the other benefits of this adaptive approach is that we can extricate from reflectance components defined in (4). The reason is that the reflections are fused in image and gather in maximum areas of image histogram by the adaptive approach, the above noises automatically illuminate in the binary images.

4 Experimental Results

UBIRIS [12] databank is used to show the robustness of the extracted features. As noted before, UBIRIS is a noisy databank in which the first session is captured in less noisy condition than the second session. In the second session, the reflection noise factor has high value. Nevertheless, the proposed approach has generated highly accurate results for both sessions. Iris stroma is the considered shape to extract both radius-vector-function—RVF—and support-function—SF—features. A feature strip code is introduced to each iris image by the following sequence:

SF1	SF2	SF3	SF4	RVF1	RVF2	RVF3	RVF4

Where SF1 relates to the first Support-Function feature with the biggest object detected from binary iris image. SF2-SF4 are the Support-Function features related to the three biggest objects after the SF1. The same relation is appropriate for RVF (radius-vector-function). Usually first features of SF and RVF are most robust because they come from the biggest object of iris stroma and have less distortion compared with the other ones.

UBIRIS [12] consists of 1877 images of 241 persons, 1214 images from the first and 663 images from the second session. Each person has five images captured in different time sequences. Table 1 shows the classification results for both sessions of UBIRIS in 3 different conditions with to two, three and four test data. The best accuracy is obtained from the first session (first condition) with 95.08% accuracy. We realized that the images with high noise levels, especially on reflection, failed in the experimental step. The other important fact is that degradation of the results from the first to the second sessions is not high showing the robustness of proposed algorithm to noisy images. False acceptance rate is one of the important facts to realize the behavior of accuracy of applied contribution by allowing system to verify the failed images in several attempts. For example, for the first session of UBIRIS after 2 attempts, the accuracy result increases to 98%. Fig. 5 shows the related argument.

Table 1. Classification results for UBIRIS databank considering three different situation

Conditions	1st Session of UBIRIS	2nd Session of UBIRIS	Degradation
1 Test Images & 4 Comparing Images	**95.08%**	**91.37%**	**3.71%**
2 Test Images & 3 Comparing Images	**93.00%**	**88.12%**	**4.88%**
3 Test Images & 2 Comparing Images	**86.09%**	**81.06%**	**5.03%**
4 Test Images & 1 Comparing Image	**78.39%**	**70.19%**	**8.22%**

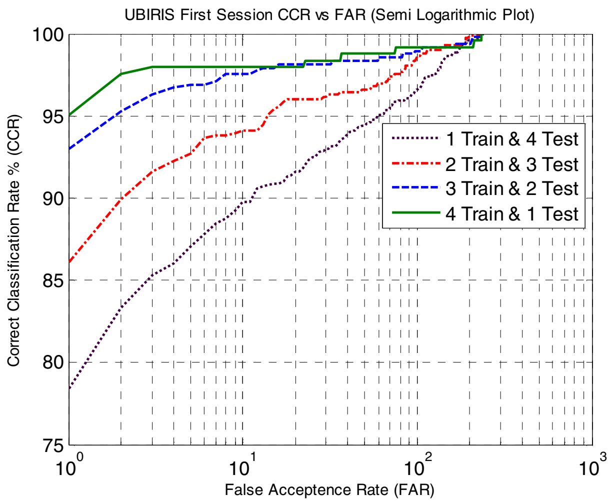


Fig. 5. CCR versus Classification attempt numbers for the first session of UBIRIS

CASIA [19] might be the most popular databank in iris recognition, where the images have been captured in near infrared. In CASIA, due to near infrared imaging, reflections do not influence the images, and they are less noisy as compared with those images captured in visible light. Applying our developed algorithm to CASIA, however, results in very poor performance. The best result of shape analysis on CASIA led on 38.88% accuracy for 1 FAR, see Fig. 6.

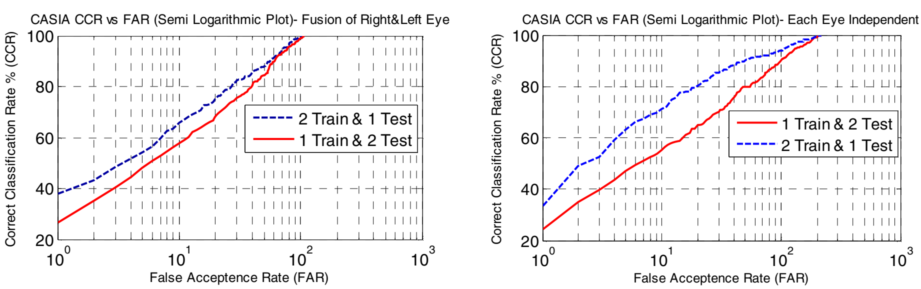


Fig. 6. a. CCR of CASIA with fusion of Left and Right eyes **b.** CCR of CASIA Each eye independent

The reason for lack of performance of our stroma shape analysis based method on CASIA lay in the fact that near infrared imaging suppress most of the information one may get from Stroma patterns. Fig. 7 compares two typical images from UBIRIS and CASIA. One can examine that the pattern generated by the radial muscles in stroma almost disappear on infrared imaging.

Fig. 7. a. Radial and Sphincter muscle structure of iris **b.** Sample image captured in visible light c. sample image capture near infrared

5 Conclusion

In this paper, a new method for iris recognition based on shape analysis is proposed. Two shape attributes (radius-vector-function and support-function) are introduced. These two features analyze the shape by considering it as a closed contour. Iris stroma is considered as a figure shape and is extracted by an adaptive segment filter which fits a Gaussian function to the image histogram. Next, the thresholding boundaries are found to create binary images for shape analysis. In the analysis step, the biggest objects are considered for the analysis. Results of accuracy on UBIRIS depicts an accuracy of 95.08% for two test images and three comparison images of 241 individuals (total of 1214 images). Currently, we consider the fusion of our proposed shape analysis based signatures with existing iris signatures for iris recognition in a hierarchical scheme.

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