Ocular Biometrics - Automatic Feature Extraction from Eye Images

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Abstract: We presents a general framework for image processing of eye images with a particular view on feature extraction. In eye imaging the process of the diagnosis and feature extraction is one complete system and extracting features from eye images can be used to automated interpretation of the images. We consider for human recognition based on the retinal and the conjunctival vasculature.

Key–Words: Retina image, Conjunctiva image, Feature extraction, Gabor transform, Texture features

1 Introduction

A biometric system is a pattern recognition system that recognizes a person on the basis of a feature vector derived from a specific physiological or behavioral characteristic that the person possesses. The problem of resolving the identity of a person can be categorized into two fundamentally distinct types of problems with different inherent complexities: (i) verification and (ii) identification. Verification (also called authentication) refers to the problem of confirming or denying a person's claimed identity (Am I who I claim to be?). Identification (Who am I?) refers to the problem of establishing a subjects identity.

We propose a new modality for eye-based personal identification that uses the blood vessel pattern in retina and conjunctiva.

The retina is a thin layer of cells at the back of the eyeball of vertebrates. It is the part of the eye which converts light into nervous signals. It is lined with special photoreceptors which translate light into signals to the brain. Every eye has its own totally unique pattern of blood vessels. The unique structure of the blood vessels in the retina has been used for biometric identification.

The conjunctiva is a thin, clear, highly vascular and moist tissue that covers the outer surface of the eye (sclera). Conjunctival vessels can be observed on the visible part of the sclera.

In computer diagnosis of eye diseases several features of retinal/conjunctival vessels as diameter, length, branching angle can be used.

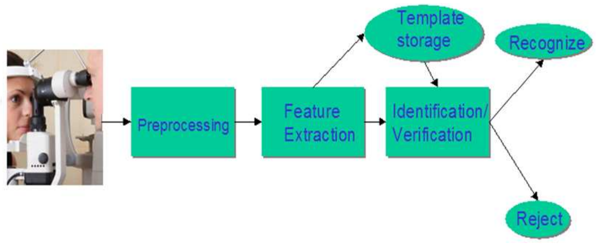


Figure 1: Typical Eye Vessel Acquisition and Biometrics System

Vessel pattern is unique for each human being even in the case of identical twins. Moreover, it is a highly stable pattern over time. Scanning is performed using a low-intensity light source and an optical coupler to scan the unique patterns and it does require the user to remove glasses, place their eye close to the device, and focus on a certain point (Figure 1). The acquisition process requires collaboration from the user and it is sometimes perceived as intrusive.

The five main stages in the feature point extraction process are:

1. Image retina/conjunctiva acquisition,
2. Image preprocessing (color transformation, edge detection, etc.),
3. Extraction of geometrical features,
4. Extraction of texture features,
5. Integration of geometrical and texture features.

ISBN: 978-1-61804-005-3

a) b)

Figure 2: Retina-1 (a) and Conjunctiva-1 (b) images.

Images which are considered in this paper as Retina-1 and Conjunctiva-1, are displayed in Figure 2.

2 Preprocessing

Before performing feature extraction, the original eye images are subjected to some image processing operations, as:

1. Color transformation. To represent eye characteristic we using luminance component (*Y*) from YC_bC_r (*YIQ*) color space (Fig 2).

$$\begin{bmatrix} Y \\ C_r \\ C_b \end{bmatrix} = \begin{bmatrix} 0,299 & 0,587 & 0,114 \\ 0,500 & -0,419 & -0,081 \\ -0,169 & -0,331 & 0,500 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

2. Image stretched. The contrast level is stretched according to

$$f_{out}(x,y) = 255 \times \left(\frac{f_{in}(x,y) - min}{max - min} \right)^{\gamma} \quad (2)$$

$f_{out}(x,y)$ is the color level for the output pixel (x,y) after the contrast stretching process. $f_{in}(x,y)$ is the color level input for data the pixel (x,y). max - is the maximum value for color level in the input image. min - is the minimum value for color level in the input image, γ - constant that defines the shape of the stretching curve.

3. Noise elimination. Noise pixels add irregularities to the outer boundary of the vessels and may have undesired effects on the recognition system. The algorithm modifies each pixel according to its initial value and to those of its neighborhood according to the following conditions:

$$\text{If } \ p = 1 \ \text{ then } \ p' = \begin{cases} 0 & \text{if } \sum_{i=1}^{8} p_i \le T_1 \\ 1 & \text{otherwise} \end{cases}$$

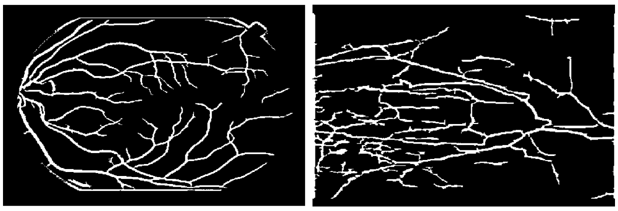
p_4	p_3	p_2
p_5	p	p_1
p_6	p_7	p_8

Figure 3: Pixel notations

$$\text{else } \ p' = \begin{cases} 1 & \text{if } \sum_{i=1}^{8} p_i \rangle T_2 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where p is current pixel value, p' the new pixel value and and T_1 are T_2 the threshold values.

4. Edge detection. To obtain the vessel binary image several alternatives method can be use from morphological to multi-resolution analysis methods. We use the typical edge detection Canny algorithm with local threshold. The results of the vessel edge detection are shown in Fig. 4.



a) b)

Figure 4: Vessel edge detection of Retina-1 (a) and Conjunctiva-1 (b) images.

3 Extraction of geometrical features

For each vessels line we specify vessel bifurcations characteristic points and cross points of vessel intersections characteristic points, used information derived from connected number of point p. When $p = 1$, the connected number N_c of p is defined by the next equation

$$N_C^4 = \sum_{k \in S} (p_k - p_k p_{k+1} p_{k+2}) \quad (4)$$

$$N_C^8 = \sum_{k \in S} (\bar{p}_k - \bar{p}_k \bar{p}_{k+1} \bar{p}_{k+2}) \quad (5)$$

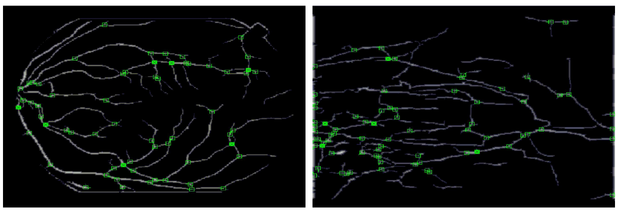
where: $S = (1,3,5,7)$ and $\overline{p}$ means $(1-p)$.

Topological properties of the pixel p are shown in Table 1.

Table 1: Topological properties of p

THE VALUE OF N_C^4 OR N_C^8	3	4
PROPERTY OF PIXEL p	Branch	Cross

The feature vector corresponding to vessel topology and consecutively the number of bifurcations and cross points are stored in the feature vector. Moreover, the coordinates of all the extracted characteristic points are stored. The feature vector for each vessels consists of the following parts: - 2 numbers corresponding to the number of bifurcation points and cross points in each vessels, - subvector in which the coordinates of the bifurcation points are stored, - subvector in which the coordinates of the cross points are stored.



a) b)

Figure 5: Geometrical features of Retina-1 (a) and Conjunctiva-1 (b) images.

The correspondence between the vessel in an image and the vessel templates is based on the similarity between their characteristic points. The characteristic points are computed for each vessel template. The characteristic points of the vessel image are then compared with the characteristic points of each vessel template. Using the correspondence between the vessel characteristic points and vessel template characteristic points, we can calculate the total number of matching points and obtain the matching results. The process is illustrated in Figure 6.

4 Texture feature from Gabor Wavelet Transform

Gabor wavelet is a powerful tool to extract texture features. Gabor functions are Gaussians modulated by complex sinusoids. In two dimensions they take the form (Fig. 7):

$$Gab(x, y, W, \theta) =$$

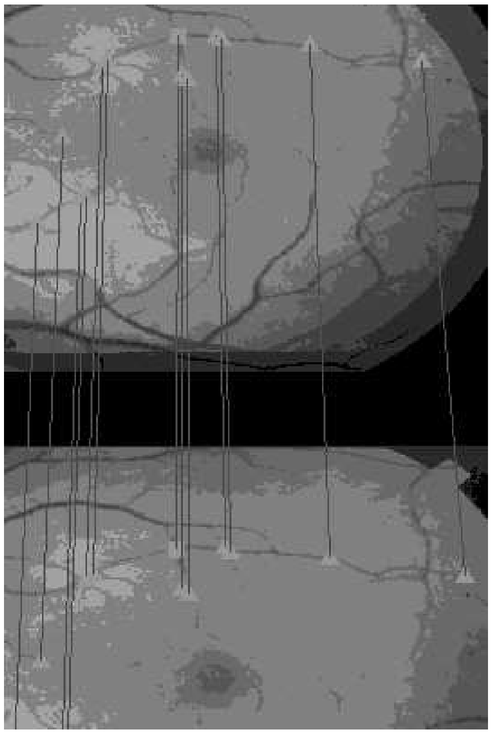


Figure 6: The correspondence between the vessel characteristic points in retina image

$$= \frac{1}{2\pi\sigma_x\sigma_y} e^{\left[-\frac{1}{2}\left(\left(\frac{x_\theta}{\sigma_x}\right)^2+\left(\frac{y_\theta}{\sigma_y}\right)^2\right)+jWx_\theta\right]} \tag{6}$$

where $j = \sqrt{-1}$ and σ_x and σ_y are the scaling parameters of the filter, W is the radial frequency of the sinusoid, $x_\theta = x\cos\theta + y\sin\theta$, $y_\theta = -x\sin\theta + y\cos\theta$ and $\theta \in [0, \pi]$ specifies the orientation of the Gabor filters.

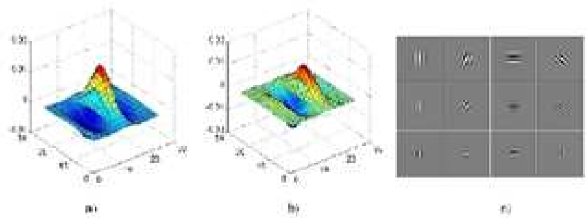


Figure 7: Real (a) and imaginery (b) parts of Gabor wavelets and Gabor kernels with different orientations (c)

In our work we use a bank of filters built from the real part of Gabor expression called as even-symmetric Gabor filter:

ISBN: 978-1-61804-005-3

$$Gab_{even}(x,y,W,\theta) = $$
$$= \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left(\left(\frac{x_\theta}{\sigma_x}\right)^2+\left(\frac{y_\theta}{\sigma_y}\right)^2\right)} \times \cos(Wx_\theta) \quad (7)$$

Gabor filtered output of the image is obtained by the convolution of the image with Gabor function for each of the orientation/spatial frequency (scale) orientation. The normalized retina or conjunctiva images are divided into blocks (Fig. 8). The size of each block in our application is $k \times l \quad (k = l = 20)$. Each block (Fig. 9) is filtered with equation (8)

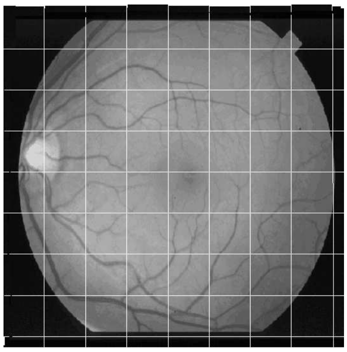


Figure 8: Original block retinal images

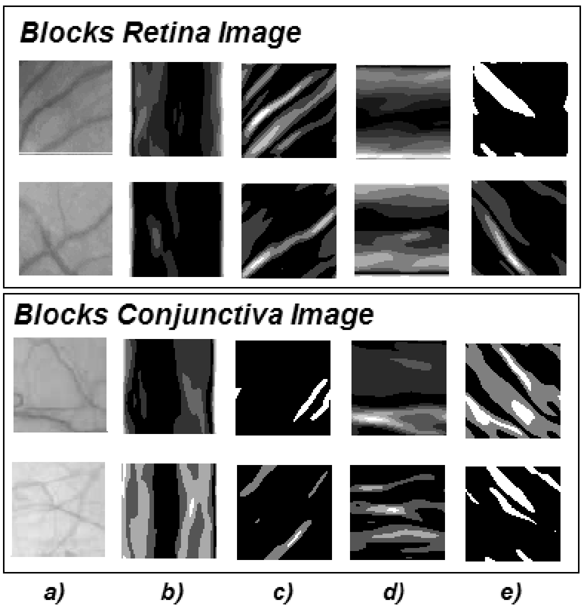


Figure 9: Original block retina image (a) and real part of $Gab(x;y;\theta_i)$ for $\theta = 0$ (b), $\theta = 45$ (c), $\theta = 90$ (d), $\theta = 135$ (e)

Given an image $f(x, y)$

$$G(x,y) =$$
$$= \sum_k \sum_l f(x-k, y-l) * Gab_{even}(x,y,W,\theta) \quad (8)$$

Features based on the Gabor filters responses can be represented by

$$\mu(x,y) = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} G(x,y) \quad (9)$$

$$std(x,y) == \sqrt{\sum_{x=1}^{X} \sum_{y=1}^{Y} (|G(x,y)| - \mu(x,y))^2} \quad (10)$$

$$Skew = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} \left(\frac{G(x,y) - \mu(x,y)}{std(x,y)}\right)^3 \quad (11)$$

where X, Y is image dimension.

The feature vector is constructed using $\mu(x, y)$, $std(x, y)$ and $Skew$ as feature components.

5 Conclusion

A new method for recognition retina vessel and conjunctiva vessel images has been presented. This method based on geometrical, and Gabor features. This paper analysis the details of the proposed method. Retina vessel and conjunctiva vessel images can be used to personal identification. Experimental results have demonstrated that this approach is promising to improve retina recognition for person identification. In case conjunctiva vessel images proposed method is suitable to improve eye diagnosis.

Acknowledgements: The research was supported by the UT&LS University by the Grant BS10/2010.

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Table 2: Features based on the Gabor filters responses some block (Fig. 9) retina image

Parameters	Retina image 1		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	46.169	28.158	1.778
$\theta = 45$	48.362	59.923	1.083
$\theta = 90$	72.346	57.654	0.868
$\theta = 135$	38.661	91.465	1.943
Parameters	Retina image 2		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	29.090	48.424	1.863
$\theta = 45$	86.280	62.709	0.407
$\theta = 90$	20.114	43.974	2.106
$\theta = 135$	18.740	22.278	2.511
Parameters	Conjunctiva image 1		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	42.222	56.712	1.922
$\theta = 45$	13.634	57.372	3.970
$\theta = 90$	53.504	46.924	1.479
$\theta = 135$	84.193	83.906	0.500
Parameters	Conjunctiva image 2		
	$\mu(\alpha, \sigma_x, \sigma_y)$	$std(\alpha, \sigma_x, \sigma_y)$	$Skew$
$\theta = 0$	97.555	71.155	-0.108
$\theta = 45$	13.337	40.936	3.013
$\theta = 90$	38.184	53.946	1.188
$\theta = 135$	36.295	89.106	2.047

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ISBN: 978-1-61804-005-3