retina, retina biometrics, vessel pattern,
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PERSONAL IDENTIFICATION USING RETINA

This paper proposes a biometric system for authentication that uses the retina blood vessel pattern. The retina biometric analyzes the layer of blood vessels located at the back of the eye. The blood vessels at the back of the eye have a unique pattern, from eye to eye and person to person. The retina, a layer of blood vessels located at the back of the eye, forms an identity card for the individual under investigation. In particular retinal recognition creates an ”eye signature” from its vascular configuration and its artificial duplication is thought to be virtually impossible.

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 behavioural 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.

The personal attributes used in a biometric identification system can be physiological, such as facial features, fingerprints, iris, retina scans, hand and finger geometry; or behavioural, the traits idiosyncratic of the individual, such as voice print, gait, signature, and keystroking.

One technology has emerged in the biometric area: retinal recognition. This paper proposes a biometric system for authentication that uses the retina blood vessel pattern.

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. The unique structure of the blood vessels in the retina has been used for biometric identification.

Retina scanning is quite accurate and very unique to each individual and typically requires the user to look into a receptacle and focus on a given point for the user's retina to be scanned. Retina scans require that the users (person) removes their glasses and positions his eye close to the unit's embedded lens, with the eye socket resting on the sight. In order for a retinal image to be acquired, the user must gaze directly into the lens and remain still, movement defeats the acquisition process requiring another attempt.

Retina recognition technology captures and analyzes the patterns of blood vessels on the thin nerve on the back of the eyeball that processes light entering through the pupil. Retinal patterns are highly distinctive traits.

The retina biometric analyzes the layer of blood vessels located at the back of the eye. The blood vessels at the back of the eye have a unique pattern, from eye to eye and person to person. The retina, a layer of blood vessels located at the back of the eye, forms an identity card for the individual under investigation. In particular retinal recognition creates an ”eye signature” from its vascular configuration and its artificial duplication is thought to be virtually impossible.

Every eye has its own totally unique pattern of blood vessels; even the eyes of identical twins are distinct. Although each pattern normally remains stable over a person's lifetime, it can be affected by disease such as glaucoma, diabetes, high blood pressure, and autoimmune deficiency syndrome.

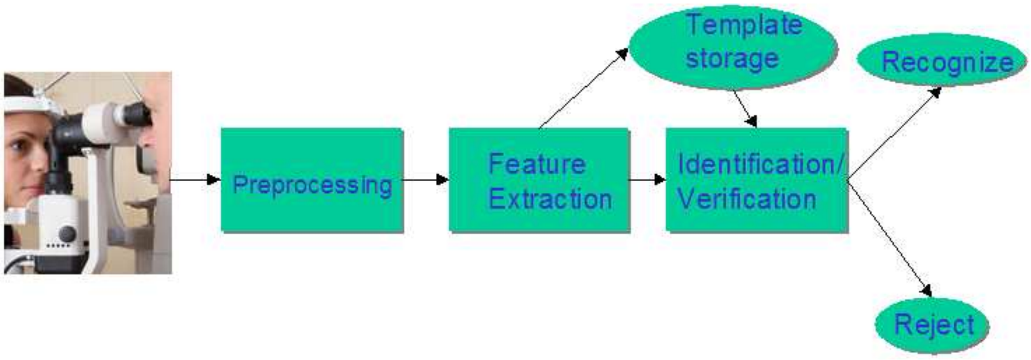

Fig. 1. Typical retina image analysis (biometrics) system

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In this paper we implementation such a system using the following steps:

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

2. PREPROCESSING

Most digital images are stored in *RGB* colour space. *RGB* colour space is represented with red *(R)*, green *(G)*, and blue *(B)* primaries and is an additive system. *RGB* colour space is not perceptually uniform, which implies that two colours with larger distance can be perceptually more similar than another two colours with smaller distance, or simply put, the colour distance in *RGB* space does not represent perceptual colour distance.

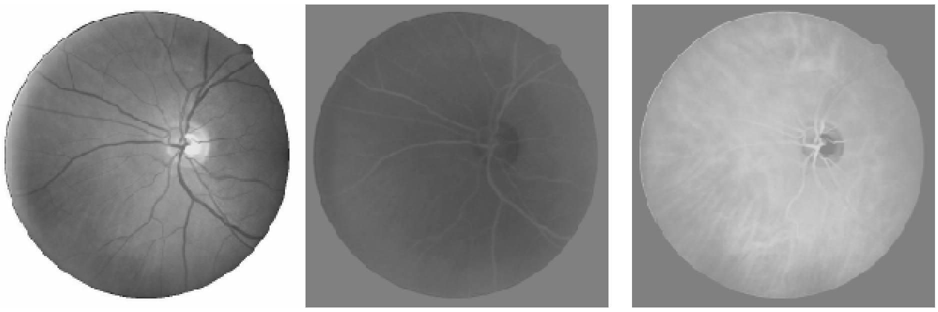
Fundus images contain full colour information. The first step is to separate channel to a *RGB* channels and from the three colour channels the green *(G)* component of *RGB* colour space for blood vessel recognition is chosen (Fig.1). Additional to represent retinal characteristic we using luminance component *(Y)* from $YC_b\,C_r$ *(YIQ)* colour space (Fig 2).

YCrCb is an encoded nonlinear *RGB* signal for image compression work. Colour is represented by luminance, computed from nonlinear *RGB*, and two chrominance components. These colour spaces separate *RGB* into luminance and chrominance information.

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

a b c d

Fig. 2. Original retina image in *RGB* colour space (a) and Red (b), Green (c) Blue (d) channels.



a) b) c)

Fig. 3. Retina image in YC_bC_r colour space: a) Y component and components C_b (b), C_r (c) respectively.

3. GEOMETRICAL FEATURE EXTRACTION

In the geometrical feature extraction steps retina image with edge binary vessels is processed. The centroid of binary image is also the centre of concentric circles of the radius r_i. The algorithm uses the surrounding circle of retina vessel line for partitioning it to o radial partitions (Fig. 4). For each contour-line we specify following characteristic points:

- contour ending points,
- contour bifurcations,
- points of contour intersections with the concentric circles.

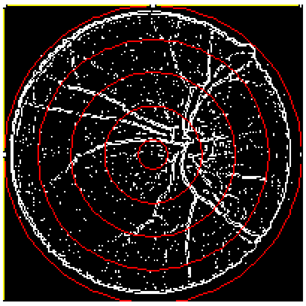


Fig. 4. Radial partitions retina image binary vessel

Let g_0 denote the current point of the contour line, so that $g_0 = g(i, j) = 1$. Contour line points are classified on the basis of the coefficient N_c^8 (Table 1):

$$N_c^8(g_0) = \sum_{k=S}(\overline{g}_k - \overline{g}_k \overline{g}_{k+1} \overline{g}_{k+2}) \tag{2}$$

where S = (1,3,5,7).

Table 1. Classification of the vessel line points g_0

Value of N_c^8	Classification of the point g_0
0	Interior (or isolated) point
1	Line ending
2	Normal point
3	Bifurcation point
4	Crossing point

The feature vector corresponding to vessel topology and consecutively the number of endings, bifurcations and intersection points with the concentric circles are stored in the feature vector. Moreover, the coordinates of all the extracted characteristic points are stored. The feature vector for each contour consists of the following parts:

– 3 numbers $(l_l, N_E, N_B)_c$ corresponding to the number of intersection points, ending points and bifurcation points in each contour,
– subvector in which the coordinates of the intersection points are stored,
– subvector in which the coordinates of the ending points are stored,
– subvector in which the coordinates of the bifurcation points are stored.

The first part of the final feature vector has always the same length, while the next parts of the vectors for contours *c* depend on the number of the extracted characteristic points. Such division of the feature vector allows faster classification.

4. TEXTURE FEATURE FROM GABOR WAVELET TRANSFORM

Gabor wavelet based texture is robust to orientation and illumination change. It is a powerful tool to extract texture features. Gabor functions are Gaussians modulated by complex sinusoids. In two dimensions they take the form (Fig. 5):

$$g(x,y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right)\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \tag{3}$$

$$G(u,v) = \exp\left\{-\frac{1}{2}\left[\frac{(u-W)^2}{\sigma_u^2}+\frac{v^2}{\sigma_v^2}\right]\right\} \tag{4}$$

where $\sigma_u = \frac{1}{2\pi\sigma_x}$, $\sigma_v = \frac{1}{2\pi\sigma_y}$.

Gabor wavelets can be obtained by appropriate dilations and rotations of *g(x,y)* through the generating function:

$$g_{mn}(x,y) = a^{-m} g(x', y'); \quad a > 1 \; m = 0,1,\ldots,S-1 \tag{5}$$

here

$x' = a^{-m}(x\cos\theta + y\sin\theta)$, $y' = a^{-m}(-x\sin\theta + y\cos\theta)$ and θ $(\theta \in [0,\pi])$ specifies the orientation of the Gabor wavelets.

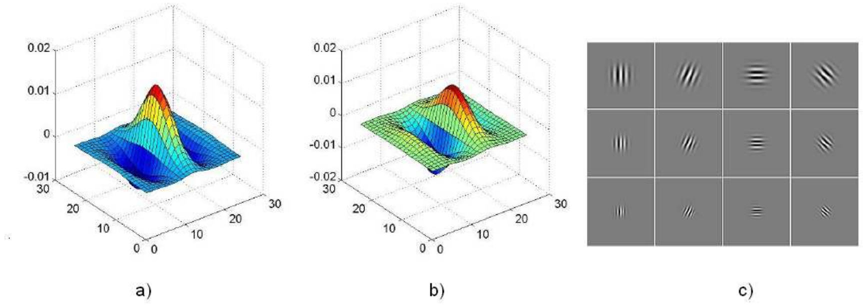


Fig. 5. Real (a) and imaginary (b) parts of Gabor wavelets and Gabor kernels with different orientations (c)

The normalized retinal image (Y components) are divided into blocks (Fig. 6). The size of each block in our application is $k \times l$ $(k = l = 20)$. Each block is filtered by (Fig. 7)

$$Gab(x,y,\alpha) = \sum_{x-\frac{k}{2}}^{x+\frac{k}{2}} \sum_{y-\frac{k}{2}}^{y+\frac{k}{2}} I(x,y) \cdot g(x,y) \tag{6}$$

The orientation angles of this set of Gabor filters are $\langle \alpha_i \mid \alpha_i = \frac{i\pi}{4},\ i = 0,1,2,3 \rangle$.

The magnitudes of the Gabor filters responses are represented by three moments

$$\mu(\alpha,\sigma_x,\sigma_y) = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y} G(x,y,\alpha) \tag{7}$$

$$std(\alpha,\sigma_x,\sigma_y) = \sqrt{\sum_{x=1}^{X}\sum_{y=1}^{Y} \left\| G(x,y,\alpha) \right| - \mu(\alpha,\sigma_x,\sigma_y) \right|^2} \tag{8}$$

$$Skew = \frac{1}{XY}\sum_{x=1}^{X}\sum_{y=1}^{Y}\left(\frac{G(x,y,\alpha) - \mu(\alpha,\sigma_x,\sigma_y)}{std(\alpha,\sigma_x,\sigma_y)}\right)^3 \tag{9}$$

The feature vector is constructed using $\mu(\alpha,\sigma_x,\sigma_y)$, $std(\alpha,\sigma_x,\sigma_y)$ and $Skew$ as feature components.

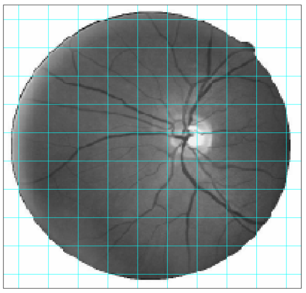


Fig. 6. Original block retinal images (Y component)

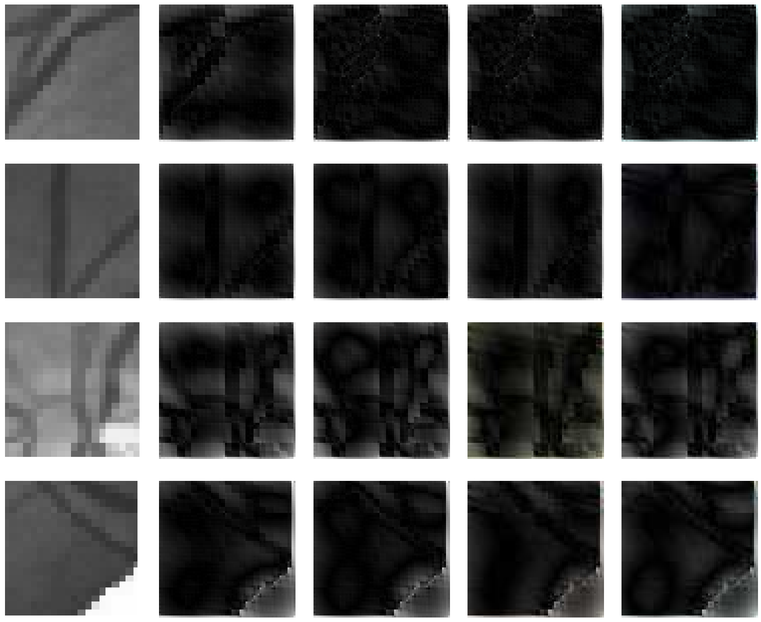


Fig. 7. Original block retina image (a) and real part of $Gab(x; y; \theta i)$ for $\theta = 0$ (b), $\theta = 45$ (c), $\theta = 90$ (d), $\theta = 135$ (e)

Table 2. Mean, standard deviation and skewness Gabor power some block (Fig. 7.) retina image

Parameters	Retinal image 1			Retinal image 2		
	$\mu(\alpha,\sigma_x,\sigma_y)$	$std(\alpha,\sigma_x,\sigma_y)$	*Skew*	$\mu(\alpha,\sigma_x,\sigma_y)$	$std(\alpha,\sigma_x,\sigma_y)$	*Skew*
$\theta = 0$	25.971	33.468	3.712	23.204	34.360	4.402
$\theta = 45$	15.867	26.176	4.614	18.494	32.176	4.655
$\theta = 90$	15.900	26.901	4.525	22.769	34.375	4.366
$\theta = 135$	15.466	25.409	4.591	16.307	27.644	4.781
Parameters	Retinal image3			Retinal image4		
	$\mu(\alpha,\sigma_x,\sigma_y)$	$std(\alpha,\sigma_x,\sigma_y)$	*Skew*	$\mu(\alpha,\sigma_x,\sigma_y)$	$std(\alpha,\sigma_x,\sigma_y)$	*Skew*
$\theta = 0$	36.916	34.387	1.992	26.650	35.364	2.655
$\theta = 45$	30.892	32.617	2.542	24.165	34.471	2.805
$\theta = 90$	31.492	28.427	2.048	25.875	32.319	2.625
$\theta = 135$	29.699	29.421	2.096	27.120	33.546	2.562

5. MATCHING AND CONCLUSION

The matching algorithm finds the proximity of two retina calculating the Average Euclidean Distance of the two features vectors. A new method has been presented for retina recognition based on geometrical and Gabor features. This paper analyses the details of the proposed method. Experimental results have demonstrated that this approach is promising to improve retina recognition for person identification.

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