Recognition of Vein Patterns for Biometric Identification based on Gabor filters

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Abstract: Vein recognition is one of many available methods used for identification. Veins possess several properties that make a good biometric feature for personal identification: 1) they are difficult to damage and modify; 2) they are difficult to simulate using a fake template; and 3) vein information can represent the liveness of person. We present the results of the recognition of veins patterns that show the suitability of the method for biometric identification purposes.

Key–Words: Vein biometrics, feature extraction, Gabor filter

1 Introduction

Biometrics realize automated measurement in real time of physiological and/or behavioral characteristics without human intervention. The behavioral characteristics measure the action performed by a person. The physiological characteristics based on physical human traits.
The core of all biometrics systems have five key modules: sensors (image/data acquisition), feature extractor, biometric database, matcher and decision-maker (Fig. 1). The two types of biometric systems are:

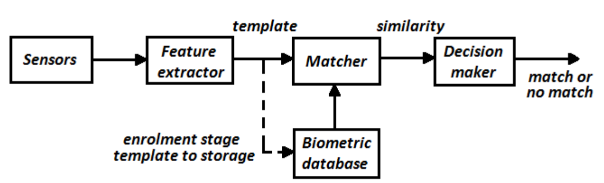


Figure 1: Biometric system

(i) identification systems (or recognition) (negative recognition) - recognize the user by comparing the submitted biometric signature to all the enrolled signatures in the database by making 1:N (one-to-many) comparisons without specific identity claim from the user.

(ii) verification systems (or authentication) (positive recognition) - validates the user's claim by making a 1:1 (one-to-one) comparison between the submitted biometric signature and enrolled biometric signature.

Biometric characteristics are presented in Table 1. Biometric categories can be divided into two types: (i) Identification systems and (ii) Verification systems.
Vein recognition is a biometric technology that is a unique and stable biometric trait with strong immunity to forgery. It was found that identical twins with the same DNA sequence have different vein patterns.
Advantages of vein-based biometrics:

- Immunity to counterfeit - vein hiding underneath the skin surface,
- Active liveness,
- User friendliness.

The metrics to measure the performance of a biometric systems are:

- False Acceptance Rate(*FAR*) defined as $FAR = \frac{Total\ \ False\ \ Acceptence}{Total\ \ False\ \ Attempts}$.
- False Rejection Rate (*FRR*) defined as $FRR = \frac{Total\ \ False\ \ Rejection}{Total\ \ True\ \ Attempts}$.
- Equal Error Rate (*EER*). *ERR* is where *FAR* = *FRR*.

The relationships between *FRR*, *FAR* and *EER* shows Figure 2.

Table 1: Biometrics characteristics

Characteristic	Description
Robustness	Describes by the probability that a submitted template will not match the enrollment the image. Measured by the ”false non-match rate”.
Distinctiveness	Show how well the biometric separates one individual from another. Measured by the ”false match rate”.
Permanence	Display how well the biometric remains the same over time. The characteristic is not changing in time.
Acceptability	Describes by polling the device users
Accessibility	Indices by the number of individuals that can be processed in a unit time
Availability	Describes by the probability that a user will not be able to supply a readable measure to the system upon enrollment
Universality	Show how commonly the biometric is found in humans
Performance	Demonstrate the accuracy of the system using the biometric
Circumvention	Indices how easily a submitted template can be spoofed
Uniqueness	No two individuals possess the same characteristic.

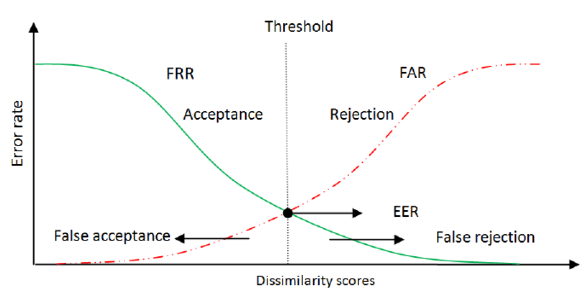


Figure 2: Relationship between FAR, FRR and EER.

Vein recognition is a method of biometric identification/verification, that uses pattern recognition techniques based on images of blood vessels. Blood vessel patterns (identified only on a live body) are unique to each individual. Vein recognition does not require contact during registering and authentication and is strongly immune to forgery.

The visibility of human vein patterns in the visible light band is low. To detect hand dorsal veins and generate a vasculature map we utilize a CCD camera with IR filter. For the application of hand vein recognition, utilizing the near-infrared band in the electromagnetic spectrum is typically the accepted technique. A database of hand-dorsa vein images contains 100 images from 25 volunteers (15 males students and 10 females students). Some image samples in the database are illustrated in Figure 3.

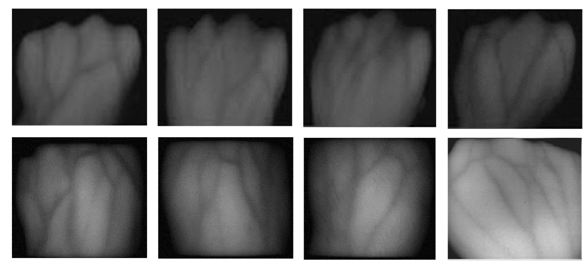


Figure 3: Dorsal hand vein images.

2 Preprocessing of Images

If the digital image contains $M \times N$ pixels, is represented by an $M \times N$ matrix

$$[f] = f_{m,n} = \begin{bmatrix} f_{0,0} & f_{0,1} & \cdots & f_{0,N-1} \\ f_{1,0} & f_{1,1} & \cdots & f_{1,N-1} \\ \vdots & \vdots & \cdots & \vdots \\ f_{M-1,0} & f_{M-1,1} & \cdots & f_{M-1,N-1} \end{bmatrix} \tag{1}$$

where $0 \leq m \leq M-1$; $0 \leq n \leq N-1$ and $0 \leq f_{m,n} \leq G-1$.
Usually $M = 2^i$, $N = 2^j$ and $G = 2^k$.

The processing generally comprises the steps of acquiring an image, improving image quality, image segmentation and features extraction for the recognition.
The gray levels are modified as

$$f'_{m,n} = \frac{(f_{m,n} - min) \times 255}{max - min} \tag{2}$$

where max and min are respectively the maximum and minimum value of image gray level values of the original image, respectively.

Median filtering is a nonlinear method used to remove noise from images. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels.

2D MF for image $f^{'}_{m,n}$, $(m, n) \in R$ is defined as

$$y_{m,n} = mediana_{A_l} f^{'}_{m,n} = \\ = mediana[f^{'}_{m+r,n+s} \quad ; \quad (r, s) \in A_l] \qquad (3)$$

where A_l is MF window.

Another important problem that has to be solved is the problem of image normalization. First, we calculate the coordinates of the center of gravity of the points of the image

$$\bar{m} = \frac{\sum_m \sum_n m \times f'_{m,n}}{\sum_m \sum_n f'_{m,n}} \\ \bar{n} = \frac{\sum_m \sum_n n \times f'_{m,n}}{\sum_m \sum_n f'_{m,n}} \qquad (4)$$

The coordinates of the center of gravity are the basis for determining ROI.

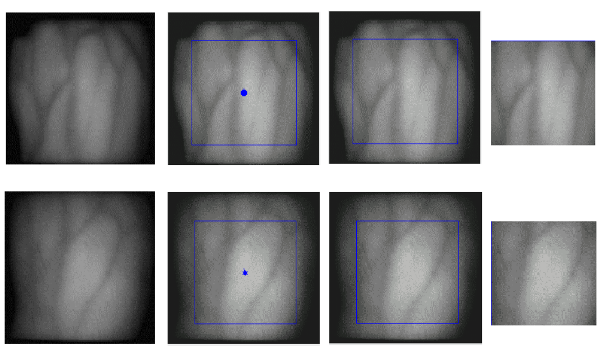


Figure 4: Image normalization and ROI detection.

3 Gabor wavelet

Gabor filters have been successfully applied in various computer vision applications and to texture analysis. The general functionality of the 2D Gabor filter family can be represented as a Gaussian function modulated by a complex sinusoidal signal.

The Gabor filters can be defined as follows

$$g(x, y)_{\sigma,\theta} = \frac{1}{2\pi\sigma_x\sigma_y} exp[-\frac{1}{2}(\frac{x'^2}{\sigma_x^2} + \frac{y'^2}{\sigma_y^2})] exp[2\pi j W x'] \qquad (5)$$

where
$x' = x \cos\theta + y \sin\theta$,
$y' = -x \sin\theta + y \cos\theta$,
σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y directions
$\theta = \frac{\pi}{k}(l) \quad l = 1, 2, \ldots, k$, and k denotes the number of orientation of the Gabor filters,
W is the radial frequency of the sinusoid.

The Fourier transform of the Gabor function in eq.(5) is given by:

$$F(u, v) = exp[-\frac{1}{2}(\frac{(u - W)^2}{\sigma_u^2} + \frac{u^2}{\sigma_v^2})] \qquad (6)$$

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

The Gabor transform of image $f_{m,n}$ is calculated as:

$$G(x, y)_{\sigma_i,\theta_k} = f_{m,n} * g(x, y)_{\sigma_i,\theta_k} \qquad (7)$$

where $*$ denotes the convolution operator, i and k are the number of scales and orientations, respectively.

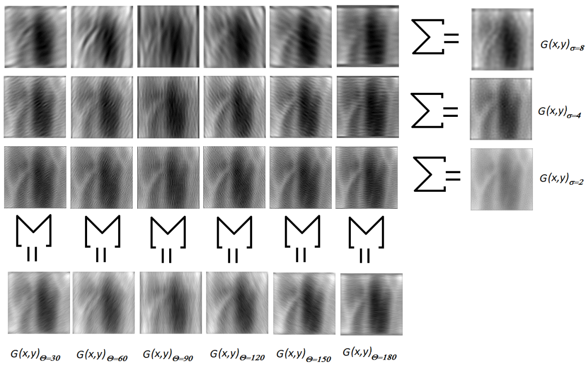
Filter banks are generated by varying scale and orientation of filter. First keep number of scale constant and vary the orientations. Then vary the number of scales and keep number of the orientation fixed. Here filters are designed for 3 scale and 6 orientations. Performance is evaluated for all filters.

4 Vein biometrics

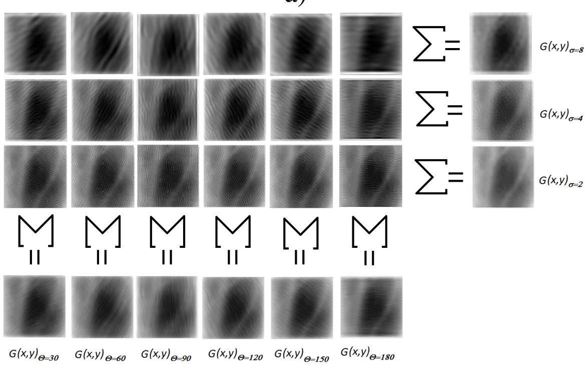
One of the most promising and intensively developed biometric methods is the method using the network of blood vessels. The pattern of blood vessels is unique for every human being, also in the case of twins. It is also stable over time.

We use the network of blood vessels associated with hand dorsal. In the process of identifying people on the basis of dorsal vein images, we use a features calculated using the Gabor filtration operation.

For 3 scales and 6 orientations we obtain 18 filters. In our case, we have $\sigma_i = \{2, 4, 8\}$, and $\theta_k = \{30°, 60°, 90°, 120°, 150°, 180°\}$. For a fixed orientation angle, we calculate the sum of images for different scales. In this way, we get 6 images marked as $G(x, y)_\theta$. Similarly, for a fixed scale parameter, we calculate the sum of images for different orientation angles. As a result, we get 3 images marked as $G(x, y)_\sigma$. The images shown in Figure 5 are the result of the convolution operation of the input image



a)



b)

Figure 5: Real part of the Gabor filter responses of a dorsal vein image. a) images correspond to top row of Figure 4, b) images correspond to below row of Figure 4. Rows correspond to $\sigma_i = \{2, 4, 8\}$, and columns to $\theta_k = \{30°, 60°, 90°, 120°, 150°, 180°\}$.

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with the above defined set of Gabor filters.

After applying Gabor filters on the image with different scale i and orientation k we calculate two parameters - energy and entropy - respectively defined by

$$E_{\sigma_i,\theta_k} = \frac{1}{M \times N} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} (G(x,y)_{\sigma_i,\theta_k})^2 \qquad (8)$$

and

$$Ent_{\sigma_i,\theta_k} = -p_{\sigma_i,\theta_k}(x,y) \times \log_2(p_{\sigma_i,\theta_k}(x,y)) \qquad (9)$$

where

$$p_{\sigma_i,\theta_k}(x,y) = \frac{E_{\sigma_i,\theta_k}}{\sum_{\sigma_i} \sum_{\theta_k} E_{\sigma_i,\theta_k}} \qquad (10)$$

Parameter values calculated in accordance with the presented procedure are presented in Table 2.

The feature vector FV of the $(3 + 6) \times 2 = 18$ dimension is constructed using E_{σ_i}, E_{θ_k} and Ent_{σ_i}, Ent_{θ_k} as feature components.

Table 2: Energy and Entropy of the Gabor images with Figure 5a and Figure 5b

Image	Image with Figure 5a		Image with Figure 5b	
θ	$E(x,y)_\theta$	$Ent(x,y)_\theta$	$E(x,y)_\theta$	$Ent(x,y)_\theta$
30	0.083548	5.092811	0.079564	5.163171
60	0.083349	5.092916	0.079160	5.189435
90	0.084440	5.090468	0.079567	5.169718
120	0.081274	5.144662	0.077984	5.204526
150	0.079948	5.188743	0.080404	5.144473
180	0.083597	5.120783	0.902485	0.178977
σ	$E(x,y)_\sigma$	$Ent(x,y)_\sigma$	$E(x,y)_\sigma$	$Ent(x,y)_\sigma$
2	0.106878	4.610757	0.085982	5.041435
4	0.087073	5.020519	0.082465	5.100535
8	0.081929	5.153033	0.074496	5.282654

$$\begin{aligned} FV = [&E_{\sigma=2}, E_{\sigma=4}, E_{\sigma=8}, \\ &E_{\theta=30}, E_{\theta=60}, \dots, E_{\theta=180}, \\ &Ent_{\sigma=2}, Ent_{\sigma=4}, Ent_{\sigma=8}, \\ &Ent_{\theta=30}, Ent_{\theta=60}, \dots, Ent_{\theta=180}] \end{aligned} \qquad (11)$$

5 Pattern matching and conclusions

The feature vector obtained from the input biometric image is compared to the feature vector from the database. The Euclidean distance is calculated - the Euclidean distance smaller than the specified threshold means that the biometric input image and the database image are "very similar".
Gabor's filtration is used in the process of calculating a vector of features based on energy and entropy parameters. This method is very perspective and gives good results.

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