

Biometric Systems Based on Palm Vein Patterns

Dorota Smorawa¹ and Mariusz Kubanek^{1,2}

¹ Institute of Computer and Information Science, Czestochowa University of Technology, Czestochowa, Poland

² Department of Computer Science, European University of Information Technology and Economics, Warsaw, Poland

Abstract—The work covers issues related to the design of biometric systems based on the hand vascular pattern. The study includes analysis of various stages of biometric systems design ranging from acquisition, feature extraction and biometric pattern creation for verification methods. The extraction methods based on two-dimensional density function and the extraction of the characteristic points – minutiae are presented. The article features the results of tests carried out on two different bases of blood vessels in a hand.

Keywords—*palm vein, pattern recognition, two-dimensional density function.*

1. Introduction

Nowadays identification and verification of people are essential and of paramount importance for society as identity items in the form of ID cards, passwords or even your social security number are not sufficient. Each of the above mentioned forms of identification or verification can be stolen, falsified or forgotten. Therefore, reliable identification and authentication become necessary. Reliable identification of people entails the use of biometrics.

Biometrics is the science dealing with identification and verification of people on the basis of specific physical and behavioral characteristics. These features are used to build a biometric system based on fingerprints, hand geometry or signature. The purpose of the biometric system is to replace previously used forms of identification (social security cards, passwords). Biometric systems are more effective and efficient than the currently used methods for identification and verification, for example in case of banking transactions, which are subject to the risk of a card being forged or PIN being peeped. In this case the use of the biometric system carries a lower fraud risk.

Although biometric systems are better than the presently used methods of effective identification and verification, still some of them have drawbacks for example the fact that a given quality does not appear with all the people. Another important disadvantage of biometric systems is that a given biometric is not possible to be measured and to do that complicated and expensive devices are needed. The alternative for all those defects overloading the biometric systems based on fingerprints, iris of the eye and the face image is to use the model of the blood vessels in a hand. Biometrics is present in all the people and is unique for each person. The process of recognizing features does not

require cooperation or complicated devices. In addition, the venous pattern, apart from its size, does not change throughout lifespan. The advantage of using hand vascular biometric system is that it cannot be forged or falsified. So far not a single case of forgery has been reported.

2. Related Work

Having analyzed the research being conducted, biometric systems based on different characteristics can be found which are seen as unique, unchangeable and unforgeable. But in almost all of these systems the biometrics can be forged, or the cost of using the system is too high. The new approach is to use the pattern of blood vessels in a hand. The pattern of blood vessels due to its reliability gained a lot of interest. In the papers [1], [2] a description of the construction of biometric systems based on hand vascular distribution can be found, which uses the wavelet transform to extract the features. In the works [3], [4] the use of the Gaussian function in the process of feature extraction of vessels in a hand are described. Various hand vein methods have been proposed for vein recognition in many works, example [5]–[7]. A lot of research work is devoted to the construction of biometric systems based on fingerprints. In the work [8] the system based on fingerprints is said to be unreliable and mainly used by the police. In order to use them in any commercial way it should be supplemented with a card identifying the user due to a fingerprint being easily forged. The author also points out that there is a 5% failure to enroll rate (FER) factor, which indicates that these people do not have lines on their fingers.

Palm blood vessel pattern is similar to a fingerprint. This similarity can be seen in the work [9], who uses the minutiae in coding of the pattern of blood vessels in a hand. Three basic characteristics occurring in fingerprint lines were used: ridge ending, bifurcation and ridge crossing.

3. Image Acquisition

The biometric vein pattern is located under the skin. To activate the the hand vascular system image the infrared light source and the active matrix infrared (IR) camera should be used. The near infrared light is partially absorbed by hemoglobin present in veins which creates a picture of the structure beneath the outer layer of the skin, presenting the natural contrast pattern of the blood vessels. The test stand

consists of a CCTV active-matrix infrared camera, IR lamp, the tripod and a plate with five supportive wheels thanks to which during the acquisition the position of a hand is always the same, the picture is taken from the same distance. This research considers the image of the palm section 256×256 pixels in size. Two bases of photos, the own one and CASIA MSPD [10] base have been used. Each of these contains data collected from 100 users, with 12 pictures of the left and right hand for each user.

4. Improving the Image Contrast

During the pattern acquisition of the hand blood vessels noise can be noticed. The blood vessels are not bulging enough which results in inaccurate feature extraction. To improve readability three operations to improve its quality are performed:

- histogram equalization operation,
- filter smoothing operation,
- image normalization process.

The first step is to use a histogram equalization method, which magnifies the visibility of blood vessels by aligning the image components:

$$L' = 255 \frac{L - L_{\min}}{L_{\max} - L_{\min}}, \quad (1)$$

where: L' – output image, L – input image, L_{\min} – minimum value of the brightness level of the all image elements, L_{\max} – maximum value of the brightness level of the all image elements.

The next step is to apply the smoothing filter, which removes the noise generated during the images acquisition:

$$w \cdot L' = \sum_{i,j \in W} w(i,j) L'(x-i, y-j), \quad (2)$$

where w is a filter mask.

The last step is to normalize the image after the contrast enhancement, which means limiting the image into the range of 0–255. Sample contrast enhancement shown in Fig. 1.

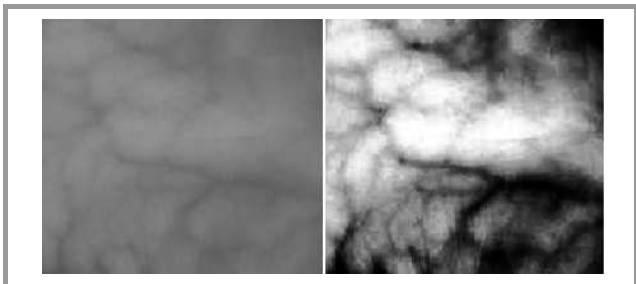


Fig. 1. Sample image of palm vein after using contrast enhancement.

5. Features Extraction

The pattern of palm blood vessels in the image looks like a dent, because the veins are darker than the surrounding area. The authors' method examines the entire hand image, pixel by pixel, and finds its value over a specified threshold, in order to capture the curvature of the image. This method is based on a two-dimensional density function:

$$f(x,y) = \frac{1}{2\pi\delta^2} e^{-\frac{(x^2+y^2)}{2\delta^2}} \quad (3)$$

One of the first steps of proposed method is the initial location of curvature in the horizontal, vertical and both diagonal directions. For modeling the curvature localizing filter the first (4), (6), (8) and the second (5), (7) derivatives of the two-dimensional density function are used.

$$f_x = \frac{\partial f(x,y)}{\partial x} = \left(\frac{-x}{\delta^2} \right) f(x,y), \quad (4)$$

$$f_{xx} = \frac{\partial^2 f(x,y)}{\partial x^2} = \frac{x^2 - \delta^2}{\delta^4} f(x,y), \quad (5)$$

$$f_y = \frac{\partial f(x,y)}{\partial y} = \left(\frac{-y}{\delta^2} \right) f(x,y), \quad (6)$$

$$f_{yy} = \frac{\partial^2 f(x,y)}{\partial y^2} = \frac{y^2 - \delta^2}{\delta^4} f(x,y), \quad (7)$$

$$f_{xy} = \frac{\partial^2 f(x,y)}{\partial x \partial y} = \frac{xy}{\delta^4} f(x,y), \quad (8)$$

where T denotes the transposition.

The filters are designed to locate same of the existing curvature of the profile for the four directions. Filters for the horizontal direction (9), vertical (10) and two diagonal (11), (12) are described by the following formulas:

$$C_{d1}(z) = \frac{f_{xx} \cdot L'}{\left(1 + (f_x \cdot L')^2\right)^{\frac{3}{2}}}, \quad (9)$$

$$C_{d2}(z) = \frac{f_{yy} \cdot L'}{\left(1 + (f_y \cdot L')^2\right)^{\frac{3}{2}}}, \quad (10)$$

$$C_{d3}(z) = \frac{0.5f_{xx} \cdot L' + f_{xy} \cdot L' + 0.5f_{yy} \cdot L'}{\left(1 + (0.5 \cdot \sqrt{2}(f_x \cdot L' + f_y \cdot L'))^2\right)^{\frac{3}{2}}}, \quad (11)$$

$$C_{d4}(z) = \frac{0.5f_{xx} \cdot L' - f_{xy} \cdot L' + 0.5f_{yy} \cdot L'}{\left(1 + (0.5\sqrt{2}(f_x \cdot L' - f_y \cdot L'))^2\right)^{\frac{3}{2}}}. \quad (12)$$

The next step is to determine the local maximal points $C_d(z)$ along the cross-section profile of the input image for all 4 directions d , where z is a position in a cross-section profile (by one pixel). These points indicate the central position of the veins. They are defined as z_i , where

$i = 0, 1, \dots, N - 1$, and N is the number of local maximum points in the cross-sectional profile. Next, scores indicating the probability that the center positions are on veins are assigned to each center position. A score $P_d(z_i)$ is defined as follows:

$$P_d(z_i) = C_d(z_i)N(i). \quad (13)$$

The variable $N(i)$ is the width of the region where the curvature is positive and one of the z_i is located.

Scores $P_d(z_i)$ are assigned to new plane $V(x, y)$. To obtain the vein pattern spreading in an entire image, all the profiles in a direction are analyzed. To obtain the vein pattern spreading in all directions, all the profiles in four directions are also analyzed. All the center positions of the veins are detected by calculating the local maximum curvatures. The next step is to connect the designated vein centers. This is done basically by checking m (where $m = 2$) pixels located to the right and left of (x, y) . If the pixel (x, y) and the pixel value located on both sides is high (in terms of brightness), a horizontal line is drawn. But if the neighboring pixel values are high, and the value of the pixel (x, y) is low, then it is treated as a gap between the veins. If the pixel value (x, y) is high and its neighboring pixels have a low value, it is treated as an interference. This operation is used for all pixels designated in an earlier step. This action can be represented by the formulas:

$$S_{d1} = \min \left\{ \max (V(x + (m-1), y), V(x + m, y)) \right. \\ \left. + \max (V(x - (m-1), y), V(x - m, y)) \right\}, \quad (14)$$

$$S_{d2} = \min \left\{ \max (V(y + (m-1), x), V(y + m, x)) \right. \\ \left. + \max (V(y - (m-1), x), V(y - m, x)) \right\}, \quad (15)$$

$$S_{d3} = \min \left\{ \max (V(y - (m-1), x - (m-1)), V(y - m, x - m)) \right. \\ \left. + \max (V(y + (m-1), x + (m-1)), V(y + m, x + m)) \right\}, \quad (16)$$

$$S_{d4} = \min \left\{ \max (V(y + (m-1), x - (m-1)), V(y + m, x - m)) \right. \\ \left. + \max (V(y - (m-1), x + (m-1)), V(y - m, x + m)) \right\}, \quad (17)$$

where m defines the scope of the filter ($m = 2$).

With so designated a vein line for all four directions considered, the final pattern of blood vessels is formed by means of the function:

$$F = \max(S_{d1}, S_{d2}, S_{d3}, S_{d4}). \quad (18)$$

The last step is to bring the early established pattern of blood vessels to binary function in order to reduce the amount of information contained therein. Binarization is performed by thresholding. The threshold value is determined by the mean value of all pixels within the image greater than 0. The result of these methods can be seen in Fig. 2.

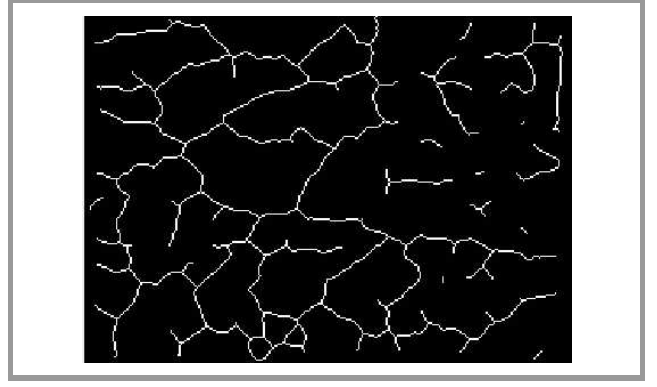


Fig. 2. The result of the detection method of palm vein pattern.

At this stage the resulting pattern of blood vessels has a lot of noise and redundant information for the feature encoding process. To eliminate unnecessary disruption and vein discontinuity several methods to improve the visibility of blood vessels have been applied. The first method is the dilatation, where the blood vessels are more protruded, which in time could result in a loss of relevant information about the veins position. Then the thinning operation is performed. This operation reduces the size of the blood vessels to one pixel, making it easier to locate the veins fork. After the dilatation and thinning operations have been performed there are still some irregularities on the image and to smooth them out some operations (removes spur pixel and removes isolated pixels) are carried out which remove unnecessary forks and image noise.

6. Fundamentals of Hidden Markov Models

A discrete Hidden Markov Model (HMM) λ can be viewed as a Markov model whose states cannot be explicitly observed. Each state has an associated probability distribution function, modeling the probability of emitting symbols from that state. More formally, a HMM is defined by the following entities [11], [12]:

- $S = S_1, S_2, \dots, S_N$ a finite set of hidden states;
- the transition matrix $A = a_{ij}, 1 \leq j \leq N$ representing the probability of going from state S_i to state S_j ,

$$a_{ij} = P[q_{t+1} = S_j | q_t = S_i] \quad 1 \leq i, j \leq N, \quad (19)$$

with

$$a_{ij} \geq 0 \quad \text{and} \quad \sum_{j=1}^N a_{ij} = 1; \quad (20)$$

- the observation symbol probability distribution in state j , $B = b_j(k)$, where:

$$b_j(S) = P[o_k \text{ at } t | q_t = S_j], \quad \begin{matrix} 1 \leq i \leq N \\ 1 \leq k \leq M \end{matrix}; \quad (21)$$

- $\pi = \{\pi_i\}$, the initial state probability distribution, representing probabilities of initial states, i.e.

$$\pi = P[q_1 = S_i] \quad 1 \leq i \leq N, \quad (22)$$

with

$$\pi \geq 0 \quad \text{and} \quad \sum_{i=1}^N \pi_i = 1. \quad (23)$$

For convenience, an HMM as a triplet $\lambda = (A, B, \pi)$ is denoted.

Three fundamental problems, namely recognition, segmentation and training can be analyzed. These problems can be defined as follows:

- recognition problem is computing the probability $P(O|\lambda)$ given the observation sequence O and the model λ ,
- segmentation problem is the determination of the optimal state sequence given the observation sequence $O = O_1, O_2, \dots, O_T$, and the model λ ,
- training problem is the adjustment of model parameters $\lambda = (A, B, \pi)$ so as to best account for the model states, this is equal to adjust the model parameters $\lambda = (A, B, \pi)$ to maximize $P(O|\lambda)$.

The training of the model, given a set of sequences $\{O_i\}$, is usually performed using the standard Baum-Welch re-estimation [11], [12] which determines the parameters (A, B, π) that maximize the probability $P(\{O_i\}|\lambda)$. The evaluation step, i.e., the computation of the probability $P(O|\lambda)$, given a model λ and a new observation sequence O , is performed using the forward-backward procedure [11], [12].

7. Encoding of Features and Matching

To carry out the studies the coding method consisting in dividing the input image into the 8×8 pixels in size sub-images was used. The coding considered the sum of pixels present in each sub-picture. The feature vector is composed of 1024 values. The sum of the pixels in each feature vector may range from 1 to 65. To make a feature vector equally long for every coding and to eliminate 0 in the vector, the following relationship is used:

$$W(n) = n + 1, \quad (24)$$

where n is the sum of the pixels in the sub-picture, and $W(n)$ is the value to be entered into the vector. This relationship facilitates use the above method of coding in the Hidden Markov Models. HMM have been used in the work to verify the identity based on palm vein pattern. It is not always possible to unambiguously determine the lines representing the palm veins, so the use of HMM allows proper verification in just such cases. As inputs to the model

are put subsequent rows of the encoded image are put as learning data to the model. Learning uses different images of the same hand.

Figure 3 shows the concept of coding.

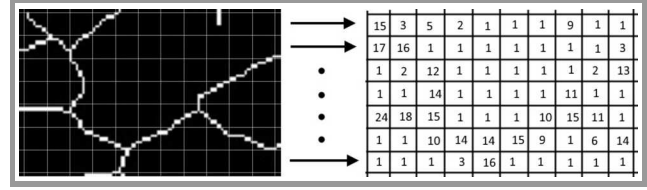


Fig. 3. Example of creating the feature vector.

8. Experiments Results

The studies included two ways of verification. The first one is based on comparing feature vectors using a Hamming distance. The second method takes into account the verification of identity, based on Hidden Markov Models. To carry out the experimental part two databases with images of the hand blood vessels were used. As part of a research database with photos and widely available database were created CASIA MSPD. Each of them contains data collected from 100 users with 12 pictures of the left and right hand each. For the stage of studying 8 photos were used, and the remaining pictures were used in the tests. To check the efficiency and effectiveness of the system the coefficient equal error rate (EER) was calculated for both ways of verification. Table 1 shows the results, taking into account verification by means of Hamming distance and Hidden Markov Models. In addition, the results of similar studies where the coding features are used in Hamming distance were considered.

Table 1
The comparison of proposed method
with other works

Methods	Left hand	Right hand
	EER [%]	EER [%]
Presented method with Hamming distance (own base)	0.29	0.26
Presented method with Hamming distance (CASIA database)	0.38	0.41
Presented method with HMM (own base)	0.24	0.20
Presented method with HMM (CASIA database)	0.26	0.23
Minutia feature points [9]	1.84	1.69
Laplacian palm [9]	2.74	1.99
Hessian phase [7]	0.83	0.91
Method using 2D Gabor Filter [13]	0.42	0.44
Eigenvein [14]	1.02	1.12
MDC method [15]	0.52	0.51

9. Conclusion

Palm vein pattern to build a biometric system is presented in the paper. A set of functions that allows image analysis of blood vessels in a hand is described. The article contains a description of how you can get a picture of the pattern of blood vessels in a hand as well as a description of the function to improve the contrast of the image feature extraction vessels and two verification methods.

Research was performed on two bases of blood vessels in a hand. The first one is the authors' own database, and the other is, generally available in the network, CASIA database. The article includes the research results performed on two bases, being represented by means of false acceptance rate (FAR) and false rejection rate (FRR) coefficients, allowing the determination the coefficient equal error rate.

The study shows that the verification method using a typical distance method does not give as good results as the use of hidden Markov models. Hidden Markov models respond much better to the observation vector encoded in that way and their effectiveness can be seen in the ERR coefficients that were designated for each verification method.

The achieved results motivate to continue further studies.

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Dorota Smorawa is a Ph.D. student at the Faculty of Mechanical Engineering and Computer Science at Czestochowa University of Technology (CUT). She received her M.Sc. in Informatics from the University of Czestochowa in 2012. Her research interest includes image processing, pattern recognition, feature extrac-

tion, biometric systems. In each of these research fields she has produced several publications in international journals.

E-mail: dorota.smorawa@icis.pcz.pl
 Faculty of Mechanical Engineering and Computer Science
 Czestochowa University of Technology
 Aleja Armii Krajowej 21
 42-201 Czestochowa, Poland



Mariusz Kubanek received his M.Sc. degree in Informatics from the University of Czestochowa, in 2002. The Ph.D. degree in Czestochowa University of Technology (CUT) in 2005. He is currently the Ph.D. in the Faculty of Mechanical Engineering and Computer Science at CUT. He also works at The European University of Inform-

ation Technology and Economics in Warsaw (EIUE). His research interest includes image processing, pattern recognition, feature extraction, biometric systems.

E-mail: mariusz.kubanek@icis.pcz.pl
 Faculty of Mechanical Engineering and Computer Science
 Czestochowa University of Technology
 Aleja Armii Krajowej 21
 42-201 Czestochowa, Poland

European University of Information Technology
 and Economics in Warsaw
 Department of Computer Science
 Bialostocka st 22
 03-741 Warsaw, Poland