

BIOMETRIC SYSTEMS BASED ON PALM VEIN AND FOREARM VEIN PATTERNS

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Abstract. The work covers issues related to the design of biometric systems based on the palm vein and forearm vein patterns. The study includes analysis of various stages of biometric system design ranging from acquisition, contrast enhancement, feature extraction and biometric pattern creation for verification methods. To extract specific features a two-dimension density function will be used. The article features the results of tests carried out on two different bases of blood vessels in a hand and forearm.

Keywords: *biometric system, recognition, palm vein, forearm vein*

1. Introduction

A biometrics system for identifying individuals using the pattern of veins in a forearm was proposed. The system has the advantage of being resistant to forgery because the pattern is inside a forearm. Infrared light is used to capture an image of a forearm that shows the vein patterns that have various widths and brightness that change temporally as a result of fluctuations in the amount of blood in the vein, depending on temperature, physical conditions, etc. The proposed method extracts the finger-vein pattern from the unclear image by using line tracking that starts from various positions. The proposed method extracts the forearm-vein pattern from the unclear image by using line tracking that starts from various positions. The algorithm described is a component of the whole system that is based on the pattern of the veins of the palm and forearm.

Image processing techniques can be used to enhance a blood vein portion of a captured image of the forearm. Image enhancement is one of the most widely researched areas of digital image processing. The primary purpose is to produce an image of better quality and interpretability from the original image. Various techniques in image processing have been widely used in divergent applications, such as biomedical, biometrics and many others. There are different approaches introduced for blood vein identification and enhancement. In work [1], they proposed a method for real-time blood vein enhancement by capturing an infrared image of a blood vein. But a costly camera and processing equipment are used to capture and process vein images. In work [2], authors used a background reduction

filter for vein contrast enhancement of finger vein patterns captured in near-infrared regions for personal identification. A Method for Hand Vein Recognition Based on the Curvelet Transform Phase Feature used the Curvelet transform of the region of interest and encoded the Curvelet coefficients phase variance, and evaluated the Chi-square distance of a coding histogram for vein recognition [3]. Image Restoration and Enhancement for Finger-Vein Recognition by authors of work [4] followed image processing by using Gabor filters. In the above cases they took images using transmitted IR rays by placing IR sources below a hand and took images of the top part of a hand. The literature [5], discusses hand vein pattern recognition using an image descriptor for biometric applications. For the biometric application, only the statistical structure of the vein is required, rather than the exact contours of the vein. In most of the studies, a blood vein pattern of fingers or a palm is extracted as an alternative to fingerprints used in biometry [6-11]. In such cases the exact structure need not be extracted as only the pattern is necessary for biometric applications. Apart from this, infra-red imaging commonly utilises transmitted infra-red images which have a higher visibility of veins. Hence, better results can be obtained from simple thresholding and normal enhancement techniques. In antecubital fossa, taking transmitted IR images are not possible. Hence reflected near infrared images, which have very low visibility of veins, are used in this research. The proposed algorithm follows a different approach for blood vein identification and enhancement efficiently. The method is mainly based on analysis of contrast and thresholding.

The proposed method follows a different approach for blood vein identification and enhancement efficiently. The method is mainly based on a two-dimension density function. The Sections 2 and 7 will give details about near infrared image acquisition of the pattern of blood vessels in a hand and forearm. The description about image contrast enhancement is in Sections 3, 4 and 5. Pattern vein extraction is described in Sections 6 and 8. Section 9 will give details about the method used for encoding and matching features. Section 10 contains description of experimental results.

2. Image acquisition

The research workstation, with which the images of a vascular system in the hand are taken, consists of:

- the camera with infrared active matrix,
- IR illuminator,
- A tripod for the camera,
- Plates with auxiliary pins.

The near-infrared light is partially absorbed by hemoglobin located in the veins, which enables a picture to be taken of the structure below the outer layer of skin to produce a natural contrast of the pattern of blood vessels.

In the process of blood vessel acquisition in the hand, only a fragment of a hand the size of 380 x 380 pixels is considered and taken.

In the studies carried out, there were two databases considered, my own base and the CASIA database [12]. Each of these contains data collected from 100 users. Each user had 12 pictures taken of the left and right hand (for 850 nm). Two pictures of the hand vein pattern were chosen from each base. A sample contrast enhancement is shown in Figure 1.

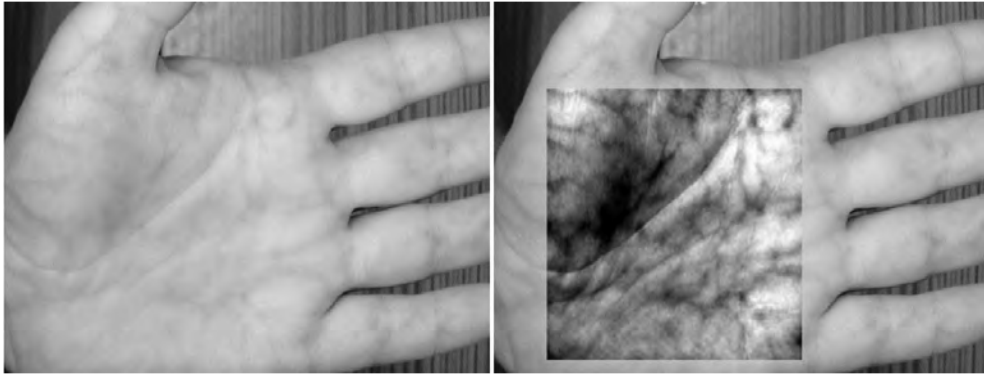


Fig. 1. Sample image of palm vein after using contrast enhancement from my own database

3. Global image transformations used to improve its contrast

The image taken during the acquisition is often low-contrast, which is manifested by difficulties in distinguishing its details. The image of the pattern of blood vessels is monochromatic and its colour scope ranges from 0 to 255. The fact that the entire available range of gray levels is not utilized may result in the low image contrast. To make the image clearer for the system methods, to enhance contrast are applied as one of the first steps while the system is being constructed.

Global methods enhancing contrast belong to the extensive group of methods to improve the contrast of the image. Knowledge of the levels of gray in a given image is commonly used here. To obtain such information, a histogram of gray levels of the image is necessary. The histogram is most commonly used in methods of stretching the histogram or histogram equalization.

One of the well-known global transforms is a single point transformation, also known as linear contrasting [13]. It involves the range of levels of brightness to be transformed to its possibly maximum width. To apply this method, we need the information about the lowest and highest values of gray levels present in the image being operated. The change of the gray levels of the input image is performed with the following formula:

$$L^*(i, j) = a \cdot L(i, j) + b \quad (1)$$

where:

a, b - coefficients,

$L(i, j)$ - the brightness level of the element with the image coordinates (i, j) ,

$L^*(i, j)$ - the new brightness level value of the image element after the conversion.

In this case, the range of gray levels $[L_{\min}, L_{\max}]$ of the image L is converted into range $[L_{\min}, L_{\max}]$. L_{\min} and L_{\max} denote respectively the lowest and the highest pixel value on the input image. The following set of equations is obtained:

$$\begin{aligned} L_{\min}^* &= a \cdot L_{\min} + b, \\ L_{\max}^* &= a \cdot L_{\max} + b \end{aligned} \quad (2)$$

where factors a and b are calculated:

$$\begin{aligned} a &= \frac{L_{\max}^* - L_{\min}^*}{L_{\max} - L_{\min}}, \\ b &= \frac{L_{\min}^* \cdot L_{\max} - L_{\min} \cdot L_{\max}^*}{L_{\max} - L_{\min}} \end{aligned} \quad (3)$$

The parameters a and b allow you to arrange the equation (2) into a simpler form (4):

$$L^*(i, j) = 255 \cdot \frac{L(i, j) - L_{\min}}{L_{\max} - L_{\min}} \quad (4)$$

Another essential global transformation, used to enhance the image contrast, is the non-linear stretching method [13], often called the gamma correction. The mathematical form of this method is based on the linear contrast method (4), where a power law is used to change the brightness level as a coefficient γ . The coefficient value ranges $0.3 < \gamma < 3$ and the non-linear stretching pattern is as follows:

$$L_{\gamma}^*(i, j) = 255 \cdot \frac{L(i, j) - L_{\min}}{(L_{\max} - L_{\min})^{\gamma}} \quad (5)$$

Another key global transform used to enhance the quality of the image is the histogram equalization method [14], which is also called linearization or flattening of the histogram. This operation is used when the greyscale range of an image is very narrow. Greyscale values are stretched to a wider band which allows you to enhance the contrast within the low level area. Transformation of histogram equalization is the point operation $F[\cdot]$, which converts the input image $L(i, j)$ into the output image $L^*(i, j)$ as follows:

$$L^*(i, j) = F[L(i, j)] \quad (6)$$

where:

$$F(L) = \sum_{x=0}^L H(x) \quad (7)$$

$H(x)$ denotes the values of the input image histogram $H(L)$.

Another popular global transformation, which is often confused with the image histogram equalization, is the stretching of the image histogram method [14]. This transform leads to such a conversion of component values range so the histogram includes all the component values. The transformation is described with the following formula:

$$L^*(i, j) = (L(i, j) - L_{\min}) \cdot \left(\frac{b - a}{L_{\max} - L_{\min}} \right) + a \quad (8)$$

where $L^*(i, j)$ denotes a new calculated value of the pixel and $L(i, j)$ is the value of the input pixel. The variable a is the lowest value and b is the highest value that a pixel can take. L_{\min} and L_{\max} denote respectively the lowest and the highest pixel value on the input image.

4. Complementary methods to enhance the image contrast

During the acquisition of the palm vein pattern some additional noise and distortion can occur. This effect is strictly connected with the conditions in which the picture was taken. Global transforms improving image contrast cannot cope with these types of problems, therefore some additional methods should be applied. Such methods include smoothing filters and normalization of the image. These methods eradicate the noise and distortion which arise from the acquisition.

The task of smoothing filters is to remove noise from an image by convolution of the input image with the appropriate masks. The convolution operation for a discrete image function L and the mask can be represented in the following equation [15]:

$$w(x, y) \cdot L(x, y) = \sum_{i, j \in W} w(i, j) \cdot F(x - i, y - j) \quad (9)$$

After the image has been filtered, the values in the image can slightly exceed its range. To do so, it is necessary to perform image normalization [16], whose task is to bring particular points of the source image $L(i, j)$ to a predetermined range of values onto the output image $L^*(i, j)$. Image normalization can be represented by the formula, where the coefficient γ has a constant value:

$$L^*(i, j) = L^\gamma(i, j) \quad (10)$$

5. Analysis of efficiency of image contrast enhancement

In terms of computer processing and monochrome images analysis, there is still a problem related to an objective assessment of its quality. In this type of images, the concept of contrast refers to the difference between the values of gray levels present in the image. The problem is the assessment of monochrome images obtained during the acquisition. The problem is also to assess whether the method to enhance contrast fulfilled its purpose or not. More specifically, the method used has improved image contrast or it worsened. For this purpose, an experimental study on two photo databases with images of blood vessels of the hand was carried out. To assess the quality of the images, three methods of image contrast were applied.

In literature, there are many different methods of image contrast assessment. The most commonly used methods of evaluating image contrast globally are measures (10) and (11). These methods take into account the maximum and minimum pixel present in the image to calculate the contrast ratio. Measure (11) in the literature is also known as the Michelson factor [17].

$$k_S = \frac{L_{\max} - L_{\min}}{\bar{L}} \quad (11)$$

and

$$k_M = \frac{L_{\max} - L_{\min}}{L_{\max} + L_{\min}} \quad (12)$$

In formulas (11) and (12), L_{\max} and L_{\min} respectively indicate the minimum and the maximum value within all gray levels in the image. Coefficient \bar{L} is the average value of gray levels in the image that can be described by the following formula:

$$\bar{L} = (M \cdot N)^{-1} \cdot \sum_{i=1}^M \sum_{j=1}^N L(i, j) \quad (13)$$

where:

$L(i, j)$ - value of the gray level assigned to the pixel coordinates (i, j) ,

M, N - image size.

In the article [16, 18], we can find the information that the image contrast assessment methods (11) and (12) are burdened with errors. The result of these methods depends on instances of individual pixels with extreme values appearing in the image. The author gives the rating function, which does not contain these errors:

$$k_W = \frac{4}{M \cdot N \cdot L^2} \sum_{i=1}^M \sum_{j=1}^N (L(i, j) - \bar{L})^2 \quad (14)$$

where:

L - the range of values that can be appointed to gray levels in a given coding method,

\bar{L} - the average value of the gray levels in the image,

$L(i, j)$ - the value of gray levels assigned to the pixel coordinates (i, j)

M, N - size of the image,

value 4 - the number that standardizes the coefficient value.

Another similar measure of contrast assessment is a modified measure (14) described by the formula (15):

$$k_{ABS} = \frac{4}{M \cdot N \cdot L} \sum_{i=1}^M \sum_{j=1}^N |L(i, j) - \bar{L}| \quad (15)$$

In this method, the square of the difference is replaced by the absolute value and the range of gray levels that can apply an image in a given coding method is not squared.

6. Extraction of palm vein based on two-dimensional density function

The pattern of palm blood vessels in the image looks like a dent, because the veins are darker than the surrounding area. Our method examines the entire profile of the hand, 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 (16) [9], presented below:

$$f(x, y) = \frac{1}{2\pi\delta^2} \exp\left(-\frac{(x^2 + y^2)}{2\delta^2}\right) \quad (16)$$

One of the first steps of our method is the initial location of curvature in the horizontal, vertical and both diagonal directions. For modelling, the curvature localizing filter the first (17)-(19) and the second (20), (21) derivatives of the two-dimensional density function are used

$$f_x(x) = \frac{\partial f(x, y)}{\partial x} = \left(\frac{-x}{\delta^2}\right) f(x, y) \quad (17)$$

$$f_{xx} = \frac{\partial^2 f(x, y)}{\partial x^2} = \frac{x^2 - \delta^2}{\delta^4} f(x, y) \quad (18)$$

$$f_y = \frac{\partial f(x, y)}{\partial y} = \left(\frac{-y}{\delta^2}\right) f(x, y) \quad (19)$$

$$f_{yy} = \frac{\partial^2 f(x, y)}{\partial y^2} = \frac{y^2 - \delta^2}{\delta^4} f(x, y) \quad (20)$$

$$f_{xy} = \frac{\partial^2 f(x, y)}{\partial x \partial y} = \frac{xy}{\delta^4} f(x, y) \quad (21)$$

The filters are designed to locate all the existing curvature of the profile for the four directions. Filters for the horizontal direction (22), vertical (23) and two diagonal ones (24), (25) are described by the following formulas:

$$C_{d1}(z) = \frac{f_{xx} \cdot L}{\left(1 + (f_x \cdot L)^2\right)^{\frac{3}{2}}} \quad (22)$$

$$C_{d2}(z) = \frac{f_{yy} \cdot L}{\left(1 + (f_y \cdot L)^2\right)^{\frac{3}{2}}} \quad (23)$$

$$C_{d3}(z) = \frac{0.5f_{xx} \cdot L + f_{xy} \cdot L + 0.5f_{yy} \cdot L}{\left(1 + \left(0.5 \cdot \sqrt{2}(f_x \cdot L + f_y \cdot L)\right)^2\right)^{\frac{3}{2}}} \quad (24)$$

$$C_{d4}(z) = \frac{0.5f_{xx} \cdot L - f_{xy} \cdot L + 0.5f_{yy} \cdot L}{\left(1 + \left(0.5 \cdot \sqrt{2}(f_x \cdot L - f_y \cdot L)\right)^2\right)^{\frac{3}{2}}} \quad (25)$$

where L denotes the input image.

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. This operation can be 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 of being in the center positions of veins, are assigned as a main scores. Score $P_d(z_i)$ is defined as follows (26):

$$P_d(z_i) = C_d(z_i)N(i) \quad (26)$$

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 basically done 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 neighbouring 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 neighbouring pixels have a low value, it is treated as interference. This operation is used for all pixels designated in an earlier step. This action can be represented by the following formulas:

$$S_{d1} = \min \{ \max(V(x + (m-1), y), V(x + m, y)) \\ + \max(V(x - (m-1), y), V(x - m, y))) \} \quad (27)$$

$$S_{d2} = \min \{ \max(V(y + (m-1), x), V(y + m, x)) \\ + \max(V(y - (m-1), x), V(y - m, x))) \} \quad (28)$$

$$S_{d3} = \min \{ \max(V(y - (m-1), x - (m-1)), V(y - m, x - m)) \\ + \max(V(y + (m-1), x + (m-1)), V(y + m, x + m)) \} \quad (29)$$

$$S_{d4} = \min \{ \max(V(y + (m-1), x - (m-1)), V(y + m, x - m)) \\ + \max(V(y - (m-1), x + (m-1)), V(y - m, x + m)) \} \quad (30)$$

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

For a designated vein line for all four directions considered, the final pattern of blood vessels is formed by means of the function (31):

$$F = \max(S_{d1}, S_{d2}, S_{d3}, S_{d4}) \quad (31)$$

The last step is to bring the early established pattern of blood vessels to a 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 Figure 2.

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 position of the veins.

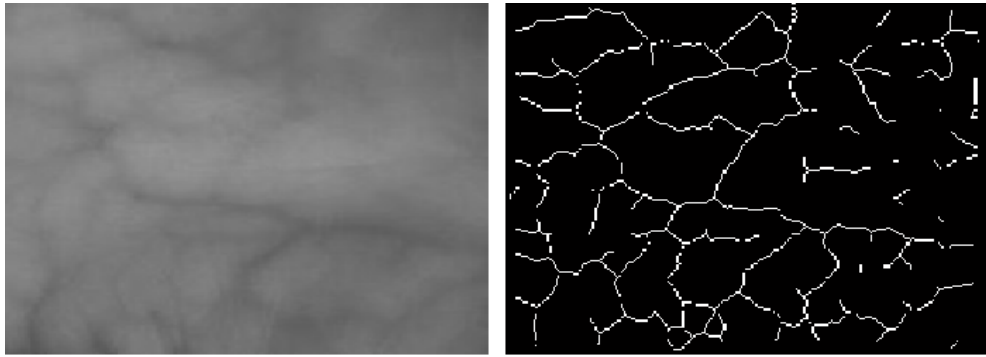


Fig. 2. The result of the detection method of palm pattern

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 dilation and thinning operations have been performed, there are still some irregularities on the image and in order to smooth them out, next morphological operations (that remove spur pixels and isolated pixels, for example) are carried out.

7. Infrared image acquisition of forearm

NIR image acquisition is done with the help of a modified digital camera. The modification is done in by replacing an IR filter of the camera placed in front of charge coupled device with a visible light filter. An IR flash is used for uniform illumination of a hand and took images with the help of reflected IR signals from the forearm. The image stored in JPEG format is shown in Figure 3.

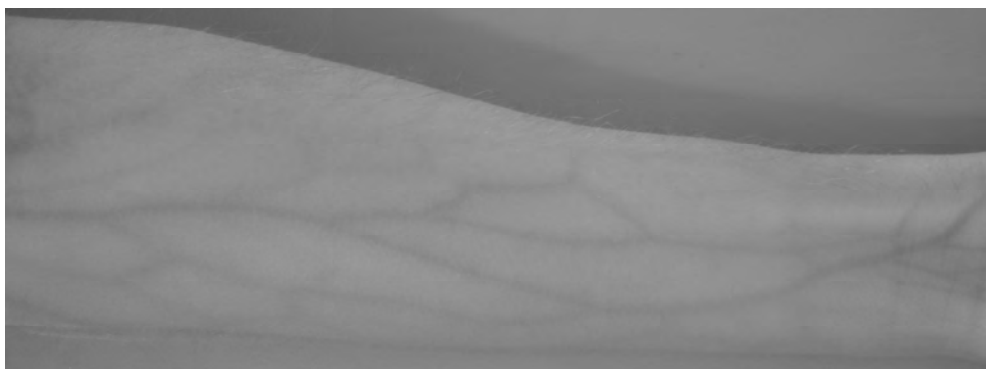


Fig. 3. Image captured using modified camera

8. Contrast enhancement and feature extraction on the forearm image

This captured image is processed for blood vein enhancement. Initially, the image was pre-processed and then converted an RGB image to greyscale. The intensity level is expressed within the range 0 to 255 in the case of an 8-bit image. The blood vein part in the forearm image is not distinctly visible compared to the body skin part. For vein image enhancement and extraction, it is necessary to distinguish blood vein from other skin. Additional imaging techniques are needed to extract the shape of the veins. Binarization and morphological denoising create a clearer picture of the veins. For proper extraction of blood veins from the surrounding skin, selection of threshold levels is crucial. A thresholding algorithm helps for finding a suitable threshold level that efficiently extracts blood veins from the image. This algorithm performs image thresholding based on clustering [14]. By assuming the image consists of two classes of pixels, this algorithm calculates an optimal threshold value to separate the classes such that their intra-class variance is minimum and inter-class variance is maximum.

Determining the brightness gradient module for each image point:

$$G(x, y) = \max\{|G_x(x, y), G_y(x, y)|\} \quad (32)$$

where:

$$G_x(x, y) = J(x+1, y) - J(x-1, y) \quad (33)$$

$$G_y(x, y) = J(x, y+1) - J(x, y-1) \quad (34)$$

Calculation of threshold:

$$t = \frac{xy^{J(x,y)G(x,y)}}{xy^{G(x,y)}} \quad (35)$$

Morphological operations have included closure operations and the removal of minor disturbances. It is necessary to perform morphological operations on the vein part extracted to get a more precise shape of the vein. Dilation and erosion are mainly carried out in the post-processing for this purpose. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. Here erosion is performed, as the operation helps to remove the unwanted sections which may get extracted with the vein. The result of the morphological transformations is shown in Figure 4.



Fig. 4. Image after morphological transformations

The formula describing dilatation operation on the image:

$$L'(m,n) = \max_{m_i, n_i \in B(m,n)} (L(m_i, n_i)) \quad (36)$$

where:

m, n - coefficients,

$L(m, n)$ - the brightness level of the element with the image coordinates (m, n) ,

$B(m, n)$ - the structural element with center point with coordinates (m, n) ,

$L'(m, n)$ - the new brightness level value of the image element after the conversion.

Erosion is the reverse transformation to dilatation.

The captured images for processing may contain portions other than the forearm part which is not the region of interest. To find the region of interest (ROI), the captured image is thresholded with a median pixel value around 100. This is the separating pixel value between the skin and background surface. The portion of the skin where the vein is present is required to be processed. Hence, the surface part is discarded, and the region of interest is extracted.

Lines are determined by the yellow-green or blue-red markers. Different colors represent different directions of veins.

The next operation involves removing lines for which the number of markers in one string is too small. Such processing leaves only the main vein patterns that have the greatest impact on the quality of recognition. The image after removing the small lines is shown in Figure 5.

Forearm blood vein identification is quite difficult. This proposed algorithm extracted and enhanced the blood vein from the forearm thus providing more

visibility apart from skin. The algorithm tested infrared forearm images and the result shows the efficiency of this algorithm. It is an element of the entire system that uses the palm vein and forearm to identify and verify users.

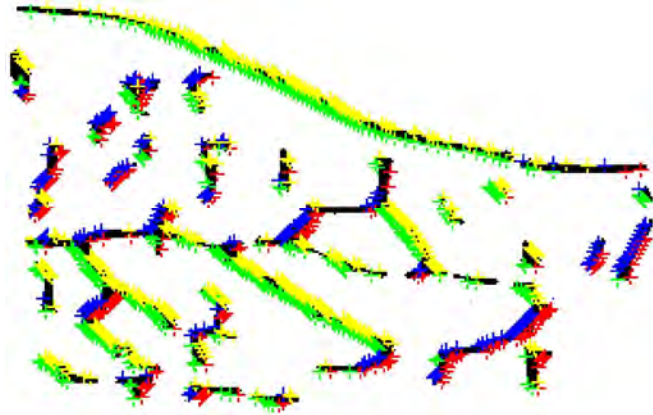


Fig. 5. Final processing effect

9. Encoding and matching patterns

9.1. Encoding of features and matching based on Hidden Markov Models

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:

$$W(n) = n + 1 \quad (37)$$

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 of the above method of coding in the Hidden Markov Models. HMM have been used in the work to verify the identity based on the palm vein pattern. It is not always possible to unambiguously determine the lines representing the palm veins, so the use of HMM allows for proper verification in just such cases. Subsequent rows of the encoded image are given as a learning data to the model. Learning mode uses different images of the same hand. Figure 6 shows the concept of coding.

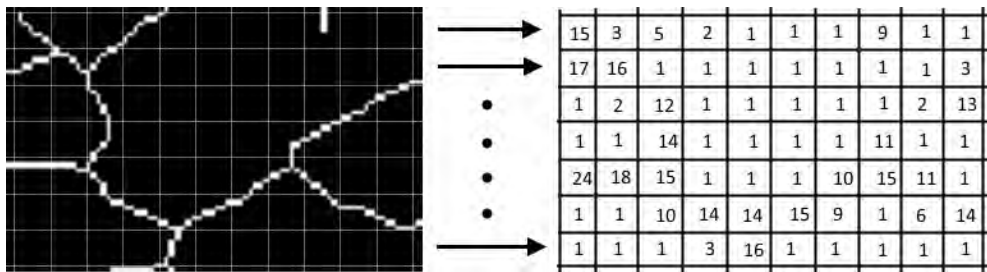


Fig. 6. Example of creating the feature vector

9.2. Encoding of features and matching based on minutiae extraction

To create feature vector, the minutiae are used as a characteristic elements. In this case bifurcations and endings of veins were taken into account. That approach is used commonly in fingerprint analysis. The procedure of minutiae extraction is divided into four steps:

- 3 x 3 pixel sub-image is considered
- The nearest neighbourhood of a given pixel is searched
- The number of block pixels is computed
 - If the number of block pixels equals exactly 2 (including the pixel being analyzed) = the beginning or the end of the line
 - If the number of block pixels equals 4 and 5 (including pixel being analyzed) = bifurcation
- Making the minutiae

The result of these methods can be seen in Figures 7 and 8.

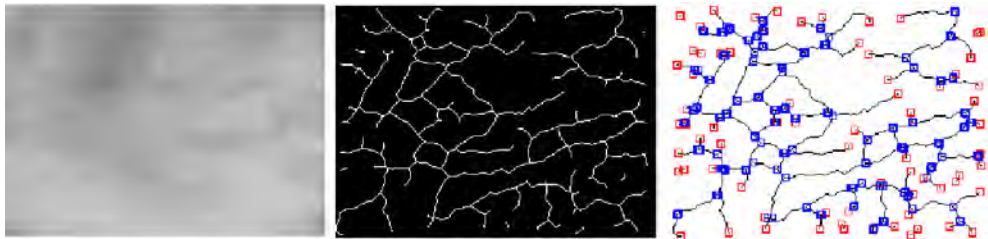


Fig. 7. The result of the detection method and minutiae extraction of the palm vein pattern

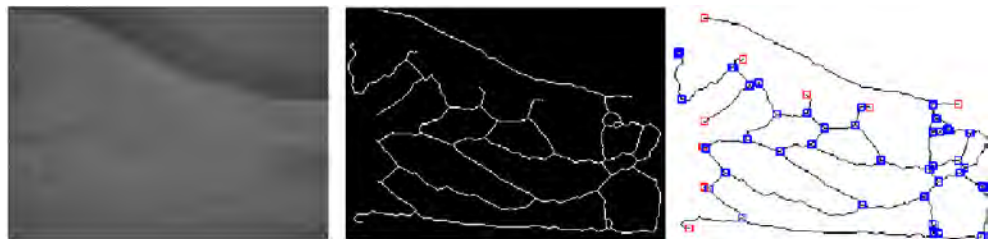


Fig. 8. The result of the detection method and minutiae extraction of the forearm vein pattern

This method assumes that each pattern of blood vessels is described by the vector of features. Specific elements of this vector - minutiae - are described by coordinates of place, type and the position angle.

The problem of minutiae matching can be defined in the following way:

$$T = \{m_1, m_2, \dots, m_m\}, m_i = \{x_i, y_i, \theta_i\}, i = 1 \dots m \quad (38)$$

$$I = \{m'_1, m'_2, \dots, m'_n\}, m'_j = \{x'_j, y'_j, \theta'_j\}, j = 1 \dots n \quad (39)$$

where:

T - vector of features saved in the data base,

I - vector of features of blood vessel pattern being verified,

m - the number of minutiae saved in the data base pattern,

n - the number of minutiae in the pattern being verified.

Minutiae m'_j which belongs to I , is considered to be matching the minutiae m_i , which belongs to T , if their distance is shorter than the predetermined threshold r^0 and the difference of direction is smaller than the predetermined tolerance angle θ_0 :

$$sd(m'_j, m_i) = \sqrt{(x'_j - x_i)^2 + (y'_j - y_i)^2} \leq r_0 \quad (40)$$

$$dd(m'_j, m_i) = \min(|\theta'_j - \theta_i|, 360^\circ - |\theta'_j - \theta_i|) \leq \theta_0 \quad (41)$$

10. Experimental results

10.1. Research methods to enhance the image contrast

To carry out the experimental part, two applications, which enhance the image contrast, were created. The first one is comprised of four global transforms, i.e.: the histogram stretching, linear and nonlinear stretching, and histogram equalization.

Four measures of evaluating the image contrast are calculated for each image which has been treated with these transforms. These measures are k_S , k_M , k_W and k_{ABS} , which were described in the above section. Such additional functions as normalization and blurring are applied on each transform by the other application. The following tables present the results obtained for our database and the CASIA database.

Table 1

Results for all photos from our own database

Measure Method	k_S	k_M	k_W	k_{ABS}
Histogram stretching	1.7876	0.9922	0.0591	0.4363
Linear stretching	1.7953	1.0000	0.0612	0.4021
Nonlinear stretching	2.3126	1.0000	0.0691	0.4538
Histogram equalization	1.9997	1.0000	0.3427	1.0147
HSNB	1.5098	1.0000	0.1160	0.5862
LSNB	1.5927	0.9173	0.2432	0.3727
NSNB	2.1006	1.0000	0.1576	0.6748
HENB	1.8018	1.0000	0.4983	1.2598
Input image	0.7246	0.4781	0.0178	0.2023

Table 2

Results for all photos from CASIA database

Measure Method	k_S	k_M	k_W	k_{ABS}
Histogram stretching	1.4843	0.9922	0.1034	0.5248
Linear stretching	1.4907	1.0000	0.1193	0.5337
Nonlinear stretching	1.7954	1.0000	0.1479	0.6481
Histogram equalization	1.9985	1.0000	0.3456	1.0108
HSNB	1.2031	1.0000	0.1728	0.6743
LSNB	1.4743	0.9917	0.1079	0.5272
NSNB	1.5575	1.0000	0.2693	0.8647
HENB	1.8171	1.0000	0.5267	1.2932
Input image	0.6598	0.3797	0.0086	0.1498

Description of tables:

HSNB - histogram stretching and normalization and blurring,

LSNB - linear stretching and normalization and blurring,

NSNB - nonlinear stretching and normalization and blurring,

HENB - histogram equalization and normalization and blurring.

10.2. Experiments results of Hidden Markov Models

The studies included two methods 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 blood vessels of the hand were used. We used the CASIA database and our database with similar assumptions. Each of them contains data collected from 100 users with 12 pictures of the left and right hand each. For the learning mode 8 photos were used, and the remaining pictures were used in the test mode.

To check the efficiency and effectiveness of the system, the coefficient equal error rate (EER) was calculated for both ways of verification. Table 3 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 3

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	1.84	1.69
Laplacian palm	2.74	1.99
Hessian phase	0.83	0.91
Method using 2D Gabor Filter	0.42	0.44
Eigenvein	1.02	1.12
MDC method	0.52	0.51

10.3. Experiments results based on minutiae extraction

To check the level of security and accuracy of the systems, the factor of recognition rate was applied. The following table summarizes the results carried out for the different methods. The coefficients of the proposed method shown in Table 4 were obtained in tests that take into account the coding method based on the minutiae.

Table 4

The comparison of own method with other works

Methods	Recognition rate [%]	Feature vector dimensions	Matching time [ms]
PCA [12]	94.19	100	–
LDA [17]	95.46	206	–
2DPCA [17]	98.07	64 x 7	2.23
2DLDA [17]	98.59	64 x 6	2.12
(2D) ² PCA [17]	98.86	8 x 8	0.46
(2D) ² LDA [17]	99.18	8 x 8	0.45
Minutiae feature [11]	97.75	–	–
Laplacjan palm [11]	96.63	128 x 128	–
Eigenvein [11]	98.31	128 x 128	–
Gaussian [11]	98.88	64 x 64	324
Proposed	99.08	–	15.04

11. Conclusions

In this paper the author presented a palm vein pattern to build a biometric system. 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 methods of verification.

Research was performed on two bases of blood vessels in a hand using the Hidden Markov Model. The first one is the our database and the other is, generally available in the network referred to as the CASIA database. The article includes the research results performed on two bases, being represented by means of the false acceptance rate (FAR) and the false rejection rate (FRR) coefficients, allowing for the determination of the coefficient equal error rate (EER).

A method of encoding and matching based on minutiae extraction was also proposed. The results are presented in the form of coefficients recognition rate. The results show that one of the most important steps in the development of our biometric system is the correct acquisition of the image. The image should contain clear patterns of veins.

The next stage is carrying out research which used features located on the inside of the forearm.

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