Jurnal Ilmu Komputer dan Informasi (Journal of a Science and Information). 11/2 (2018), 95-102
DOI: http://dx.doi.org/10.21609/jiki.v11i2.576

MULTISPECTRAL DORSAL HAND VEIN RECOGNITION BASED ON LOCAL LINE BINARY PATTERN

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Abstract

Nowadays, dorsal hand vein recognition is one of the most recent multispectral biometrics technologies used for the person identification/authentication. Looking into another biometrics system, dorsal hand vein biometrics system has been popular because of the privilege: false duplicity, hygienic, static, and convenient. The most challenging phase in a biometric system is feature extraction phase. In this research, feature extraction method called Local Line Binary Pattern (LLBP) has been explored and implemented. The straight-line shape of LLBP can extract robust features from the images with unclear veins therefore, recognition performance of dorsal hand vein image will be good. We have used this method to our 300 dorsal hand vein images obtained from 50 persons using a low-cost infrared webcam. In recognition step, fuzzy *k*-NN classifier is adopted since it does not need any learning algorithm, so that it can decrease the processing time. The experimental result showed that LLBP method is reliable for feature extraction on dorsal hand vein recognition with a recognition accuracy up to 98%.

Keywords: *biometrics, dorsal hand vein, fuzzy k-NN, local line binary pattern, vein recognition.*

Abstrak

Saat ini pengenalan *dorsal hand vein* merupakan salah satu teknologi terbaru dalam biometrika *multispectral* yang digunakan untuk mengidentifikasi seseorang. Dibandingkan dengan sistem biometrika lainnya, sistem biometrika berbasis *dorsal hand vein* lebih sering digunakan karena memiliki beberapa kelebihan seperti sulit untuk diduplikasi, higienis, bersifat tetap (tidak berubah-ubah) dan mudah (untuk diaplikasikan). Tahapan yang penting dalam sistem biometrika adalah tahap ekstraksi fitur. Dalam penelitian ini, dilakukan pengkajian dan pengimplementasian salah satu metode ekstraksi fitur yaitu Local Line Binary Pattern (LLBP). Bentuk filter LLBP yang berupa garis dapat menghasilkan fitur vein yang lebih jelas sehingga menghasilkan pengenalan *dorsal hand vein* yang lebih baik. Metode ini diuji menggunakan 300 citra pembuluh darah pada telapak tangan (*dorsal hand vein*) yang berasal dari 50 individu yang diakuisisi dengan *webcam* inframerah. Pada tahap pengenalan, metode fuzzy *k*-NN digunakan karena metode ini tidak membutuhkan algoritma pembelajaran sehingga diharapkan dapat mengurangi waktu pemrosesan. Hasil pengujian menunjukkan bahwa metode LLBP dan fuzzy *k*-NN memiliki kinerja yang baik untuk ekstraksi fitur pada pengelan *dorsal hand vein* dengan akurasi pengenalan mencapai 98%.

Kata Kunci: *biometrika, dorsal hand vein, fuzzy k-NN, local line binary pattern, pengenalan pembuluh darah*

1. Introduction

Multispectral dorsal hand vein recognition is one of the most recent multispectral biometrics technologies used for the person identification because of its strengths. 1) The form of the vascular patterns in the dorsal hand is distinct from each other. 2) The image of a dorsal hand vein pattern can be captured only by a live body too. Thus, it is very difficult to falsify it [1]. 3) As the veins are internal features the state of the skin, humidity, temperature does not have much effect on the vein image [2]. 4) Since it acquires a dorsal hand vein pattern image without direct contact with the hand or with the vein pattern-extracting sensor, there is no contamination [3] and 5) the pattern of the vessels of back of the hand is fixed and unique with repeatable biometric features [4].

Most of the currently available approaches for dorsal hand vein recognition have similarities on the feature extraction method. The examples of feature extraction methods which already used for hand vein recognition are Hough Transform [5], multi-scale second-order differential model [6], and Fuzzy-Neuro [7]. Those methods show a good performance due to the high qualities of hand vein

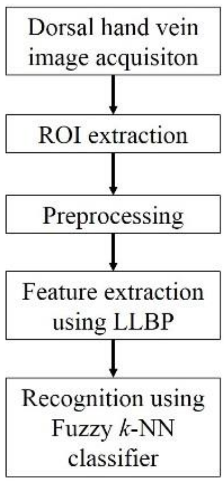

Figure. 1. The overview of proposed method for dorsal hand vein recognition

images. However, sometimes hand vein images are not clear due to the low qualities of sensor or noise. Unclear extracted vein can become the problem in hand vein recognition.

In 2014, [8] conducted palm vein recognition using Local Binary Pattern (LBP) features. Local Binary Pattern (LBP) is a feature that resist variations of illumination conditions [9]. LBP stores the texture pattern into the binary vector where each binary value is obtained by the result of the difference between the central pixel with the neighbourhood pixels. Although the result of this difference is not influenced by varying illumination conditions [10], but shape-based feature extraction puts the forward higher requirement for the original image. Specifically, the vein edge should be clear to avoid the occurrences of the broken and blurred vein. It may affect recognition process and degrades recognition accuracy. So that, it is important to focus on capturing vein pattern from a segmented blood vessel network and utilized the features from the segmented blood vessel network for recognition.

In the recent years, some research conducted the experiment using a new variant of LBP called local line binary pattern (LLBP) [11] to overcome the problem of unclear extracted finger vein [2] and palm vein [12]. Those experiments result in the EER of 1.89% and accuracy of 97.3% respectively. Therefore, it is evident that the LLBP method can achieve good performance in the accuracy of finger-vein and palm-vein recognition system although it is proposed for the first time by [13] in 2009 for face recognition system.

Local Line Binary Pattern (LLBP) is a good oriented feature representation method extended from local binary pattern (LBP) [14]. The main difference between LLBP and LBP is its neighborhood shape is a straight line with length N pixel, unlike in LBP, which is a square [11]. The straight-line shape of LLBP can extract robust features from the images with unclear veins, it is more suitable to capture the pattern inside a vein image [12]. In line with this, we propose dorsal hand vein recognition system based on the local feature using Local Line Binary Pattern (LLBP) method. Therefore, recognition performance of dorsal hand vein image will be good.

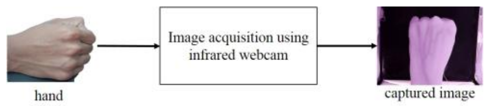

Figure. 2. The dorsal hand vein image acquisition

Figure. 3. The sample of captured dorsal hand vein image

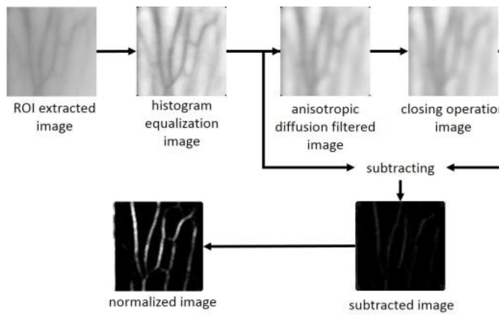

Figure. 4. The results of preprocessing steps

In recognition stage, there are two types of methods that can be used. The first one is using threshold distance [15] and the other one is using classification methods. There is a weakness when we use threshold distance [16]. The accuracy result from dorsal hand vein recognition will be strongly depend on the threshold value. It can make the optimal accuracy result hard to find. So that, classification method is implemented for a number of studies in hand vein recognition cases such as fuzzy-neuro technique [17], k-NN [16], fuzzy k-NN [12] and back-propagation neural network [17]. In this experiment, we considered the fuzzy k-NN to be a suitable classifier since it does not need any learning algorithm, unlike in fuzzy-neuro technique and back-propagation neural network, so that it can decrease the processing time [18]. Moreover, due to the feature of dorsal hand vein image that similar to each other, we choose fuzzy k-NN method over k-NN method to avoid the false recognition of dorsal hand vein image.

The aim of this paper is to apply feature extraction techniques, LLBP, to obtain a good

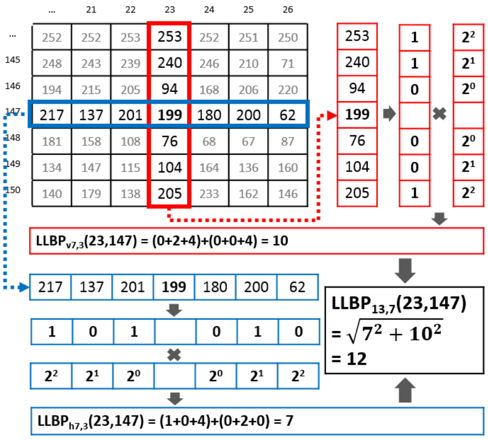

Figure. 5. Example of LLBP operator

definition of the vein pattern. And to adopt classification method, fuzzy *k*-NN, to obtain a good performance in the accuracy with speedy matching. After analysing the related works in the section on Introduction, we will briefly introduce the proposed method for dorsal hand vein recognition in the section on Methods. Experimental results are presented and discussed in the section on Results and Analysis to verify the validity of the proposed approach. Finally, concluding remarks and future works are given in the section on Conclusion.

2. Methods

The block diagram of the proposed method for dorsal hand vein recognition showed in Figure 1. The method consists of five main stages: image acquisition, ROI (Region of Interest) extraction, preprocessing, feature extraction by Local Line Binary Pattern (LLBP) and dorsal hand vein recognition by the Fuzzy k-NN classifier.

Image Acquisition

To the best of our knowledge, there is no currently publicly available dorsal hand vein database. Therefore, in this paper, we set up multispectral dorsal hand vein image databases with our vein image capture device. One of the purposes of our research is to create a capture setup that is efficient and has a low cost. A cheap infrared webcam (M-Tech Webcam) was chosen to be used for taking the pictures of the hand. The camera has been modified so it can capture NIR images. As the infrared light can penetrate biological tissue and the venous blood absorbs more infrared light than the surrounding tissue, the vein appears darker than the surrounding tissue in an NIR image. A vein pattern reveals the vast network of blood vessels underneath the skin [3].

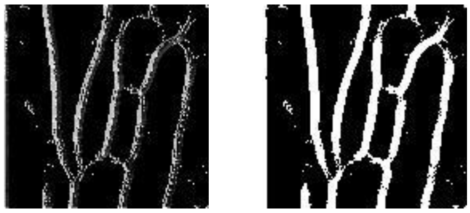

Figure. 6. The extracted feature using LBP (a) and LLBP (b)

We capture a total of 300 dorsal hand vein images. This dataset consists of 6 left dorsal hand vein images of 50 individuals (six samples per individual). These 6 images were acquired from each user with variant rotation. The collected dorsal hand vein image sample is shown in Figure 3. The dark line in the captured image is the vein.

ROI Extraction

The features of vein patterns extracted from the same region in different dorsal hand vein images are compared for recognition step. The extracted region is known as the region of interest (ROI). The acquired image is first converted to a grayscale image and then its ROI extracted using default cropping function from Matlab. Therefore, in this work, the ROI of dorsal hand vein image has been manually located.

Preprocessing

After ROI extraction, the next step is preprocessing. To ensure that the proper vein features can be extracted from the dorsal hand vein image, it is essential to preprocess the images. First, resize the image using Bicubic Interpolation method which the dimension is 128 x 128 pixels. The resized dorsal hand vein patterns were then preprocessed using Histogram Equalization function which enhances the contrast of the images. This method is useful if the researcher uses FIR imaging technique since this method redistributed the pixel intensity thus changing the sharpness and contrast of image [17]. Thirdly, we use Anisotropic Diffusion filter to make the image smoother so the edge can be detected more specific in the next step. The Morphological operations namely closing operation are applied to the filtered image to get a thinned image. Then, subtract the filtered image with the closing operation image to get the pattern of the vein. Finally, normalize the subtracted image. The following figure shows the results of the preprocessing steps.

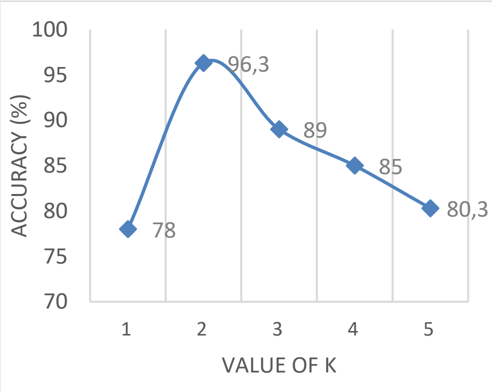

Figure. 7. The Testing Result of Different *k* Values

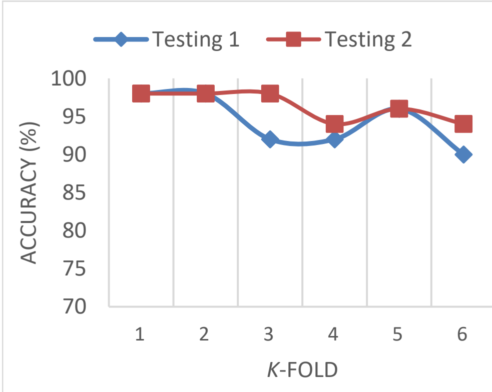

Figure. 8. Testing results of two different extracted ROI image datasets

Feature Extraction

In this research, the texture feature of dorsal hand vein image is extracted so that vein can be seen clearly. We use the Local Line Binary Pattern (LLBP) method to extract the feature and compare the result of LLBP with the result of the previous method, Local Binary Pattern (LBP) method.

The Local Binary Pattern (LBP) operator is a texture descriptor based on the gray level comparison of a neighborhood of pixels [9]. The original operator considers a 3×3 neighborhood of 8 pixels in around a center pixel ic. The threshold value, s(x), for these neighborhood pixels, is the value of the center pixel and the result considered as a binary number or its decimal equivalent LBP (xc, yc) [9]. LBP operator showed in Equation (1), and the threshold for the neighborhood pixels showed in Equation (2) [11].

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \quad (1)$$

$$s(x) = \begin{cases} 1, & if\ x \geq 0 \\ 0, & if\ x < 0 \end{cases} \quad (2)$$

Motivated by LBP, Petpon and Srisuk [13] proposed an LLBP operator for face recognition. The operator consists of two components: horizontal component (LLBPh) and a vertical component (LLBPv). The magnitude of LLBP can be obstained by calculating the line binary codes for both components. The main difference between LLBP and original LBP are as follows: 1) the LLBP operator has a straight shape line, this will greatly assist LLBP operator in capturing the change in image intensity. 2) The pattern of the image at left and right side of the center pixel of the line are a mirror because of the distribution of binary weight at left, and the right side is equal. Thus, the number of patterns can be reduced [5]. The illustration of LLBP operator is shown in Figure 5, and its mathematic definitions are given in Equations (3) - (5) [11].

$$LLBP_{hN,c}(x,y) = \sum_{n=1}^{c-1} s(h_n - h_c) \cdot 2^{c-n-1} + \sum_{n=c+1}^{N} s(h_n - h_c) \cdot 2^{n-c-1} \quad (3)$$

$$LLBP_{vN,c}(x,y) = \sum_{n=1}^{c-1} s(v_n - v_c) \cdot 2^{c-n-1} + \sum_{n=c+1}^{N} s(v_n - v_c) \cdot 2^{n-c-1} \quad (4)$$

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \quad (5)$$

LLBPh, LLBPv, and LLBPm are LLBP on horizontal direction, vertical direction, and its magnitude, respectively. N is the length of the line in the pixel, hn is the pixel along with the horizontal line, and vn is the pixel along with the vertical line. c = N/2 is the position of the center pixel, hc on the horizontal line and vc on the vertical line, and s(•) function defines a thresholding function as in Equation (2).

Employing Equations (2) and (3), the horizontal component of LLBP (LLBPh) extracts a binary code of N − 1 bits for each pixel. The same numbers of bits are extracted by the vertical component of LLBP (LLBPv) using Equations (2) and (4). Each ROI vein image is extracted by this coding method into LLBP feature vectors which dimension is 128 x 128. Figure 6 shows the results of feature extraction using LBP and LLBP, respectively.

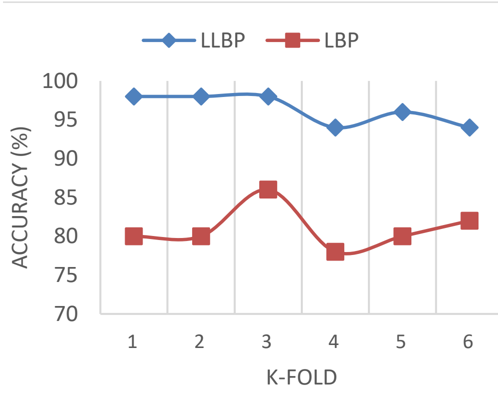

Figure 9. The performance comparison of LBP and LLBP method

Recognition

We use a Fuzzy k-NN classifier to match the extracted dorsal hand vein image from testing data with the one from training data. The basic concept of this classifier is to assign membership as a function of the object's distance from its k-nearest neighbors and the memberships in the possible class l.

Consider W = {w1, w2, ..., wm} a set of m labeled data, x is the input for classification, k is the number of closest neighbors of x, and E is the set of k nearest neighbors (NN). Let μi(x) is the membership of x in the class i, m be the number of elements that identify the classes l, and W be the set that contains some m elements. To calculate μi(x), we use Equation (6) [18].

$$\mu_i(x) = \frac{\sum_{j=1}^{k} \mu_{ij} \left(\frac{1}{\|x - m_j\|^{2/(m-1)}} \right)}{\sum_{j=1}^{k} \left(\frac{1}{\|x - m_j\|^{2/(m-1)}} \right)} \quad (6)$$

Since we use the Fuzzy k-NN method, each element of x testing data is classified in more than one class with membership value μi(x). The decision to which class the element of x testing data belongs is made according to which class the element of x testing data has the highest membership value μi(x).

3. Results and Analysis

The proposed method was implemented in Matlab R2011b and evaluated using our multispectral dorsal hand vein database. To demonstrate the robustness of the proposed approach, in our experiments, the total number of dorsal hand vein

TABLE 1
THE TESTING RESULT OF LLBP METHOD ON RIGHT DORSAL HAND AND LEFT DORSAL HAND VEIN DATABASE

K-Fold	Accuracy (%)	
	Right-hand	Left-hand
1	100	100
2	90	100
3	90	90
4	100	90
5	100	100
6	100	100
Average (%)	96.7	96.7

TABLE 2
COMPARISON OF FUZZY *K*-NN AND THE OTHER CLASSIFICATION METHOD

Method	Accuracy (%)	Time (s)
Neural Network	97.25	187.5
K-Nearest Neighbor	78	37.5
Fuzzy *K*-Nearest Neighbor	98	37.8

images contains over 50 classes. There are 6 sample images of each left dorsal hand. In total, the database contains 300 images. The spatial and depth resolution of the dorsal hand vein images were 1280 × 960 pixel and 256 gray levels, respectively.

To evaluate the proposed method for dorsal hand vein recognition, the experiments were conducted in five modes. The first experiment is conducted to show the comparison of fuzzy k-NN and k-NN method in recognition stage. Thus we use k=1 (for k-NN method) and k=2, k=3, k=4, k=5 (for fuzzy k-NN). The second experiment is conducted to show how parameter N of LLBP affects the recognition result of the proposed method. The third experiment is conducted to analyze the relationship between ROI image extraction and performance of the proposed method. The fourth experiment is conducted to evaluate the effectiveness of the proposed method for dorsal hand vein recognition by comparing its accuracy with LBP method. Then, the fifth experiment is conducted to apply the approach method on 60 right dorsal hand vein images obtained from 10 individuals (six samples per individual). These ten individuals are randomly chosen from our database.

In all experiments, if the test sample and the found template are from the same class, this is a correct recognition. Therefore, the proposed algorithm can be measured by correct recognition rate (CRR), the ratio of the number of samples being correctly classified to the total number of test samples. Using K-fold cross-validation procedure with K=6, we split data into six folds. In every K-fold, data was divided into 250 databases and 50 testing data that each dorsal hand of a person will have 5 sample images as database and an image sample as testing data, respectively.

In the first experiment, we used five different k values: k=1 (for k-NN), and k=2, k=3, k=4, k=5 (for fuzzy k-NN). Then, we compare the accuracy of each k, k is the number of closest neighbors that used when data is being classified. Figure 7 shows the experimental results.

As can be seen in Figure 7, the highest recognition result obtained from k=2 (fuzzy k-NN) with 96.3% of accuracy while the lowest is obtained from k=1 (k-NN) with 78% of accuracy. Considering the result of experiment 1, we use k=2 (fuzzy k-NN) for the next four experiments.

In this paper, we used the LLBP method to extract the features of the dorsal hand vein. However, there is an N-variable that represents the amount of neighbourhood pixel that used in LLBP. Therefore, in the second experiment, we tested LLBP method with six different N values (N= 7, 9, 11, 13, 15, and 17). And we find that all six different N values are equal in accuracy with the highest recognition result obtained from k-fold 1-3 with 98% of accuracy while the lowest is obtained from k-fold 4-5 with 94% of accuracy. This result proves that the number of neighbourhood pixel used for LLBP does not affect the recognition performance in this research. Therefore, we use the standard value of N, N=13 [13], as the number of neighborhood pixels for LLBP method for the next following experiments.

A further analysis of the proposed method is made by conducting the third experiment. In this experiment, we use two different extracted ROI image datasets: Testing 1 and Testing 2. Testing 1 is the extracted ROI image datasets which obtained randomly whereas Testing 2 obtained with fixing process. The experimental results of these two different extracted ROI image datasets is showed in Figure 8.

As can be seen in Figure 8, Testing 2 has higher accuracy compared to Testing 1. From 6-fold cross validation, the Testing 2 has accuracy up to 96.3% whereas the Testing 1 has accuracy up to 92.70%. These experimental results demonstrate that our current method depends on extracted ROI image. Thus, it is evident that the fixing process has a significant influence on the accuracy of verification. Since the ROI has been manually located, it cannot ensure that the ROI will always be in the same position in different dorsal hand vein images. Because of the unstable ROI extraction, there are some false recognized dorsal hand vein images. It is important to fix the ROI in the same position of different dorsal hand vein images to ensure the stability of the principal extracted vein features.

In this research, we also applied the LBP method on our dorsal hand vein image database to extract the vein feature and compare its accuracy with LLBP method. This experimental result will demonstrate the eminent performance of the proposed method. From the results shown in Figure 9, we can find that our proposed method, LLBP method, has higher accuracy compared to LBP method. From 6-fold cross validation, LLBP has accuracy up to 96.3% whereas LBP method has accuracy up to 81.0%.

The LLBP method, is a new approach of Local Binary Pattern (LBP). The LLBP operator has a straight-line shape; this will greatly assist LLBP operator in capturing the change in image intensity. Therefore, LLBP can extract robust features from the images with unclear veins it is more suitable to capture the pattern inside a dorsal hand vein image. Vein feature in extracted image using LLBP method is more distinct than vein feature in extracted image using LBP method as can be seen in Figure 6. The more distinct feature extracted, the higher the accuracy we get. Furthermore, we find that the accuracy of our proposed method, LLBP, is better than the accuracy of the previous method, LBP.

To further prove the effectiveness of the proposed method, we employed 60 right dorsal hand vein images obtained from 10 different individuals that we randomly choose from our database. Then, we make a detailed comparison between right dorsal hand vein images and left dorsal hand vein images with same total images. Table 1 details the experimental result.

From the results shown in Table 1, we can find that our proposed method has a good performance of 96.7% recognition accuracy for both right dorsal hand vein and left dorsal hand vein database. It is because our method well characterizes line-based features of the dorsal hand vein. Additionally, this method keeps the original form of local shape and achieves good information of the vein texture. Thus, we conclude that LLBP method is suitable for dorsal hand vein feature extraction.

Further analysis of classification method is made by comparing the performance of fuzzy k-NN and the other classification method, k-NN [16] and Neural Network algorithm [17] using 300 dorsal hand vein images. From the result shown in Table 2, we can find that fuzzy k-NN tends to be faster on matching time and provides the highest accuracy of recognition

4. Conclusion

We present a reliable and robust biometric-based recognition approach by using our multispectral dorsal hand vein images. To capture the line-based features of the dorsal hand vein and match different dorsal hand vein images, we proposed the Local Line Binary Pattern (LLBP) method. Compared to the existing method such as Local Binary Pattern (LBP), LLBP method is more reliable than LBP method for feature extraction on dorsal hand vein recognition with a recognition accuracy up to 98% on our left dorsal hand vein database. Moreover, using fuzzy k-NN method, the system can achieve higher recognition accuracy than the other classification method. Therefore, we conclude that the proposed method, LLBP for feature extraction and fuzzy k-NN method for recognition stage, is promising for dorsal hand vein recognition.

Through experimentation, it is also found that different techniques of ROI extraction give different results which have an impact on the later stages. The result proves that a well-defined extracted vein pattern gives better performance and leads to a more secure biometric authentication system. In future, an experiment conducted to obtain the better extracted ROI image is needed

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