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LOCAL LINE BINARY PATTERN FOR FEATURE EXTRACTION ON PALM VEIN RECOGNITION

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Abstract

In the recent years, palm vein recognition has been studied to overcome problems in conventional systems in biometrics technology (finger print, face, and iris), such as convenience and performance. However, due to the image of palm vein that is not always clear, the veins are not segmented properly, therefore, the recognition accuracy may be degraded. To overcome this problem, we propose a palm vein recognition system using Local Line Binary Pattern (LLBP) method that can extract robust features from the palm vein images that has unclear veins. LLBP is an advanced method of Local Binary Pattern (LBP), a texture descriptor based on the gray level comparison of a neighborhood of pixels. There are four major steps in this paper, Region of Interest (ROI) detection, image preprocesssing, features extraction using LLBP method, and matching using Fuzzy k-NN classifier. The proposed method was applied on the CASIA Multi-Spectral Image Database. Experimental results show that the proposed method using LLBP has a good performance with recognition accuracy 97.3%. In future, experiments will be conducted to observe which parameter can affect processing time and recognition accuracy of LLBP is needed.

Keywords: *Fuzzy k-NN, LLBP, Local Line Binary Pattern, palm vein.*

Abstrak

Saat ini penelitian tentang pengenalan pembuluh darah pada telapak tangan (*palm vein recognition*) telah banyak dilakukan untuk mengatasi masalah dalam teknologi biometrika yang lainnya (pengenalan sidik jari, wajah dan iris) seperti ketidaknyamanan pengguna saat akusisi citra maupun tingkat keakuratan pengenalannya. Namun masalah yang sering muncul dalam sistem pengenalan pembuluh darah pada telapak tangan (*palm vein*) adalah fitur tekstur pembuluh darah (*vein*) yang kurang jelas. Untuk mengatasi masalah tersebut, paper ini mengusulkan sistem pengenalan *palm vein* menggunakan metode *Local Line Binary Pattern* (LLBP) yang telah teruji dapat mengekstraksi fitur pembuluh darah pada gambar dengan jelas. LLBP merupakan metode pengembangan dari *Local Binary Pattern* (LBP), metode yang menggunakan kombinasi nilai-nilai biner dari piksel ketetanggaannya. Empat tahapan utama dalam penelitian ini yaitu deteksi *Region of Interest* (ROI), *preprocessing* yang terdiri dari *resize*, penghilangan noise dan *subtract* citra, ekstraksi fitur menggunakan metode LLBP dan pengenalan menggunakan Fuzzy k-NN. Metodologi yang diusulkan telah diuji pada *database* citra *palm vein* CASIA Multi-*Spectral*. Hasil percobaan menunjukkan bahwa metodologi yang diusulkan dapat mencapai akurasi sampai dengan 97.3%. Untuk penelitian selanjutnya, diperlukan observasi untuk mengetahui parameter yang mempengaruhi waktu proses dan akurasi pengenalan dari metode LLBP.

Kata kunci: *Fuzzy k-NN, LLBP, Local Line Binary Pattern, palm vein*

1. Introduction

Biometrics is the technology of identifying a person by using physical human features. There have been several kinds of biometric recognition systems such as fingerprint, palm print, face, iris, etc. These conventional systems have some problems in terms of convenience and performance. In fingerprint and palm print recognition systems, users have to touch the surface of the input sensor by their finger and palm. This can cause much inconvenience for the user and it is also possible to steal latent information from the fingerprint sensor. In addition, the condition of the finger surface (e.g. sweat, dryness) and skin distortion can cause degraded recognition accuracy. For face recognition, performance highly depends on facial expressions and illuminations, which can change. Iris

TABLE 1
EXPERIMENT IN RECOGNITION SYSTEM

Recognition System	Feature Extraction	Matching	Result
Palm Vein[5]	LBP	ROC Curve	Accuracy 93%
Finger Vein[6]	LLBP	Hamming Distance	EER 1.89%
Face[7]	LLBP	Local Discriminant Analysis	Accuracy 100%

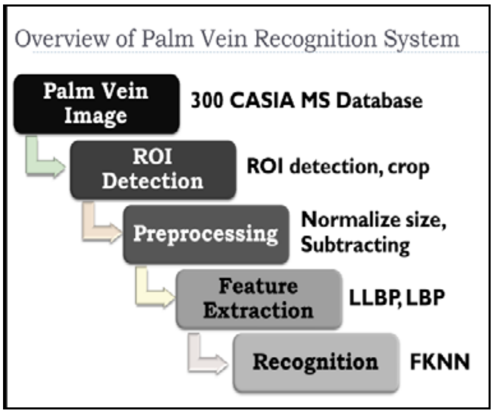


Figure 1. The overview of proposed method for palm vein recognition.

recognition is most reliable in terms of accuracy, but the capturing device is expensive and can be inconvenient compared to other biometric systems [1]. To overcome these problems, vein patterns such as palm vein and finger vein have been studi-ed. Vein recognition uses internal information fr-om a person's body and vein patterns, which can be seen with infrared light illuminators and a ca-mera. Compared to finger vein, palm vein has mo-re features that used for recognition. Otherwise, it can show better result for recognition system. Pa-lm vein recognition technology is secure because the authentication data exists inside the body and so it is very difficult to forge [2]. It is highly accu-rate. Palm vein recognition system consists of five key steps: Infrared pal m images captured, detec-tion of Region of Interest (ROI), pre-processing, feature extraction and feature matching [3].

Most of the current available approaches for palm vein recognition have similarities on the fea-ture extraction method which utilized the features from the segmented blood vessel network for re-cognition. In 2011, [5] proposed a method for ex-tract the texture feature of palm vein image using Local Binary Pattern (LBP) with accuracy of 93%. The experiment shows that unclear vein can become the problem in palm vein recognition. At the same year, [6] conducted an experiment for fi-nger vein recognition using a new variant of LBP called local line binary pattern (LLBP) to over-

Figure 2. The sample of palm vein image.

come the problem of unclear vein. LLBP method is proposed for the first time by [7] in 2009 and it applied to face recognition.

Palm vein images are not always clear, there-fore, segmentation errors can occur during feature extraction process due to the low qualities of palm vein images. When the veins are not segmented properly, the recognition accuracy may be degra-ded. To overcome these problems, we propose pa-lm vein recognition system based on local feature using LLBP (Local Line Binary Pattern) method. The main difference between LLBP and LBP is its neighborhood shape is a straight line with leng-th N pixel, unlike in LBP, which is a square [6]. The straight-line shape of LLBP can extract ro-bust features from the images with unclear veins it is more suitable to capture the pattern inside a pa-lm vein image. Therefore, recognition performan-ce of palm vein will be good (see Table 1). For recognition step, we considered the fuzzy k-NN [8] to be a suitable classifier since it does not need any learning algorithm so that it can decrease the processing time. Moreover, due to the feature of palm vein image that similar to each other, we choose fuzzy k-NN method over k-NN method to avoid the false recognition of palm vein image.

2. Methods

Figure 1 shows the block diagram of the proposed method for palm vein recognition. The method consists of five main stages: image acquisition (image is downloaded from CASIA Database), ROI (Region of Interest) detection, preprocessing, feature extraction by Local Line Binary Pattern (LLBP) and palm vein recognition by Fuzzy k-NN classifier.

Dataset

The dataset used in this work is downloaded from the CASIA Multi-Spectral Palmprint Image Data-base V1.0 [9]. This dataset consists of palm vein images of 50 individuals (six samples per indivi-

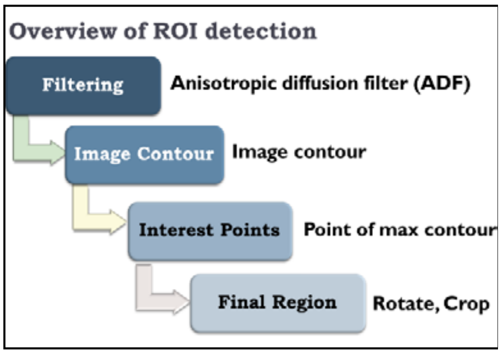


Figure 3. The overview of ROI detection.

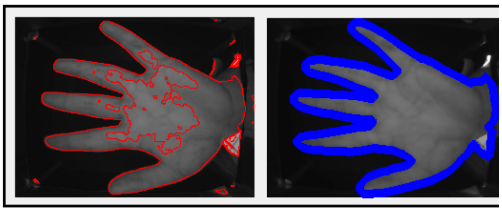


Figure 4. The result of image contour (left) and max contour (right).

dual), captured under six different NIR illuminetors. These six images were acquired from each user and these images were acquired in two different data acquisition sessions (three images in each session) with a minimum interval of one month. Palm veins are most visible under the illuminator at 940 nm wavelength. The sub-set used here contains all samples from all individual left hands under 940 nm illuminator [5]. Figure 2 shows the sample of palm vein image used in this research.

ROI Detection

To increase the recognition accuracy and reliability, it is important to extract the features of vein patterns from the same region within different palm vein images. This process is known as extraction of region of interest (ROI). Figure 3 shows the overview of ROI detection step in this research, which consist of edge detection using anisotropic diffusion filtering, find the maximum image contour, find interest point and final region (ROI) detection.

Annisotropic Diffusion Filtering (ADF)
Annisotropic diffusion used in edge detection algorithms. By running the diffusion with an edge seeking diffusion coefficient for a certain number of iterations, the image can be evolved towards a piecewise constant image with the boundaries between the constant components being detected as

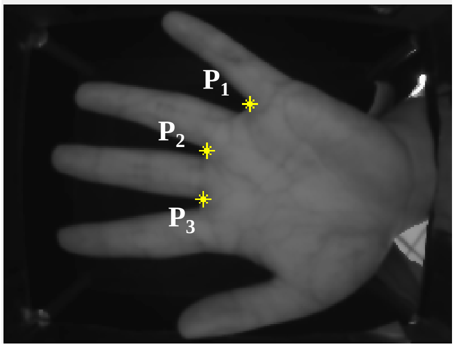


Figure 5. The interest points of palm vein image.

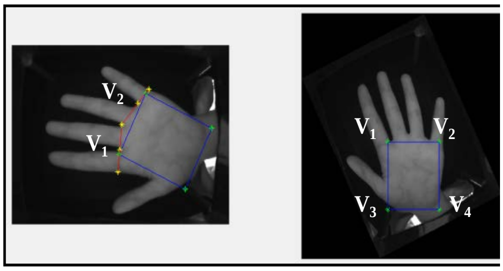


Figure 6. The final region (ROI) detection.

edges [10]. Annisotropic Diffusion make image more smooth so in the next step edge can detected more specific. That is because the diffusion coefficient is chosen to vary spatially, in such a way, as to encourage intra region smoothing in preference to inter region smoothing. As the region boundaries a high quality edge detector which successfully exploits glob al information. In this research we use 13 neighborhood pixels for diffusion and because we want to detect edge of image (*I*) we maintaining high contrast compared to the low contrast.

Image Contour
The principle of image contour is similar to edge detection. But the image contour detected the curve while the edge detection detected edge. Detection of the curve is used as a straight line to suffer the effects of discretization that create zigzag lines in accordance with the tilt angle. Image contour is done after filtering using aniso-tropic diffusion filter by pulling on the contour plot of the intensity of the image.

At first axes image contour detection is to detect areas that contrast with the background including hand edge and the edge of the palm vein. Then max contour to thicken the layout contour edges on the outside with maximizing of x and y that are detected is the edge of the hand. With the edge being detected we can separate the foreground (hand) and the background.

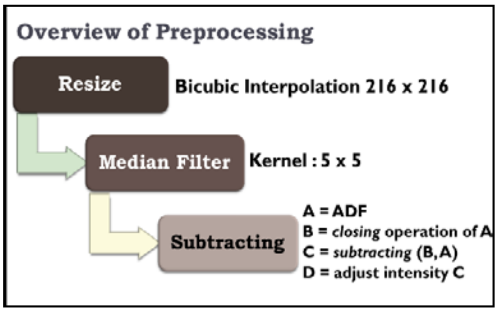


Figure 7. The overview of preprocessing step.

Interest Point
Interest point is some points in the hand that have specific interest maximum point on the contour. Which the maximum is set to the 3 highest contours. The three points are the point of the arch between the fingers. Those points located between pinkie and ring finger (P_1), ring finger and middle finger (P_2) and also between the middle finger and index finger (P_3).

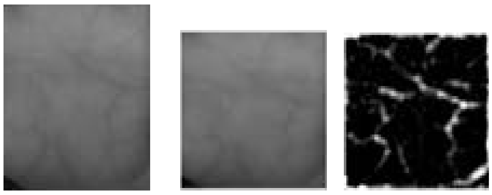
Final Region
Next step is to pull out line from P1 to the furthest edge and set the middle point in between (V_1). The second line is to pull out from P3 to the furthest edge in index finger area and also set the middle point in between (V_2). Then, the points V_1 and V_2 showed in Figure 6 (left) can be located. With the points V_1 and V_2, the ROI is defined as a rectangular region V_1–V_2–V_3–V_4, where $lV_1V_3 = 1.25 \times lV_1V_2$. Figure 8(a) shows the result of the extracted ROI for the palm vein image in Figure 6 (right). The image with ROI detected is rotated then so that line V_1V_2 is horizontal. The rectangular region is cropped and used for feature extraction to get the texture of vein.

Preprocessing

After ROI extraction, the next step is preprocesssing that showed in Figure 7. First, resize the image using *bicubic* interpolation which the dimension is 216 x 216 pixels, then enhance the image using median filter with the 5 x 5 kernel. The last step of preprocessing is subtracting the original image from the background. Figure 8(b) and Figure 8(c) shows the results of resizing and subtracting step.

Feature Extraction

After preprocessing, the next step is to extract the feature of image. In this research, the texture feature of palm vein image is extracted so that vein can be seen clearly. We use the Local Line Binary



(a) (b) (c)

Figure 8. (a) Extracted ROI, (b) resized image and (c) subtracted imageP.

Pattern (LLBP) method to extract the feature and compare the result of LLBP with the result of 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 [4]. The original operator considers a 3×3 neighborhood of 8 pixels i_n around a center pixel i_c. The threshold $s(x)$ for these neighborhood pixels is the value of the center pixel and the result considered as a binary number or its decimal equivalent $LBP(x_c, y_c)$ [5]. LBP operator showed in equation(1) and the threshold for the neighbor-hood pixels showed in equation(2).

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

Motivated by LBP, Petpon and Srisuk [7] proposed an LLBP operator for face recognition. The operator consists of two components: horizontal component (*$LLBP_h$*) and vertical component (*$LLBP_v$*). The magnitude of LLBP can be obtained by calculating the line binary codes for both components.

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

The main difference between LLBP and original LBP are as follows: 1) the LLBP operator has a straight line shape, this will greatly assist LLBP operator in capturing the change in image intensity, 2) the pattern of image at left and right side of the center pixel of the line are mirror because of the distribution of binary weight at left and right side are equal, Thus, the number of pattern can be reduced. The illustration of LLBP operator is shown in Figure 9, and its mathematic definitions are given in equations(3)–(5).

$LLBP_h$, $LLBP_v$ and $LLBP_m$ are LLBP on horizontal direction, vertical direction, and its magnitude, respectively. N is the length of the line in pixel, h_n is the pixel along with the horizontal line and v_n is the pixel along with the vertical line. c =

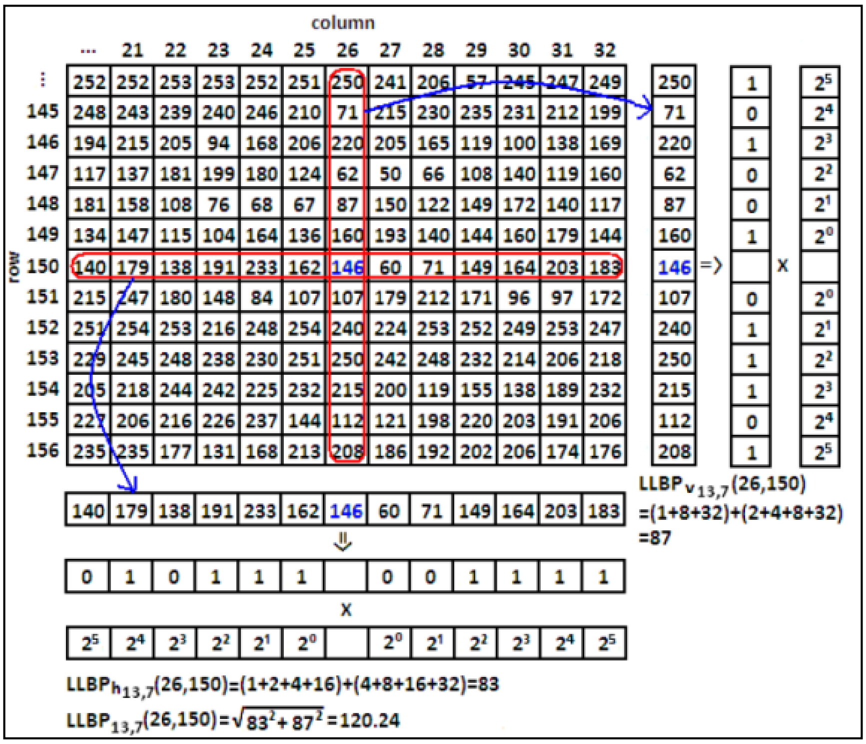


Figure 9. Example of LLBP operator [6].

$N/2$ is the position of the center pixel, h_c on the horizontal line and v_c on the vertical line, and $s(\bullet)$ function defines a thresholding function as in equation(2).

Employing equations(2) and (3), the horizontal component of LLBP ($LLBP_h$) extracts a binary code of N−1 bits for each pixel. The same numbers of bits are extracted by the vertical component of LLBP ($LLBP_v$) using equations(2) and (4). Consequently, by concatenating the binary codes from $LLBP_h$ and $LLBP_v$, the total binary code of LLBP for each pixel is $2(N-1)$ bits. In Figure 9, the binary sequence for horizontal (vertical) component is defined from left (top) as 010111-001111(2) (101001011101(2)). Hence, the binary code for LLBP is 010111001111101001011101 (2). Figure 10 shows the results of feature extraction using LBP and LLBP, respectively.

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

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

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

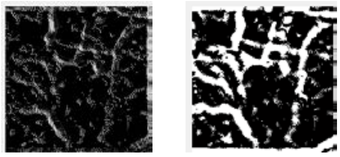
Matching (Recognition)

We use fuzzy k-NN classifier to match the extracted palm 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. The pseudo-code of fuzzy k-NN classifier presented in Figure 11.

Consider $W = \{w_1, w_2, ..., w_m\}$ 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 $\mu_i(x)$ 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 contain the m elements. To calculate $\mu_i(x)$, we use equation(6) [8].

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

(6)



(a) (b)

Figure 10. The extracted feature of image using (a) LBP and (b) LLBP.

```
BEGIN
Input x, (testing data)
Set k, 1 ≤ k ≤ m
Initialize i=1
DO UNTIL (KNN from x is found)
   Calculate distance from x to xi
   IF (i ≤ k)
       THEN add xi to E
   ELSE IF (xi is closer to x than any
   previous NN) THEN
       Delete the farthest neighbor
       and include Xi in the set E
   END IF
END DO UNTIL
Initialize i=1
DO UNTIL (x has membership value of all
class i)
   Calculate μi(x)
   Increment i
END DO UNTIL
END
```

Figure 11. Pseudo-code of fuzzy k-NN classifier.

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

3. Results and Analysis

The proposed method was implemented in Matlab R2011b and evaluated using CASIA palm vein database [9]. There are 50 sets of left palm used with 6 sample images for each palm of a person. In total, the database contains 300 images. The spatial and depth resolution of the palm vein images were 768×576 pixel and 256 gray levels, respectively.

Using K-fold cross validation procedure with *K*=6, we split data into 6 folds. In every K-fold, data was divided into 250 database and 50 testing data that each palm of a person will has 5 images as database and 1 image as testing data, respectively.

There are three experiments in this research. Experiment 1 and 2 are conducted to show how parameters k of fuzzy k-NN and *N* of LLBP affect the verification accuracy of this research, while experiment 3 conducted to compare the accuracy of LBP and LLBP method.

TABLE 3
THE RESULT OF EXPERIMENT 2

N	Accuracy (%)			
	k=2	***k=3***	***k=5***	***k=7***
9	97.3	97.0	94.3	94.0
13	97.3	97.0	94.3	94.0
17	97.3	97.0	94.0	94.7
21	97.3	97.0	94.0	94.7

TABLE 2
THE RESULT OF EXPERIMENT 1

***K*-Fold**	Accuracy (%)			
	k=2	*k=3*	*k=5*	*k=7*
1	98	96	90	90
2	96	96	92	94
3	96	96	96	94
4	98	98	96	98
5	98	98	96	92
6	98	98	96	96
Mean (%)	**97.3**	97	94.3	94

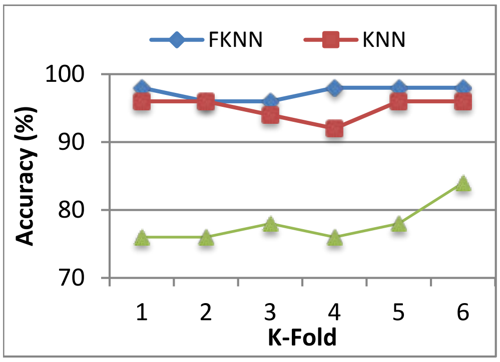


Figure 12. Comparison accuracy of FKNN, FKNN and SVM.

$$Acc = \frac{Number\ of\ correctly\ recognized}{Number\ of\ data\ set}\ x\ 100\% \quad (7)$$

Experiment 1: we used 4 different *k* values in fuzzy k-NN: *k*=2, *k*=3, *k*=5, *k*=7 and compare the accuracy of each *k*, *k* is the number of closest neighbors that used when data is being classified. Motivated by [7], in this experiment, we use the standard value of *N*, *N*=13, as the neighborhood pixel for LLBP method. Since we used 6-fold cross-validation procedure, the predictive accuracies on the testing data of the 6 runs of each k are averaged and reported as the predictive accuracies. In Table 2, classification result with predicttive accuracy is reported for all of *k* values. Accuracy is a comparison between the number of correctly recognized data and total number of data set. The accuracy is calculated using equation(7).

As can be seen in Table 2, the highest recognition result obtained from *k*=2 with 97.3% of mean accuracy while the lowest is obtained from *k*=7

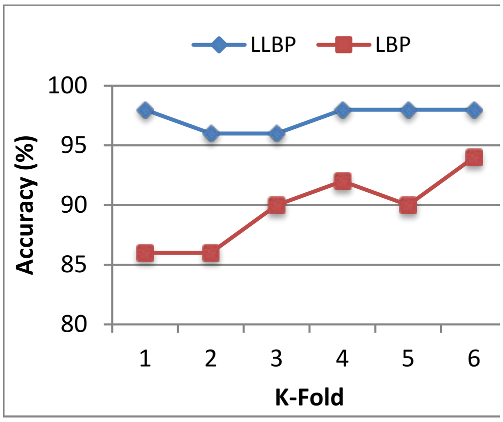


Figure 13. Comparison accuracy of LBP and LLBP.

with 94% of mean accuracy. Experiment with higher *k* shows the lower value of mean accuracy. This result also affected by the behavior of the data set used in this experiment that has many classes (50 classes) but few instances (5 instances). Considering the result of experiment 1, we use *k*=2 as the optimum value for experiment 3.

Due to the feature of palm vein image that si-milar to each other, we choose fuzzy k-NN method over k-NN method to avoid the false recognition of palm vein image. To provide that FKNN is more suitable with the data on this experiment, we also compare the accuracy of FKNN and the other classification method such us KNN and SVM (*support vector machine*). Figure 12 shows the comparison accuracy of palm vein recognition using FKNN, KNN and SVM.

As can be seen in Figure 12, FKNN method has better accuracy than KNN method and SVM method. FKNN has 97.3% of mean accuracy whereas KNN method has 95% of mean accuracy and SVM method has 78% of mean accuracy. Thus we conclude that FKNN method is more suitable than KNN and SVM method for classification the feature of palm vein image in this experiment.

Experiment 2: we used 4 different values of N that represent the number of neighborhood pixel that used in LLBP: *N*=9, *N*=13, *N*=17 and *N*=21 and we tested each N value with 4 different values of k for fuzzy k-NN: *k*=2, *k*=3, *k*=5, *k*=7. Table 3 shows the result of experiment 2. The accuracy is the mean accuracy of 6-fold cross-validation.

As can be seen in Table 3, there is no significant difference of mean accuracy for each *N* value of LLBP. This shows that the number of neighborhood pixel used for LLBP not affect the verification of accuracy in this research. But according to [6], parameter *N* will affect the processsing time, the bigger the *N* value, the longer the processing time for feature extraction. In this research, we do not conducted experiment to observe how the *N* value can affect the processing time.

Experiment 3: we also use the LBP method to extract the feature in order to compare its accuracy with LLBP method. According the result of experiment 1, we used *k*=2 as the optimum value for recognition using fuzzy k-NN. The result of experiment 3 showed in Figure 13.

We have compared our proposed method results with the result of LBP method using *k*=2 for Fuzzy k-NN classifier. We use K-fold cross validation procedure [11] to validate the accuracy for both methods. As can be seen in Figure 13, for all of K-fold, our proposed method, LLBP method, has higher accuracy compared to LBP method. From 6-fold cross validation, LLBP has 97.3% of mean accuracy whereas LBP method has 90.3% of mean accuracy.

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 palm 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 10. The more distinct feature extracted, the higher the accuracy we get. Thus we conclude that LLBP method is more reliable than LBP method for extract the feature on palm vein recognition.

4. Conclusion

This paper has proposed LLBP method, a new approach of LBP, for reliable personal identify-cation using palm vein representations. The LLBP method can capture the pattern inside a palm vein image with recognition accuracy of 97.3% from the left hand palm vein images of the CASIA database. The result of this research shows that LLBP method is more reliable than LBP method for feature extraction on palm vein recognition. In future, experiment conducted to observe what parameter that can affect the processing time and recognition accuracy of LLBP is needed.

References

[1] K. R. Park, “Finger vein recognition by combining global and local features based on SVM,” *Computing and Informatics*, vol. 30, pp. 295-309, 2012.

[2] Palm Vein Pattern Authentication Technology, Fujitsu white paper, 2005.

[3] L. Mirmohamadsadeghi, & A. Drygajlo, “Palm vein recognition with local binary patterns and local derivative patterns,” *In*

Biometrics (IJCB), 2011 International Joint Conference on , pp. 1-6, 2011.

[4] T. Ojala, M. Pietikainen, & T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 24, pp. 971-987, 2002.

[5] L. Mirmohamadsadeghi, & A. Drygajlo, “Palm vein recognition with local texture patterns,” *IET Biometrics*, vol. 3, pp. 198-206, 2014.

[6] B. A. Rosdi, C. W. Shing, & S. A. Suandi, “Finger vein recognition using local line binary pattern,” *Sensors*, vol. 11, pp. 11357-11371, 2011.

[7] A. Petpon, & S. Srisuk, Face recognition with local line binary pattern. *In Image and Graphics, 2009. ICIG'09. Fifth International Conference on*, pp. 533-539, 2009.

[8] J. M. Keller, M. R. Gray, & J. A. Givens, “A fuzzy k-nearest neighbor algorithm. Systems, Man and Cybernetics,” *Systems, Man and Cybernetics, IEEE Transactions on*, vol. 15, pp. 580-585, 1985.

[9] CASIA Multi-Spectral Palmprint Image Database V1.0 http://biometrics.idealtest.org/dbDetailForUser.do?id=6.

[10] P. Perona, & J. Malik, “Scale-space and edge detection using anisotropic diffusion,” *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 12, pp. 629-639, 1990.

[11] R. Kohavi, “A study of cross-validation and bootstrap for accuracy estimation and model selection,” *In IJCAI*, vol. 14, pp. 1137-1145, 1995.