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LOCAL LINE BINARY PATTERN AND FUZZY K-NN FOR PALM VEIN RECOGNITION

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ABSTRACT

Recently, palm vein recognition has been studied to overcome the problem in terms of convenience and performance of conventional systems in biometrics technologies such as fingerprint, palm print, face, and iris recognitions. However, palm vein images that are used in palm vein recognition systems are not always clear but sometimes can show irregular shadings and highly saturated regions that can slow the processing time. To overcome this problem, we propose palm vein recognition system using Local Line Binary Pattern (LLBP) method that was reliable against irregular shadings and highly saturated regions. LLBP is a texture descriptor based on the gray level comparison of a neighborhood of pixels. Proposed method have been conducted in three major steps: preprocessing that includes Region of Interest (ROI) detection, image resizing, noise removal and image enhancement, feature extraction using LLBP method, and matching using Fuzzy k-NN classifier. We use CASIA Multi-Spectral Image Database as dataset to examine proposed method. Experimental results show that the proposed method using LLBP has a good performance with 93.2% recognition accuracy.

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

1. INTRODUCTION

Biometrics is the technology of identifying people using human physiological features. There are several kinds of biometrics recognition systems such as fingerprint, palm print, face, iris, etc. [1][2]. Fingerprint and palm print systems have some problems in terms of convenience and performance because users have to touch the surface of the input sensor by their finger and palm. In addition, degradation of recognition accuracy may occur in fingerprint recognition because the condition of the finger surface (e.g. sweat, dryness) and skin distortion [3]. Whereas in performance of face recognition highly depends on facial expressions and illuminations, which can change. In fact, iris recognition is most reliable in terms of accuracy, but the capturing device is expensive and can be inconvenient compared to other biometrics systems [1][4]. Therefore, many researcher focus on vein recognition in the study of biometric technology [1–12].

The hand contains an amount of information. The characteristics of palm vein that captured from the hand, is more reliable than another biometric characteristic. It's because vein located in volume, so feature more robust and secure [1][5].

Both of feature extraction and feature matching methods take effect in the accuracy of palm vein recognition. Palm vein imaging can be seen by infrared light illuminators and a camera [6][11]. Different methods to extract features from infrared images have been studied. Recently, local texture descriptor also gained attention wherein a good texture descriptor is one of the key issues for palm vein feature extraction method.

A variety of different descriptor for the performance of image patches has been developed. The Local Binary Patterns (LBP) operator has been proposed for palm vein recognition [6], face recognition [13], and facial expression recognition [14]. The Local Derivative Patterns (LDP) has been proposed for palm vein recognition [6] and face recognition [13]. However, proposed Local Line Binary Pattern (LLBP) for finger vein recognition [10] and face recognition [15] has shown that LLBP descriptor better than LBP and LDP.

Beside feature extraction, feature matching also one of the main step in palm vein recognition. We considered the fuzzy *k*-NN [16] to be a suitable classifier since it does not need any learning algorithm so that it can decrease the processing time.

Therefore, in this paper, we proposed to investigate palm vein recognition using Local Line Binary Pattern as a new variant of LBP feature extraction approach and Fuzzy k-NN as feature matching approach. This research has been conducted to address what the best descriptor for palm vein recognition to overcome the problems in infrared images feature extraction. Also, identifying what the appropriate feature extraction approach that combined with Fuzzy k-NN matching approach.

2. LITERATURE REVIEW

There are four key steps in palm vein recognition system: Infrared palm images captured, detection of Region of Interest (ROI), pre-processing, feature extraction and feature matching [6][12].

Many approaches have been studied in palm vein recognition [6][7][8]. Most of the currently available approaches for palm vein recognition have similarities on the feature extraction method which utilized the features from the segmented blood vessel network for recognition [7][9]. However, palm vein images are not always clear but irregular shadings and highly saturated regions may be occur. Therefore, segmentation errors can be occurred during the feature extraction process due to the low quality of palm vein images. When the networks are not segmented properly, the recognition accuracy may be degraded. Also, the step of palm vein extraction can slow the processing time.

To solve the problem, Leila and Andrzej [6] proposed a method for palm vein recognition using Local Binary Pattern (LBP) and Local Derivative Pattern (LDP). They modifying Gaussian high-pass filter to enhance the captured palm vein images. Then, LBP and LDP are applied to extract the binary codes from the enhanced images. The measurement of similarity between the extracted and enrolled binary using Hamming distance. The recognition accuracy when LDP is used as feature extraction method is good, but the processing time is 2.5 times longer than the LBP. Moreover, LDP needs the memory size four time bigger to store the binary codes than those of the LBP [11].

The main difference between LLBP and LBP or LDP is its neighborhood shape which is a straight line with length N pixel, while in LBP or LDP it is a square [11]. The straight-line shape of LLBP can extract robust features from the images with unclear veins, it is suitable to capture the pattern inside a palm vein image and reliable against irregular shadings and highly saturated regions [10]. Therefore, recognition performance of palm vein will be good.

3. PROPOSED METHOD

Figure 1 shows the block diagram of the proposed method for palm vein recognition. The method consists of four main stages: image acquisition (image is downloaded from CASIA Database), preprocessing, feature extraction using Local Line Binary Pattern (LLBP) descriptor and palm vein matching/recognition using Fuzzy *k*-NN classifier.

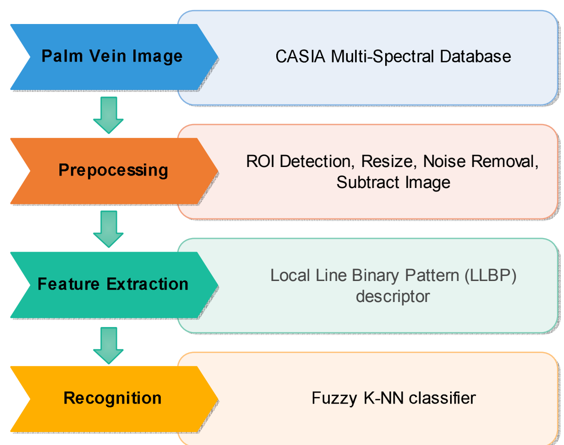

Figure 1: The Proposed Method For Palm Vein Recognition

2.1 Palm Vein Database

The database used in this work is downloaded from the CASIA multi-spectral Palm print Image Database V1.0 (CASIA database/ http://www.cbsr.ia.ac.cn/english/Palmprint%20Databases.asp). This database consists of palm vein images of 100 individuals (six samples per individual), captured under six different NIR illuminators. 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 [10]. Figure 2 shows the sample of palm vein image used in this research.

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Figure 2: The Sample Of Palm Vein Image

2.2 Preprocessing

There are three major steps in the preprocessing stage, which are ROI extraction, image resizing and image enhancement. The figure of ROI extraction phase is shown in Figure 3.

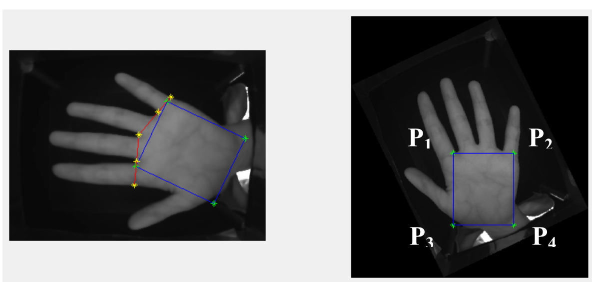

Figure 3: The Processing Of ROI Extraction

Step 1: The contour of the hand is extracted by a threshold.
Step 2: For each point on the hand contour, the distance to the mid-point of the wrist is calculated, and then the four valley points between the fingers can be located. We can find the valley point between the thumb and forefinger as the distance between these points and the mid-point of the wrist is calculated. Then, the points P_1 and P_2 showed in Figure 3(right) can be located.
Step 3: With the points P_1 and P_2, the ROI is defined as a rectangular region P_1–P_2–P_3–P_4, where lP_1P_3 = 1.25 × lP_1P_2. Figure 5(a) shows the result of the extracted ROI for the palm vein image in Figure 3(right).

Figure 4: The procedure of ROI detection of palm vein image

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. The second and fourth finger webs are selected to fix the region that is defined as ROI. The procedures are shown in Figure 4 [10].

After ROI extraction, the next step is image resizing using cubic interpolation which the dimension is 216 x 216 pixels, then image enhancement with subtracting the original image from the background. Figure 5(b) and 5(c) show the results of both steps.

(a)
(b)
(c)

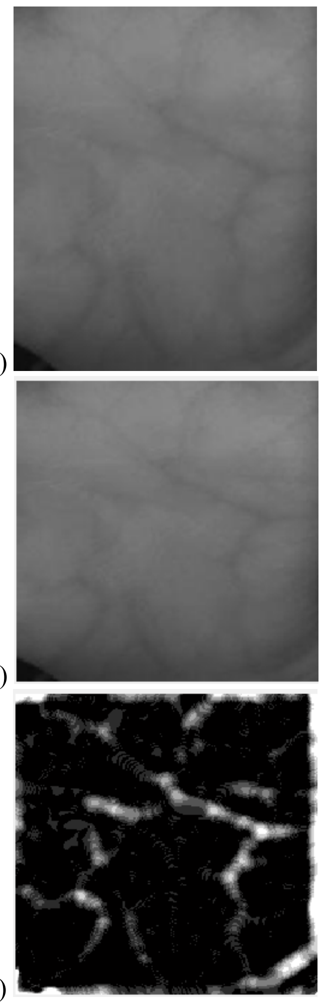

Figure 5: Extracted ROI (A), Resized Image (B) And Subtracted Image (C)

2.3 Feature Extraction

The Local binary pattern (LBP) operator is a texture descriptor based on the gray level comparison of a neighborhood of pixels. The original operator considers a 3×3 neighborhood of 8 pixels around a center pixel. This neighborhood is thresholded by the value of the center pixel and the result considered as a binary number or its decimal equivalent [10]. LBP operator as defined in Equation (1).

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

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

Petpon and Srisuk [11] proposed an LLBP operator for face recognition. The operator consists of two components: horizontal component ($LLBP_h$) and a vertical component ($LLBP_v$). The magnitude of LLBP can be obtained by calculating the line binary codes for both components.

The main differences between LLBP and original LBP are as follows: 1) the LLBP operator has a straight line shape, it will greatly assist LLBP operator in capturing the change of image intensity. 2) the image patterns in the left and right side of the center pixel of the line are a mirror because of the distribution of binary weight at left and right side are equal, Thus, the number of the pattern can be reduced.

The illustration of LLBP operator is shown in Figure 6, and its mathematic definitions are given in Equations (3), (4), and (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, $c = N/2$ is the position of the center pixel h_c on the horizontal line and v_c 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 ($LLBP_h$) 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 6, the binary sequence for the horizontal (vertical) component is defined from the left (top) as $010111001111_{(2)}$ ($101001011101_{(2)}$). Hence, the binary code for LLBP is $010111001111101001011101_{(2)}$. Figure 7 shows the results of feature extraction using LBP and LLBP, respectively.

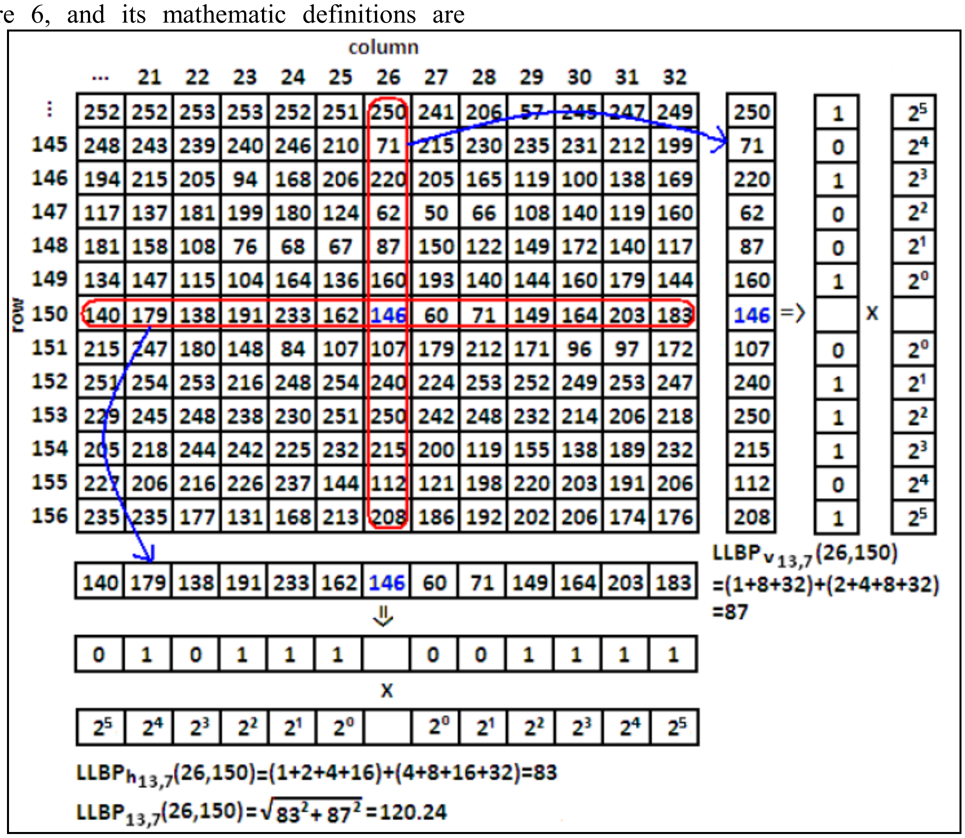

Figure 6: Example Of LLBP Operator [10].

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

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

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


(a)
(b)

Figure 7: The Extracted Feature Of Image Using LBP (A) And LLBP (B)

2.4 Matching/Recognition

We use a fuzzy k-NN classifier to match the extracted palm vein images 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 8.

```
Set k
{Calculating the NN}
  for i = 1 to t
     Calculate distance from x to m_i
     if i<=k
       then add m_i to E
     else if m_i is closer to x than any
          previous NN
       then delete the farthest
            neighbor
            and include m_i in the set E
```

Figure 8: Pseudo-Code Of Fuzzy K-NN Classifier

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 class i, m be the number of elements that identify the classes l, and W be the set that contains the m elements. To calculate $\mu_i(x)$, we use Equation (6) [16].

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

Since we use the fuzzy k-NN method, each element of x testing data is classified in more than one class with membership value $\mu_i(x)$. 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 $\mu_i(x)$.

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4. EXPERIMENT RESULT AND ANALISYS

The proposed method was implemented in Matlab and evaluated using palm vein image from CASIA Palmprint databases (http://www.cbsr.ia.ac.cn/english/Palmprint%20Databases.asp). There are 50 sets of left palm used with 5 image samples for each palm of a person. In total, the database contains 250 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=5, we split data into 5 folds. In every K-fold, data was divided into 200 training data and 50 testing data that each palm of a person will have 4 images as training data and 1 image as testing data, respectively.

There are two experiments in this research. Experiment 1: we used 5 different *k* values in fuzzy *k*-NN: *k*=2, *k*=3, *k*=5, *k*=7, *k*=9 and compared the accuracy of each *k*, *k* is the number of closest neighbors that used when data is being classified. Since we use 5-fold cross-validation procedure, the predictive accuracies on the testing data of the 5 run of each *k* are averaged and reported as the predictive accuracies. In Table 2, classification result with predictive accuracy is reported for all of the *k* values. Accuracy is a comparison between the number of correct recognized data and a total number of data set. The accuracy is calculated using Equation (7).

$$Accuracy = \frac{Number\ of\ \ correct\ recognized\ data}{Number\ of\ data\ set}\ x\ 100\% \tag{7}$$

Table 1: Experiment Result

K-Fold	Accuracy (%)				
	***k*=2**	***k*=3**	***k*=5**	***k*=7**	***k*=9**
1	96	94	84	84	82
2	98	94	92	86	86
3	92	92	90	86	86
4	88	86	84	80	78
5	92	86	88	84	80
Mean (%)	**93.2**	90.4	87.6	84	82.4

As shown in Table 1, the highest recognition result obtained from *k*=2 with 93.2% of mean accuracy while the lowest is obtained from *k*=9 with 82.4% 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 (4 instances). Considering the result of experiment 1, we use *k*=2 in experiment 2.

Experiment 2: we also use the LBP method to extract the feature in order to compare its accuracy with LLBP method. The result of experiment 2 shown in Figure 9.

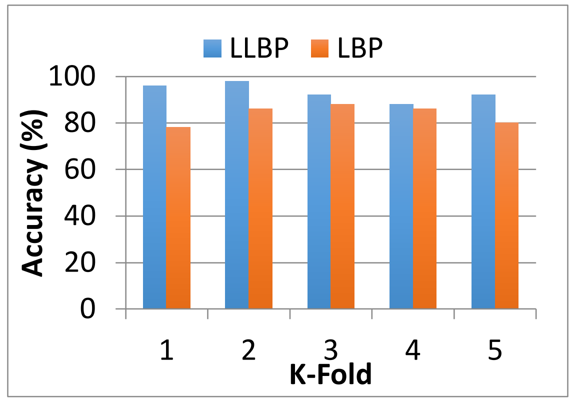

Figure 9: Comparison Accuracy Of LBP And LLBP

We have compared our proposed method results with the result of LBP method using *k*=2 for the Fuzzy *k*-NN classifier. As can be seen in Figure 9, our proposed method, LLBP method, has a higher accuracy (93.2%) compared to the LBP method (88%), it is validated by 5-fold cross validation procedure. 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 7. The more distinct feature extracted, the higher the accuracy we get. Thus we conclude that LLBP method is more reliable than LBP method for extracting the feature on palm vein recognition.

This paper has proposed LLBP method, a new approach of LBP, for reliable personal identification using palm vein representations. The LLBP method can capture the pattern inside a palm vein image with recognition accuracy of 93.2% 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, but more dataset and learning machine for classification are needed to increase the recognition accuracy of this proposed method. Also, for future work, we plan to investigate and compare the various combination of other feature extraction method with fuzzy-KNN classifier in palm vein

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recognition to understand the appropriate feature extraction method which can improve the recognition accuracy.

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