Demonstration of Palm Vein Pattern Biometric Recognition by Machine Learning

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***Abstract*—This paper aims to demonstrate the extraction of palm vein pattern features by local binary pattern (LBP) and its different recognition rate by two types of classification methods. The first classification method is by K-nearest neighbour (KNN) while the second method is by a support vector machine (SVM). Whilst SVM is optimized for direct classifications between two classes, the KNN is best for multi-class classifications. Based on the biometric recognition framework shared in this paper, both techniques shared comparable performance in terms of the recognition rate. The differences in the recognition rate can only be seen if the LBP features extracted for the classification are different. In general, a higher recognition rate can be achieved for palm vein pattern biometric system if all LBP bins are used for the classification, compared to if only selected features are used for the purpose. The best recognition rate that can be achieved by the three datasets demonstrated in this paper are 60%, 70% and 100% respectively for the CASIA, PolyU and self-dataset. It shows that different input dataset may behave differently even by using the same machine learning approach in its biometric recognition process.**

Keywords*—biometric recognition, k-nearest neighbour (KNN), local binary pattern, support vector machine (SVM)

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I. INTRODUCTION

PALM vein pattern is one of the trusted biometric modalities that can be used as a human identifier because of its unique pattern for every individual [1]. Its pattern can be recorded with the assistance of an additional near infrared (NIR) illumination with NIR-sensitive image sensor [2]. Since its direct visualization is vague in the acquired image, additional image processing is needed for a palm vein pattern to be revealed. Techniques in enhancing a palm vein pattern image include region-of-interest (ROI) extraction, image resize, contrast enhancement and noise reduction [3]. The techniques for enhancement depend on the features that are intended to be enhanced, either for line patterns or texture information respectively. Once the images are enhanced, the features will be extracted accordingly for classification.

Some of the methods that can be used for feature extraction include the Frangi vesselness filter [4], the Laplacian filter [5], the local binary pattern (LBP) [6], and the scale-invariant feature transform (SIFT) [1]. While the filtering method utilizes image processing in extracting the vein pattern, other methods utilize image statistical values and properties in describing the vein features. The features extracted will then be classified according to the palm samples for biometric recognition. The techniques for palm samples classification are subjected to the features extracted earlier.

Several classification techniques in machine learning that have been used for palm vein pattern recognition are the support vector machine (SVM) [7], k-nearest neighbor (KNN) [8], and principle component analysis (PCA) [9]. Each technique in machine learning can be grouped into either supervised or unsupervised learning method. Depending on the researchers' concern, supervised learning is computationally expensive but its accuracy rate is higher, while unsupervised learning requires less computation but with the price of compromised accuracy rate [10].

In this paper, a palm vein biometric classification framework using supervised machine learning method will be demonstrated. Although there are also other combinations of techniques shared in this area, this paper differs in which it also shares the result obtained from a self-developed dataset. Two supervised learning methods, that are KNN and SVM will be compared as the classifiers in this paper, to show their applicability for biometric recognition purpose. With that, this paper will be organized in such that the following section will describe more on the proposed biometric recognition framework. Section III will discuss the result and analysis of the demonstrated framework. The last section will provide an insight on the significant findings and future work related.

II. PROPOSED BIOMETRIC RECOGNITION FRAMEWORK

The processes involved in palm vein pattern biometric recognition in this paper is illustrated in Fig. 1. The processes are summarized into five main blocks which are palm vein image dataset / acquisition, ROI extraction, palm vein pattern enhancement, palm vein features extraction and palm vein classification. Each block will be described in the following subsections.

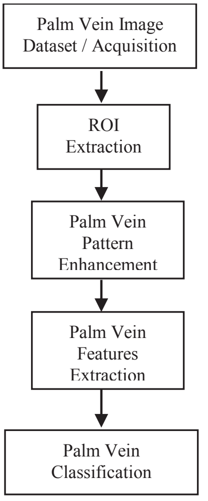
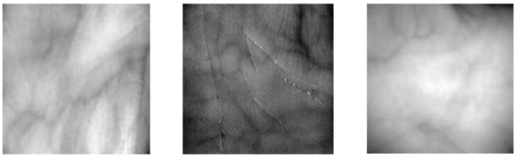


Fig. 1. Processes involved in palm vein pattern biometric recognition.

A. Datasets

In this paper, there datasets of palm images were used for the biometric recognition demonstration. The three datasets were obtained respectively from the: (a) Chinese Academy of Sciences' Institute of Automation (CASIA) [11], (b) Hong Kong Polytechnic University (PolyU) [12], and (c) self-dataset gathered by self-configured image acquisition device [13]. Each dataset consisted of a total of 60 images which represented 10 subjects with six samples each.

Palm images in CASIA dataset were acquired through unguided acquisition process in a controlled environment [14], while PolyU dataset were acquired in guided and controlled environment [15]. The near infrared (NIR) peak wavelength used for illumination for the CASIA and PolyU datasets were 850 nm and 880 nm respectively. The self-datasets were gathered through unguided process in an uncontrolled environment, utilizing a combination of 850 nm and 870 nm NIR peak wavelength as the illuminators [16]. The palm images were sampled to a same size and specified regions before they were processed for palm vein pattern enhancement using the region-of-interest (ROI) extraction processing. Fig. 2 shows a sample ROI from the three datasets.



(a) (b) (c)

Fig. 2. Sample of ROI image for each dataset: (a) CASIA, (b) PolyU, and (c) self-dataset.

B. Palm Vein Pattern Enhancement

Palm images in the datasets (specifically its ROI image) were processed according to the framework of operations as described in [3]. Samples of enhanced palm vein image is shown in Fig. 3. After the processing, the extraction of palm vein pattern were done on the enhanced image by Local Binary Pattern (LBP) descriptors, which will be detailed in the following subsection.

(a) (b) (c)

Fig. 3. Sample of enhanced image for each dataset: (a) CASIA, (b) PolyU, and (c) self-dataset.

C. Local Binary Pattern as Palm Vein Pattern Descriptor

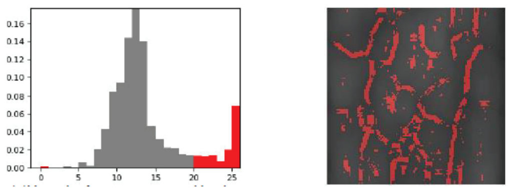
Local Binary Pattern (LBP) is a binary code generated from an image, after a central pixel and its neighbourhood were compared [17]. The generated binary code can be summarized into a histogram with each bin equal to the pattern of binary codes in decimal. For example, if the binary code generated is 11110110_2, the bin in decimal is 246_{10} and its frequency depends on how many times the pattern is generated from the image.

For the purpose of palm vein pattern descriptor, the 'rotation-invariant uniform' bins were used where these specific patterns correspond to the edge information in the enhanced palm vein image, and the bin had been simplified to the numbers of occurrence of '1' in the binary pattern. The 'rotation-invariant uniform' LBP code constructed the following equations (1) and (2) where P is the number of neighbourhood pixels, R is the radius of the neighbours, g_p is the grey-scale value of the neighbourhood pixels, gc is the grey-scale value of the central pixel, $U(LBP_{P,R})$ is number of spatial transition in the LBP code and g_0 is the grey-scale value of the pixel (0,R) in the rotation axis [17].

$$LBP_{P,R}^{RI} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_c) \, if \; U(LBP_{P,R}) \leq 2 \\ P+1 \qquad otherwise \end{cases} \tag{1}$$

$$U(LBP_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{P=1}^{P-1} |s(g_P - g_c) - s(g_{P-1} - g_c)| \tag{2}$$

Based on the generated LBP code from the enhanced palm vein image, not all edge information in the image corresponded to the palm vein pattern. A sample of histogram for 'rotation-invariant uniform' LBP code is shown in Fig. 4 (a), where only the bin highlighted in red corresponds to the vein pattern as detected in Fig. 4 (b). As such, the classification of palm vein pattern will be shown in both, either by using full bins or only vein feature bins, as the LBP descriptors.



(a) (b)

Fig. 4. Generation of 'rotation-invariant uniform' LBP code of an enhanced palm vein image from CASIA dataset shown in: (a) LBP code histogram, and (b) extracted vein features for the highlighted bin.

D. Vein Feature Matching and Accuracy

Each dataset was then divided into two groups, either to be used for the training and validation (45 images), or for the performance assessment (15 images). The training was done by 5-fold cross-validation technique using two of the supervised machine learning methods that are K-nearest neigbour (KNN) and support vector machine (SVM) for comparison.

1) K-nearest Neighbour (KNN)

The K-nearest neighbour (KNN) is a classification method that utilized the distance between a data and its feature space [18].

During the training, the groups of data are classified to their nearest class based on distance k to its nearest neighbour. The training for KNN classification follows equations (3) and (4), where $C(y)$ is the class for trained pattern using KNN. $R(x,y)$ is defined in equation (4), N is the neighbouring size, x is the class pattern, and y is the train pattern [19].

$$C(y) = \sum_{x \in N}^{N} R(x,y)C(x) \tag{3}$$

$$R(x,y) = \frac{\|y-x\|^{-2/(m-1)}}{\sum_{j \in N} \|y-j\|^{-2/(m-1)}} \tag{4}$$

Another group of data for validation was tested to check the accuracy of the constructed KNN model after the training. Five values of k were tested to determine the best KNN model for the palm vein biometric recognition in this paper. The values of k are 5, 7, 9, 11 and 13 respectively. The accuracy of the training will be shared in Section III. Based on the best accuracy, the respective value of k was chosen for the final KNN model for performance assessment.

2) *Support Vector Machine (SVM)*

Support vector machine (SVM) is a linear classification technique that focuses on separating two sets of class [20]. Even so, it can be used for multi-class (non-linear case), where each data is mapped to another feature space for classification, using some kernels [10]. In this paper, the SVM model used a 'linear' kernel in its training. The training data is mapped to several other planes with the tuning parameter C that can be adjusted to ensure that each class is well-separated between one another. However, the tuning parameter C is forced to be '1' in the work presented in this paper as it resulted in the best accuracy during the training.

III. RESULTS AND OBSERVATION

The performance of the best KNN and SVM model were measured by its percentage of accuracy in predicting the biometric data recognition. The machine learning process was done in R studio, utilizing the default parameters in the *caret* package. The results of the machine learning training and model assessment will be presented in the following subsections.

A. *Accuracy by KNN Classifier*

Table I shows the accuracy of the KNN training for different values of k (5, 7, 9, 11 and 13). The accuracy is presented for the three datasets using the two LBP bins groups that are either full bins or vein features bins. The best k if full bins were used as the LBP descriptors are 5, 7 or 9, and 5 respectively for CASIA, PolyU and self-dataset. If only vein features bins were used as the LBP descriptors, the best k is 5 for all datasets.

TABLE I. ACCURACY OF KNN TRAINING

Datasets	LBP Bins	Accuracy for Different Values of k				
		$k = 5$	$k = 7$	$k = 9$	$k = 11$	$k = 13$
CASIA	Features	28%	22%	18%	18%	14%
	Full	40%	32%	28%	30%	16%
PolyU	Features	42%	44%	32%	44%	38%
	Full	62%	76%	76%	68%	52%
Self	Features	68%	64%	58%	54%	48%
	Full	98%	94%	80%	72%	52%

The accuracy of the palm vein biometric recognition for the three datasets when the best k (obtained during the training) for the KNN model is used for the performance assessment are shown in Fig. 5. It can be seen that the accuracy of the palm vein biometric recognition is increased if the full LBP bins were used as its descriptors, compared to only vein features bin were used as its descriptors. This indicates that although the vein features were characterized by some of the 'rotation-invariant uniform' LBP bins, the distinguishing factor is not accurate enough to be used as palm vein pattern descriptor for biometric recognition purpose. Still, the best accuracy obtained using the full bins are 100%, 60% and 60% for the self-dataset, CASIA, and PolyU datasets respectively.

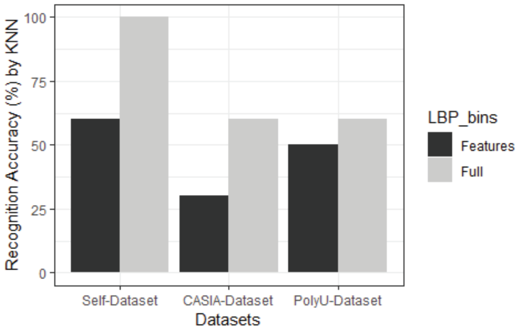


Fig. 5. Recognition accuracy with KNN classifiers.

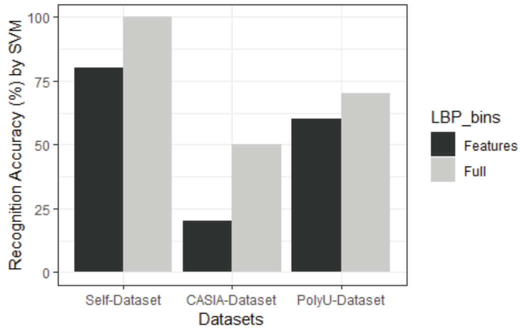


Fig. 6. Recognition accuracy with SVM classifiers.

B. Accuracy by SVM Classifiers

The accuracy of the SVM training for the three datasets are shown in Table II. The same three datasets extracted by the two LBP bins groups; that are either full bins or vein features bins, where used for the SVM training to compare its accuracy with the KNN model. The result consistently showed that the accuracy of the training is higher if all 'rotation-invariant uniform' bins of the LBP code were used as the descriptors, compared to if only selected bins (vein features) were used as descriptors for the three datasets.

TABLE II. ACCURACY OF SVM TRAINING

Datasets	LBP Bins	Accuracy
CASIA	Features	32%
	Full	50%
PolyU	Features	56%
	Full	94%
Self	Features	54%
	Full	96%

The performance of the SVM after the model fitting is shown in Fig. 6. The performance is consistent with the training result, where the accuracy of the SVM model is higher if all 'rotation-invariant uniform' bins were used as the descriptors. The best accuracy obtained using the full bins were 100%, 50% and 70% for the self-dataset, CASIA, and PolyU datasets respectively. When comparing both machine learning models (KNN and SVM), the best recognition accuracy that can be achieved are 100%, 60% and 70% respectively for self-dataset, CASIA and PolyU datasets.

IV. CONCLUSION

This paper shared the process in extracting palm vein features by local binary pattern (LBP) and its recognition rate by K-nearest neighbor (KNN) and Support Vector Machine (SVM). In general, both machine learning methods can be used for classification; however, the accuracy of the model for biometric recognition purpose depends on the nature of the input dataset. While the self-dataset in this paper is configured and fully supervised during the acquisition process, the other two datasets (CASIA and PolyU) are publicly available to be used by researchers in the area. The low recognition rate scored by the two datasets compared to the self-dataset might be due to the nature of the input data that was obtained in its grey-scale value (format), compared to the self-dataset which was originally obtained in its 24-bits value before the required post-processing. Even so, the aim of this paper is not to compare the performance of the datasets for biometric recognition purpose but rather to share the possibility of applying the machine learning technique for palm vein pattern biometric recognition.

As such, it is observed that improvements had to be made especially with regard to the taylor-made image enhancement and palm vein pattern feature extraction, if the machine learning methods need to be utilized for biometric classification purpose. Since the best recognition accuracy that can be achieved are 100%, 60% and 70% respectively for self-dataset, CASIA and PolyU datasets; surely improvements have to be made to the framework if the machine learning method is to be used for biometric recognition, with respect to the performance of the two publicly available datasets (CASIA and PolyU). As palm vein pattern in this paper relied heavily on the LBP code generated as its descriptors, future work can be done in using other descriptors to improve the biometric recognition performance.

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