Analysis of local binary pattern using uniform bins as palm vein pattern descriptor

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Abstract. Palm vein authentication technology which reads the features of palm vein has been widely used in recent years as it offers high accuracy identification and difficult to be forged or impersonated. This paper demonstrates a palm vein recognition system using uniform Local Binary Pattern (LBP) through the Python language and R. Python language was used for contrast enhancement, noise reduction and LBP implementation while R was used for classifying palm vein pattern using K-Nearest Neighbour (KNN) classifier. The palm samples come from two datasets which are from the Chinese Academy of Sciences Institute of Automation (CASIA) and self-dataset. The outcomes were the extracted and classified palm vein pattern based on subjects and their accuracy based on each dataset. The accuracy for all uniform LBP bins and selected uniform LBP bins from self-dataset were 87% and 53% respectively; while for CASIA dataset were 60% and 27% respectively. The results show that the accuracy is higher if all uniform LBP bins are used for the recognition purpose.

1. Introduction

The palm vein pattern is one of the biometric data that can provide a great level of accuracy. The palm contains complex vein pattern that causes the recognition to become more secure against spoof attack [1]. Furthermore, the vein pattern of palm image is also stable that it can be used over a long period of time. Besides, there is no hygiene issue as the contactless design has been introduced. Palm contains thicker veins than the finger, and it is easier to identify. It is also insensitive against environments such as cold temperature, creamy hands, and skin scratches and also detectable only when blood is flowing [2].

The focus of this paper on the uniform bins of Local Binary Pattern (LBP) operator that can be used to describe the palm vein pattern from the human palm. Besides this operator and method, there are other different methods that were used in extracting palm vein pattern, but with their own advantages and disadvantages. Example of other methods are Histogram of Gradient (HOG) and Speeded Up Robust Feature (SURF). Each of the technique has its own speciality and capability in recognizing a pattern of an object. However, LBP consists of several advantages in which it is easy to be implemented, invariance to monotonic illumination changes and also low in computational complexity [3]. Besides, LBP had been previously investigated as descriptors for palm vein pattern [4]. The analysis of uniform LBP in this paper is demonstrated by Python language using Spyder environment shown in Figure 1 and
then continued with the K-Nearest Neighbour (KNN) classifier implemented in R Studio shown in Figure 2.

**Figure 1.** Python in Spyder environment. **Figure 2.** R Studio for KNN classification.

KNN classifier is used in this paper to classify the palm according to the subjects based on the extracted uniform LBP bins. Besides KNN, Support Vector Machine (SVM) has also been used in pattern recognition; particularly to recognize offline and online handwritten characters [5]. SVM can perform efficiently on a dataset that contains many characteristics. However, it has limitation in speed and size during both training and verification phase, and also in the process of selection of kernel function parameters [6]. Hence, the KNN classifier was chosen in this paper as it is the most suitable method to classify data and is the simplest algorithm to be implemented. Besides, the KNN algorithm also performs competently with multi-modal classes as the basis of its decision is derived from a small neighborhood of similar objects. Thus, the algorithm can still lead to good accuracy even with multi-modal target class [6].

### 2. Palm image dataset

The palm image datasets in this paper were obtained from the Chinese Academy of Science Institute of Automation (CASIA) [7] and self-dataset. The self-dataset was collected by a setup, as shown in Figure 3 [8]. It uses near-infrared (NIR) spectrum illumination to record the palm vein pattern in the image. During the acquisition process, users were orally instructed to place their palm at the requested position. The example of a palm image for both datasets are shown in Figures 4 and 5. There are a total of 15 palms from each dataset where each palm consist of six versions of images. Thus, the total palm images for both datasets were 90 samples respectively. The images will be forwarded for several processes before they can be used for vein pattern extraction by LBP. The processes involved will be explained in the following section.

**Figure 3.** Illustration of the setup to capture palm image [8].
3. Methodology and demonstration

The processes to be executed on the palm images are shown in Figure 6 [9]. The palm image then was going through the process of Region-of-Interest (ROI) extraction where the image was manually cropped and resized to a specific size of 200x200 pixels. This process must be done in order to let all the size of the palm image standardize with each other.

Next process after the ROI extraction is contrast enhancement. The purpose of contrast enhancement is to bring out the obscured detail or to highlight a certain feature of interest in an image. Contrast enhancement can be done by using Contrast Limited Adaptive Histogram Equalization (CLAHE) technique [10]. CLAHE technique is simple and widely used in the process of image enhancement. The technique originated from histogram equalization; where the contrast enhancement technique is applied in the spatial domain by using the histogram of an image. Histogram equalization usually raises the global contrast of the processing image, which makes the method beneficial for either bright or dark images [11].

Right after the contrast enhancement, noise reduction of the image was made. This operation is fulfilled by two processes which are bilateral filtering and morphological dilation. Bilateral filtering is one of the smooth filtering operations that can be used for the noise reduction process [12]. It involves filtering operation in both spatial and frequency domain that focuses on image intensity variations. Input to bilateral filtering operation is obtained from CLAHE operated image. To decrease the size of the vein pattern which had been increased during smooth filtering operation, morphological dilation process was executed on the image. One of the morphological operation is dilation. The objects were expanded in dilation operation. Thus small holes in the image will probably be filled, and disjoint objects were

**Figure 6.** Processes in palm vein pattern recognition [9].
connected [13]. The outcome of the mentioned processes to a sample of palm image in self-dataset is shown in Figure 7.

![Image after the implementation each process demonstrated by a palm image from self-dataset: (a) resized ROI, (b) CLAHE image, (c) bilateral filtered image, and (d) dilated image.](image)

**Figure 7.** Image after the implementation each process demonstrated by a palm image from self-dataset: (a) resized ROI, (b) CLAHE image, (c) bilateral filtered image, and (d) dilated image.

Next process is vein segmentation or extraction by LBP. LBP is an effective texture descriptor which can characterize the variance of the spatial structure of an image patch. The main idea of the LBP approach is to locally threshold the brightness of a pixel’s neighborhood at the center pixel grey level to form a binary pattern [14]. If the neighborhood (P) consists of 8 pixels, a total of $2^8$ (256) different labels can be acquired depending on the relative grey values of the center and the pixels in the neighborhood [15]. The central pixel of the image, a real number, which is the LBP value of the pixel, is computed by comparing its intensity value with those of its neighborhoods as shown in Figure 8.

![LBP neighbour sets under different configuration of P and radius (R).](image)

**Figure 8.** LBP neighbour sets under different configuration of $P$ and radius ($R$).

An LBP value is uniform if its uniformity measure or transition is at most 2. Example includes the following LBP value patterns: (a) 00000000 (0 transitions), (b) 00011000 (2 transitions) and (c) 11001111 (2 transitions) are uniform; while the patterns: (d) 11001001 (4 transitions) and (e) 01010011 (5 transitions) are not uniform. For the uniform LBP bins, a histogram graph produced is shown in Figure 9 [15]. In this paper, the neighborhood size, $P$ is chosen to be 24, while the radius, $R$ is 3.

![Example of LBP extraction in histogram bin representation.](image)

**Figure 9.** Example of LBP extraction in histogram bin representation [15].
The classification of vein pattern, according to the subject, is a crucial part of the palm vein pattern recognition system. In this paper, the classification was done by KNN classifier. KNN classifier aims to match the extracted LBP bins in a palm vein image from the testing data with the one from the training data. The basic concept of KNN classifier is to allocate membership as a function of the object’s distance from its k-nearest neighbours and the memberships in the possible class [16]. The training of KNN classifier was done through 5-fold cross-validation technique. During the training and testing, the neighborhood, \( k \) was chosen to vary between 5 to 23. The \( k \) with best training result was chosen for the validation purpose, in which the \( k \) for CASIA dataset is 5, while for self-dataset is 7.

4. Results and discussion
The palm vein pattern extraction by uniform LBP bins and the corresponding pixels highlighted in the palm image are shown in Figure 10. There are 5 sets of bins which are grouped into (a) “set a”, (b) “set b”, (c) “set c”, (d) “set d”, and (e) “set e”. Each set presents the range of different uniform LBP bins extracted from the enhanced image, coloured in ‘red’ in the histogram. Based on the selection of bins in Figure 10, a group of uniform LBP bins was chosen and shown in Figure 11; representing the extracted palm vein pattern in the image.

![Figure 10. Plots of extracted vein pattern for a sample of palm image in self-dataset for different sets of uniform LBP bins: (a) “set a”, (b) “set b”, (c) “set c”, (d) “set d” and (e) “set e”.

![Figure 11. Selected uniform bins for palm image 1.](image)

The first LBP bins set, which is “set a” that consists of bins 9 - 13 in Figure 10 shows that the output image revealed the foreground extraction. As for “set b”, the bins selected were bins 1 - 6, and bins 12 - 14. The pattern extraction by “set b” bin shows some likeliness to the vein pattern in the image. The observation is similar with “set c” which shows some likeliness to vein pattern but not with clear vision.
As for “set c” and “set d”, the bins selected are bins 16 - 19; and bins 1 - 7 with bins 16 - 24 respectively. Here, the pattern started to show more likeness to the vein pattern. In order to get the most accurate result, both of “set c” and “set d” were combined. Thus, the last output of the vein pattern extracted in Figure 11 comes from bins 1 - 7 and bins 16 - 24.

Based on the selected bins in Figure 11, the vein pattern was extracted from each image in both datasets and grouped into “selected uniform LBP bins”. Another group of data was created consisting of all uniform LBP bins and named as “all uniform LBP bins”. For “all uniform LBP bins” group, it contains all of the uniform bins which are bins 0 - 25 with a total of 26 bins. In each group, the data was divided accordingly depending on the original dataset; either it is a palm image from the CASIA or self-dataset. With a total of 90 images for each dataset, a screenshot of the compiled data is shown in Figure 12. In Figure 12, the data shown is coming from the CASIA dataset for “all uniform LBP bins” group.

Figure 12. Example of overall of CASIA dataset.

Figure 13 shows a sample of “Confusion Matrix and Statistics” obtained by R after the KNN classification operation. The accuracy shown in Figure 13 was obtained from “all uniform LBP bins” group for self-dataset. When the values of ‘Reference’ and ‘Prediction’ equal to 1, the subject tested was matched with its reference template. The accuracy in Figure 13 equals to 0.8667 becomes 87% when multiplied by 100 in order to indicate the system accuracy in percentage. The same “Confusion Matrix and Statistics” were acquired for another three groups of data to obtain the recognition accuracy for different groups of LBP bins and datasets.

Figure 13. Confusion matrix and statistics.
The recognition accuracy by all uniform LBP bins is 87% and 60% for self-dataset and CASIA dataset respectively. While the recognition accuracy for selected uniform LBP bins are 53% and 27% each for self-dataset and CASIA dataset. The resulted accuracy was shown in Figure 14. It indicates that the recognition accuracy for palm vein pattern extracted by all uniform LBP bins (bin 0 - 25) is higher than selected uniform LBP bins that characterizes the vein pattern (bin 1 - 7 and bins 16 – 24). It also shows that although the selected uniform LBP bins can extract the palm vein pattern visually, the operators are not enough to be used for biometric recognition purpose. Hence, all uniform LBP bins are proposed to be used for accurate palm vein pattern recognition.

![Figure 14](image_url) Accuracy percentage for each dataset.

5. Conclusion
Palm vein pattern had been extracted using uniform LBP bins from two datasets which are: (a) CASIA and (b) self-dataset. Each dataset consists of a total of 90 images comprise of 15 palms with six image samples each. A selected uniform LBP bins that contain bins 1 - 7 and bins 16 – 24 can be used to extract vein pattern visually from the palm image. However, if the selected uniform LBP bins were used for the palm vein pattern biometrics, the resulted accuracy is quite low compared to if all uniform LBP bins were used for the recognition.

As for that, future works can be done by increasing the number of palm images in the datasets to check if the recognition accuracy can be affected by the number of subjects. Other than that, the combination of LBP operators and KNN classifiers can be extended its work for recognition system using other biometrics data to see the robustness of the methods as pattern descriptors and classifiers.

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