

Multi-feature Fusion Using SIFT and LEBP for Finger Vein Recognition

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Abstract

In this paper, multi-feature fusion using Scale Invariant Feature Transform (SIFT) and Local Extensive Binary Pattern (LEBP) was proposed to obtain a feature that could resist degradation problems such as scaling, rotation, translation and varying illumination conditions. SIFT feature had a capability to withstand degradation due to changes in the condition of the image scale, rotation and translation. Meanwhile, LEBP feature had resistance to gray level variations with richer and discriminatory local characteristics information. Therefore the fusion technique is used to collect important information from SIFT and LEBP feature. The resulting feature of multi-feature fusion using SIFT and LEBP feature would be processed by Learning Vector Quantization (LVQ) method to determine whether the testing image could be recognized or not. The accuracy value could achieve 97.50%, TPR at 0.9400 and FPR at 0.0128 in optimum condition. That was a better result than only use SIFT or LEBP feature.

Keywords: *finger vein, scale invariant feature transform, local extensive binary pattern, multi-feature fusion, learning vector quantization*

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1. Introduction

The finger vein pattern is one of biometric fields that has recently received much attention as an alternative for human recognition. Compared with other biometric fields, human recognition based on finger vein has distinct advantages, such as hard to copy or forge and little external factors can damage it [1].

In general, finger-vein recognition consists four stages: image capturing, preprocessing, feature extraction and recognition [2]. Feature extraction is a critical step in the finger vein recognition process [3,4]. Various methods have been proposed for feature extraction stage. The examples of feature extraction methods which already used for finger vein recognition are line tracking [1], maximum curvature [5], and mean curvature [6]. Those methods are more focus on capturing vein pattern from a segmented blood vessel network, meanwhile the scaling, rotation, transition, and varying illumination problems remain unsolved. Unfortunately, finger vein images are susceptible to scaling, rotation, transition, and varying illumination conditions [7,8]. It may affect recognition process and degrades recognition accuracy. So that, it is important to pay attention to the selection of features that are resistant to these conditions.

SIFT feature have proven to give a better performance compared with other features to the case of extracting feature from images with scaling, rotation, and transition effects [9]. This feature has been implemented on several cases, such as object matching [10], image retrieval [11], palm vein recognition [12], ear recognition [13], and face recognition [14]. However, SIFT feature gives a poor performance if extracted from the image with varying illumination conditions which caused by differences in lighting intensity [15]. This is because the SIFT feature highly dependent on the result of keypoints. While the number of keypoints can be influenced by differences in lighting intensity.

Local Binary Pattern (LBP) is a feature that resist variations of illumination conditions [8]. 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 neighboring pixels. The result of this difference is not influenced by varying illumination conditions. Some of other methods are proposed to improve the performance of LBP features, such as Local derivative Pattern (LDP) [16], Local Line Binary Pattern (LLBP) [17], and Local Directional Code (LDC) [18]. The newer

one is LEBP feature that resist variations of illumination conditions with richer and discriminatory local characteristics information [7]. Therefore, LEBP feature can be used to cover the lack of SIFT feature that gives a poor performance if extracted from the image with varying illumination conditions.

It is necessary to process SIFT and LEBP feature with a certain method to obtain a single feature that is resistant to scaling, rotation, transition, and varying illumination conditions. That single feature must provide an information that can not be gained with only using one of two features which already previously mentioned, SIFT or LEBP feature. Previously, there is a method called fusion method that has been used to obtain the new representation of feature resulted from multiple features processing [19]. In [19], SIFT feature and color histogram are used in video matching problem. Fusion method combines multiple sources of data through particular process to obtain a better information [20]. This method can be used to obtain information from SIFT and LEBP feature and produces a single feature that is resistant to scaling, rotation, transition, and varying illumination conditions.

Therefore, this study proposes a multi-feature fusion using SIFT feature and LEBP feature for finger vein recognition. SIFT feature are used to produce feature that are resistant to scaling, rotation, and transition. Meanwhile LEBP feature is used to produce feature that are resistant to variations illumination conditions. After SIFT and LEBP feature extracted, both features are processed by fusion method. The resulting feature is represented into histogram vector and classified by Learning Vector Quantization (LVQ). LVQ is used to determine whether the finger vein image can be recognized or not. Multi-feature fusion using SIFT and LEBP feature is expected to improve the performance of the finger vein recognition that extracted from images with scaling, rotation, transition, and varying illumination problems.

The structure of this paper is as follows: the first part is the introduction, the second part explains the proposed algorithms along with the methods that are used, the third part is the experiment results and the last part is conclusion.

2. Research Method

There are four stages of the finger vein recognition that will be explained in this paper. These stages consist of preprocessing, base feature extraction, multi-feature fusion and recognition. A flowchart of finger-vein recognition system is provided in Figure 1.

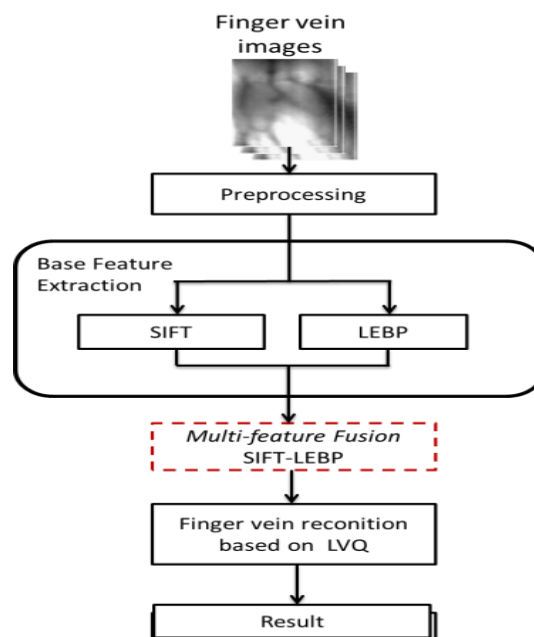


Figure 1. Design of Finger-Vein Recognition System

2.1. Preprocessing

Finger vein images which were taken with infrared rays cause human body tissues can easily be fetched. So that the pattern of finger vein will be captured as shadows and looked sketchy. It will be difficult to differentiate between background and foreground. To overcome these difficulties, there is preprocessing stage which consist of median filter, frangi filter, CLAHE, morphology operation, extracting ROI, and size normalization.

CLAHE is used to improve image contrast, so that we can differentiate between foreground and background clearly. Frangi filter is used to accentuate the pattern of finger vein. Median filter is used to reduce noise from the image. Meanwhile, morphological operations is used to get the pattern of finger vein in the representation of the binary image. Then, the next step is selecting ROI to reduce a portion of the background image. The last step of preprocessing stage is size normalization of the result images become 250x95 pixels. Figure 2 shows the Preprocessing steps of finger-vein recognition.

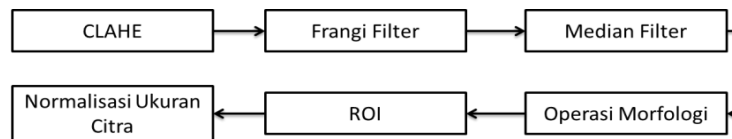


Figure 2. Preprocessing Steps of Finger-Vein Recognition

2.2. SIFT Feature Extraction

Grayscale images which are the result from the preprocessing stage becomes the input images for SIFT feature extraction stage. The result of SIFT feature extraction is the set of keypoints along with their descriptors. The main steps to obtain SIFT features are as follows [9]:

1. Scale-space detection using difference-of Gaussian (DoG) methods.

If scale-space image is defined as a function $L(x, y, \sigma)$ with the input image $I(x, y)$ and a scale factor σ , then scale-space $L(x, y, \sigma)$ can be obtained from the convolution with variable-scale Gaussian $G(x, y, \sigma)$ which follows the equation(1).

$$L(x, y, \sigma) = G(x, y, \sigma) \cdot I(x, y) \quad (1)$$

Whereas to detect stable keypoints efficiently, it is used equation(2). This equation is a calculation of the difference between the nearest scale space separated by a constant multiplier k .

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma)) \cdot I(x, y) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (2)$$

In order to detect the local extrema of $D(x, y, \sigma)$, each sample point is compared to its eight neighbors in the current image and nine neighbors in the scale above and below it. Local extrema is selected only if it is larger or smaller than all of these neighbors.

2. Keypoint localization.

Adjusting the model as detailed as possible using 3D quadratic function so that the candidate keypoints which have low contrast, sensitive to noise, and are located around the edge can be eliminated. Hessian matrix is used to remove candidat keypoints which poorly localized along on edge. Hessian matrix with size 2×2 is followed the equation(3).

Meanwhile the standard measurement of the stable keypoints is followed equation(4) with r values define comparison between largest and smallest eigenvalue.

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \quad (3)$$

$$\frac{(D_{xx} + D_{yy})^2}{D_{xx}D_{yy} - D_{xy}^2} < \frac{(r + 1)^2}{r} \quad (4)$$

3. Orientation assignment.

The gradient value $m(x, y)$ and the orientation value $\theta(x, y)$ is obtained from the result of pixels calculation on each sample image $L(x, y)$ which is followed equation and equation.

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \quad (5)$$

$$\theta(x, y) = \tan^{-1} (L(x+1, y) - L(x-1, y)) / (L(x, y+1) - L(x, y-1)) \quad (6)$$

4. Representation of Keypoint Descriptor. Descriptors for each keypoint is divided into 4x4 subregions. An histogram with 8 bins is used for representing the orientation of the points in each of the sub-regions. The descriptor vector has $(4 \times 4) \times 8 = 128$ entries.

2.3. LEBP Feature Extraction

Features LEBP is one of the feature that is extracted based on the local characteristics of a finger vein image. LEBP features is a combination of features LmBP (Multilayer Local Binary Pattern) and features LdBp (Directional Local Binary Pattern) [7]. LmBP feature is the variation of LBP feature and LdBp feature is modification of the LDC feature. This combination can capture the local characteristics of the finger vein better.

To extract LmBP feature, it is used window kernel with a size $n \times n$, $n > 3$. For this case, LmBP feature use $n=7$. The center pixel is compared with the neighboring pixels in the first, second, and third layer. Then, the pixels in the first layer are compared with the second layer and the pixels in the second layer are compared with the third layer. The comparison result can be valued at 0 or 1. If the gray value of the center pixel is more than the gray value of neighboring pixel then the result is 1, whereas if the gray value of the center pixel is less than the gray value of neighboring pixel then the result is 0. The same thing also applies to the comparison result between inner layer and outer layer. LmBP feature will be represented in feature vector length of 64 ($LmBP_{64}$).

The first step to get LdBp feature is calculating the LDC value. It uses the difference of the neighbours of a pixel as the two components v_v and v_h of the local direction [18]. The equation(7) and equation(8) is followed to obtain v_v and v_h value.

$$v_h = a_7 - a_3 \quad (7)$$

$$v_v = a_5 - a_1 \quad (8)$$

LdBp feature is the result of the comparison of t value on the central pixels with t value of neighbour pixels, where the t value obtained from equation(9) with the value of T is the number of neighboring pixels that are involved. The value of θ' is obtained from equation(10). While the value of the gradient orientation θ obtained from equation(11).

$$t = \text{mod}\left(\frac{\theta'}{2\pi/T}, T\right) \quad (9)$$

$$\theta' = \arctan 2(v_v, v_h) + \pi, \arctan 2(v_v, v_h) = \begin{cases} \theta & v_h > 0, v_v > 0 \\ \pi + \theta & v_h > 0, v_v < 0 \\ \theta - \pi & v_h < 0, v_v < 0 \\ \theta & v_h < 0, v_v > 0 \end{cases}, \theta \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right] \quad (10)$$

$$\theta(m) = \arctan\left(\frac{v_h}{v_v}\right) \quad (11)$$

Finally, we can get a feature vector $LdBp_8$. Thus, the LEBP can be defined as $LEBP_{72} = [LmBP_{64}, LdBp_8]$.

2.4. Fusion SIFT-LEBP Feature

In order to make the process of fusion, SIFT and LEBP feature need to be converted into a similar vector representation. Vector representation that is used is histogram vector. A flowchart of feature fusion process is provided in Figure 3.

The process to obtain the SIFT feature descriptor in the histogram representation uses a collection keypoint as a reference. The keypoints will be processed by Bag Of Visual Words (BVW) algorithms. BVW is an algorithm to obtain the so-called visual vocabulary by utilizing local descriptor of an image [21]. There are two main stages to represent an image into a histogram with BVW algorithms. First stage is visual words construction. The steps to obtain visual words are shown as follows:

1. Form a matrix with size $k \times d_{128}$ for each image where k is the number of keypoints obtained from SIFT feature extraction and d_{128} is the length dimension of SIFT feature descriptors.
2. Cluster the overall descriptors from training image to obtain visual descriptor words of SIFT features. Visual words are a set of keypoints as the center of each cluster which is obtained from the K-Means algorithm.

The last step to get the histogram representation of SIFT feature is the retrieval step which follows:

1. Classifying each keypoint of the matrix $k \times d_{128}$ for each testing images as a member of the visual words.
2. Mapping the visual words as the x-axis histogram that shows the number of bin histogram. While the y-axis is the frequency which states the number of members of each visual word as a cluster center.

Meanwhile the process to obtain the histogram representation of LEBP feature is described in the following steps.

1. Dividing the vector $LEBP_{72}$ into smaller vectors with a length of 8 bits ($LEBP_8$). Each vector contains a binary value representing a particular pattern.
2. Converting each binary vector pattern $LEBP_8$ to decimal value in the range of 0 to 255. This value is expressed a gray level value which will be mapped into the histogram.
3. Mapping the gray level values into histogram with the the number of bin is 256.

After obtaining the histogram of SIFT and LEBP feature, then the next step is concatenating both histogram into one.

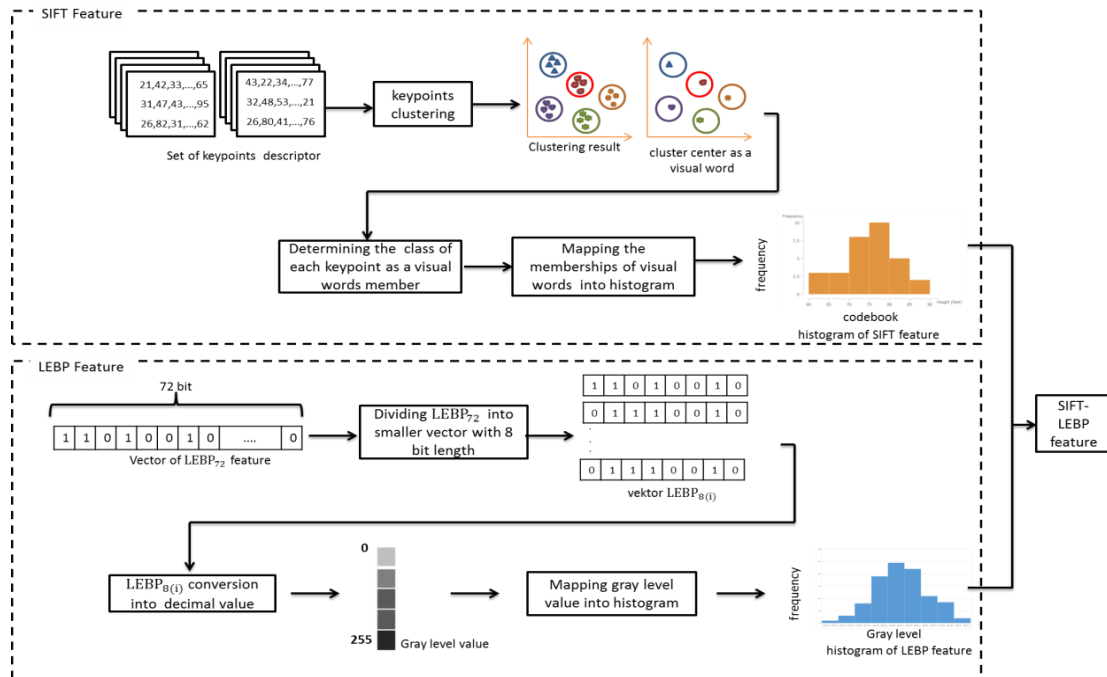


Figure 3. Design of SIFT-LEBP Feature Fusion Process

3. Results and Analysis

The images of finger vein are obtained from finger-vein dataset from Hong Kong Polytechnic University [22]. The number of images that were used in the experiments is 300 finger vein images from 50 persons. After that, the data images are divided into two groups: 200 images were taken as a training dataset and the remaining 100 images are used as testing dataset for checking recognition performance. There were three models that are conducted in these experiments. The first and second model use one feature, SIFT or LEBP feature only. The last model use SIFT-LEBP feature fusion which is proposed in this paper. The performance of the three models compared by evaluation metrics: accuracy, FPR (False Positive Rate), and TPR (True Positive Rate). The value of those evaluation metrics are derived from the analysis of the confusion matrix that can be seen in Table 1. From the results of the analysis, the equation to calculate the accuracy, FPR, and TPR shown in equation(12), equation(13), and equation(14) respectively.

Table 1. Table of Confusion Matrix [23]

Prediction	Actual	
	Within Class	Between Class
Within Class	True Positive (True Accept, Hit)	False Positive (False Accept, False Alarm)
Between Class	False Negative (False Reject, Miss)	True Negative (True Reject)

$$accuracy = (TP + TN) / (TP+FN+ FP+TN) \quad (12)$$

$$TPR = TP / (TP + FN) \quad (13)$$

$$FPR = FP / (FP + TN) \quad (14)$$

The evaluation results are given in Table 2. From the table, it can be seen that the accuracy value using SIFT-LEBP feature has exceeded the accuracy value using a single feature. When using SIFT-LEBP feature, the accuracy is 97.50%, while using SIFT and LEBP feature, the accuracy are 97.34% and 97.32%, respectively. So it can be said that the fusion technique to obtain SIFT feature-LEBP is correct. In addition, a finger vein recognition system is said to have a good performance when has a high true positive value and a low false negative value. If we look at the results of finger vein recognition using SIFT-LEBP features in Table 2, it can be seen that the value of true positive and false negative are relatively better when compared to using only a single feature whether LEBP or SIFT feature. When using SIFT and LEBP feature, the TPR are 0.8200 and 0.8300, respectively. While using SIFT-LEBP feature, the TPR increase to 0.9400. For FPR value, when using SIFT and LEBP feature, it gets 0.0135 and 0.0137, while using SIFT-LEBP feature, the FPR decrease to 0.0128.

Table 2. The Performance Comparison of Finger Vein Recognition Using SIFT, LEBP, and SIFT-LEBP Feature

Fitur	FPR	TPR	Accuracy (%)
SIFT	0.0135	0.8200	97.34
LEBP	0.0137	0.8300	97.32
SIFT-LEBP	0.0128	0.9400	97.50

The high value of TPR is caused by the ability of SIFT-LEBP feature to recognize a finger vein image with scaling, rotation, transition, and varying illumination conditions. While a single feature only has a capability to overcome only some image degradation. For example, the images in Figure 4 is able to be identified using SIFT features and SIFT-LEBP feature while LEBP feature can not recognize them. The other example, the images in Figure 5 is able to be identified using LEBP features and SIFT-LEBP feature but SIFT feature is not able to recognize them. SIFT-LEBP feature also has capability to recognize images that are not able to be

recognized by the SIFT feature and LEBP feature. The examples of the image are shown in Figure 6.

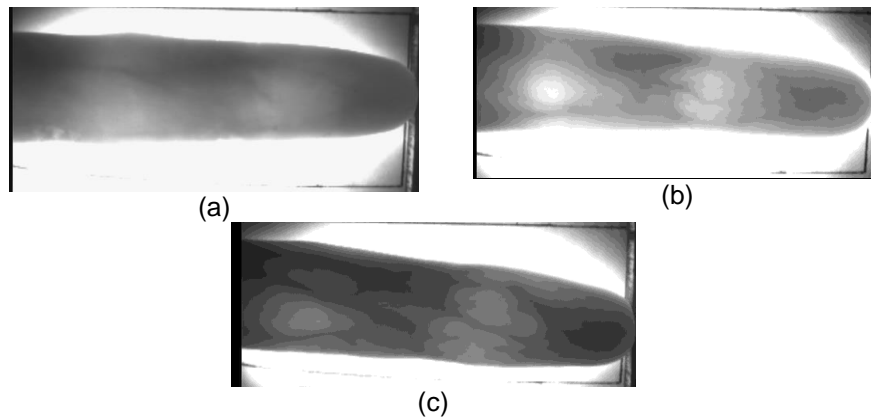


Figure 4. The Examples of Images which can be Recognized by the Finger Vein Recognition System Using SIFT Feature (a) The Image with Translation Effect (b) The Image with Rotation Effect (c) The Image with Translation and Rotation Effect

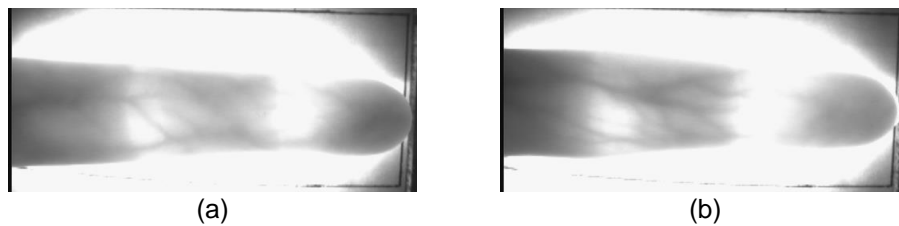


Figure 5. The Examples of Images which can be Recognized by the Finger Vein Recognition System Using LEBP Feature (a),(b) The Image with Varying Illumination Conditions

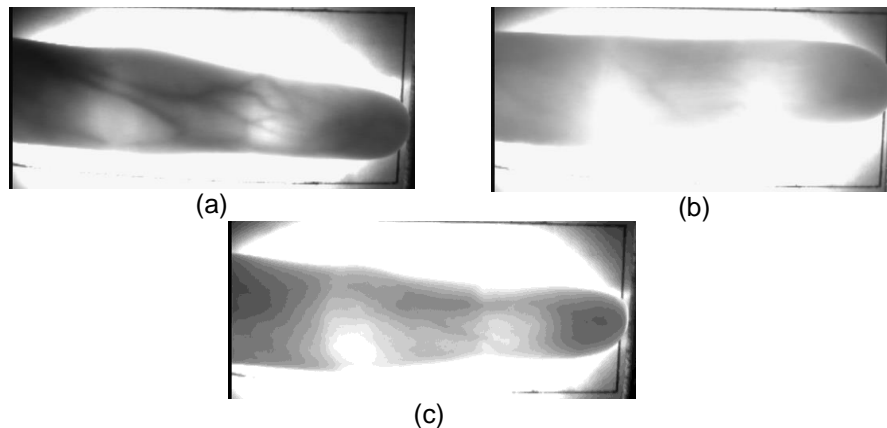


Figure 6 The Examples of Images which can be Recognized by the Finger Vein Recognition System Using SIFT-LEBP Feature (a),(b),(c) The Image with Geometric Degradation and Varying Illumination Conditions

4. Conclusion

In this paper, we propose a multi-feature fusion using SIFT and LEBP feature for finger vein recognition in images with scaling, rotation, translation and varying illumination conditions. Fusion method that is used to form the SIFT-LEBP feature have shown relatively good results with the accuracy value are not much different from the result that has been obtained if only

using a single feature whether SIFT or LEBP. The accuracy of finger vein recognition using SIFT-LEBP feature at the optimum condition reach to 97.50%. Therefore, it can be said that the multi-feature fusion using SIFT and LEBP is applicable for finger vein recognition in images with scaling, rotation, translation and varying illumination conditions. In addition, SIFT-LEBP feature provides relatively better results when compared to using only a single feature whether SIFT or LEBP. This can be seen from the value of TPR and FPR that are 0.9400 and 0.0128, respectively.

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