

# A Palm-vein recognition algorithm based on LPP and HM-LBP

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**Abstract.** In this paper, an algorithm based on locality preserving projection (LPP) for palm-vein was proposed. The feature of palm-vein was extracted by Hierarchical multiscale local binary pattern(HM-LBP), and then the dimension was reduced by LPP. Lastly, the palm-vein was classified by normalized correlation classifier. The algorithm was tested on the near-infrared database of the multi-spectral palm database of Hong Kong polytechnic university. The experiment results show that the algorithm can achieve ideal recognition accuracy of 99.92% and the speediness is able to fit for the real-time palm-vein recognition system.

## 1. Introduction

Palm-vein recognition is one of the most popular research directions in biometric recognition. In addition to universality, uniqueness, acquisition and stability, vein has its own advantages. Venous blood vessels are distributed under the skin and are hard to wear and forge. These characteristics make vein recognition one of the hot research spots at home and abroad. At present, vein recognition is mainly divided into palm vein and hand back vein identification. Since palm vein can be collected together with the palmprint, it has a good application prospect.

The current vein recognition algorithms are mainly divided into two categories [1]: learning method based on the overall subspace and curve-based matching method. The subspace-based learning method is a method that uses the whole palm vein as a overall description and projects it to the subspace to extract features for matching. Typical methods include: principal component analysis (PCA) [2], linear discriminant analysis(LDA) [3], fisher linear discriminant(FLD) [4], locality preserving projection(LPP) [5] and local derivative pattern(LDP) [6]. Curve-based matching method extracts the palm vein curve characteristics or linear features, typical methods are using different filters to encode palm vein image and extract palm vein texture features [7-9].

Vein distribution has good texture features which can be extracted with less valid information loss, thus leading to higher feature dimension by hierarchical multiscale local binary pattern[10]. Locality preserving projection, as a linear dimension reduction method, draws from the idea of Laplacian Eigenmaps and can effectively retain the nonlinear structure of the data after dimensionality reduction mapping of high-dimensional data. In this paper, the two methods are combined together to extract the characteristics of the palm vein and then classify them through relevant classifier, yielding good experimental results.

## 2. Feature extracting for palm-vein

### 2.1. Hierarchical multiscale local binary pattern



The local binary pattern (LBP) operator is one of the best performing texture descriptors and has been widely applied in various fields. But Guo et al. [10] found that the performance of single LBP operator easily makes lots of useful information lost and the percentage of information loss increased with increasing the radius value. When the radius value is 3, about 30% of the information was lost. They proposed hierarchical multiscale LBP to resolve this problem and the concept of this algorithm is as following. First, LBP map of the biggest radius for each pixel is built and the pixels are divided into “uniform” and “non-uniform” two groups. A sub histogram is built for those “uniform” patterns. Second, the “non-uniform” pixels are further processed to extract their LBP patterns by smaller radius until the smallest radius. Third, all histograms are concatenated into one multiscale histogram which named Hierarchical multiscale local binary pattern feature. Figure demonstrates the Hierarchical multiscale LBP mappings for different radii and different neighbors:  $R = (3,2,1)$  and  $P = (8,8,8)$ .

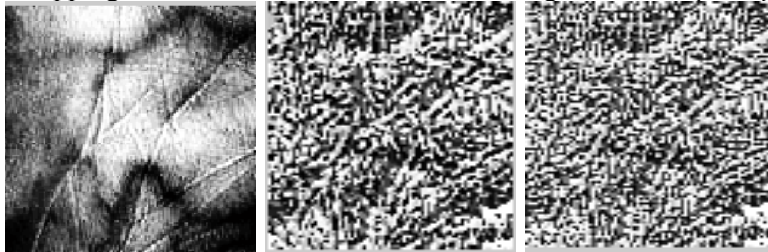


Figure 1 Hierarchical multiscale LBP feature of palm-vein

From the figure 1 we can see that Hierarchical multiscale LBP can extract more useful texture feature of the palm-vein. If the original image size is  $128 \times 128$ ,  $R$  value is 2 and the neighbor is 8, the dimension of the Hierarchical multiscale LBP is 3744 which will be increased the computational burden of the subsequent processing. In this work, locality preserving projections (LPP) was used for feature dimension reduced.

## 2.2. Locality Preserving Projections

Locality preserving projection algorithm is proposed by He Xiaofei et al in 2002[11]. It is a linear approximation of Laplacian Eigenmaps. Besides the features of linear dimensionality reduction method such as simple calculation and high processing speed, it also has the features absent in linear algorithm such as maintaining the local invariance of high-dimensional data, obtaining low-dimensional projection of new sample points and so on. It is widely used in pattern recognition.

Given a set  $x_1, x_2, \dots, x_m$  in  $R^n$ . find a transformation matrix  $A$  that maps these  $m$  points to a set of points  $y_1, y_2, \dots, y_m$  in  $R^k$  ( $k \ll n$ ), such that  $y_i$  represents  $x_i$ , where  $y_i = A^T x_i$ . The objective function of Lpp is as follows:

$$\sum_{ij} (y_i - y_j)^2 W_{ij}$$

$W_{ij}$  is the weight of the connection between  $x_i$  and  $x_j$ , and  $W_{ij} = W_{ji}$ ,  $W$  is the weight matrix. The simplified guideline function is

$$\begin{aligned} \frac{1}{2} \sum_{ij} (y_i - y_j)^2 W_{ij} &= \frac{1}{2} \sum_{ij} (a^T x_i - a^T x_j)^2 W_{ij} \\ &= a^T X(D - W)X^T a = a^T XLX^T a \end{aligned}$$

$D$  is a diagonal matrix whose diagonal elements are sum of the elements of same row or the same column with  $W$ , and  $L = D - W$  is called a Laplacian matrix. The criteria function translates into minimizing the problem:

$$\arg \min a^T XLX^T a$$

The minimization problem can be translated into the following generalized eigenvalue:

$$XLX^T a = \lambda XDX^T a$$

Let the column vectors  $a_0, a_1, \dots, a_{k-1}$  be the solutions of equation, ordered according to their eigenvalues,  $\lambda_0 > \lambda_1 > \dots > \lambda_{k-1}$ . Thus the embedding is as follows:

$$\begin{aligned} x &\rightarrow y = A^T x \\ A &= W_{PCA} W_{LPP} \\ W_{LPP} &= [a_0, a_1, \dots, a_{k-1}] \end{aligned}$$

### 2.3. Normalized Correlation Classifier

In this paper, we use the normalized correlation classifier to classify the vein features.  $LBP_{LPP}$  stands for the vein features to be measured,  $LBP_{LPP}$  represents the characteristics of the vein training samples. Use following formula to normalize the correlation between the two features

$$NC_{LPP} = \frac{1}{nm\sigma_{LPP1}\sigma_{LPP2}} \sum_{i=1}^n \sum_{j=1}^m (LBP_{LPP1}(i, j) - \mu_{LPP1})(LBP_{LPP2}(i, j) - \mu_{LPP2})$$

The proposed algorithm steps are as follows:

1. Extract the effective area of the vein, with the size of 128 \* 128, and then increase the gray balance, the train samples matrix is 3000\*128\*128.
2. Then extract hierarchical multiscale LBP feature, the feature matrix size is 3000 \* 3744.
3. Use LPP to reduce the hierarchical multiscale LBP features, after dimensionality reduction, the feature matrix size is 3000\*80.
4. Use the relevant classifier for classification and six cross for validation. Compare sample to be tested with training samples one by one. If they are from the same palm, then it is the correct match, otherwise the false match.

## 3. Experimental results

### 3.1. Database

The hand vein blood vessels are subcutaneous tissue. Hemoglobin in human venous blood can absorb infrared light of specific wavelengths. The data shows that the hemoglobin has two absorption peaks at the wavelength of 760nm and 850nm. The multi-spectral palmprint database of the Hong Kong Polytechnic University [12] has images of four wavelengths among which the near-infrared image uses a near-infrared light of 880 nm wavelengths which can be absorbed by hemoglobin in the venous blood and hence the distribution image of palm venous vein can be collected. A total of 250 volunteers' information is collected in the database. 6000 images from the volunteer are collected from volunteers left and right hands with each palm were collected six images in two times at an average interval of 9 days.

### 3.2. Experimental results and analysis

This paper we take the samples collected for the first time as training samples, and samples collected for second times as test samples. If the two samples are from the same palm, it is considered as correct matching, otherwise as false matching. In order to verify the effectiveness of combining hierarchical multiscale LBP with LPP, three experiments were carried out in the following.

The first experiment is to test the algorithm only using hierarchical multiscale LBP. First, extract the palm-vein hierarchical multiscale LBP feature, and then use correlation classifier to classify. The correlation distribution between classes and within classes is shown as figure 2, and the FRR and FAR distribution is shown as the figure 3.

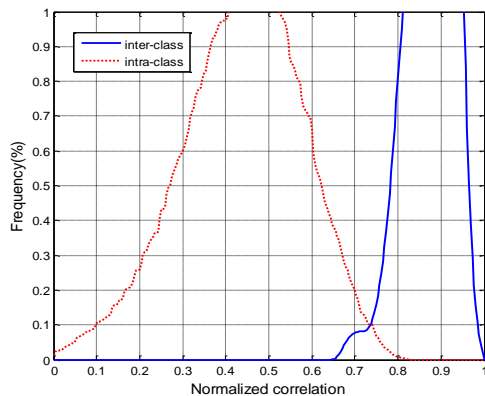


Figure 2 distribution of normalized correlation

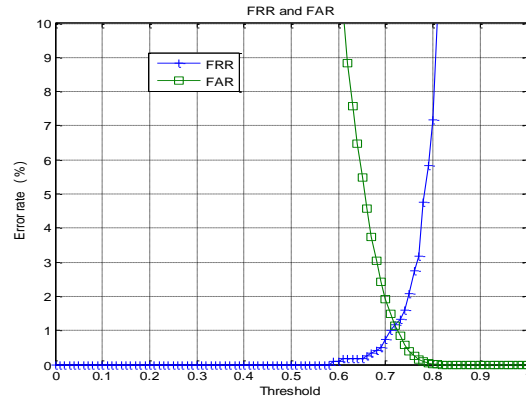


Figure 3 the distribution of FRR and FAR

From figure 2, we can see that the distribution have two peaks at 0.48 and 0.88, so the classification of veins can be distinguished by the normalized correlation classifier. From figure5, we see that the EER is 1% only using Hierarchical multiscale LBP feature.

The second experiment is to test the algorithm only using LPP. First, the original palm-vein images was reduced to lower dimension by LPP, and then use correlation classifier to classify,. The correlation distribution between classes and within classes is shown as figure 4, and the FRR and FAR distribution is shown as the figure 5.

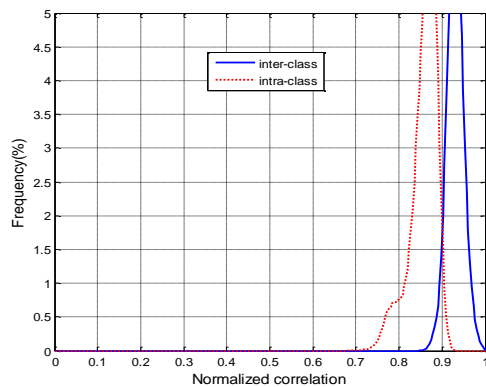


Figure 4 distribution of normalized correlation

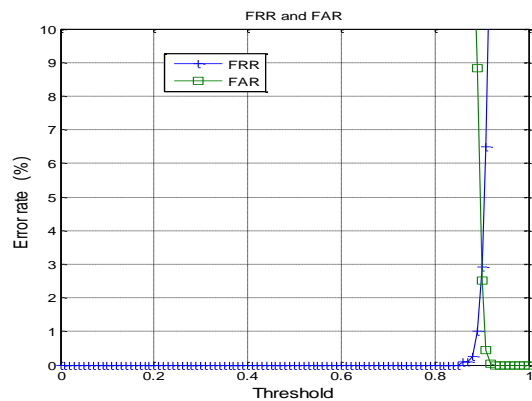


Figure 5 distribution of FRR and FAR

From figure 4, we can see that the distribution have two peaks at 0.85 and 0.95, so the classification of veins can be distinguished by the normalized correlation classifier. From figure5, we see that the EER is 3% only using LPP feature.

The third experiment is to test the algorithm proposed in this paper. First, extract the palm-vein Hierarchical multiscale LBP feature, then use LPP to reduce dimension, and then use correlation classifier to classify,. The correlation distribution between classes and within classes is shown as figure 6, and the FRR and FAR distribution is shown as the figure 7.

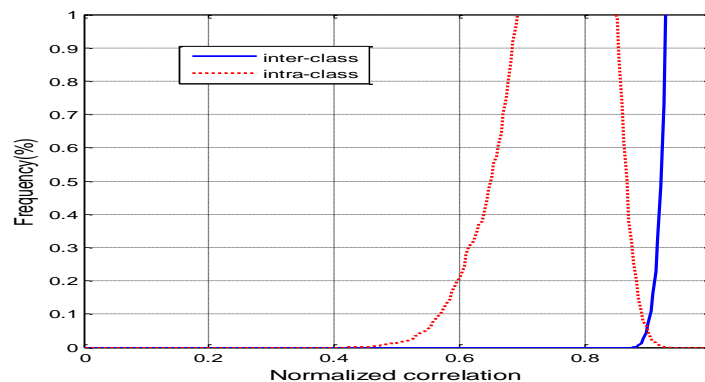


Figure 6 the distribution of the normalized correlation for the palmprint Hierarchical multiscale LBP and LPP

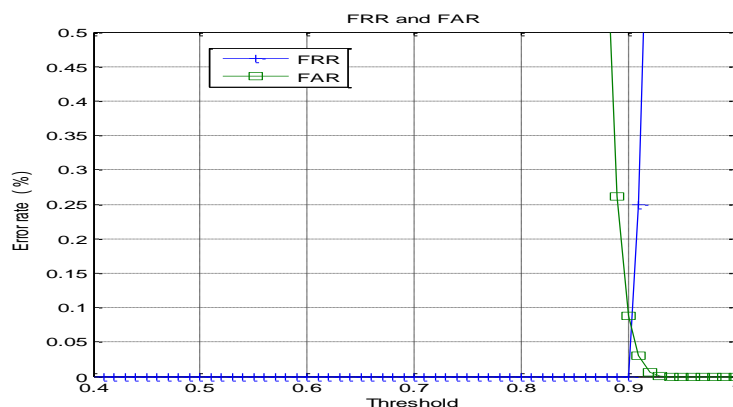


Figure 7 the distribution of FRR and FAR using hierarchical multiscale LBP and LPP

From figure 6, we can see that there are two peaks of distribution, and the classification of veins can be distinguished by the normalized correlation classifier.

From figure 7, we see that the EER is reduced to 0.08%. The results are far better than using single character of hierarchical multiscale LBP and LPP for palm-vein, so combining hierarchical multiscale LBP and LPP for feature extracting, the recognition effect is greatly improved.

#### 4. Conclusions

In this work, a novel algorithm for palm-vein recognition was proposed. The feature was extracted by Hierarchical multiscale local binary pattern which dimension was reduced using LPP. The normalized correlation classifier was used as classifier. The algorithm was tested on the public database and got ideal recognition rate.

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