International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.7, No.1 (2014), pp.33-44
http://dx.doi.org/10.14257/ijsip.2014.7.1.04

Palm Vein Verification Using Multiple Features and Isometric Projection

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Abstract

Biometric authentication has been widely studied for many years and attracted much attention due to its large ability security application. Palm vein is more immovable and more difficult to fake than other biometrics such as fingerprint, palm print and face. Since palm veins exist inside of the body, it is exceedingly hard to be forged. Palm vein authentication uses the unique patterns of the palm vein to identify individuals at a high level of accuracy. In the proposed work, the palm vein image enhancement algorithm proposed based on Gaussian matched filtering and then two types of feature extraction are extracted. The global features based on wavelet coefficients and locale feature based on local binary pattern (LBP). In the propose work, a linear dimensionality reduction algorithm, called Isometric Projection is used. Finally, the Manhattan Distance (MHD) matching method is proposed to verify the test palm vein images. The experimental result shows the EER to the proposed method is 0.17488%.

Keywords: *Palm Vein, Wavelet-LBP, Isometric Projection*

1. Introduction

Recently, many personal authentication methods have proposed the vein patterns such as palm veins and finger veins have been used in security applications. In palm vein recognition, use the internal information from a person's body and vein patterns, which are visible with near-infrared (NIR) light illuminators and cameras. It is difficult to counterfeit veins using forged vein patterns. The palm vein recognition systems are widely used because the recognition accuracy is very high [1]. The speedy growth in the use of e-commerce applications requires faithful user identification for effective and secure access control [2]. In the system that employs biometrics for personal recognition, there are a number of other issues that should be considered, including:

- Performance, which indicates the achievable recognition accuracy and speed.
- Acceptability, which refers to the extent to which people are willing to accept the use of a particular biometric identifier (characteristic) in their daily lives.

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ISSN: 2005-4254 IJSIP

- Circumvention, which reflects how easily the system can be fooled using counterfeit methods.

Palm vein authentication has high level of authentication accuracy due to the singularity and intricacy of vein patterns of the palm. The palm vein patterns are difficult methods to forge because it is internal in the body.

Palm vein system is more robust than another biometric authentication such as face, iris, and retinal [3]. Most of the existing vein recognition methods extract features from the structure of vein patterns. Kumar [2] presented a new approach to authenticate individuals using triangulation of hand vein images and simultaneous extract the knuckle shape information. Since most of the vein information has been missed during minutiae feature's extraction, vein recognition systems based on minutiae features can hardly get a high accuracy. Zhang [5] proposed a multi-scale Gaussian scheme, which used two different scales of filters to extract veins. These methods based on vein extraction methods are heavily influenced by noise. However, they evaluated the method using small database (144 images), making it hard to draw strong conclusions. Zhang [6] worked on (PolyU) database that is used in the proposed method. The researcher combined the palm print and palm vein. The method that is used to extract the vein is matching filter. The EER to the palm vein system is 0.3091%. However, they fused the palm print with palm vein features to evaluate the system. Lee [19] considers the palm vein as a piece of texture and apply texture based feature extraction techniques to a palm vein authentication. A 2D Gabor filter is applied for extracting the local features in the palm vein. The researcher proposed a directional code technique to encode the palm vein features in bit string representation called vein code. The similarities between two vein codes are measures by normalized Hamming distance. Sun [20] worked on the (PolyU) database that is used in the proposed method. They used a multiscale curvelet transform as a feature extraction and used subset from these features as a feature vector and for matching propose they used the Hamming distance. The lowest EER to the system is 0.66% reach when select (40%) from the features set. All the above studies they implemented using fusing multimodal or used a small database or the accuracies are low. In the previous work [21], we are implementing a palm vein verification system. The feature's extraction is depended on the Gabor filter with eight scales and eight directions. A new dimension reduction method is proposed call FisherVein. The matching step is depending on the Nearest Neighbour method. The EER to the system is 0.2335%.

This paper proposed a multiple extraction features (global and locates) features methods. The global features extracted using wavelet transform coefficients and the Local Binary Pattern (LBP) represents the locale features for the palm vein image. Based on the propose palm vein feature representation methods, a palm vein authentication system is constructed. The Isometric mapping method is implemented to dimensional reduction. Then by using the Manhattan Distance method, matching the test palm vein images. The system flowchart is shown in Figure 1. First of all, the palm vein image is enhancement using Gaussian matched filtering and then the features are extracted. And then a dimension reduction method using Isometric projection is implemented. After the similarity measure for each feature's vector, fusion techniques are applied to fuse all the matching scores to obtain a final decision.

The rest of this paper is organized as follows. Section 2 describes the preprocessing. In Section 3, describe the feature extraction methods. In Section 4, describe the dimension reduction using Isometric mapping projection. In Section 5, we describe the matching and matching score fusion strategy used in this work. Finally, the experimental result and conclusions are drawn in Section 6.

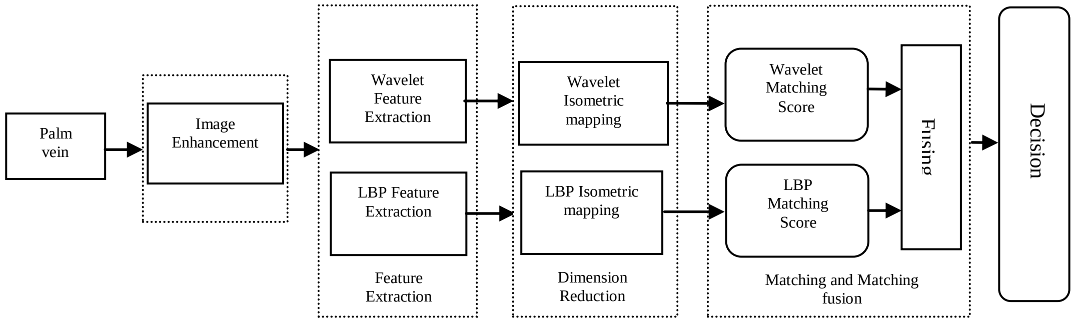


Figure 1. System Flowchart

2. Preprocessing

The Gaussian function shape is similar to the cross-sections of the palm vein. The Gaussian matched filters are widely used in retinal vessel extraction, due to that it can be a good technique to extract these palm veins [4-6]. The Gaussian matched filters are Gaussian shaped filters along an angle θ:

$$g_\theta^\sigma(x,y) = -\exp\left(-\frac{x'^2}{\sigma^2}\right) - m \text{ For } |x'| \le 3\sigma, |y'| \le L/2 \quad (1)$$

Where $x' = x\cos\theta + y\sin\theta, y' = -x\sin\theta + y\cos\theta$, σ the standard deviation of Gaussian, m is the mean value of the filter, and L is the length of the filter in y direction, which is set empirically. The filter is designed as a zero-sum to repress the background pixels. For each pixel, six different angle filters (θj = jπ/6, where j = {0, 1, 2, 3, 4, 5}) are applied, and the maximal response among these six directions is kept as the final response for the given scale

$$\begin{aligned} R_F^\sigma &= \max\left(R_{\theta j}^\sigma(x,y)\right), j = \{0,1,2,3,4,5\} \\ R_{\theta j}^\sigma(x,y) &= g_{\theta j}^\sigma(x,y) * f(x,y) \end{aligned} \quad (2)$$

Where $f(x,y)$ is the original image and * denotes the convolution operation [4-6]. The value of σ and L is set by experimental as shown in Figure 2 the result of palm vein enhancement.

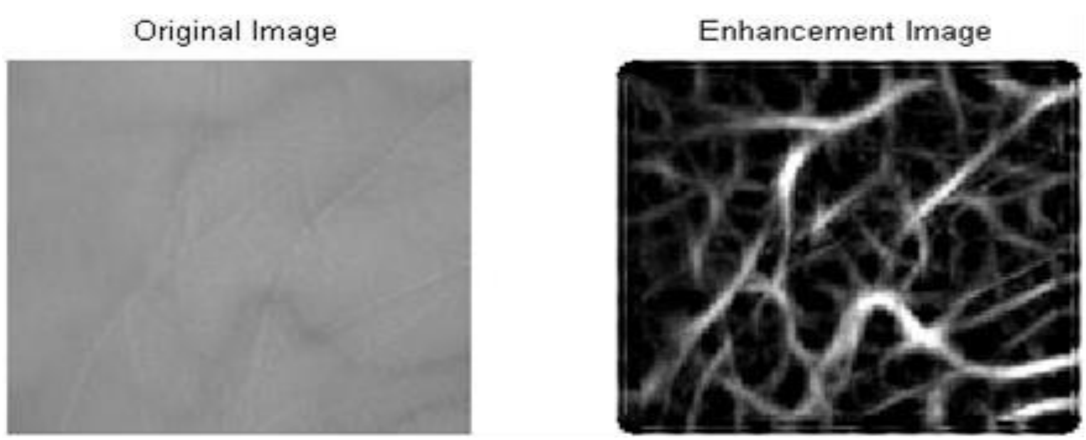


Figure 2. Palm Vein Enhancement

3. Feature Extraction

The feature extraction step goal to extract the existing features of the palm vein pattern, from an image, that then are going to be used for matching. If the image is an enrolled sample, the features are saved in a training database for later matching. Once the features are extracted, they are compared with the ones in the database and based on that comparison a decision is taken. In the propose work, we used two types of features. The first type is global feature (two dimension wavelet transform) coefficient, and the second type is the local feature (Local Binary Pattern (LBP)).

3.1. Feature Extraction based on 2D-Wavelet Transform

Wavelets are powerful tools of multi-resolution analysis, which have been used extensively in biometrics based identity recognition system. The biometrics features have different directions and different resolution due to that it can use a 2D wavelet transform that decompose the image in several directions at different resolution (scale), which is very advantageous to characterize biometrics. Moreover, to a no oscillating pattern, the amplitudes of the wavelet coefficients increase, whereas, to a high frequency oscillating pattern; the amplitudes of wavelet coefficients at large scales are much smaller than at the fine scale which matches the spatial frequency of the oscillations [7]. Wavelet transforms are finding inverse use in fields as diverse as telecommunications and biology. The appropriateness analyzing to non-steady signals, the 2D wavelet is more alternative to Fourier's method in many applications. The main benefit of the wavelets is that they have a variable in window size, being vast for low frequencies and close to the high ones, so leading to an optimum time-frequency resolution in all the frequency ranges. Furthermore, because windows are altered to the transients of each scale, wavelets lack the need of fixed [8]. The wavelet is widely used in the analysis of textual images since 1990. Accordingly, the human visual system sees textures through different channels associated to specially frequency bands and directions; and wavelet representations offer this type of decomposition. To make an efficient texture analysis, by extracted simple features from each sub band and describe the image at different scales and orientations [9]. In the propose work, the feature extraction from palm vein image is the wavelet transform. The approximation coefficients to the third level are calculated and used its values as features. The wavelet families selected are the Daubechies (db2) and Symlets (sym2). Figure 3 shows the Daubechies and Symlets families:

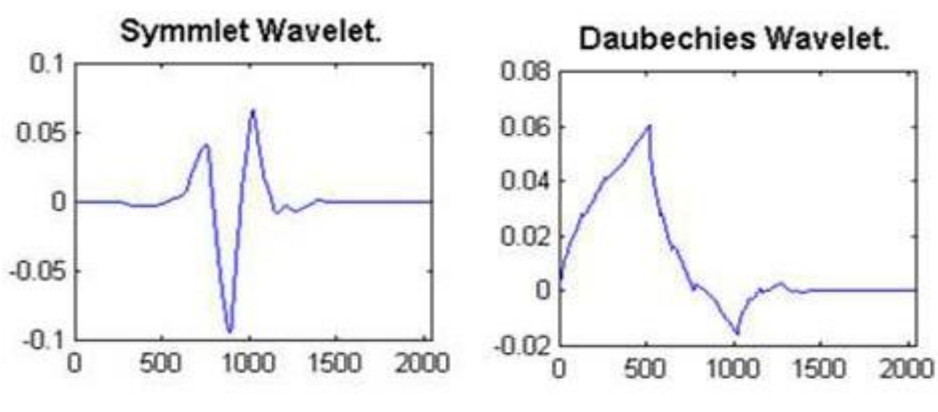


Figure 3. Daubechies and Symlets Wavelet Families

3.2. Feature Extraction based on LBP

LBP is a gray-scale texture operator which characterizes the spatial structure of the local image texture. Given a central pixel in the image, a pattern number is computed by comparing its value with those of its neighborhoods:

$$LBP_{P,R} = \sum_{p=0}^{P=1} s\left(g_P - g_c\right) 2^p \tag{3}$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{4}$$

Where g_c is the gray value of the central pixel, g_P is the value of its neighbours, P is the number of neighbours, and R is the radius of the neighbours. Suppose the coordinates of g_c are (0,0), then the coordinates of g_P are given by $\left(-R\sin\left(2\pi/P\right), R\cos\left(2\pi/P\right)\right)$. Figure 4 shows examples of circularly symmetric neighbours sets for different configurations of (P, R). The gray values of neighbours that are not in the center of grids can be estimated by interpolation [10].

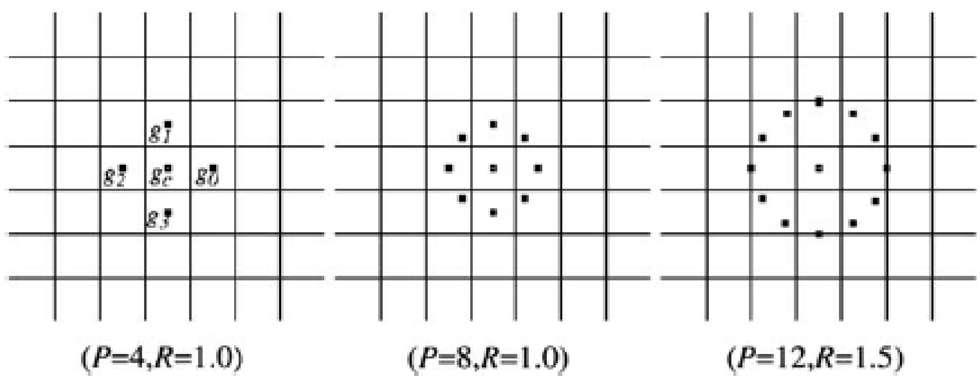


Figure 4. LBP Neighbours Sets for Different (P, R) [10]

LBP is a well-known local feature extractor for texture descriptors. LBP has several interesting properties [11]:

- It does not require high computational power to calculate;
- It is very robust to illumination changes and rotations.

In the propose system, two feature vectors are created. The first vector from an approximation coefficient of the wavelet functions (Daubechies (db2) and Symlets (sym2) Wavelet), and the second feature vector is created from the LBP. Figure 5 shows the flowchart of creation the feature vectors. The *z*-normalization is proposed here for normalization the feature's vector [6]:

$$FeatureVector_{Normalize} = \frac{FeatureVector - \mu}{\sigma} \tag{5}$$

Where μ the mean of the feature vector is, σ is the standard deviation of the feature vector.

4. Dimension Reduction based on Isometric Projection

Dimensionality reduction means that samples are projected from a high dimensional observation space to a low dimensional feature space through linear or nonlinear mapping to find out meaningful low dimensional structure hidden in high dimensional observation data. With advantages that can't be compared by linear dimensionality reduction method, nonlinear dimensionality reduction method is ideal to be applied to reduce the dimensionality of high dimensional data, perform cluster analysis and find out internal structure of data and hidden information.

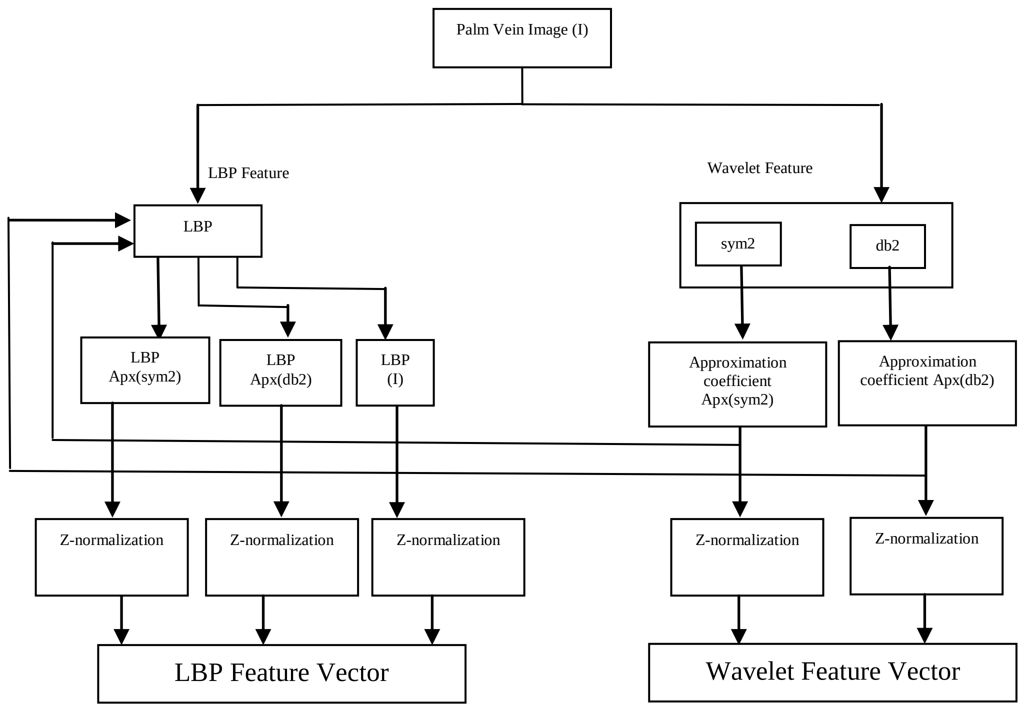


Figure 5. Flowchart of the Feature Vectors Extraction

Dimensionality reduction is an important task in machine learning, for it facilitates classification, compression, and visualization of high-dimensional data by mitigating undesired properties of high-dimensional spaces [12]. The problem of the dimensionality reduction process has received a more interest in many fields of information processing. In the case the data is sampled from a low dimensional manifold which is embedded in high dimensional Euclidean space. The most common manifold learning algorithms include ISOMAP, Locally Linear Embedding and Laplacian Eigenmap.

However, these algorithms are nonlinear and only provide the embedding results of training samples. Another linear dimensionality reduction algorithm, called **Isometric Projection**. Isometric Projection constructs a weighted data graph where the weights are discrete approximations of the geodesic distances from the data manifold. A linear subspace is then obtained by preserving the pairwise distances [13, 14]. Isometric projection (IP) is a supervised learning algorithm. Based on the assumption that, palm vein images, are points in a high dimensional manifold *M*, IP aims to find a euclidean embedding such that the euclidean distances in $\Re^d$ give a good approximation to the geodesic distances over the manifold *M*. IP yields a transformation matrix from $\Re^n$ to $\Re^d$ that satisfies the above property

[13, 15]. In the proposed work, used the Isometric projection (IP) algorithm as implemented in Reference [15]:

1) Construct a weighted graph over all data points using K-nearest neighbours (KNN) or epsilon (set an edge between two points *x*, *y* if *y* is from the k nearest neighbors of *x*, or the Euclidean distance between them is less than epsilon). The Geodesic distances matrix *DG* is calculated by finding the shortest path between each pair of points.

2) Compute the inner product matrix for the Geodesic distances $\tau(D_G)$. The aim is to minimize $\left\| \tau(D_G) - \tau(D_Y) \right\|^2$ where D_Y is the target Euclidean distance matrix, and $\tau(D_Y)$ represents its inner product matrix.

3) Let $Y = (y_1, y_2, ..., y_m) = a^T X$, where *X* is a set of original data points and *Y* is a set of points in a Euclidean space whose distances are almost equal to the original geodesic distances i.e. $\tau(D_Y) = Y^T Y = X^T a a^T X$, Which results in the generalized eigenvalue problem: $X \tau(DG) X^T a = \lambda XX^T a$; where ***a*** denotes the eigenvectors and λ are the eigenvalues.

5. Matching and Matching Score Fusion

A pattern in the test data is classified by calculating the distance to all the pattern in the training data; the class of the training pattern that gives the shortest distance determines the class of the test pattern. The distance functions most widely employed to perform similarity queries over vector spaces are those of the Minkowski family (or *Lp* norm). Where the objects are identified with *n* real-valued coordinates. Considering two feature vectors $F = \{f_1, ..., f_E\}$ and $G = \{g_1, ..., g_E\}$ the *Lp* distances are defined as:

$$Lp\big((f_1, ..., f_E), (g_1, ..., g_E)\big) = \sqrt[P]{\sum_{j=1}^{E} \left| f_j - g_j \right|^P} \tag{6}$$

Varying the value assigned to *p* we obtain the *Lp* family of distance functions. They are additive, in the sense that each feature contributes positive and independently to the distance calculation. The well-known Euclidean distance corresponds to *L*2. The *L1* distance, also called city block or Manhattan Distance (MHD), corresponds to the sum of coordinate differences. In the propose system, we have two feature vectors (Wavelet feature vector and LBP feature vector), by using the Manhattan Distance compute the matching distance matrix to each feature vector. The weighted sum fusion rule is applied to combine the two matching distance matrices to obtain a final matching score to decide a decision as the show in Figure 1. If the optimal weight's sum of two modalities is searched exhaustively, it needs a twofold loop to reach to the smallest value of EER. In this work, we test sum and weighted sum on Wavelet feature vector and LBP feature vector matching score fusion:

$$FD_{sum} = D_{wavelet\ feature} + D_{LBP\ feature} \tag{7}$$

$$FD_{weightsum} = W_{wavelet\ feature} D_{wavelet\ feature} + W_{LBP\ feature} D_{LBP\ feature} \tag{8}$$

Where $D_{wavelet\ feature}$ and $D_{LBP\ feature}$ are the wavelet feature and LBP feature matching scores obtained by equation (6). $W_{wavelet\ feature}$ and $W_{LBP\ feature}$ are the weights for wavelet feature and LBP feature in the fusion.

6. Experimental Results and Conclusion

6.1. Experimental Results

The Biometric Research Centre (UGC/CRC) at The Hong Kong Polytechnic University has developed a real time multispectral palm print capture device which can capture palm print images under blue, green, red and near- infrared (NIR) illuminations, and has used it to construct a large-scale multispectral palmprint database. Multispectral palmprint images were collected from 250 volunteers, including 195 males and 55 females. The age distribution is from 17 to 60 years old. The samples are collected in two separate sessions. In each session, the subject was asked to provide six images for each palm. Therefore, 24 images of each illumination from 2 palms were collected from each subject. In total, the database contains 6,000 images from 500 different palms for one illumination. The average time interval between the first and the second sessions was about nine days. The proposed method used the near-infrared (NIR) illumination's images of PolyU multi-spectral palm print database [22].

To establish the sturdiness of the proposed method in the experiment the total number of the palm vein images was 6000 images, which were collected from 500 persons each with 12 images captured at two sessions. In verification, receiver operating characteristics (ROC) curve is used to show the behavior of the propose method. In the experimental randomly select six images from each person for training set and the other for testing set. The Manhattan Distance method is used to verify the feature vector from test set with the train set feature vectors and take the minimum distance for verification. The distance distribution of genuine and impostor of the palm vein images is shown in Figure 6 (a), and the ROC curve is shown in Figure 6 (b), and the EER is 0.222% by using Manhattan Distance matching with sum fusion as equation (7). The distance distribution of genuine and impostor of the palm vein images is show in Figure 7 (a), and the ROC curve is shown in Figure 7 (b) and the EER to the propose system is 0.17488% by using Manhattan Distance matching with weight sum fusion as equation (8). As the shown in Figure 1, the system has many steps (preprocessing and multiple features and dimension reduction). Table 1 shown some experimental on the system by don't implement one of its step.

Table 1. Some Experimental

Method	Matching Method	EER
Without Preprocessing	Manhattan Distance	0.5526%
	Euclidian Distance	0.5382%
Without Dimension Reduction	Manhattan Distance	2.3395%
	Euclidian Distance	2.2342%
Without Wavelet Transform	Manhattan Distance	7.081%
	Euclidian Distance	6.6507%
Without LBP	Manhattan Distance	0.2836%
	Euclidian Distance	0.3218%
Proposed system	Manhattan Distance	0.17488%
	Euclidian Distance	0.1998%

As the show from Table 1, when implement the system without preprocessing or select one method for feature extraction or without dimension reduction, the value of EER is high. The preprocessing is an important step because the palm vein images are not clear and have some noise. The EER is high due to the relatively low quality of palm vein images. Also the EER is high when not used the wavelet feature because the Wavelet is commonly used for multi-resolution analysis and representing image variations at different scales. The biometrics features have different directions and different resolution due to that it can use a 2D wavelet transform that decompose the image in several directions at different resolution (scale), which is very advantageous to characterize biometrics. And the EER also high when not used the LBP because the LBP is a gray-scale texture operator which characterizes the spatial structure of the local image texture. By proposed multiple features (wavelet and LBP) we can get lowest EER. And by projected the feature space from a high dimensional observation space to a low dimensional feature space through Isometric projection to find out meaningful low dimensional structure hidden in high dimensional observation data to get the lowest EER.

Four methods for palm vein authentication are proposed for comparison. In the [6, 20, 21] all work on the same database (polyU), and in [19] we implement him method and tested on the same work database. Table 2 shown the comparison of our method and all above methods.

Table 2. Comparison Methods on our Palm Vein Images Database

Method	EER
David [6]	0.3091 %
Lee [19]	1.111%
Sun [20]	0.66%
Ali [21]	0.2335%
Proposed method using Manhattan Distance	0.17488%

From the result illustrate in Table 2 and Figures 7 (a) and (b), we can find that the proposed methods have better performance from the methods that describe in [6, 19, 20, 21] and the smallest EER is 0.17488% by using the Manhattan Distance. The experimental results show that our method has the better results than [6, 19, 20, 21] methods. The main benefit of the proposed method, is that used the multiple features local and global feature vectors (wavelet and LBP) and then implement the dimensional reduction using Isometric projection method and proposed the matching score fusion method that reached to lowest EER value.

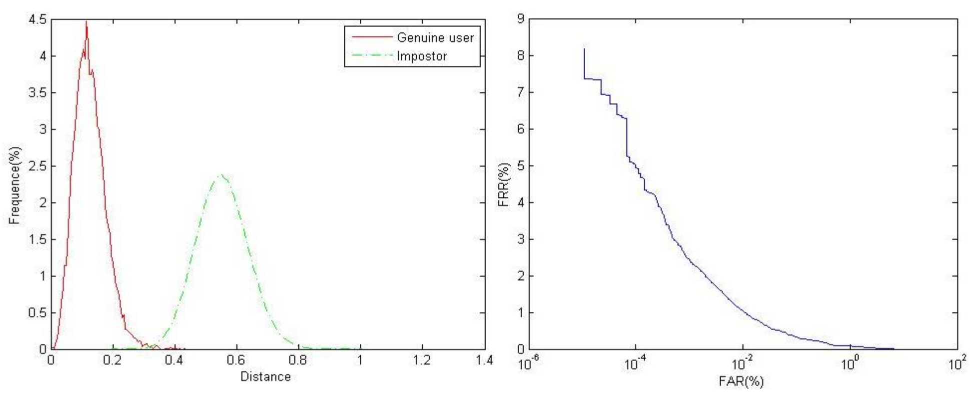
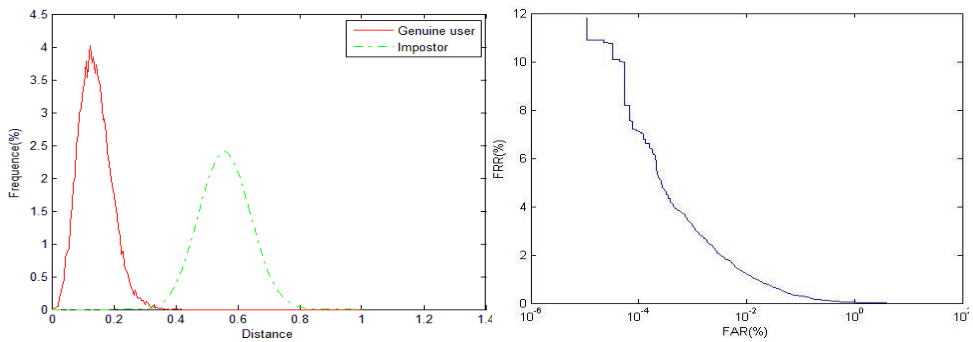


Figure 6. (a) - Matching Distance Distribution of Palm Vein for Sum Fusion (b) - ROC Curve for Sum Fusion



(a) **(b)**

Figure 7. (a) -Matching Distance Distribution of Palm Vein for Weight Sum Fusion
(b) - ROC Curve for Weight Sum Fusion

6.2. Conclusion

Palm Vein authentication uses features of the veins, which are inside the palm. The palm vein patterns like other biometric patterns are unique. In addition, palm vein patterns are virtually impossible to replicate because they are inside the body. Using the palm vein is extremely robust, demonstrating a unique ability to easily cope with sweaty, dry palm. In this study, Gaussian matched filter was used for palm vein enhancement. The wavelet and LBP are used to perform features extraction. Isometric projection is used to dimension reduction. Manhattan Distance was then used to perform matching between the input image and the template. The weight sum is used to get the final decision. Further improvement could be achieved by the proposed local and global features and use the dimension reduction and fusion scheme for matching score. Through experiments on a large database, our system shows that it can verify a person with EER only about 0.17488%.

Acknowledgement

This work was supported by the Natural Science Foundation of China (Grant No. 61073125), the Program for New Century Excellent Talents in University (Grant No. NCET-08-0155), the Fok Ying Tong Education Foundation (Grant No. 122035), and the Fundamental Research Funds for the Central Universities (Grant No. HIT. NSRIF. 2013091).

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