# Palm Vein Verification Using Gabor Filter

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## Abstract

Palm vein authentication is one of the modern biometric techniques, which employs the vein pattern in the human palm to verify the person. The merits of palm vein on classical biometric (e.g. fingerprint, iris, face) are a low risk of falsification, difficulty of duplicated and stability. In this research, a new method is proposed for personal verification based on palm vein features. In the propose method, the palm vein images are firstly enhanced and then the features are extracted by using bank of Gabor filters. Then Fisher Discriminated Analysis (FDA) is used to reduce the dimension of the features vectors. For vein pattern verification, this work uses Nearest Neighbors method. The EER of the proposed method is 0.2335%.

**Keywords:** Palm vein, Gabor Filter, EigenVein, FisherVein.

## 1. Introduction

Biometric technology refers to a pattern recognition system which depends on physical or behavioral features for the person identification. Many biometric systems exist today by using fingerprint, face, iris, etc. Palm vein is a new member of biometric family. Palm vein is defined as vascular patterns under the skin of the palm [1]. Like the fingerprint, the pattern of vain very state in the life and different in each part in same body. Because the vein pattern is hidden underneath the skin and invisible directly by the eye, the vein pattern is difficult to copy compared with other biometric types [2]. Besides, the palm vein is impossible to fake [1]. The researcher and the communities are increasingly interested in vein pattern recognition. In [3] the researchers take the shape and texture of the hand vein for person authentication. They used Hausdorff distance and like edge mapping for shape authentication and Gabor filter for feature vein extraction.

However, the researchers work on a database of 1600 images and get recognition rate is 80%, which makes this system have not a good result. In [2] the researchers analyzed the infrared back hand image. They used the minutiae features extracted from hand vein pattern for recognition. This pattern includes bifurcation point and ending point as fingerprint. However, they evaluated the method using small database (141 images), making it hard to draw strong conclusions. In [4] the researchers built a multimodal identification system based on fusion of the palm print and palm vein on image level. By using the novel integrated line preserving and contrast enhancement fusion method the palm print and palm vein are fused. The modified multiscale edge of palm vein and palm print images are combined additionally the image contrast and interaction point (IP) of palm vein line and palm print are enhanced. By using the IP, the feature vectors of the combine images are extracted. However, they implement the image acquisition using two separated cameras and requires a time consuming registration procedure, which makes it difficult to use in real time. In [14], the researchers worked on the same database (PolyU) that is used in the proposed method. They combined the palm print and palm vein. The method that is used to extract the vein is matching filter. The EER to the system is 0.3091%. However, they fused the palm print with palm vein features to evaluate the system. In [19], the researchers consider 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 similarity between two vein codes is measure by normalized Hamming distance. All the above studies they implemented using fusing multimodal or used a small database or the accuracy are low.



In this paper, we proposed a new method for palm vein extraction and features reduction dimensional and matching to get a less EER to make the used method is more secure. The remainder of this paper is organized as follows. Section 2, perform the palm vein features extraction using Gabor Filter. Section 3, used the fisher discriminated analysis to dimensional reduction and remove the redundancy in the features vector. Section 3, verify the test data by using Nearest Neighbors method.

## 2. The framework of the propose method

As show in figure 1, the propose method is consisted of three parts, preprocessing, feature extraction and matching. Then based on the matching method, can verify the user.

## 2.1 Preprocessing

Palm vein images are preprocessing by enhancement vein pattern before feature extraction. In the propose method, the method that is used for vein image enhancement is histogram equalization as show in figure 2.

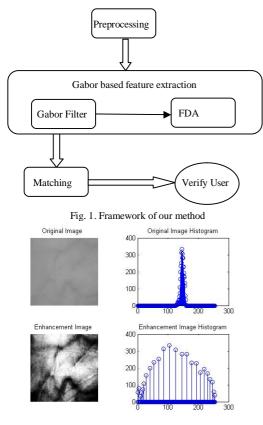


Fig. 2. Palm Vein Image Enhancement

# 3. Feature Extraction Based on Gabor Filter

The feature extraction is implement using Gabor filter. Gabor filter is a band pass filter which have orientationselective and frequency-selective features and optimal joint resolution in both spatial and frequency domain [5, 6]. Gabor filters have been extensively used for extracting texture information, that they were powerful in capturing some specific local features in the texture image. A twodimensional Gabor filter is a combine function with two components: a complex plane wave and a Gaussianshaped function. It is defined as following:

$$G(x, y) = k \exp\left\{-\frac{1}{2}\left(\frac{x_{\circ}^{2}}{\sigma_{x}^{2}} + \frac{y_{\circ}^{2}}{\sigma_{y}^{2}}\right) + j 2\pi f_{\circ} x_{\circ}$$
(1)

$$x_{\circ} = x \cos \emptyset + y \sin \emptyset \tag{2}$$

$$y_{\circ} = -x\sin\emptyset + y\cos\emptyset \tag{3}$$

Where  $k = \frac{1}{(2\pi\sigma_x \sigma_y)}$ ,  $j = \sqrt{-1}$ ,  $\theta$  is the orientation of Gabor filter,  $f_{\circ}$  represent the filter center frequency,  $\sigma_x$  and  $\sigma_y$  are the scale of the Gaussian shape,  $x_{\circ}$  and  $y_{\circ}$  are the two vertical Gaussian axes. The most important parameters  $f_{\circ}, \sigma_x$  and  $\sigma_y$  in Gabor function that make the filter appropriate for some specific application. The Gabor filter can be split to imaginary part and real part. The imaginary part (odd symmetric) Gabor filter is used for edge detection. The real part (even symmetric) Gabor filter is used for detecting the ridge in the image [7, 8, 16]. To analysis the Gabor filter in terms of real part and imaginary part, can be represented as following:

$$G_{mk}^{e}(x, y) = k \exp\left\{-\frac{1}{2}\left(\frac{x_{\circ}^{2}}{\sigma_{x}^{2}} + \frac{y_{\circ}^{2}}{\sigma_{y}^{2}}\right) \cos(2\pi f_{mk}x_{\circ k}) \quad (4)$$
$$G_{mk}^{o}(x, y) = k \exp\left\{-\frac{1}{2}\left(\frac{x_{\circ}^{2}}{\sigma_{x}^{2}} + \frac{y_{\circ}^{2}}{\sigma_{y}^{2}}\right) \sin(2\pi f_{mk}x_{\circ k}) \quad (5)$$

where *m* is the scale index, *k* is the channel index and  $f_{mk}$  is represent the center frequency of the real part and imaginary part of Gabor filter at the k<sup>th</sup> channel. After create a bank of Gabor filter, the enhanced palm image is convolved with the Gabor filter bank. The best output to the Gabor filter is depend on its parameters  $(f_{\circ}, \sigma_x, \sigma_y \text{ and } \emptyset)$ . In the propose method,  $\theta$  is begin from 0 to  $\pi$  by increment is equal to  $\pi/8$  and the center frequency  $f_{mk}$  is change with the orientation. In [7] propose a method to determine the relation between  $\sigma$  and  $f_{mk}$  and we used it in the research which is defined as following

$$\sigma f_{mk} = \frac{1}{\pi} \sqrt{\frac{\ln 2}{2}} \frac{2^{\Delta \emptyset_{mk}} + 1}{2^{\Delta \emptyset_{mk}} - 1} \tag{6}$$

where  $\Delta \emptyset_{mk} \ (\in [0.5, 2.5])$  is represent the spatial frequency bandwidth to the Gabor filter in the k<sup>th</sup> channel and m scale.  $\Delta \emptyset$  are put as  $\Delta \emptyset_1 < \Delta \emptyset_5 < \Delta \emptyset_2 < \Delta \emptyset_3 < \Delta \emptyset_4, \Delta \emptyset_2$ =  $\Delta \emptyset_8, \Delta \emptyset_3 = \Delta \emptyset_7, \Delta \emptyset_4 = \Delta \emptyset_6.$ 

In the propose method we built a bank of Gabor filter with 8 channels and 8 orientations and the central frequency is change depending on Eq. (6). Figure 3 shows some sample of the bank of Gabor filter. Assume that I(x; y) denote a palm-vein image, F(x; y) denotes a filtered I(x; y), we can obtain

 $F(x, y) = \sqrt{\left(G_{mk}^{e}(x, y)^{*}I(x, y)\right)^{2} + \left(G_{mk}^{o}(x, y)^{*}I(x, y)\right)^{2}}$ (7)

where \* denotes convolution in two dimensions. Thus, for a palm-vein image, 64 filtered images are generated by a bank of Gabor filters.

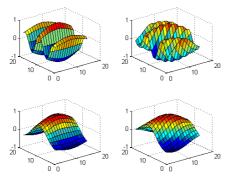


Fig. 3: A bank of Gabor filter

After creating the filter bank, the convolution operation is performed with the enhanced image in figure 2 with all the Gabor filters. The some sample of the results are shown in figure 4.

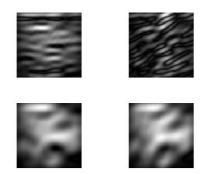


Fig. 4: The output of convolution operation

#### 4. Dimensional Reduction

Dimensionality reduction of the feature set is a common preprocessing step used for pattern recognition and classification applications. Feature selection is effective in the data decreasing and increasing accuracy and improving the result of the pattern recognition system[9]. In many applications such as data mining, pattern recognition and information retrieval the data reduction is very important. LDA is the most popular dimensionality reduction. By implement the eigen-decomposition on the scatter features matrix of the training data can get an optimal projection of the LDA. In the propose method, when implement the Gabor filter and used all filtered images pixels value as a features vector, the number of features is more than the number of sample, that lead a non-stable solution of LDA. To solve this problem the scatter features matrix must be non-singular. The preprocessing steps as PCA (Principle Component Analysis) and SVD (Singular Value Decomposition) must be implemented to ensure the features scatter matrix is a non-singularity. PCA techniques, also known as Karhunen-Loeve methods, choose a dimensionality reducing linear projection that maximizes the scatter of all projected samples [10].

# 4.1 EigenVein

PCA aims to find a subspace whose basis vectors correspond to the maximum-variance directions in the original space. The features extracted by PCA are the best description of the data, but not the best discriminated features [20]. Assume a set of N sample images  $\{x_1, x_2, ..., x_N\}$  taking values in an n-dimensional image space, and assume that each image belongs to one of c classes  $\{X_1, X_2, ..., X_c\}$ . Let us also consider a linear transformation mapping the original n-dimensional image space into an m-dimensional feature space, where m < n. The new feature vectors  $y_k \in R^m$  are defined by the following linear transformation [11].

$$w_k = W^T x_k$$
  $k = 1, 2, ..., N$  (8)

where  $W \in \mathbb{R}^{n \times m}$  is a matrix with orthonormal columns. If the total scatter matrix  $S_T$  is define as following:

$$S_{T} = \sum_{k=1}^{N} (x_{k} - \mu) (x_{k} - \mu)^{T}$$
(9)

where N is the number of sample images, and  $\mu \in \mathbb{R}^n$  is the mean image of all samples, then after applying the linear transformation  $W^T$ , the scatter of the transformed feature vector  $\{y_1, y_2, ..., y_N\}$  is  $W^T S_T W$ . In PCA the



projection  $W_{opt}$  is chosen to maximize the determinant of the total scatter matrix of the projected samples.

$$W_{opt} = \arg \max_{W} |W^{T}S_{T}W|$$
  
= [W<sub>1</sub>, W<sub>2</sub>,...,W<sub>m</sub>] (10)

where  $\{W_i | i = 1, 2, ..., m\}$  is the set of n-dimensional eigen-vector of  $S_T$  corresponding to the *m* largest eigenvector. Thus if PCA is implemented with images of vein, the projection matrix  $W_{opt}$  will contain principle

components, we will refer it's as EigenVein.

# 4.2 Fisher Discriminated Analysis

Fisher Discriminated Analysis (FDA) is a well-known approach for feature extraction and dimension reduction. It computes a linear transformation by maximizing the ratio of between-class distance to within-class distance, thereby achieving maximal discrimination [21]. FDA finds the set of the most discriminated projection vectors that can map high dimensional samples onto a lowdimensional space. Using the set of projection vectors determined by FDA as the projection axes, all projected samples will form the maximum between-class scatter and the minimum within-class scatter simultaneously in the projective feature space [20].The FDA is find the set of basis vectors which maximizes the ratio between class scatter and within class scatter [11-13]. Let the between class scatter is define as following

$$S_B = \sum_{i=1}^{c} N_i (\mu_i - \mu) (\mu_i - \mu)^T$$
(11)

The within class scatter matrix be define as following:

$$S_{w} = \sum_{i=1}^{c} \sum_{x_{k} \in X_{i}} \left( x_{k} - \mu_{i} \right) \left( x_{k} - \mu_{i} \right)^{T}$$
(12)

Where  $\mu_i$  is the mean image of class  $X_i$ , and  $N_i$  is the number of samples in class  $X_i$ . If  $S_w$  is a non-singular, the optimal projection  $W_{opt}$  is chosen as the matrix with orthonormal columns which maximizes the ratio of the determinant of the between class scatter matrix of the projection samples to determinant of the within class scatter matrix of the projection samples, i.e.:

$$W_{opt} = \arg \max_{w} \frac{\left| W^{T} S_{B} W \right|}{\left| W^{T} S_{w} W \right|}$$
$$= [W_{1}, W_{2}, ...W_{m}]$$
(13)

where  $\{W_i | i = 1, 2, ..., m\}$  is the set of generalized eigenvector of  $S_B$  and  $S_W$  corresponding to the m largest generalized eigenvector  $\{\lambda_i | i = 1, 2, ..., m\}$  i.e.

$$S_B w_i = \lambda_i S_w w_i, \qquad i = 1, 2, \dots, m \tag{14}$$

To avoid the difficulties of a singular  $S_w$ , substitute the principle in Eq.(13). This method, which we call FisherVein, avoids this problem by projecting the images set to a lower dimensional space so that the resulting within class scatter matrix  $S_w$  is non-singular. This is implement by using PCA to reduce the dimension of the feature space to N-c and then applying the standard FLD defined by Eq. (13) to reduce the dimension to c-1. The  $W_{opt}$  will become [11]:

$$W_{opt}^{T} = W_{fld}^{T} W_{pca}^{T}$$
where
$$W_{pca} = \arg \max_{W} \left| W^{T} S_{T} W \right|$$

$$W_{fld} = \arg \max_{W} \left| \frac{W^{T} W_{pca}^{T} S_{B} W_{pca} W}{W^{T} W_{pca}^{T} S_{W} W_{pca} W} \right|$$
(15)

In this paper, the used database contains 500 different person palms (12 images to each person). Split the database into two sets and used one of the set images to obtain the eigen basis vectors. Then the remaining set is projected into those vectors. After implement PCA, the FDA finds a set of basis vector which maximizes the ratio between class scatter and within the class scatter.

### 5. Palm Vein matching

The nearest neighbor method is used to compute the matching between the train set and test set. To measure the similarity between two biometric feature vectors, we used Euclidean distance as a similarity measures. Let y denoted the test feature vector and  $x_i^k$ ,  $i = 1, ..., C_k$ , k = 1, ..., C represent the *i*<sup>th</sup> gallery image of subject  $ID_k$ , where  $C_k$  is the number of images of subject  $ID_k$  and C is the totally numbers of the images in the train set. The smallest Euclidean distance [17].

$$ID_{y} = \arg\min_{k} \left\| y - x_{i}^{k} \right\|^{2}$$
(16)

#### 6. 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 а 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 6 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 9 days. The proposed method used the near-infrared (NIR) illuminations images of PolyU multi-spectral palm print database [15].

To establish the sturdiness of the propose method in the experiment the total number of the palm vein images was 6000 images, which were collected from 500 person each with 12 images captured at two session. In verification, receiver operating characteristics (ROC) curve is used to show the behavior of the propose method. In the experimental randomly select 6 images from each person for training set and the other for testing set. The nearest neighbor 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 show in figure 5, and the ROC curve is show in figure 6. As show from figure 5 the EER is 0.2335% by using Euclidean distance. The Min-max normalization is used to normalize the matching scores. This normalization maps the raw matching scores to interval [0,1] and retains the original distribution of matching scores except for a scaling factor. Given that max(X) and min(X) are the maximum and minimum values of the raw matching scores, respectively, the normalized score is calculated as [18].

$$x' = \frac{x - \min(X)}{\max(X) - \min(X)}$$
(17)

Two methods for palm vein authentication are proposed in [14] and [19] are also implemented for comparison. The method in Ref.[14] is tested on the same database. Table 1 show the comparison of our method and all above methods. Figure 5 show the distance distribution of the impostor and genuine and figure 6 show the ROC curve of the proposed method. From the result illustrate in table 1 and figure 5 and 6, we can find that the propose method has better performance from the methods that describe in [14] and [19].

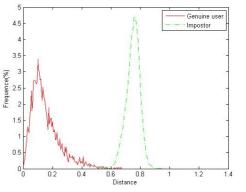


Fig. 5. Matching distance distribution of palm vein

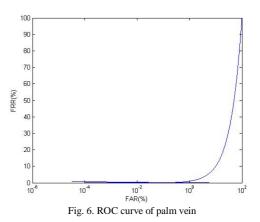


Table 1: Methods comparison on our palm vein images database.

Method	EER %
David [14]	0.3091 %
Lee [19]	1.6312%
Proposed method using EigenVein	6.5250%
Proposed method using FisherVein	0.2335%

The experimental results show that our method has better result than David [14] and Lee [19] and propose EigenVein methods. The main benefit of the proposed method, is that implement the Gabor filter with 8 scale and 8 direction and after that implement the dimensional reduction using FisherVein method that give best authentication features to reach to lowest EER value.

#### 8. Conclusion

A new method of personal authentication based on palm vein has been discussed indetail. First, the palm vein images are enhancement using histogram equalization. Then a bank of Gabor filter is created and convolution on the enhanced images and used the convolution images as feature vectors. The dimensional reduction is implemented using FDA to get best features for verification. Finally, the palm vein verification was implemented using Nearest Neighbor classifier. In our used database of 6000 images to 500 person, we get an EER is 0.2335%.

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## References

[1] Ashok Rao, Mohammad Imran, Raghavendra R, Hemantha Kumar G," Multibiometrics: analysis and robustness of hand vein & palm print combination used for person verification", International Journal of Emerging Trends in Engineering and Technology, Vol. I, No. 1, 2011, pp 11-20.

[2] LingyuWang, Graham Leedham, David Siu-Yeung Cho," Minutiae feature analysis for infrared hand vein pattern biometrics", Pattern Recognition, Vol. 41,2008, pp. 920 – 929.

[3] Zhonhli Wang, Baochang Zhang, Weiping Chen, Yongsheng Gao," A performance Evaluation of Shape and Texture based method for Vein Recognition", Congress on Image and Signal Processing, Vol. 2, 2008, pp. 659-661.

[4] Jian-Gang Wang, Wei Yun Yan, Andy Suwandy, Eric Sung, "Fusion of Palm print and Palm Vein Images for Person Recognition Based on Laplacianpalm Feature", IEEE conference on computer vision and image processing, 2007, pp. 1-8.

[5] Chao Ni, Qi Li, Liang Z. Xia, "A novel method of infrared image denoising and edge enhancement" , Signal Processing, Vol. 88, 2008, pp. 1606-1614

[6] Yi Hu, Xiaojun Jing, Bo Zhang, Xifu Zhu," Low Quality Fingerprint Image Enhancement Based on Gabor Filter ", International Conference on Advance Computer Control (ICACC), 2010, pp. 195-199.

[7] Jinfeng Yang , Yihua Shi, Jinli Yang," Personal identification based on finger-vein features", Computers in Human Behavior, Vol. 27, 2011, pp. 1565–1570.

[8] Jianwei Yang, Lifeng Liu, Tianzi Jiang, Yong Fan," A modified Gabor filter design method for fingerprint image enhancement", Pattern Recognition Latter, Vol. 24, No. 12, 2003, pp. 1805-1817.

[9] Lei Yu, Huan Liu "Feature Selection for High-Dimensional Data: A Fast Correlation-Based Filter Solution", Proceedings of

the Twentieth International Conference on Machine Learning, Washington DC, 2003, pp. 856-863.

[10] Deng Cai, Xiaofei He, and Jiawei Han "SRDA: An Efficient Algorithm for Large-Scale Discriminant Analysis", IEEE transaction on knowledge and data engineering, VOL. 20, NO. 1, 2008, pp. 1-12.

[11] Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection", IEEE transactions on pattern analysis and machine intelligence, VOL. 19, NO. 7,1997, pp. 711-720.

[12] Deng Cai, Xiaofei He, Yuxiao Hu, Jiawei Han, Thomas Huang," Learning a Spatially Smooth Subspace for Face Recognition", IEEE computer society conference on computer vision and image processing , 2007, pp. 1-7.

[13] Hamid M. Hasan, Waleed A. AL.Jouhar , Majed A. Alwan," Face Recognition Using Improved FFT Based Radon by PSO and PCA Techniques", International Journal of Image Processing, Vol. 6, No. 1, 2012, pp. 26-37.

[14] David Zhang, Zhenhua Guo, Guangming Lu, Lei Zhang, Yahui Liu, Wangmeng Zuo," Online joint palmprint and palmvein verification", Expert Systems with Applications, Vol. 38, 2011, pp. 2621–2631.

[15] Multispectral PolyU database, www4.comp.polyu.edu.hk/~biometrics/.

[16] Jen-Chun Lee," A novel biometric system based on palm vein image ", Pattern Recognition Letters , Vol. 33, 2012, pp. 1520–1528.

[17] Muhammad Talal Ibrahim, YongjinWang, Ling Guan, Anastasios N. Venetsanopoulos," A Filter Bank Based Approach for Rotation Invariant Fingerprint Recognition ", J Sign Process Syst, Vol. 68, 2012, pp. 401–414.

[18] Mingxing He, Shi-JinnHorng, PingzhiFan, Ray-ShineRun, Rong-JianChen, Jui-LinLai, MuhammadKhurramKhan, KevinOctaviusSentosa," Performance evaluation of score level fusion in multimodal biometric systems ", Pattern Recognition, Vol. 43, 2010, pp. 1789–1800.

[19] Jen-Chun Lee "A novel biometric system based on palm vein image", pattern recognition letter, Vol. 33,2012, pp. 1520-1528.

[20] Lei Wang, Hongbing Ji, Ya Shi," Face recognition using maximum local fisher discriminated analysis",18th IEEE International Conference on Image Processing, 2011,pp.1737-1740.

[21] Jing Liu, Yue Zhang, "Palm-Dorsa Vein Recognition Based on Two-Dimensional Fiher Linear Discriminated ", Proceeding of International Conference on Image Analysis and Signal Processing, 2011,pp. 550-552.

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