Biometric Authentication System Based on Palm Vein

Ali Mohsin Al-juboori, Xiangqian Wu and Qiushi Zhao
Biocomputing Research Center, School of Computer Science and Technology
Harbin Institute of Technology (HIT)
Harbin, China
alimuhsen80@yahoo.com, {xqwu, zhaoqs522}@hit.edu.cn

Abstract— **Palm vein recognition systems are one of the newest biometric technologies to have arisen in the recent past. Palm vein authentication uses the vascular patterns of an individual's palm of the hand as personal identification data. Veins and other subcutaneous features in the human hand present large, robust, stable and largely hidden patterns. In the proposed work, we present a palm vein verification system. In the proposed work, the Gaussian-Second-Derivative (GSD) is proposed for enhancement the palm vein images. Secondly, a new feature extraction method based on Gabor filter and Fisher Discriminated Analysis (FDA) is proposed called Gabor Fisher Vein Feature (GFVF). Finally, the Cosine Distance method is proposed for verify the tested palm vein. The EER to the proposed system is 0.0333%.**

Keywordst; Palm Vein; GSD ; Gabor Fisher Vein; Cosine Matching.

I. INTRODUCTION

Biometrics is the science of identifying a person using their physiological or behavioral features. Recently, vein pattern biometrics has attracted increasing interest from both research communities and industries. A vein pattern is the physical structure of the vast network of blood vessels underneath a person's skin [1]. Recently, a new biometric technology based on human palm vein patterns has attracted the attention of biometrics based identification research community. Compared with other traditional biometric characteristics (such as face, iris, fingerprint, etc.), palm vein exhibits some excellent advantages in application. For instance, apart from uniqueness, universality, permanence and measurability [2]. Palm vein hold the following merits [3]:

- The human palm vein pattern is extremely complex and it shows a huge number of vessels.
- The biometric information is located inside the human body, and therefore it is protected against forgery and manipulation.
- The position of the palm vein vessels remain the same for the whole life and its pattern is absolutely unique.
- Skin colour, skin dirtying, surface wounds, skin humidity, skin temperature, aging do not have major influence to enroll and to authenticate the palm vein pattern correctly.

Many studies on vein recognition methods are proposed. Lingyu Wang et al. 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 [4]. Zhongli Wang et al. used Gabor wavelet is exploited to extract the discriminative feature. Two kinds of shape matching methods are used, which are based on Hausdorff distance and Line Edge Mapping (LEM) methods. In evaluate the system performance, a dataset of 100 persons of different ages above 16 and different gender, each has 5 images per person is used. Experimental results show that Hausdorff, LEM and Gabor based methods achieved 58%, 66%, 80% individually [5]. Jian-Da Wu and Siou-Huan Ye extracted the features using Radon transform. The Radon transform can concentrate the information of an image in a few high-valued coefficients in the transformed domain. The neural networks are used to develop the training and testing modules. The artificial neural network techniques using radial basis function network and probabilistic neural network are proposed to develop a driver identification system. The experimental results indicated they proposed system performs well for personal identification. The average identification rate of PNN network is over 99.2% [6]. Ajay Kumar and K. Venkata Prathyusha computed the minutiae triangulation based on these minutiae points. Since most of the vein information has been missed during minutiae features extraction, vein recognition systems based on minutiae features can hardly get a high accuracy [7]. Wonseok Song et al. used the mean curvature method to views the vein image as a geometric shape and finds the valley-like structures with negative mean curvatures. Then the matched pixel ratio is used in matching vein patterns [8]. Jen-Chun Lee 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 [9]. Kuanquan Wang et al. the finger vein recognition has been identified using local binary pattern variance (LBPV). Global

978-0-7695-5125-8/13 $26.00 © 2013 IEEE
DOI 10.1109/CSA.2013.19

matching method is used to get more speeding and to decrease feature dimensions using distance measurement. The classification rate of this method is tested using support vector machine (SVM) [10]. Junwen Sun and Waleed Abdulla worked Multispectral PolyU database, they used a multiscale curvelet transform as a feature extraction and used a subset from the features for matching using Hamming distance. When used (40%) from the features set, the lowest EER is 0.66% [11]. Wei Bu et al. proposed vein feature representation method called orientation of local binary pattern (OLBP) which is an extension of local binary pattern (LBP). Based on OLBP feature representation, construct a hand vein recognition system employing multiple hand vein patterns include palm vein, dorsal vein, and three finger veins (index, middle, and ring finger). Images vein are enhanced using Gaussian matched filter, and extracted OLBP features and matched. Finally, the matching scores are fused using support vector machine (SVM) to make a decision [12]. In our previous work, Histogram Equalization is proposed for the image enhancement. The Gabor filter is proposed to use with real part and imaginary part by 8 scales and 8 directions. The Euclidean Distance classifier is proposed. The EER to that system is 0.2335% [13].

The rest of this paper is organized as follows. Section 2 describes the preprocessing. In section 3, describe the feature extraction methods based on Gabor Fisher Vein. In Section 4, we describe the Cosine Matching Classifier. Finally, the experimental result and conclusions are drawn in Section 5. Fig. 1 shown the flowchart of the propose work.

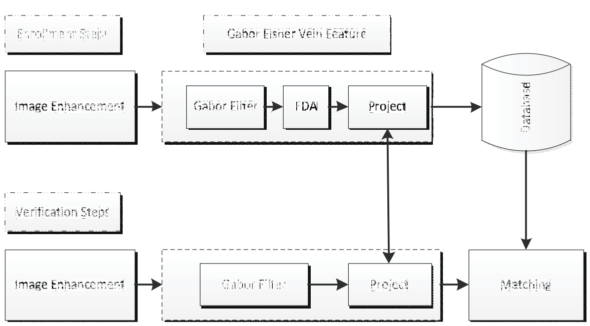

Figure 1. Flowchart of the proposed work

II. PREPROCESSING

In order to get good performance of an identification and verification the system depends on the quality of palm vein images. The image should be separated from other unnecessary data in the captured image such as the irregular shades and noises that result from the different thickness between the hand bones and muscles and the contrast of the image oscillation due to light intensity fluctuations. It is for this reason that needed to enhance the quality of the palm vein images before the extraction of features. Gaussian-Second-Derivative (GSD) method is proposed for image enhancement. The second derivative of the Gaussian filter is defined as [14-16]:

$$GSD(x',y',\delta,\theta) = ((x'^2 - \delta^2)(y'^2 - \delta^2)/(2\pi\delta^{10}))\exp(-(x'^2 + y'^2)/\delta^2) \quad (1)$$

where $x' = (x - x_\circ)\cos\theta + (y - y_\circ)\sin\theta$, $y' = -(x - x_\circ)\sin\theta + (y - y_\circ)\cos\theta$, $(x_\circ, y_\circ)$ is the center of the function and σ is the scales. The values of δ and θ is set empirically. In the proposed work the value of δ is $(\sqrt{2}, 2, 2\sqrt{2})$ and for one δ , 12 different angle filters $\theta_j = \pi j/12$), where j = {1, 2, 3... 12}) are applied for each pixel, and the maximal response among these twelve directions is kept as the final response for the given scales

$$\begin{gathered} Enhancement(x,y) = \max(GSD(x',y',\delta_{ij},\theta_{ij}) * I(x,y)) \\ i = \{1,2,3\},\ j = \{1,2..12\} \end{gathered} \quad (2)$$

where $I(x,y)$ is the original image and * denotes the convolution operation. Fig. 2 has shown the result of proposed enhancement method.

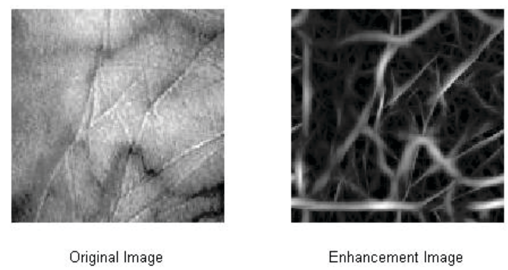

Figure 2. Image enhancement

III. GABOR FISHER VEIN FEATURE (GFVF)

A. Gabor Filter

For the palm vein, the network of veins is usually stable, since it cannot be broken unless palm veins suffer rupture. Hence, methods describing the palm vein textures more reliably often are desirable for palm vein feature extraction. In the spatial domain, Gabor filters have been widely used for analyzing texture information, and have been demonstrated that they were powerful in capturing some specific local characteristics in an image. A bank of Gabor filters therefore is designed to acquire the palm vein features in the spatial domain [2]. In the spatial domain, Gabor filters have been widely used for analyzing texture information, and have been demonstrated that they were powerful in face, iris, fingerprint, palmprint and finger-vein recognition [17]. Using Euler formula, Gabor filter can be decomposed into a real part and an imaginary part. The real part, usually called even-symmetric Gabor filter, is suitable for ridge detection in an image, while the imaginary part, usually called odd-symmetric Gabor filter, is beneficial to edge detection. Since the palm veins appear dark ridges in image plane, even-symmetric Gabor filter here is used to exploit the underlying features from the palm vein network. A 2-D real Gabor filter is defined as following [13, 18]:

$$G_{mk}(x,y) = K\exp\{-0.5((x_\theta^2/\sigma_x^2) + (y_\theta^2/\sigma_y^2))\}\cos(2\pi f_{mk} x_{\theta k}) \quad (3)$$

$$\begin{bmatrix} x_\theta \\ y_\theta \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (4)$$

Where $K = 1/2\pi\sigma_x\sigma_y$ and f_{mk} is the frequency of the sinusoidal plane wave, σ_x and σ_y are the space constants of the Gaussian envelope along x_θ and y_θ axis respectively, θ denotes the orientation of Gabor filter, *m* is the scale index and *k* is the channel index. In [2] determine the relation between the σ and f_{mk} . The f_{mk} is change with the orientations as following:

$$\sigma f_{mk} = 1/\pi\,(\sqrt{\ln 2/2})((2^{\triangle\phi mk}+1)/(2^{\triangle\phi mk}-1)) \qquad (5)$$

where $\triangle\phi_{mk}\,(\in[0.5, 2.5])$ denotes the spatial frequency bandwidth of a Gabor filter at the *k*th channel and *m* scale. Here, the constrain to $\triangle\phi$ is imposed as $\triangle\phi_1 < \triangle\phi_5 < \triangle\phi_2 < \triangle\phi_3 < \triangle\phi_4, \triangle\phi_2 = \triangle\phi_8, \triangle\phi_3 = \triangle\phi_7, \triangle\phi_4 = \triangle\phi_6$.

In the proposed work we used *m*=2 and *k*=8 and $\theta_k = (k\pi/8)$. Assume *I(x, y)* is the enhanced image from GSD method. We create a bank of Gabor filter with 16 filters (2 scales 8 channels).

$$F(x, y) = G_{mk}(x, y) * I(x, y) \qquad (6)$$

F(x, y) denoted the result from the convolution operation. Fig. 3 showed the Gabor filter bank and Fig. 4 shown the result of convolution operation.

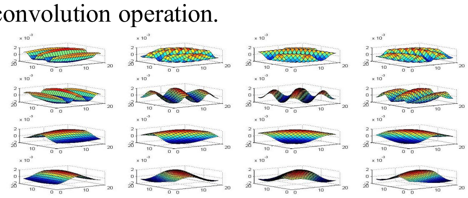

Figure 3. Gabor Bank

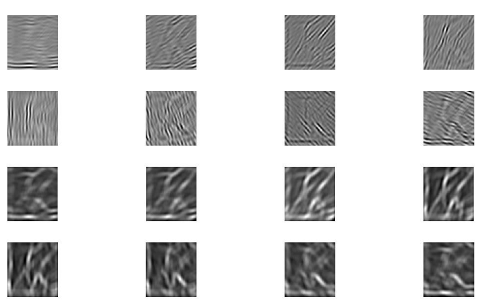

Figure 4. Convolution Operation

B. 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 [19]. FDA finds the set of the most discriminated projection vectors that can map high dimensional samples onto a low-dimensional 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 [21-24]. Let the between class scatter is define as following:

$$S_B = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^T \qquad (7)$$

within the class scatter matrix be define as following:

$$S_w = \sum_{i=1}^{c}\sum_{x_k \in X_i}(x_k - \mu_i)(x_k - \mu_i)^T \qquad (8)$$

where μ_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.:

$$\begin{aligned} W_{opt} &= \arg\max_{w} \left|W^T S_B W\right| / \left|W^T S_W W\right| \\ &= [W_1, W_2, .., W_m] \end{aligned} \qquad (9)$$

Where $\{W_i \mid i = 1, 2, \ldots, m\}$ is the set of generalized eigen-vector of S_B and S_W corresponding to the m largest generalized eigen-vector $\{\lambda_i \mid i = 1, 2, \ldots, m\}$ i.e.

$$S_B w_i = \lambda_i S_w w_i, \qquad i = 1, 2, ..., m \qquad (10)$$

To avoid the difficulties of a singular S_w , substitute the principle in Eq. (9). 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 implementing by using PCA to reduce the dimension of the feature space to $N - c$ and then applying the standard FLD defined by Eq. (9) to reduce the dimension to $c - 1$ .The W_{opt} will become [21]:

$$W_{opt}^T = W_{fld}^T W_{pca}^T \qquad (11)$$

where

$$W_{pca} = \arg\max_{W} \left|W^T S_T W\right|$$

$$W_{fld} = \arg\max_{w} \left|W^T W_{pca}^T S_B W_{pca} W\right| / \left|W^T W_{pca}^T S_W W_{pca} W\right| \qquad (12)$$

Assume a $N \times N$ palm vein image can be considered as a N^2 vector and each pixel corresponds to a component. That is, $N \times N$ palm vein images can be regarded as points in a high dimensional space (N^2-dimensional space), called the original palm vein space (OPVS). Generally, the dimension of the OPVS is too high to be used directly. For example, the dimension of the original 128X128 palm vein image space is 16,384 and in the proposed work each image is convolve using Gabor filter with 2 scales and 8 channels that mean each image space multiply by 16 (16*16384). We should, therefore, reduce the dimension of the palm vein image and, at the same time, improve or keep the discriminability between palm vein classes. GFVF is created by convolve the palm vein image with Gabor filter and then projection the filtered image to low space and considering it as a feature vector. In the proposed work the PolyU database contain 6000 images for 500 persons. Each one has 12 images. We select randomly 6 images for training and the other for testing. The FDA is execute on the training set and compute the Eigen vectors and projected to low dimension space. By using the same Eigen vector that computed form training set to project the testing set.

IV. MATCHING SCORE COMPUTATION

As any biometric system, the palm vein recognition is also based on pattern classification. Hence, the discriminability of the proposed GFVF determines its reliability in personal identification. To test the discriminability of the extracted GFVF, the cosine similarity measure classifier here is adopted for classification. The classifier is defined as [2, 25]:

$$\tau = \arg \min_{R_m^K \in C_K} \varphi(R_m, R_m^K)$$

$$\varphi(R_m, R_m^K) = 1 - R_m^T R_m^K \Big/ \left(\|R_m\| \|R_m^K\| \right) \tag{13}$$

where R_m and R_m^K , respectively denote the feature vector of an unknown sample and the *k*th class, C_K is the total number of templates in the *k*th class, $\|\bullet\|$ indicates the Euclidean norm, and $\varphi(R_m, R_m^K)$ is the cosine similarity measure. Using similarity measure $\varphi(R_m, R_m^K)$, the feature vector R_m is classified into the τ th class.

V. EXPERMINTAL RESULT

Our experiments are performed to evaluate the effectiveness of proposed palm vein verification methods based on PolyU database. The biometric research centre 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. The database contains 6,000 images from 500 different palms for each one illumination. The proposed method used the near-infrared (NIR) illuminations images of PolyU multi-spectral palm print database [26].

Each person has 12 palm vein images. We use 6 palm vein image for the enrollment and 6 images for the test of each individual in our experiments. We used two performance measures, namely the false rejection rate (FAR) and the false acceptance rate (FRR). For computing FRR value, we compare the biometric reference with all samples of the same individual. For computing FAR value, we compare the biometric reference of an individual with all samples from different individuals. We plot the disparities distribution between intraclass and interclass matching result. It shows the separation between genuine and impostors. Our receiver operating characteristic (ROC) curve is between FRR and FAR. Equal error rate (EER) is the point where FRR is equal to FAR, and the smaller EER indicates a better performance. In our system we have many steps as image enhancement and the feature extraction based on Gabor filter and Fisher Discriminated Analysis. Fig. 5 shown the distribution between genuine user and impostor and Fig.6 shown the ROC curve when implement the system without image enhancement.

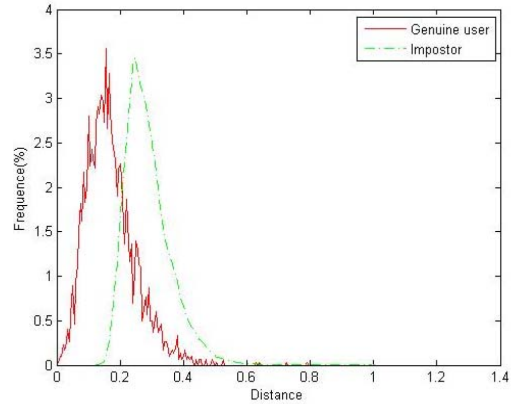

Figure 5. Distribution of the Genuine user and Impostor without Enhancement

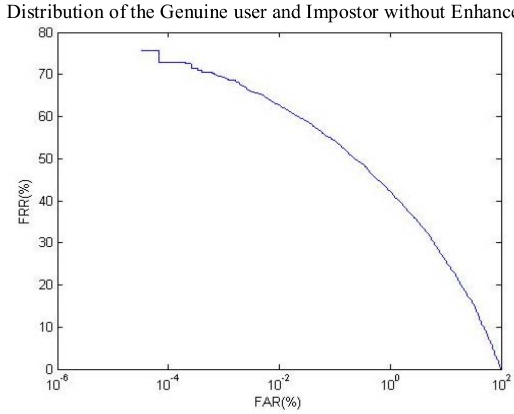

Figure 6. ROC Curve without Enhancement

As show form the above figures (5 and 6) the enhancement step is very important because the images is not clear and have some noise. The value of EER is 19.5896% to the system when implement without image enhancement. Fig. 7 shown the distribution between genuine user and impostor and Fig.8 shown the ROC curve when implement the system without using Fisher Discriminated Analysis.

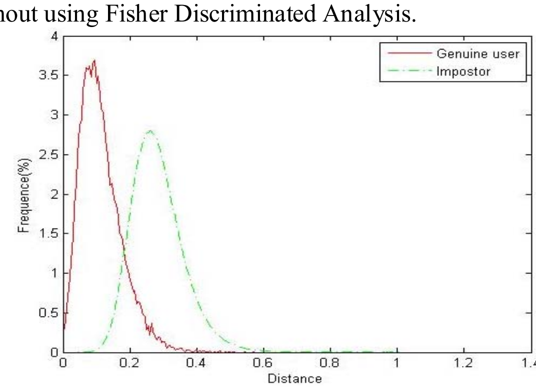

Figure 7. Distribution of the Genuine user and Impostor without FDA

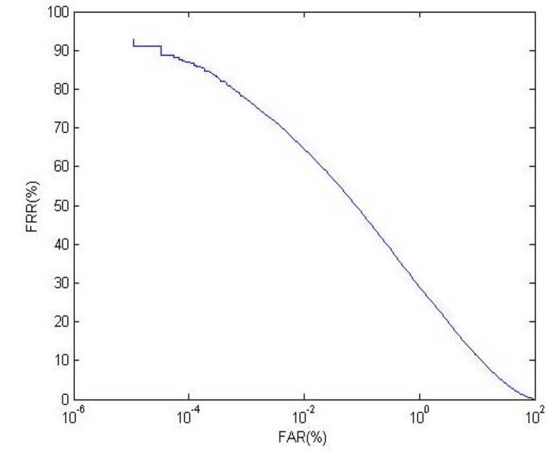

Figure 8. ROC Curve without FDA

As show form the above figures (7 and 8) the FDA step is very important because it can remove all the redundancy in the values of the Gabor coefficients. The value of EER is 10.7322% to the system when implement without FDA. Fig. 9 shown the distribution between genuine user and impostor and Fig.10 shown the ROC curve when implement the system with all steps that shown in the Fig.1.

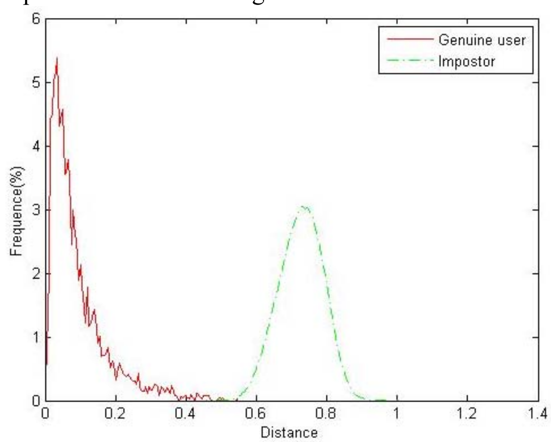

Figure 9. Distribution of Genuine user and Impostor

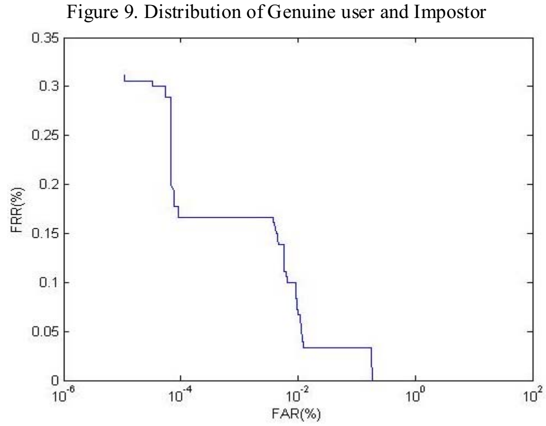

Figure 10. ROC Curve

As show form the above figures (9 and 10) the system get better performance and smallest value of EER is equal to 0.0333%. That result is get when implement the system with image enhancement that removes all the noise and the blurred the vein image. And also the combination between the Gabor filter with FDA and created the GFVF is best method for extracted the vein features vector.

In this paper, we also make a comparison between the proposed method and the method of the Curvelet Transform [11], the researchers are worked on the PolyU database. And the Orientation of LBP [12], implemented the researcher method and tested on PolyU database. TABLE 1 show that our method outperforms the other two methods in terms of EER. Because our proposed method has image enhancement method with GFVF and the cosine distance classifier it allows a good separation between genuine user and impostors.

TABLE I. THE EER COMPARATION WITH OTHET METHOD

	Our method	Oriented LBP	Curvelet Transform
EER%	0.0333	0.1559	0.66

VI. CONCLUSTION

This paper has addressed the problems of palm vein segmentation and verification. The GSD filters are exploited to extract palm vein pattern. The GFVF features are extracted based on Gabor filter with 2 scales and 8 channels and combine with the Fisher Discriminated Analysis to describe the palm vein pattern. Then the matching GFVF feature associations between the registered and test images are computed using Cosine distance to verify the personal identification. At last, the experimental results illustrate that our matching method effective and competitive with other approaches in the literature. In the future, we intend to fuse another type of the palm vein features. By the proposed method we get a lower EER value equal to 0.0333%.

ACKNOWLEDGMENT

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).

REFERENCES

[1] L. Wang, G. Leedham and S.-Y. Cho, “Infrared imaging of hand vein patterns for biometric purposes”, IET Comput. Vis., Vol 1, pp. 113-122, 2007.

[2] Jinfeng Yang, Yihua Shi, Jinli Yang, “Person identification based on finger-vein features”, Computers in Human Behavior, Vol. 27, pp. 1565–1570, 2011.

[3] Hao Luo, Fa-Xin Yu, Jeng-Shyang Pan, Shu-Chuan Chu, Pei-Wei Tsai,”A survey of Vein Recognition Techniques”, Information Technology Journal, Vol. 9, pp.1124-1149, 2010.

[4] Lingyu Wang, Graham Leedham, David Siu-Yeung Cho, “Minutiae feature analysis for infrared hand vein pattern biometrics”, Pattern Recognition, Vol. 41, pp. 920 – 929, 2008.

[5] Zhongli Wang, Baochang Zhang, Weiping Chen, Yongsheng Gao,” A performance Evaluation of Shape and Texture based methods for Vein

Recognition”, Congress on Image and Signal Processing , pp. 659-661, 2008.

[6] Jian-Da Wu, Siou-Huan Ye, “Driver identification using finger-vein patterns with Radon transform and neural network”, Expert Systems with Applications, Vol. 36, pp. 5793–5799, 2009.

[7] Ajay Kumar, K. Venkata Prathyusha,” Personal Authentication using Hand Vein Triangulation and Knuckle Shape”, IEEE Transactions on Image Processing, vol. 38, pp. 2127-2136,2009.

[8] Wonseok Song, Taejeong Kim, Hee Chan Kim, Joon Hwan Choi, Hyoun-Joong Kong, Seung-Rae Lee, “A finger-vein verification system using mean curvature “, Pattern Recognition Letters, Vol. 32, pp.1541–1547,2011.

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

[10] Kuan-Quan Wang, Anne S. Krisa, Xiang-Qian Wu, Qiu-Shi Zhao, “Finger Vein Recognition Using LBP Variance With Global Matching”, International Conference on Wavelet Analysis and Pattern Recognition, pp.196-200, 2012.

[11] Junwen Sun, Waleed Abdulla,” Palm Vein Recognition using Curvelet Transform”, Proceedings of the 27th Conference on Image and Vision Computing, pp.435-439,2012.

[12] Wei Bu, Xiangqian Wu, Enying Gao,” Hand Vein Recognition Based on Orientation of LBP”, International Society for Optical Engineering, Vol. 8371, pp.1-12, 2012.

[13] Ali Mohsin Al-juboori, Wei Bu, Xingqian Wu and Qiushi Zhao,” Palm Vein Verification Using Gabor Filter”, International Journal of Computer Science Issues, Vol. 10, 2013.

[14] Feng Yue, Wangmeng Zuo, Kuanquan Wang,” A Performance Evaluation of Filter Design and Coding Schemes for Palmprint Recognition”, International Conference on Pattern Recognition, 2008.

[15] Somsak Choomchuay, Keokanlaya Sihalath, “ An Application of Second Derivative of Gaussian Filters in Fingerprint Image Enhancement”, International Conference on Bioinformatics and Biomedical Engineering, 2010.

[16] Ritwik Kumar, Amelio V´azquez-Reina, Hanspeter Pfister,” Radon-Like Features and their Application to Connectomics”, IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Workshops, 2010.

[17] Jinfeng Yang, Xu Zhang,“ Feature-level fusion of fingerprint and finger-vein for personal identification”, Pattern Recognition Letters, Vol. 33, pp. 623–628, 2012.

[18] Xiangqian Wu, Ning Qi, Kuanquan Wang, David Zhang,” A Novel Cryptosystem based on Iris Key Generation”, Fourth International Conference on Natural Computation, pp. 53-56,2008.

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

[20] 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, pp. 550-552, 2011.

[21] 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, pp. 711-720, 1997.

[22] 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 Pattern Recognition, 2007.

[23] Xiangqian Wu, David Zhang, Kuanquan Wang,” Fisherpalms based palmprint recognition”, Pattern Recognition Letters, Vol. 24, pp. 2829–2838, 2003.

[24] 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, pp. 1-12, 2008.

[25] Venkata Gopala Rao S., Bhanu Prasad A.,” Space and Cosine Similarity measures for Text Document Clustering”, International Journal of Engineering Research & Technology, Vol. 2,pp. 1-5, 2013.

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