A Review of Finger Vein Recognition System

Eiwei.Ting, M.Z.Ibrahim
Applied Electronic and Computer Engineering Cluster, Faculty of Electrical and Electronic,
University Malaysia Pahang, 26600, Pekan, Pahang, Malaysia
zamri@ump.edu.my

***Abstract*—Recently, the security-based system using finger vein as a biometric trait has been getting more attention from researchers all over the world, and these researchers have achieved positive progress. Many works have been done in different methods to improve the performance and accuracy of the personal identification and verification results. This paper discusses the previous methods of finger vein recognition system which include three main stages: preprocessing, feature extraction and classification. The advantages and limitations of these previous methods are reviewed at the same time we present the main problems of the finger vein recognition system to make it as a future direction in this field.**

***Index Terms*—Biometric Trait; Finger Vein; Preprocessing; Feature Extraction; Classification.**

I. INTRODUCTION

In this information era, many applications and devices are designed and introduced for security systems. Security is defined as a state or condition where a person is free from danger. The development of science and technology increases the demand for the security of personal and private information. The security system can be categorised into two main types which are known as traditional methods and biometrics methods [1][2]. The traditional security methods such as key, smart card, passwords and Personal Identification Number (PIN) are easy to be forgotten and stolen. Nowadays, these traditional identification methods are getting replaced by the biometrics methods. The physiological traits include fingerprint, face, iris, etc. [3]. However, these conventional biometric systems have their limitations regarding performance and convenience. For face recognition, the facial expression and illumination which can change during human growth affect the performance of the recognition system. For iris recognition, the capturing device is expensive and inconvenience compared to other biometric methods [3]. The fingerprint recognition system causes much inconvenience as the users have to touch the surface of the input sensor using their fingers. Besides that, the distortion of the skin surface degrades the system's accuracy [4]. Furthermore, the possibility of the personal information being stolen through the fingerprint sensor is very high.

To overcome these problems, finger vein biometric has been studied. Yanagawa has proven through his studied that finger vein could be appropriately used for personal identification [5]. They showed that the human finger has entirely different vein patterns. This feature has proven that the finger vein can become a biometric trait to differentiate humans.

Finger vein recognition and verification is a new emerging biometrics technology. It has several advantages and benefits compared to others biometric methods. First and foremost, it is immune to counterfeit as the veins located underneath the finger skin surface [6], make the duplication of vein pattern become an impossible task. Second, the active liveness of the vein makes the artificial vein unavailable during system application as the vein information will disappear with muscle that is losing energy [7]. Besides that, it has high security as it cannot be stolen and duplicated easily. Also, the cost of the capturing device is low.

Despite the finger vein has advantages compared to others, there are still a lot of key problems and challenges that still need to be dealt to achieve high performance. The main problem is the quality of the image captured. The quality is greatly affected by the image acquisition device. The optical blurring, poor lighting, finger position might decrease the recognition rate [8][9]. Besides that, the finger vein image sometimes shows irregular shadings and highly saturated regions. The noises of the captured finger vein image always reduce the accuracy and performance of the system.

A typical finger vein recognition system consists of four main stages which are known as image acquisition, image preprocessing, feature extraction, and matching. Figure 1 shows the block diagram of a finger vein identification system. In this paper, the main methods and techniques involving the four stages mentioned above will be reviewed.

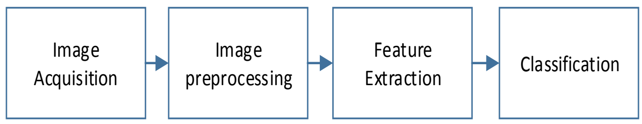


Figure 1: Block diagram of finger vein identification system

II. IMAGE ACQUISITION AND DATABASE

This section discusses the previous and current devices to capture the images of the finger vein. At the same time, a number of public finger vein databases are comparing and discussed. The present study had stated the difficulties to observe the finger vein pattern under visible light. It is captured by the infrared Light Emitting Diode (LED) and charge-coupled device (CCD) camera. A 760-1000nm infrared LED light can penetrate the finger skin, at the same time, the haemoglobin absorbs the infrared light causing the CCD camera to detect and capture using a near-infrared filter [10]

The capture devices are commonly divided into two types which are light reflection type and light transmission type. The light transmission type can capture high contrast finger vein images compared to the reflection of the light method [11][12].The difference between the reflection method and transmission method is the position and location of the Near Infrared Light (NIR) and the image sensor (CCD Camera) as shown in Figure 2 [13].The finger vein capture device includes NIR illuminators with the wavelength between 750-

1000nm, a webcam with CCD sensor, and a hot mirror.

There is five finger vein databases that can be found publicly and these are shown in Table 1. These databases were built differently in a number of images, number of fingers, the format of images, resolutions, etc. All the finger vein databases were built from a sample of more than 100 subjects except the UTFV database which consists of 60 subjects only. Besides that, all the database capture the index, ring and middle finger for both hands except THU-FVFDT1. Some of the databases provided misaligned and skewed finger images which are irrelevant and specific to a particular application.

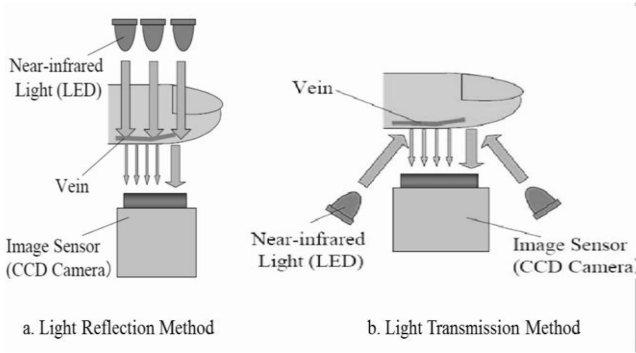
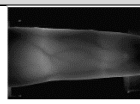
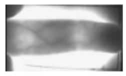
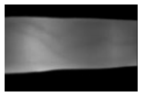
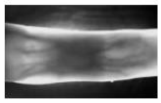


Figure 2: A prototype of finger vein capture device [13]

Table 1
The Comparison Between Public Finger Vein Databases

Database	Image No	Subject No	No of Finger per Subject	No of Image per Finger	Resolution of Image (pixels)	Typical Image
SDMULA–HMT [14]	3816	106	6 (index, ring, middle) both hands	6	320X240	
HKPU-FV [15]	6264	156	3 (index, ring, middle) left hands	12/6*	513X256	
MMCBNU_6000 [16]	6000	100	6 (index, ring, middle) both hands	10	480X640	
THU-FVFDT1 [17]	440	220	1	1	720X576 (raw)	
UTFV [18]	1440	60	6(index, ring, middle) both hands	4	672X380	

*Only 105 subjects turned up for the imaging during the second session, so every finger from these subjects have six images, but other fingers each has 12 images

III. PREVIOUS CONVENTIONAL METHOD

The finger vein recognition system involves the three main processes known as image preprocessing, feature extraction and classification. The system can be classified into three main types; one is the conventional method, one is machine learning method, and one is the combination of machine learning method and the conventional method. The conventional methods always involve a series of preprocessing method and algorithms to improve the quality of the captured images.

Image preprocessing is a process that increases the reliability of optical inspection. It usually includes noise reduction, image enhancement, image normalisation and segmentation. The commonly used methods are normalisation, edges filters, median filter, and histogram equalisation and so on. The low quality of the NIR images is low contrast and blur. Hence, they need to undergo preprocessing methods to improve the quality of the images before undergoing feature extraction.

Feature extraction is a method that preprocesses and reduces the computation complexity of a data system. Extensive feature dimensions can cause huge computation and the memory cost of the classifier training and classification. Feature extraction is an essential method as the output of the process will affect the result of the classification and matching accuracy. It can be clearly seen that the finger vein pattern was extracted in different methods before the system underwent the matching process.

Table 2 summarises the conventional methods including their preprocessing, feature extraction and classifier with their performance. This table includes some of the research from 2011 until now. The comparison of the accuracy was non-ideal as the use of the finger vein database is different among the researchers. Some of the researchers built up their own databases, and some of them used the public databases. From Table 2, we can observe clearly that finger vein recognition consists of three main processes which are preprocessing, feature extraction and classifier.

For the preprocessing stage, it always involves image resizing, noise reduction, a region of interest detection and image enhancement. The work in [6][21][28] applied to image enhancement at the preprocessing stage, and the performance of the system reached a high accuracy compared to the others which do not involve image enhancement. The enhancement of the images improves image quality by improving the contrast and brightness as well as reducing the noise.

For feature extraction, the methods can be categorised into vein pattern-based methods, dimensionality reduction-based methods and local binary-based methods. The vein pattern based methods which include [6][21][23][27] are mainstream in the extraction of finger vein. The geometric and the topologies structure of the extraction vein pattern is used for matching among pixel-by pixels translation and rotation. Dimensionality reduction is the method that keeps discriminating information and removes noise by transforming the image to a low dimensional image as stated in [22][23]. The example of dimensionality reduction methods is Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). For the local binary-based methods such as Local Binary Pattern (LLP) [3], Local Line Binary Pattern (LLBP) [28] and Local Directional Code (LDC) [23], the feature extractions are in binary formation. Most of these methods used Hamming distance and Euclidean distance as classifiers to measure the similarities between the finger vein input and the database.

Table 2
Conventional Methods of Finger Vein Recognition System

Reference	Preprocessing	Feature Extraction	Classifier	Accuracy / EER
(Yang et al. 2011) [6]	1. Image normalisation 2. Image enhancement 3. Noise reduction	1. Gabor filter	1. Matching	Accuracy= 98.079%
(Liu & Song 2012) [25]	1. ROI detection 2. Image enhancement 3. Image resizing 4. Histogram Equalization	1. Fractal model	1. Blanket dimension distance HD 2. Lacunarity distance HΛ	EER=0.07%
(Yang et al. 2013) [28]	1. ROI extraction 2. Image Enhancement 3. Size normalization	1. Local Line Binary Pattern(LLBP)	1. PWM-LLBP	Accuracy= 99.67%
(Tallam et al 2014) [19]	1. Image enhancement. 2. Normalization. 3. Resizing.	1. Canny edge detection	1. Euclidean Distance	FAR=0.0% FRR=20%
(Li, Li, Xiao, Wang, & Ren, 2014) [23]	1. ROI detection 2. Size normalisation	1. 2DPCA 2. Mean Curvature 3. Local Directional	1. Matching	Accuracy= 98.01%
(Sujata Kulkarni2015) [25]	1. ROI detection 2. Resizing 3. Image enhancement	1. Kekre Wavelet Transform	1. Euclidean Distance	Accuracy =86.3%
(Gupta & Gupta, 2015) [24]	1. ROI Detection 2. Multi-scale Vein Enhancement 3. Line Tracking Vein enhancement	1. Variation fusion + Thresholding	1. Sum of square differences	EER= 4.47%
(Kaur, Babbar, & Landran, 2015) [21]	1. Image binarization 2. ROI detection 3. Image enhancement	1. Repeated line tracking 2. Even Gabor filter 3. Even Gabor with morphology	1. Multi-linear discriminant analysis	Accuracy= 99.50%
(Shrikhande, 2016) [22]	1. Sobel edge detection 2. ROI detection 3. Size normalization	1. 2-D Rotated Wavelet Filters (RWF) and Discrete Wavelet Transform (DWT)	1. Canberra distances	Accuracy= 93.67%
(Hsia, Guo, & Wu, 2017) [26]	1. Image Normalization 2. ROI extraction 3. Parametric-Oriented Histogram Equalization (POHE)	1. Eight directional Sobel operator	1. Matching	EER= 0.014%

IV. PREVIOUS MACHINE LEARNING METHOD

The machine learning method has advantages in being robust to noise and solve the complex pattern recognition problems. This is because the finger vein traits captured from the first and second time will not exactly be the same. The machine learning methods such as neural networks, support vector machine and fuzzy logic are effective in feature extraction and matching process for biometrics. To make the finger vein recognition system more practical in real life, the system should have a high recognition rate and high recognition speed.

The machine learning method is less used in the finger vein recognition system although it is more popular in vein verification system. In 2008, Wu and Ye used a neural network in finger vein identification. The Probabilistic Neural Network achieved an average identification rate of 99.2%. The sample included 25 people with both fore and middle fingers. Ten images were taken of each finger [10]. In 2011, Park proposed to support a vector machine (SVM) in their finger vein recognition system with a database that consists of 50 persons, where ten images for every eight fingers without involving thumb for both hands. The research achieved a low EER rate of 0.0982seconds [3]. The SVM machine learning method was used by Wu & Liu and Khellat with different feature extraction methods. In 2011, Wu and Liu combined PCA and LDA for dimensional reduction and feature extraction. The accuracy of the classification using SVM reached 98% within 0.0156 seconds [29]. Khellat combined the Gabor filter in feature extraction with SVM and achieved a high accuracy of 98.75%.

The machine learning methods from previous work have a similarity where the machine learning was applied at classification. The SVM is the most popular machine learning methods compare to the neural network. It is mainly used for training and testing processes.

The finger vein recognition system consists of four main steps namely image acquisition, image pre-processing, feature extraction and classification. Each step plays an important role. This research focuses more on image preprocessing and feature extraction. It is important to improve and enhance image quality and contrast to extract more clear vein pattern. To achieve a high accuracy of the finger vein recognition system, the method of preprocessing and feature extraction is very important.

Table 3 shows the existing machine learning methods used by different researchers on finger vein recognition system. The comparison in Table 3 includes the preprocessing, feature extraction, classifier (machine learning), accuracy and time executed.

Table 3
Conventional Methods of Finger Vein Recognition System

Reference	Preprocessing	Feature extraction	Classifier (Machine- learning)	Accuracy/EER	Time executed (S)
(Park 2011) [3]	1. ROI localisation 2. Image stretching	1. Local Binary Pattern 2. Wavelet transform	Support Vector Machine	EER= 0.011%	0.0982
(Wu & Liu 2011) [29]	1. ROI extraction 2. Image resizing	1. PCA+LDA	Support Vector Machine	Accuracy= 98%	0.0156
(Khellat-kihel et al. 2014)[30]	1. Histogram equalization 2. Median Filter 3. Gabor Filter	1. Gabor Filter	Support Vector Machine	Accuracy= 98.75%	-
(Xie et al. 2014) [31]	1. ROI detection 2. Image resizing 3. Hough Transform	1. Guided Directional filter	Feature component based ELMs	Accuracy= 99.53%	0.0087
(Radzi & Khalil-hani 2016) [32]	1. Image resizing 2. Image binarization 3. Image normalization	1. Radon Transform	Convolution neural network	Accuracy= 99.38%	0.1574

V. Existing Problems and Future Works

A lot of research has been done by applying different methods. However, some issues of finger vein recognition still exist.

First and foremost, the problem occurs at the image acquisition stage. The quality and the contrast of the images was always the main problem which affects the finger vein recognition performance. Currently, the cost of the finger vein capture device is expensive. The low-cost capture device will always face the problem of capturing high-quality images. Hence, image acquisition is an essential stage in the future to capture high-quality images. Image quality is a space to improve the performance of finger vein recognition. Secondly, some of the finger vein recognition systems need longer processing time. Even though its performance is good, the long processing time makes the system not practical in real life applications. As for the public database, several finger vein databases existing for research purposes, but they are facing the problems of low contrast, image blurring, brightness, noise and size of the database. Even though some public databases are readily accessible, most of the existing research works developed their own database. Hence, for future work, a large-scale standard finger vein database needs to be built to evaluate the existing methods and to increase the accuracy of the result. To overcome the issue of the finger vein being replicated by a second party, the research must put the focus on the ways to detect the aliveness of the finger vein before proceeding to the finger vein verification process. In 2013, Nguyen et al. proposed Fourier and wavelet transform to detect fake finger vein [33] Even though the outcomes are still in the preliminary stage; however, it can be a primary focus in future works to develop a system that can detect fake veins with high accuracy. Furthermore, the finger vein trait can also be combined with other biometrics such as fingerprint, face and others as stated in [34]. The fingerprint and finger vein are firstly extracted using Gabor filter, followed by local- preserving canonical relation analysis method to generate a fingerprint – vein feature vector in feature level fusion.

VI. Conclusion

Many recent existing finger vein recognition systems including image preprocessing, feature extraction and classification stage have been reviewed. Research should focus on the key problem and the future works that are discussed in this paper in to overcome the weaknesses of the previous methods in order to develop a more powerful finger vein-based identification or verification system.

Acknowledgements

This work was supported by University Malaysia Pahang and funded by Ministry of Higher Education Malaysia under FRGS Grant RDU160108.

References

[1] L. Chunyi, L. Mingzhong, and S. Xiao, "A Finger Vein Recognition Algorithm Based on Gradient Correlation," *AASRI Procedia*, vol. 1,(2012) 40–45.

[2] F. Cui and G. Yang, "Score Level Fusion of Fingerprint and Finger Vein Recognition," vol. 16, (2011) 5723–5731.

[3] K. R. Park, "Finger vein recognition by combining global and local features based on SVM," *Comput. Informatics*, vol. 30, no. 2, (2011) 295–309.

[4] R. Tallam Temgire, S. and Zirange, R., "Finger Vein Recognition System Using Image Processing," *Proc. 4th IRF Int. Conf. Pune*, no. 5, (2014)65–68.

[5] Yanagawa, T. et al.: Human Finger Vein Images Are Diverse and Its Patterns Are Useful for Personal Identification. MHF 2007-12, (2007)1–7.

[6] J. Yang, Y. Shi, and J. Yang, "Personal identification based on finger-vein features," *Comput. Human Behav*. vol. 27, no. 5, pp. 1565–1570, Sep. 2011.

[7] Jinfeng Yang, Jinli Yang, and Yihua Shi, "Finger-vein segmentation based on multi-channel even-symmetric Gabor filters," in *2009 IEEE International Conference on Intelligent Computing and Intelligent Systems*, (2009)500–503.

[8] Lee EC, Park KR. Image restoration of skin scattering and optical blurring for finger vein recognition. Optics and Lasers in Engineering (2011)49(7):816–28

[9] Podgantwar UD, Raut U. Extraction of Finger-Vein Patterns using Gabor Filter in Finger vein Image Profies (2013).

[10] J.-D. Wu and C.-T. Liu, "Finger-vein pattern identification using SVM and neural network technique," *Expert Syst. Appl*., vol. 38, no. 11 (2011). 14284–14289.

[11] Miura, N., Nagasaka, A., Miyatake, T.: Extraction of finger-vein patterns using maximum curvature points in image profiles. *IEICE Transactions on Information and Systems* (2007) E90-D(8): 1185–1194.

[12] Kumar, A., Zhou, Y.B.: Human identification using finger images. *IEEE Transactions on Image Process*, 21(4): 2228–2244, 2012.

[13] L. Yang, G. Yang, Y. Yin, and L. Zhou, "A survey of finger vein recognition," in *Chinese Conference on Biometric Recognition*, 2014, pp. 234–243.

[14] Yin, Y.L., Liu, L.L., Sun, X.W.: SDUMLA-HMT: a multimodal biometric database. *The 6th Chinese Conference on Biometric Recognition*, LNCS 7098(2011). 260-268, Beijing, China.

[15] Kumar, A., Zhou, Y.B.: Human identification using finger images. IEEE Transactions on Image Process, 21(4)(2012) 2228–2244.

[16] Lu, Y, Xie, S.J., Yoon, S., Wang, Z., Park, D.S.: An Available Database for the Research of Finger Vein Recognition. In Proceedings of *International Congress on Image and Signal Processing* (2013): 386-392, Hangzhou, China.

[17] Zhou, F., Liao, Q.M.: Comparative competitive coding for personal identification by using finger vein and finger dorsal texture fusion. *Information Sciences*, 268(6) (2013) 20-32.

[18] Ton, B.T., and Raymond N.V.: A high quality finger vascular pattern dataset collected using a custom designed capturing device. In *Proceedings of International Conference on Biometrics* (2013): 1-5, Madrid, Spain.

[19] R. Tallam Temgire, S. and Zirange, R., "Finger Vein Recognition System Using Image Processing," *Proc. 4th IRF Int. Conf. Pune*, no. 5, (2014)65–68.

[20] Sujata Kulkarni, R. D. Raut, and P. K. Dakhole, "Vein pattern for personal authentication," *Int. J. Electron. , Commun. Soft Comput. Sci. Eng*(2015)1–5.

[21] M. Kaur, G. Babbar, and C. E. C. Landran, "Finger Vein Detection using Repeated Line Tracking , Even Gabor and Multilinear Discriminant Analysis (MDA)," vol. 6, no. 4(2015). 3280–3284.

[22] S. P. Shrikhande, "Finger Vein Recognition using Rotated Wavelet Filters," vol. 149, no. 7(2016)28–33.

[23] T. Li, X. Li, R. Xiao, S. Wang, and C. Ren, "Score-level Fusion for Finger Vein Recognition ⋆," vol. 13 (2014). 5675–5687.

[24] P. Gupta and P. Gupta, "An accurate finger vein based verification system," *Digit. Signal Process*, vol. 38, (2015)43–52.

[25] Z. Liu and S. Song, "An Embedded Real-Time Finger-Vein Recognition System for Mobile Devices," *IEEE Trans Consum. Electron*, vol. 58, no. 2, (2012) 522–527.

[26] C.-H. Hsia, J.-M. Guo, and C.-S. Wu, "Finger-vein recognition based on parametric-oriented corrections," (2017)Multimed. Tools Appl.

[27] Yang J, Li X. Efficient finger vein localization and recognition. *2010 20th International Conference on Pattern Recognition (ICPR)*, (2010) IEEE.

[28] Yang G et al. Finger vein recognition based on personalized weight maps. *Sensors*(2013)13(9):12093–112.

[29] J.-D. Wu and C.-T. Liu, "Finger-vein pattern identification using SVM and neural network technique," *Expert Syst. App*, vol. 38, no. 11 (2011) 14284–14289.

[30] S. Khellat-kihel, N. Cardoso, J. Monteiro, and M. Benyettou, "Finger Vein Recognition Using Gabor Filter and Support Vector Machine," *Image Process. Appl. Syst. Conf. (IPAS)*, 2014 First Int(2014) 1–6.

[31] S. J. Xie, S. Yoon, J. Yang, Y. Lu, D. S. Park, and B. Zhou, "Feature Component-Based Extreme Learning Machines for Finger Vein Recognition," *Cognit. Comput*., vol. 6, no. 3(2014) 446–461.

[32] S. A. Radzi and M. Khalil-hani, "Finger-vein biometric identification using convolutional neural network," no. August (2016), 1863–1878.

[33] D. T. Nguyen, Y. H. Park, K. Y. Shin, S. Y. Kwon, H. C. Lee, and K. R. Park, "Fake finger-vein image detection based on Fourier and wavelet transforms," *Digit. Signal Process*. vol. 23, no. 5, (2013) 1401–1413.

[34] J. Yang and X. Zhang, "Feature-level fusion of fingerprint and finger-vein for personal identification," *Pattern Recognit. Lett.*, vol. 33, no. 5, (2012) 623–628.