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A Survey of Vein Recognition Techniques

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Abstract: Biometric technology is an efficient personal authentication and identification technique. As one of the main-stream branches, vein recognition has drawn much attention among researchers and diverse users. This study proposes a survey of vein recognition techniques. The basic principle, key techniques, performance evaluation metrics, application fields and future trends are extensively analyzed. In particular, in the key techniques, most previous work is systematically described and compared in three parts, i.e., vein image acquisition and preprocessing, feature extraction and feature matching. According to the available work in theoretical analysis reports in literatures and commercial utilization experiences, vein recognition has been proved to be an effective, secure and reliable choice of high precision among biometrics techniques. It maintains an excellent promise in various applications.

Key words: Vein recognition, biometrics, personal authentication and identification

INTRODUCTION

As an efficient technique against digital impersonation, biometrics has drawn much attention among researchers, establishments, managers, governments, etc. It is proved more reliable and secure than the traditional hedges against identity theft such as passwords and personal identification numbers (PINs).

Biometrics is one of the popular used techniques for the question of who you are. In general, it can be divided into behavioral-based and physiological-based methods (Weaver, 2006). The former category is composed by signature recognition, voice recognition, handwriting recognition, keystroke dynamics analysis and gait analysis, hand gesture recognition, etc. The biometrics employed in the latter category consists of fingerprint, iris and retina scans, face, hand shape (Kumar and Zhang, 2007), palm-print (Han *et al*., 2003; Michaela *et al*., 2008), tongue shape, ear shape geometry, human body shape, vein pattern, nail bed, odor, lips, hip-print, heart sound, DNA, etc. The classification of biometrics techniques is shown in Table 1. The physiological-based methods have been widely used due to the properties of universality, uniqueness, permanence, collectability, performance, acceptability and circumvention. Pros and cons of these available techniques are considered in the factors including precision, field of application, defect, security, sensor and equipment cost. For example, fingerprint recognition is a secure widely used technique, but the contact type (need to touch the sensor) image acquisition may be regarded as unsanitary. For another example, iris recognition is a high precision choice, but the cost of image scanner may be unacceptable in some scenarios. In addition, some obstruction objects such as glasses, beards, hairs may cause the distortions during sample image acquisition.

Table 1: Classification of biometrics techniques

Behavioral-based techniques	• Signature recognition
	• Voice recognition
	• Handwriting recognition
	• Keystroke dynamics analysis
	• Gait analysis
	• Hand gesture recognition
Physiological-based techniques	• Fingerprints recognition
	• Iris and retina scans recognition
	• Face recognition
	• Hand shape recognition
	• Palm-print recognition
	• Tongue shape recognition
	• Ear shape geometry
	• Human body shape
	• Vein pattern
	• Nail bed recognition
	• Odor recognition
	• Lips recognition
	• Hip-print authentication
	• Heart sound authentication
	• DNA

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Nowadays, the most widely used biometric techniques are fingerprint and iris scans. However, in recent years, the development of vein recognition technique makes it become a promise choice. According to a large quantity of test results reported in literatures, it outperforms the fingerprints and iris scans recognitions in the aspects of high security and reliability to some extent. The advantages of vein recognition lie in the following aspects. (1) The vein image acquisition is non-contact (also called touch-less, i.e., need not to touch the sensor) and the problem of public hygiene is alleviated. (2) No obstructions are involved and thus the quality of vein patterns is acceptable to be further processed (3) Vein recognition belongs to the kind of live body identification, while fingerprint or hand shape recognition may be not (4) Vein pattern is an internal feature and difficult to forge. Because of this and the live body identification, high security of vein recognition is preserved.

It is also demonstrated that this technique can be utilized in many applications, such as surveillance, driver identification, bank ATM (Automatic Teller Machine) systems, etc. Hence, this paper focuses on the vein recognition techniques.

PRINCIPLE AND GENERAL FRAMEWORK OF VEIN RECOGNITION

Principle of vein recognition: Here, the principle and key techniques of vein recognition are described. In the early years, researchers found that the infrared light with 740-960 nm wavelengths can pass through the human hand skin and absorbed by the hemoglobin in the vein. As the reflections of the veins are less than their surroundings, the vein patterns can be observed with an infrared sensitive CCD (charge-couple device) camera. This mechanism makes the vein recognition possible. A human hand vein image captured with a near infrared camera is shown in Fig. 1. Clearly, the vein patterns in fingers and palm are visible.

Although most available vein recognition techniques are based on near infrared sensitive camera, it is necessary to point out that in some literatures (Wang *et al.*, 2008b) effectiveness of far infrared light is also demonstrated.

In available vein recognition techniques, the used vein images can be classified into three categories, hand dorsal vein (Lin and Fan, 2004; Choi and Tran, 2007; Crisan *et al.*, 2010; Kumar and Prathyusha, 2008, 2009; Im *et al.*, 2001; Wang and Leedham, 2005, 2007; Wang *et al.*, 2008b; Bouzida *et al.*, 2008; Sebastian and Albano, 2003), finger vein (Kono *et al.*, 2002; Miura *et al.*, 2004; Liu *et al.*, 2010; Lee and Park, 2009; Shimooka and Shemizu, 2004; Vlachos and Dermatas, 2008) and palm vein (Zhang *et al.*, 2007; Watanabe, 2008), as shown in Fig. 2. Specifically, in finger vein recognition systems, the forefinger, middle-finger (Wu and Ye, 2009), ring finger and little-finger (Miura *et al.*, 2004) are all appropriate. Existing work shows these three kinds of vein images are all applicable for personal authentication and identification. It is necessary to note that no analysis shows some of them outperform others. Generally speaking, the finger vein recognition corresponds to relatively smaller size equipments in practical applications. Consequently, in bank ATM or driver identification, finger vein recognition systems are more popular. Considering the public hygiene, the equipments in these three kinds of vein image acquisition can be designed non-contact. In most methods, a gray level vein pattern is sufficient for recognition. Besides, a color vein image usually captured by a thermal imaging device is also applicable.

Fig. 1: Human hand vein image captured with a near infrared camera

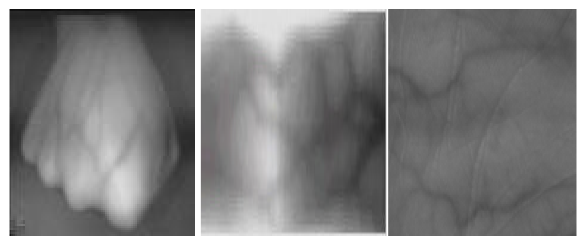

Fig. 2: Human vein images, (a) hand dorsal vein, (b) finger vein, (c) palm vein

General framework of vein recognition: As vein recognition can be used for personal authentication and identification, a general architecture with these two

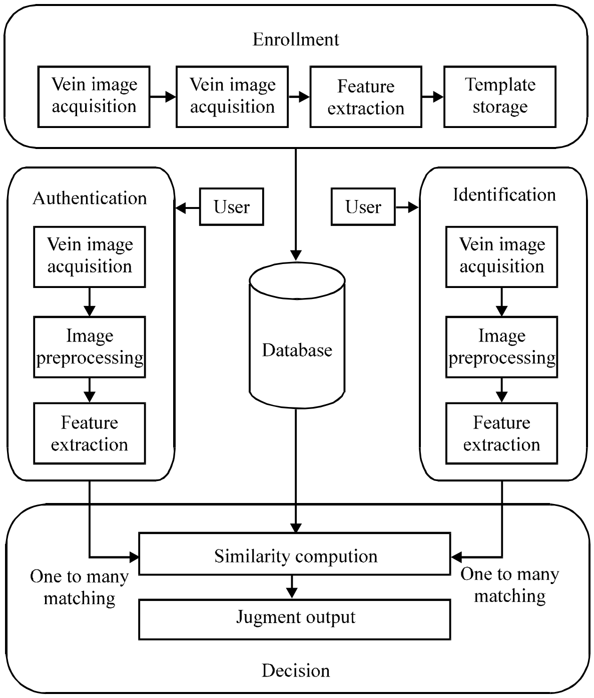

Fig. 3 A general framework of vein recognition

applications included. As shown in Fig. 3, this architecture consists of four parts, enrollment, authentication, identification and decision:

Enrollment: The enrollment stage is called registration and composed by the operations of vein image acquisition, image preprocessing and feature extraction. At last, the generated templates are stored in a database.

Authentication: The authentication stage is called verification. It is a one-to-one matching processing. For a specific user, the vein image must be captured, preprocessed, feature extracted and transformed into a feature vector according to an organization mechanism designed in advance.

Identification: Compared with authentication, the identification stage is a one-to-many matching processing. The operations are similar as those in the stage of authentication.

Decision: The key procedure of decision stage is feature matching. That is, calculate the similarity between the query feature template and the counterparts read out from database one by one. Then a judgment can be made according to the computed similarity.

For authentication, the user's identity confirmation can be made as long as the similarity is no less than a threshold selected in advance. On the contrary, if the similarity is smaller than the threshold, the user is regarded as an imposter.

For identification, the user can be confirmed as the person whose vein feature data have the maximum similarity score.

KEY TECHNIQUES OF VEIN RECOGNITION

The key techniques of vein recognition can systematically described in three parts, i.e., vein image acquisition and preprocessing, feature extraction and feature matching.

Vein image acquisition and preprocessing: Similar as other biometric recognition techniques, the first work is to gather biometric samples and register them associated with owners one by one. This process is usually called enrollment.

Different from fingerprint, vein pattern is not easily seen in visible light and thus cannot be captured by ordinary CCD camera. Instead, in most existing vein recognition methods it is captured by two ways, a near infrared CCD sensitive camera, or an array of near infrared Light-Emitting Diode (LED) (Wu and Ye, 2009). The used near infrared wavelength can be about 850 nm. In general, to each people, several samples (e.g., 10 images) are captured.

After the raw image captured, it is required to be preprocessed before feature extraction. In the preprocessing, the samples are usually sent for image enhancement (Wang *et al*., 2008b). After that, all the samples are cut into moderate dimension images of the same size, usually called region of interest (ROI). Here, assume the ROI area is selected before vein pattern analysis.

Next, these biometric samples are reduced to mathematical templates and only these enrolled templates are stored in system database. Obviously, a template size should be applicable (e.g., 256 or 512 bytes) in order to alleviate the burden of limited storage space.

Actually, the storage of templates instead of raw images is beneficial to avoid reduce a "replay" attack to some extent. The replay attack refers to an attacker steals the raw images and replays it electronically for impersonation an individual who is not physically present.

Feature extraction: Feature extraction plays an important role in biometrics recognition because the performance of feature matching is greatly influenced by its output. The vein pattern to be extracted from infrared-ray images is represented as dark lines. To extract these lines, edge detection, morphological operators are usually used.

Besides matching precision, the robustness of feature extraction is also need to be considered. If refers in some specific situation such as inhomogeneous illumination (e.g., irregular shading) around camera or sensors, target geometrical variations in 3D space, etc., a high recognition precision is still preserved. In addition, the robustness also includes the tolerance to quality degradation of sample images, such as loss of minutiae features.

Feature matching: This stage is essential to achieve the purpose of personal authentication or identification. Actually, feature matching can be reduced to the task of similarity computation. Further, how to effectively calculate the similarity is of great importance. Generally, there are several popular used approaches for similarity measurement.

Hamming distance: The Hamming distance is widely used in biometrics template comparison (Weaver, 2006).

Modified Hausdorff Distance (MHD): Wang *et al.* (2008b), adopted the MHD algorithm is for its sensitivity to geometrical transformations. Its effectiveness is demonstrated by measuring the similarity between two point sets based on their spatial information.

Intelligent classifier: Here the intelligent classifier denotes those classification methods with artificial intelligence or machine learning principle used. For example, Wang *et al.* (2008a) combined, support vector machines (SVM) aided K-Nearest Neighbor (KNN) and Minimum Distance Classifier (MDC) presentedfor feature matching. Liu *et al.* (2010), point manifold distance, a novel metrics, is presented with effectiveness proved.

In most cases, a perfect match may be not obtained. Thus a predetermined threshold is usually set for making a judgment. Usually the threshold is selected based on a large quantity of experimental results. Obviously, a larger database corresponds to a more reliable threshold in statistics.

AVAILABLE METHODS CLASSIFICATION

Available vein recognition methods can be classified into two categories according to the processing principle. One is based on low-level image processing and the other is based on high-level image processing. Suppose in this paper, the former and latter category methods are called type I and II methods, respectively.

Type I methods: In the type I methods, traditional image processing techniques, such as image enhancement, Li *et al.*, 2007a, b; 2009; Li and Pan, 2007, 2008) segmentation, edge detection, etc. are used. For example, Rothaus *et al.* (2009), proposed some methods of vessel segmentation for the utilization in separation of the retinal vascular graph in arteries and veins.

Besides spatial domain operations, some transforms are also employed as supplementary tools, such as Discrete Fourier Transform (DFT), discrete cosine transform (DCT), Discrete Wavelet Transform (DWT) (Wang *et al.*, 2008a), Radon transform (Wu and Ye, 2009), etc. As high correlation exists among neighboring image pixels, most of these transforms exhibits high efficiency in energy compaction of highly correlated data and thus can concentrate the vein image content in a few coefficients in transform domain. Nevertheless, some transforms are robust against affine transforms (e.g., rotation). This is useful for pose variation occurs during vein acquisition.

Similar as fingerprint, global and local features are contained in each vein pattern. To exact the global features, the graph-based methods can be used. While Wang *et al.* (2008b), Choi *et al.* (2007), Watanabe (2008), Lin *et al.* (2004), Toh *et al.* (2005), extracted some minutiae features. One of the typical Type I methods is proposed by Wang *et al.* (2008b). In it, the infrared image of hand dorsal vein is captured for analysis and the bifurcation and ending points are extracted as minutiae features. Averagely, 13 minutiae points including 7 bifurcation and 6 ending points are included in each vein image. Thus the task is reduced to extract and match these 13 feature points.

Type II methods: In contrast, in the Type II methods, personal authentication or identification is considered as a problem of pattern classification. The common characteristics is some artificial intelligence (Wu and Ye, 2009) or machine learning (Liu *et al.*, 2010) techniques.

Liu *et al.* (2010) introduced manifold learning, one of the machine learning techniques, is for vein recognition for the first time. Wu and Ye (2009) proposed a driver identification system using finger-vein technology proposed in which radial basis function (RBF) network and Probabilistic Neural Network (PNN) are employed as the classifiers. Experimental results show the average identification rate of PNN network is no less than 99.2%.

Up to now, the Type II techniques are under further development. It is reasonable that some pattern recognition-based methods for other biometric feature (e.g., human face) analysis (Li and Pan, 2007a, b,c, 2008; Li *et al.*, 2009) can be extended for vein pattern recognition.

To the present, many vein recognition techniques belong to type I have been embedded in commercial products. In comparison, as a training procedure is usually involved, most of the type II methods are under further investigation and performance evaluation. As an emerging development trend, many type II methods are also expected to be put into commercial applications in the near future.

PERFORMANCE EVALUATION

To quantitatively evaluate the accuracy of a vein recognition algorithm, there are following factors are usually used. As illustrated in Table 2, properties of some typical methods are given in an ascending chronological order.

Database: In each method, a database must be constructed in advance for recognition. Size of the database constructed based on the number of participants and samples of each participant. The number of participants depends on the specific scenarios and the diversity must be considered. For example, a representative database should contain samples collected from males, females, different races (Wang *et al.*, 2008b), adults and children in diverse ages, etc.

It is necessary to note that to each participant (host hand or finger), at least two vein images are required to be captured. If only two images are captured (Kono *et al.*, 2002), one is used for enrollment and the other is used as query image for testing algorithm's performance. If more than only two images are captured (Lin and Fan, 2004), they are divided into two parts, one for enrollment and the other for testing.

Performance indicators

False Acceptance Rate (FAR): FAR is also called False Match Rate (FMR). It refers to the probability that the system incorrectly matches the input pattern to a non-matching template in the database. In other words, it measures the percent of invalid inputs which are incorrectly accepted.

False Rejection Rate (FRR): FRR is also called false non-match rate (FNMR). It is defined as the probability that the system fails to detect a match between the input pattern and a matching template in the database. That is, it measures the percent of valid inputs which are incorrectly rejected.

It is reasonable that the FAR decreases but the FRR increases due to the sensitivity of the biometric device increases. In practical applications, the FAR should be very low to provide high enough confidence and the FRR must be sufficiently low. If the threshold set in the decision stage is reduced, it is expected that less false non-matches but more false accepts generated. In other words, a higher threshold corresponds to a smaller FAR and a larger FRR.

Receiver Operating Characteristic (ROC) curve: The ROC curve is used for illustrating the relationship between FAR and FRR. It is a visual characterization of the trade-off between the FAR and the FRR, i.e., in a ROC curve the vertical and horizontal axes are FAR and FRR or vice versa, respectively.

Equal Error Rate (EER): EER is also called Crossover Error Rate (CER). It refers to the error rate at which the FAR equals to the FRR and hence can be easily obtained from the ROC curve. In addition, it is usually used for comparing the accuracy of devices with different ROC

Table 2: Properties of some typical vein recognition methods

		Database size			
Method	Vein image	Total images	No. of people	Samples of each people	Performance indicators
Im *et al.*, (2001)	Palm-dorsum	5000	Not mentioned	Not mentioned	FAR = 0.001% Reliability = 99.45%
Kono *et al.* (2002)	Left little-finger	1356	678 (479 males, 199 females)	2	FAR = 0.000035~0.043% FRR = 0.1%
Lin and Fan (2004)	Palm-dorsum	960	32 (3 females, 29 males)	30	FAR = 2.3% FRR = 2.3%
Miura *et al.* (2004)	little-finger	678	339 (30% females, 70% males)	2	EER = 0.145%
Zhang *et al.* (2007)	Palm	144	24	6	recognition rate = 98.8% FAR = 5.5%
Wang *et al.* (2008a)	Palm-dorsum	820	82	10	FAR = 0.46% FRR = 5.08% EER = 1.96%
Wang *et al.* (2008b)	Palm-dorsum	141	47 (Chinese, Indian, Caucasian adults)	3	EER = 0%
Watanabe (2008)	Palm	150000	75000	2	FAR<0.00008% FRR = 0.01%
Kumar *et al.* (2009)	Palm-dorsum	300	100 (81 males, 19 females)	3	FAR=1.14% FRR = 1.14%
Lee *et al.* (2009)	Forefinger, middle-finger, ring finger, little-finger	6400	80	80 (10 of each finger except thumbs of both hands)	EER = 0.76%
Wu *et al.* (2009)	Middle-finger	250	25	10	Identification rate>99.2%
Crisan *et al.* (2010)	Palm-dorsum	612	306	2	FAR = 0.012% FRR = 1.03%
Liu *et al.* (2010)	Middle-finger	11480	164	70	Identification rate = 97.8%, verification EER = 0.8%

curves. A lower EER indicates a more accurate system. Some results in these publications report EER as low as 0% (Wang *et al.*, 2008b). However, as a relatively small database (only 47 participants) utilized, this experimental result cannot reflect the real world conditions and thus confidence of this accuracy is not sufficient to some extent.

Generally, the EER for fingerprint recognition can be achieved as 0.2 to 0.4%. However, Miura *et al.* (2004), the reported EER of vein recognition is 0.145% for a mismatch ratio of 37.6%. Thus, the performance of vein recognition is better than fingerprint to some extent. A simple method of calculating the EER can be found by Miura *et al.* (2004).

Failure to enroll rate (FTE or FER) and Failure to Capture Rate (FTC): Besides FAR, FRR and ROC, there are other two factors usually considered in a vein recognition system. One is the failure to enroll rate often caused by low quality inputs. It means the rate at which attempts to create a template from an input is unsuccessful. The other is called failure to capture rate. It refers to the probability that the system fails to detect a correctly presented biometric input.

Response time: In practical application, the response time must be taken into account. It is jointly determined by two factors. One is the computational complexity of vein recognition algorithm and the other is the capability of processing platform including the adopted software, performance of CPU and the size of memory, etc. For example, the average response time reported by Miura *et al.* (2004) is only 460 m sec, including 450 m sec for feature extraction and 10 m sec for feature matching, respectively. The results are obtained by a computer with a 550 MHz CPU and a 128MB memory and the software platform involved is Visual C++ 6.0.

APPLICATIONS

Although developed later than traditional biometrics such as fingerprint and iris recognition, vein recognition has been put into practical applications instead of a technique in conception. It is reported the first commercial product was developed in 1997. Later, various products are on the market. For example, since 2003 Fujitsu and Hitachi have developed a series of commercial vein recognition products independently. The only difference lies in that palm vein is used in Fujitsu's products, while finger vein is used in Hitachi's products. Vein recognition has been investigated for the applications as follows:

- Driver identification system
- Door security system
- Login authentication
- Financial and bank services
- Physical access control and time attendance
- Travel and transportation
- Hospitals
- Construction sites
- Schools

Wu *et al.* (2009) proposed a finger-vein recognition based driver identification system. Watanabe (2008) investigated the application of a palm vein authentication device in door security system, login authentication and financial services. Choi *et al.* (2007) extensively discussed the application of palm-dorsum recognition in finance and banking, travel and transportation, hospitals, construction sites and schools.

FUTURE TRENDS

There are two development trends on vein recognition and the related techniques as described as follows.

Multimodal fusion: Multimodal fusion biometrics recognition is a main-stream trend in the future. The reasons mainly lie in two aspects. On one hand, as many biometric features are deep investigated, it is possible for the applications of multimodal fusion biometrics recognition. On the other hand, different biometric features have different characteristics inherently. Multimodal fusion provides an opportunity to employ the advantages of several biometric features.

Hao *et al.* (2007) investigated technique with hand biometrics including fingerprint, palm-print, hand geometry and vein pattern. Toh *et al.* (2005) proposed a biometrics technique combined the palm vein and crease texture are proposed. Pavesic *et al.* (2006) combined biometrics technique the visible image of hand palm and the infrared image of hand dorsum are proposed. The difference of these two methods mainly lies in the light source position. Toh *et al.* (2005) study both the infrared and visible light sensors are seated at the same side of a hand palm, while in (Pavesic *et al.*, 2006) study they are located at the opposite sides of a hand.

Ideal device design: An ideal device should be designed with factors taken into account including hygienic contactless, user-friendly, compactness, etc. Among these, compactness is also a crucial factor must be carefully considered. In practical applications, miniaturization is beneficial to a lower cost and portable device. Therefore, a relative small part of vein pattern captured is adequate for the task achievement of recognition. Compactness is beneficial to integrate the device in bank ATMs and portable equipments such as notebook computers. Watanabe (2008) study size of a palm vein sensor is $35\times35\times27$ mm^3. Both the illumination and capturing device are included in this compact sensor. In (Miura *et al.*, 2004), the finger-vein sensor is of the size $7\times6\times4$ cm^3 with a 1/3-inch CCD camera included.

In addition, consideration of the device cost is also necessary. In commercial products, one or several infrared LEDs are used instead of an infrared camera used as in theoretical analysis. It can be expected a lower cost vein recognition device will be on the market.

CONCLUSIONS

This study presents a survey of vein recognition techniques for biometric authentication and identification. The state-of-the-art overview consists of the principle, general framework, key techniques, available methods classification, performance evaluation, application fields and status and future trends. As a new biometric feature exploited, validity and efficiency of this promise technique are demonstrated in both theoretical analysis and commercial applications.

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