A survey of finger vein recognition

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Abstract. As a new biometric technique, finger vein recognition has attracted lots of attentions and efforts from researchers, and achieved some progress in recent years. A survey of progress in finger vein recognition is given in this paper. It mainly focuses on three aspects, i.e., the general introduction of finger vein recognition, a review of the existing research work on image acquisition and feature extraction methods. We finally present the key problems and future directions in order to enlighten finger vein recognition research domain.

Keywords: Biometrics, finger vein recognition, survey, future directions

1 Introduction

Finger vein recognition is a personal physiological characteristics-based biometric technique, and it uses vein patterns in human finger to perform identity authentication. Near-infrared light (wavelengths between 700 and 1,000 nanometers) is usually used to capture finger vein image [1, 2]. The principle is that, near-infrared light can be absorbed intensively by the hemoglobin in the blood of vein, but transmits other tissues of finger easily, therefore vein pattern in finger will be captured as shadows.

As a biometric characteristic, finger vein has several desirable properties, such as universality, distinctiveness, permanence and acceptability. In addition to, compared with other biometric characteristics (for example, face, gait, fingerprint and so on), it has other distinct advantages in the following two points [1]: (1) Living body identification. It means that only vein in living finger can be captured, and further used to perform identification. (2) Internal characteristic. It is hard to copy or forge finger vein, and very little external factor can damage finger vein, which guarantee the high security of finger vein recognition. These two advantages make finger vein an irreplaceable biometric characteristic, and attract more and more attentions from research teams. A typical finger vein identification system mainly includes image acquisition, preprocessing, feature extraction and matching, as shown in Fig.1.

Kono et al [3], Japanese medical researchers, proposed finger vein based identity identification, and gave an effective feature extraction method. Yanagawa et al [4] proved the diversity of human finger vein patterns and the usefulness of finger veins for identity identification on 2, 024 fingers of 506 persons. They show that, two finger

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vein patterns are identical if and only if they are from the same finger in the same hand of the same person. These two literatures are the foundation of finger vein recognition, which open the era of finger vein recognition. In the early days of finger vein recognition, there are two significant literatures, which are all from Miura et al. The first one [1] is about a feature extracted method, named repeated line tracking. Line tracking starts at various positions, and moves along the direction of vein pattern pixel by pixel. In the second literature, in order to overcome the influence of vein patterns' various widths and brightness, maximum curvature [5] was developed to extract the centerlines of vein.

Fig.1A typical finger vein identification system

By the development of the past decade, finger vein recognition ushers in the evolution period now. The most representative literature is Ref. 6, in which authors used Gabor to extract finger vein patterns, and fuse finger vein and finger texture. Beside, Yang et al [7] proposed to use the width of phalangeal joint as a soft biometric trait to enhance the recognition accuracy for finger vein. Although, there are some valuable works in finger vein recognition, lots of key problems are unsolved, for example, the acquisition of high quality image, the high recognition rate, the large scale applications.

In this paper, first we comprehensively review main techniques of finger vein recognition, which include image acquisition devices, existing public databases and some typical feature extraction and matching methods. And then, the unsolved key problems and potential development directions in finger vein recognition are analyzed. Last, we conclude this paper.

2 Image Acquisition and Public Databases

In this section, we mainly describe image acquisition and public finger vein databases. In detail, two ways of image acquisition, one typical device and its acquired images are given firstly. Next, the existing public databases are shown, the comparison between different databases, about the number of images, the size of image and so on, are presented.

There are two ways of finger vein image acquisition, i.e., light reflection method and light transmission method [2], as shown in Fig.2. The main difference between two methods is the position of near-infrared light. In detail, in light reflection method, near-infrared light is placed in finger palmar side, and finger vein pattern is captured by the reflected light from finger palmar surface. Conversely, near-infrared light is placed in finger dorsal side in light transmission method, and the light will penetrate finger. Compared with light reflection method, light transmission method can capture high-contrast image, so most of image acquisition devices employ light transmission method [1, 5, 6, 8, 9, 10].

A typical device of light transmission method [8] is introduced. The schematic cross-section of device, practical imaging device and the captured images are shown in Fig.3. The near-infrared light is on the top plate, and finger will be placed in the groove of the device below the top plate.

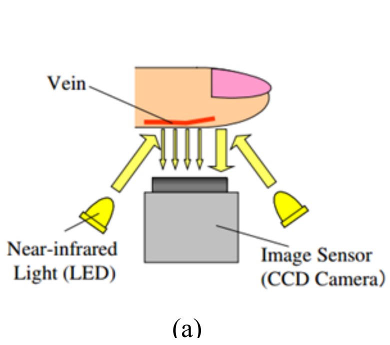


Fig.2 Two ways of finger vein image acquisition [2]:
(a). Light reflection; (b). Light transmission.

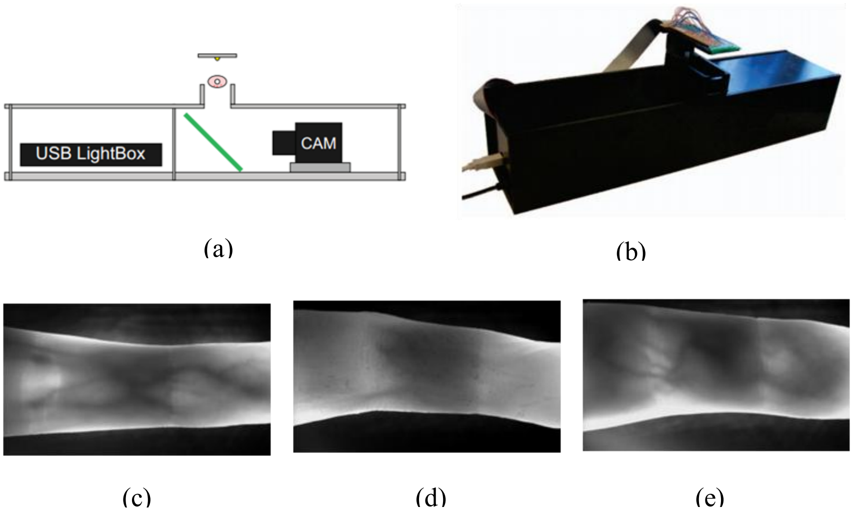
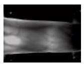
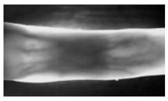
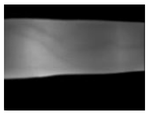


Fig.3 A typical image acquisition device and the captured images [8]: (a). The schematic cross-section of device; (b). The practical imaging device; (c, d, e). The captured images by (b).

There are multiple public finger vein databases, and five typical databases are introduced in the Table 1. The first one was built by Shandong University, named SDUMLA-FV database, and it was a part of a homologous multimodal database [11]. Another finger vein database was published by Ajay and Zhou [6], and it also was a part of a homologous multimodal database. We call it HKPU-FV database in the following. The third database was from University of Twente, abbreviated UTFV database. Recently, two finger vein databases were published, which were from Tsinghua University [12] and Chonbuk Nation University [13] respectively. The previous database is a part of a homologous multimodal database, and we call it THU-FV database in this paper. The other one is named MMCBNU_6000 database. In Table 1, light transmission-based image acquisition advice was used on all three databases. And for three databases, the number of subject/finger is limited. Besides, images from different databases have different sizes, different contrast, different backgrounds, and different quality.

Table 1. The comparison between typical public finger vein databases.

Database	Acquisition way	Subject number	Finger number per subject	Image number per finger	Image size (pixels)	Typical image
SDUMLA-FV[11]	light transmission	106	6	6	320×240	
HKPU-FV[6]	light transmission	156	2	12/6*	513×256	
UTFV[8]	light transmission	60	6	4	672×380	
THU-FV [12]	light transmission	610	1	2	200×100	
MMCBNU_6000[13]	light transmission	100	6	10	640×480	

*Only 105 subjects turned up for the imaging during the second session, so each of fingers from these subjects has 6 images, but other fingers each has 12 images.

3 Feature Extraction and Matching

Feature extraction is one key process in finger vein recognition. In this section, some feature extraction methods and corresponding matching methods are listed. These feature extraction methods can be classified into three groups, i.e., vein pattern-based methods, dimensionality reduction-based methods and local binary-based methods. Methods in each group and their corresponding matching methods are introduced in the following.

3.1 Vein Pattern-based Methods

There are six typical vein pattern-based feature extraction methods, including repeated line tracking [1], maximum curvature [5], Gabor [6], mean curvature [14], region growth [15], and modified repeated line tracking [16].This group of method is the mainstream in finger vein extraction. In these methods, the vein patterns are segmented firstly, and then the geometric shape or topological structure of vein pattern is used for matching.

Repeated line tracking, maximum curvature, region growth and modified repeated line tracking all use the cross-section of image to extract vein pattern. This is due to the fact that the cross-section of vein pattern looks like a valley, and these methods make use of this point to demerge vein pattern from images, but the special methods of recognizing vein pixel are different. However, mean curvature views the intensity surface of finger vein image as a geometric object, and pixels with negative mean curvature will be seen as vein pattern. Different from the above methods, which extract vein pattern in spatial domain, Gabor transforms image into frequency domain to extract vein pattern.

The vein patterns, extracted by this kind of methods, are binary, so the matched pixel ratio is general used in matching. The matched pixel ratio means the ratio of the number of the matching vein pixels to the total number of the vein pixels in the two vein patterns. As image acquisition is non-contact, finger displacement, i.e., finger rotation and translation, make genuine matching score small. Therefore, in matching, the best match among the pixel-by-pixel translations and rotation with certain degree of testing image are adopted.

3.2 Dimensionality Reduction-based Methods

Subspace learning methods usually transform image into low-dimensional space to classify. In transformation, they keep discriminating information and remove noises. In finger vein recognition, PCA [17], LDA [18], $(2D)^2$PCA [19], and manifold learning [20]have been used. These methods need the training process to learn a transformation matrix. When there are new enrolled users, the transformation matrix need to learn again. So this kind of methods may be not very practical. Classifiers are used in matching for these methods. For example, neural network technique is used in Ref. 17 and 18, and Ref. 19 used *k* nearest neighbor.

3.3 Local Binary-based Methods

Methods in last group are based on local area, and the extracted features are in binary formation. The local binary pattern (LBP) [9, 23], the local line binary pattern (LLBP) [21], the personalized best bit maps (PBBM) [10], personalized weight maps (PWM) [29] and the local directional code (LDC) [22] are all in this group. In LBP and LLBP, the local binary code is obtained by compare the gray level of the current pixel and its neighbors. PPBM and PWM further explore the stability of the binary codes, and use the stable binary codes in matching. Different from the four methods, LDC codes the local gradient orientation information. For most of these methods, hamming distance (HD) was used to measure the similarity between the enrolled and input binary vein features.

3.4 Performance and Discussions

In this section, we make a summary and comparison for all methods about the size of used databases, the equal error rate (EER) or recognition rate (RR), and processing time, shown in Table 2.From the table, we can see that some methods, for example, maximum curvature [5] and PBBM [10], report promising performance. At the same, there are two problems: (1)The size of databases are general limited, so it cannot be predict how the performance will be on a large scale database; (2)The processing time is long, although they can be used in real time applications. Beside, as vein patterns are the main discriminating information used in finger vein recognition, so in our opinion vein pattern-based methods are the mainstream. Other methods in the second and third groups employ whole image to perform recognition, but it is questionable whether there are the discriminating information in background area of image, i.e., non-finger vein area. In addition, in large scale applications, dimensionality reduction-based methods may be not a good choice, as transformation matrix learning will be a big problem with lots of users.

Table 2. Summary and comparison of finger vein recognition methods

Group	Method	Database	EER/RR	Time
vein pattern-based methods	repeated line tracking [1]	678 fingers × 2images	EER= 0.145%	450ms
	maximum curvature[5]	678 fingers × 2 images	EER= 0.0009%	N/A
	Gabor [6]	312 fingers × 6 or 12 images*	EER=0.65%	N/A
	mean curvature [14]	320 fingers ×5 images	EER=0.25%	118ms
	region growth [15]	125 fingers × 9 images	EER= 0.0369%	210 ms
	modified repeated line tracking [16]	200 images	N/A	N/A
dimensionality reduction-based methods	PCA [17]	10 fingers × 10 images	RR=99%	45 s
	LDA [18]	10 fingers × 10 images	RR=98%	0.0156 s
	$(2D)^2$PCA [19]	80 fingers × 18 images	RR=99.17%	N/A
	manifold learning [20]	328 fingers × 70 images	RR=97.8% EER=0.8%	N/A
local binary-based methods	(LBP) [9]	240 fingers × 10 images	EER=0.21%	44.7 ms
	(LLBP) [21]	204 fingers × 10 images	EER= 3.845%	67.1ms
	(PBBM) [10]	106 fingers × 14	EER=0.38%	439.9

		images		ms
	(PWM)[31]	136 fingers ×20 images	EER=0.41%	455.7 ms
	(LDC) [22]	136 fingers × 30 images	EER=1.02%	28 ms

*The first 210 fingers each has 6 images, but the remainder 102fingers each has 12 images.

4 Key Problems and Future Directions

Although some advancements have been made, there are still some problems in finger vein recognition. The first problem is the distinctiveness of finger vein pattern. Yanagawa et al [4] proved the diversity of human finger vein patterns on 2, 024 fingers of 506 persons, but medical evidence is not enough. So, in large scale applications, we cannot confidently predict how the recognition rate will be and if the classification result is reliable. And it also concerns if finger vein can be used in judiciary like fingerprint and face. Besides, the medical evidence about the stability of finger vein is not enough, either. In practical applications, the corresponding problem is the effectiveness of the enrolled finger vein template. In other word, it means if it is necessary to replace the enrolled template every 5 or 10 years. And if the surrounding environment and diseases can affect the finger vein pattern is uncertain.

The second problem is about image acquisition. The price of finger vein acquisition device is still high now, which is one factor that limits the application of finger vein recognition. In public databases, there are some common issues about image quality, for example, low contrast, image blurring, excessive brightness, excessive dark and stains. So, there is a space for the performance improvement of image acquisition device. Dai et al [29] used nonuniform intensity infrared light to capture finger vein image, and the quality of captured image has been improved at certain extent. In total, the device with low price and high performance will vastly promote the development of finger vein recognition.

The third problem is finger displacement during image acquisition. Finger displacement can be divided into 2 dimensional posture changes, i.e. shift along x-axis, y-axis and z-axis, and 3 dimensional posture changes, i.e., rotation around x-axis, y-axis, z-axis [24, 25].Compared with 2 dimensional posture changes, it is harder to handle 3 dimensional posture changes. Transformation models, which were based on binary finger vein pattern [24] and minutia points [25], were used to finger alignment. And some works align displaced fingers in preprocessing [26, 27, 28], but these methods mainly focus on overcoming 2 dimensional posture changes. It may be easier to handle this problem from device, for example, adding a groove to fix finger.

The last one is lack of large scale practical application. Hitachi LTD. has researched finger vein recognition since 1997, and applied finger vein recognition into many domains, for example, ATM automatic teller machine and car lock. The inland industrial communities, which research product of finger vein recognition, start late, and the scale of application is relatively small.

There are many remains to be done on finger vein recognition to further improve its performance, and promote its practical application. Two main remaining problems are discussed here. The first is about large scale applications. A large scale public finger vein database is needed to build, which can be used to evaluate the existing and new methods in laboratory environment. And finger vein image classification and indexing are also very meaningful for large scale applications. The second is liveness detection. Finger vein lies in the inside of finger, but liveness detection is still an urgent work for the application of finger vein recognition. Nguyen et al [30] used fourier and wavelet transforms to detect fake finger vein image. Although it performs preliminary study, there are some shortcomings.

5 Conclusions

In this paper, we review the recent development of finger vein recognition, and give some representative works in this field. In particular, we focus on the technique employed in image acquisition and feature extraction. Besides, we present some key problems of finger vein recognition, and analysis its potential development directions.

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