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Review of Research on Feature Extraction Algorithms for Finger Vein Images

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Abstract: With the development of social informatization, biometric identification has become the key technology of modern information security. Finger vein recognition has become a hot spot of current research due to its advantages such as high security and living body recognition. Finger vein feature extraction is the key link in the finger vein recognition process, which is crucial to the overall performance of the recognition system. This paper firstly introduces the finger vein recognition system and organizes and summarizes the public datasets; then, with deep learning as the boundary, it classifies and researches the applications of vein feature extraction in recent years, and combs and analyzes the feature extraction algorithms that are the focus of each category; secondly, it summarizes the evaluation indexes in the field of finger vein recognition; and finally, it sums up the status quo of the finger vein feature extraction and the challenges it faces.

Keywords: Information Security; Finger Vein Recognition; Deep Learning; Feature Extraction.

1. Introduction

With the development of informationization and intelligence in society, identity verification has become an indispensable part of people's daily lives. From logging into computers and electronic accounts to using ATMs and access control systems, authentication is ubiquitous. Traditional authentication methods, such as passwords and access cards, are no longer able to meet the demands for security and convenience in modern society. Biometric technology significantly improves security and convenience by using human behavioral and physiological characteristics for identity authentication [1], solving problems such as forgotten passwords and lost cards. Therefore, biometrics has become a key solution for identity authentication.

Biometrics refers to technologies that utilize unique, measurable human characteristics to identify individuals. These biometric features are usually classified into two categories: (1) behavioral features, such as signature, gait, and voice; and (2) physiological features, such as fingerprints, faces, irises [2], palm prints [3], and finger veins [4]. Currently, the most mature and widely used technologies are face recognition and fingerprint recognition. However, in some special cases, these methods may be limited. For example, face recognition [5] is susceptible to light variations and facial angles. Fingerprint recognition [6] is susceptible to forgery because fingerprints are often exposed; in addition, dryness or sweating of the fingers can prevent a clear pattern from being obtained, which in turn affects the recognition effect.

Finger vein recognition has been investigated to overcome the limitations of current face and fingerprint-based recognition systems [7]. Yanagawa et al. [8] demonstrated that each finger has a unique vein pattern that can be used for personal verification. Finger vein-based biometrics have several advantages over biometric methods [9]. (1) First of all, finger vein pattern is an internal feature, and not only its quality is not easily affected by the skin condition is difficult but also difficult to replicate. (2) In addition, the contactless capture of finger vein recognition ensures user convenience and hygiene. (3) Finally, finger vein recognition is a living body recognition, therefore, when finger veins are used for authentication, the subject who successfully captures the finger veins must be a living body, which is a natural and unforgeable evidence.

Finger vein recognition consists of four main stages: (1) image acquisition, (2) preprocessing, (3) feature extraction, and (4) feature matching. Some scholars have discussed the different stages of finger vein recognition systems in their review studies. For example, Yin et al [10] wrote a review focusing on feature extraction methods and analyzed how to reduce the price of acquisition equipment, improve image quality, and other application aspects. Wang et al [11] conducted a study on finger vein region of interest extraction, summarized the main work on region of interest extraction, and summarized the representative methods in each project. Literature [12] conducted a retrospective study on deep neural networks in the field of finger vein recognition. Li et al. first introduced the publicly available datasets in the field of finger vein, and then classified the deep learning methods in finger vein recognition in recent years according to the deep neural network learning tasks, and introduced the design techniques of finger vein recognition in terms of lightweight network, data augmentation, and attention mechanism. They also evaluated the existing literature in terms of accuracy and equal error rate.

The above research makes a significant contribution to further promote finger vein recognition in the field of biometric identification. In recent years, deep learning-based methods have performed well in the fields of object detection, face recognition and image processing. Similarly, the research on finger vein feature extraction takes deep learning as the demarcation point. Before the introduction of deep learning, feature extraction mainly relied on features such as vein's grain, texture and detail points, whereas nowadays, deep learning neural networks can automatically perform image feature extraction and matching for integration. Therefore, this review divides the methods of feature extraction into two categories with deep learning as the demarcation point: non-deep neural network methods and deep neural network methods.

In 2000, Kono et al [13] proposed a biometric method based on finger vein recognition, and since then countless scholars have begun to investigate finger vein recognition. Nowadays, a large number of feature extraction methods have been proposed, including the use of images, repetitive linear tracking, curvature, local binary patterns, dimensionality reduction, and machine learning. This review aims to contribute in the following three directions: (1) to systematically review the feature extraction methods proposed in recent years; (2) to compare and analyze the latest and state-of-the-art research results, and to point out their shortcomings; and (3) to summarize and look forward to the research prospects of feature extraction methods for finger vein recognition.

The rest of this paper is organized as follows: section 2 will provide an overview of the technologies related to finger vein recognition systems, especially the process after the introduction of deep learning; section 3 will sort out and summarize the public datasets used in finger vein research; section 4 will categorize the feature extraction methods, bounded by deep learning; section 5 will sort out and summarize the evaluation metrics that are commonly used in the field of finger vein recognition; section 6 will summarize and analyze the future challenges facing the field.

2. Finger Vein Recognition System Introduction

2.1. Principles of Finger Vein Imaging

By analyzing the anatomy and internal physiological behavior of finger veins, medical researchers have found that hemoglobin within the veins does not carry oxygen molecules and therefore absorbs near-infrared (NIR) light at wavelengths in the range of 690 to 980 nm. In contrast, arteries and other tissues of the fingers can be easily penetrated by NIR light in this wavelength range. Based on this principle, as shown in Figure 1, a light source emitting NIR light can be utilized to irradiate a finger, and the NIR light passing through the finger can be captured by a NIR light camera, thereby capturing the vein structure within the finger. Imaging modalities for finger vein recognition [14] mainly include transmission imaging, reflection imaging, double side scattering imaging and single side scattering imaging.

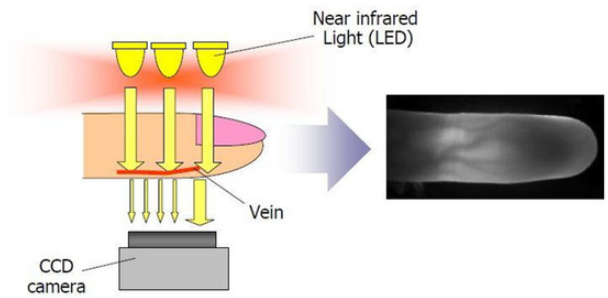

Figure 1. Imaging principles (transmission imaging)

2.2. Recognition Process

The main process of finger vein recognition includes finger vein image acquisition, image preprocessing, finger vein feature extraction and feature matching. Figure 2 shows the overall process of finger vein recognition.

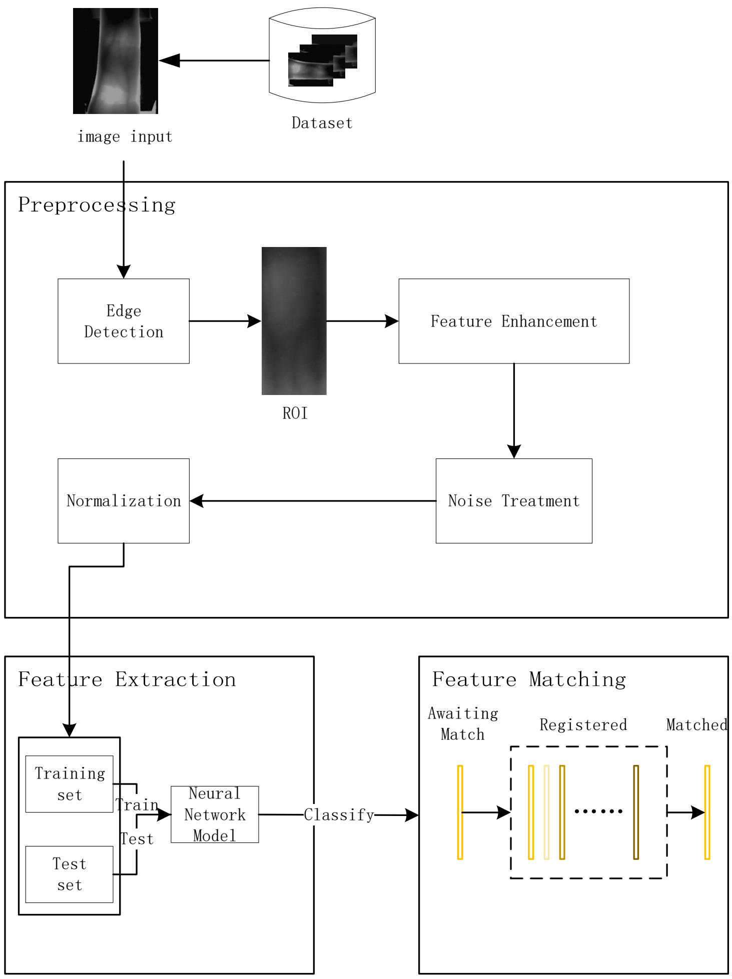

Figure 2. Finger vein recognition flowchart

There are two main routes for image acquisition: self-constructed datasets using finger vein image acquisition devices and access to publicly available datasets. The preprocessing stage requires operations such as Region of Interest (ROI) extraction, normalization, and feature enhancement to highlight the features. The task of feature extraction is to segment the vein features from the background region and extract features such as vein texture or texture. Subsequently, the extracted feature images are registered to the feature template library. In the feature matching stage, matching algorithms such as similarity metrics are combined to classify and recognize the input images.

3. Dataset

As an important support in the field of deep learning, datasets have a crucial role in the development of deep learning, and neural networks can greatly improve the generalization ability of the model after learning from a large number of datasets. There are five most common datasets in finger vein recognition, which are the Universiti Teknologi Malaysia finger dataset FV-USM [15], Shandong University Machine Learning and Data Mining Experimental Finger Vein dataset SDMULA [16], Hong Kong Polytechnic University Finger Vein dataset HKPU [17], Jeonbuk National University Finger Vein dataset MMCBNU-6000 [18], Switzerland Finger vein dataset VERA [19] at the Dal-Moore Institute for Perception Artificial Intelligence Sensing, Switzerland. There are also the University of Twente Finger Vein Dataset UTFVP [20] in the Netherlands. Details of the publicly available finger vein image database are shown in Table 1.

Table 1. Details of publicly-available finger-vein image databases

Database	Number of Fingers	Details of Fingers	Imagers Per Finger	Sessions	Image Size	Total Images
FV-USM	492	Left & right hand index & middle finger	12	2	640×480	5904
SDUMLA	636	Left & right hand index, middle & ring finger	6	1	320×320	3816
HKPU	312	Left hand index & middle finger	12	2	513×256	3132
MMCBNU_6000	600	Left & right hand index, middle & ring finger	10	1	640×480	6000
VERA	220	Left & right hand index, middle & ring finger	2	1	665×250	440
UTFVP	360	Left & right hand index, middle & ring finger	4	2	672×380	1440

4. Feature Extraction Algorithm

Compared with other biometric identification technologies, finger vein identification technology has the advantages of high security and high privacy, and has received extensive attention and research at home and abroad. At present, finger vein feature extraction is mainly categorized into non-deep neural network methods and deep neural network methods, which are described in detail below.

4.1. Non-deep Neural Network Approach

The key to traditional finger vein recognition lies in the extraction of finger vein features. Existing finger vein feature extraction algorithms are mainly classified into the following categories: vein pattern based approach, vein texture-based feature extraction approach*, and detail point-based feature extraction methods.*

(1) Vein pattern based approach

The vein texture-based approach involves extracting the vein network from the vein grayscale image and then matching it using the texture, which can effectively represent the overall topology of the veins. Miura et al [21-23] first proposed an algorithm called repetitive linear tracking (RTL), which utilizes the valleys of the finger veins in the pixel grayscale values and finds out the vein texture by repetitive linear tracking Yu et al [24] improved the RTL algorithm to obtain better segmentation performance, but it still suffers from the drawbacks of low robustness and high complexity. A modified repetitive linear tracking method is proposed in the literature [25], which utilizes a threshold image segmentation algorithm to obtain a vein image and estimate the vein width based on the image, and then corrects the parameters based on the width, and then performs the modified repetitive linear tracking method, which is more stable and efficient than the traditional RTL. Gabor filters are commonly used in biometrics recognition, including iris, fingerprint, and palmprint recognition. In literature [26] a set of Gabor filters are used to extract finger vein features, and based on the filtered image, local and global finger vein features are extracted to construct a finger vein code (FVCode). Literature [27] the algorithm is optimized and an adaptive Gabor filter is proposed to determine the optimal parameters of individual filters to obtain effective vein pattern images. Curvature is a physical quantity that describes the change in curvature of a curve, and in the case of venous vessels, the value of curvature is relatively large. Therefore, by calculating the curvature of individual points in the image can be a good way to distinguish blood vessels from other background structures. Liu et al [28] used the enhanced maximum curvature (EMC) method to extract the vein features and utilized the best matching region score (SMRS) and support vector machine (SVM) for hierarchical feature extraction. Literature [29] designed a set of spatial curve filters (SCFs) with curvature and orientation variations, and weighted the SCFs using a variable Gaussian model to fit the vein curves tightly locally. Song et al [30] proposed the mean curvature method, which treats the vein image as a geometrical shape and identifies the valley-like structures with negative mean curvature, and achieved good vein texture extraction Effect.

(2) Vein texture based feature extraction approach

Local binarization-based methods obtain Local Binary Patterns (LBP) by converting the difference between the center pixel of a local window and its neighboring pixels into binary encoding, which is used to represent the local features of finger veins. Lee et al [31] proposed a feature fusion method that uses simple binarization, Local Binary Patterns (LBP) and Local Derivative Pattern (LDP) for finger vein recognition, which exhibits higher recognition accuracy and shorter processing time. The Local Line Binary Pattern (LLBP) method was applied to finger vein recognition in the literature [32], and the performance of using LLBP was better than Local Binary Pattern (LBP) and Local Derivative Pattern (LDP).Yin et al. proposed a local descriptor called Local Directional Code (LDC), which is a square local descriptor that requires only four neighborhoods for coding, thus the computational complexity of LDC is much lower than that of LLBP and better reflects the directional information and local features. A new feature extraction method called Multi-scale Sobel Angles Local Binary Pattern (MSALBP) is proposed in the literature [33], which fuses the Sobel orientation angles with the Multi-scale Local Binary Pattern (MSLBP), and the resulting features are divided into non-overlapping blocks and statistically computed to form texture vector.

(3) Vein minutia based feature extraction approach

In finger vein recognition, detail points, which are the endpoints and bifurcations of finger veins, are an important feature of finger vein images. Using endpoints and bifurcations in the finger vein pattern for matching, locally invariant feature descriptors can characterize these detail points, and the obtained features are robust to deformation, translation, rotation, and scaling changes. Yu et al [34] extracted bifurcations and endpoints from the vein pattern to represent the vein's topology, and proposed an improved Hausdorff distance algorithm to evaluate the ability to recognize the shape of the vein of all possible relative positions. Mantrao et al [35] proposed a method using detail point matching by first preprocessing the finger vein image and then generating a grayscaled image of the finger vein image and then extracting the detail points of the finger vein using morphological operations. In literature [36] a convolutional method was proposed to extract the detail points of the veins. The detail point feature extraction involves extracting the endpoints and bifurcation points from the vein skeleton map. Prabhaka et al [37] proposed a finger vein recognition method based on the detail point feature extraction and pseudo-detail point removal to make the recognition more accurate. Bansal et al [38], on the other hand, fused the detail point extraction and curve analysis methods, applied refinement techniques to extract the finger vein skeleton and calculate the detail points, and finally obtained the curve and further analyzed it by calculus methods.

4.2. Deep Neural Network Methods

Traditional finger vein recognition mainly utilizes a manually designed feature-based approach to recognition, with a complex process and features that are difficult to characterize the various gesture changes of the finger, and poor algorithmic robustness and mobility. With the rise of deep learning, feature extraction is gradually optimized and more automated. For example, Convolutional Neural Network (CNN), a popular deep learning model, has a feature extraction layer that is capable of extracting optimized vein features from training images. Radzi et al [39] first attempted to use a deep learning model in finger vein biometrics in 2016, where convolutional and subsampling layers were fused into a lower-complexity, 4-layer CNN, which was tested on an in-house dataset Hong et al [40] used a pre-trained VGG-Net-16 model for finger vein recognition, which consisted of 13 convolutional layers, 5 pooling layers, and 3 fully connected layers, and was tested on the SDUMLA database and other datasets. Huang et al [41] proposed a model based on VGG-Net-16 called " Deep Vein" method based on VGG-Net-16 using a deep CNN (D-CNN)-based architecture for finger vein recognition, which achieves model simplification by modifying the network structure. Qin et al [42] proposed a deep neural network (DNN) consisting of three convolutional layers, three maximal pooling layers, two fully-connected layers, and a soft-maximal layer, which is capable of predicting the quality and labeling of finger vein images. vein image quality and perform labeling. A finger vein recognition system based on convolutional neural networks was also proposed in literature [43], where the network performance was tested on four publicly available databases, achieving high stability and accuracy on vein images of different qualities.

In addition to the traditional CNN model, there are many variants of the model combining CNNs that show better results. A deep learning model combining CNN model and Long Short-Term Memory (LSTM) model for extracting vein features was proposed in literature [44]. Devkot et al [45] proposed an improved Lightweight Convolutional Neural Network (ILCNN) for finger vein recognition which combines Diverse Branch Block (DBB), Adaptive Polyphase Sampling (APS) and Coordinate Attention Mechanism (CoAM) to improve performance. In addition, with the increased use of Transformer architecture in computer vision, many researchers have started to use Transformer for vein recognition. In the literature [46], a data enhancement strategy using a random sliding window was designed to mitigate the problem of finger pose variation. Meanwhile, a lightweight Transformer-based finger vein feature extraction model was proposed to improve the recognition efficiency. Qin et al [47] proposed an Interactive Vein Transformer (IVT) consisting of three branches, namely spatial attention, channel attention, and convolutional module for extracting vein features.

5. Evaluation Indicators

Finger vein recognition system commonly used evaluation indexes are False Accept Rate (FAR), False Reject Rate (FRR), Equal Error Rate (EER), Accuracy, etc., and ROC (Receiver Operator Characteristic curve) curve visualization algorithm performance.

The following lists the assessment matrices used to evaluate the indicators, as well as the common terms used to define these matrices: TP (True Positive - the number of correctly identified users), TN (True Negative - the number of correctly identified non-users), FP (False Positive - the number of incorrectly identified users) and FN (False Negative - the number of incorrectly identified non-users).

(1) False Accept Rate (FAR): the percentage of users who are not authorized but are mistaken for valid users. the FAR is calculated using the following formula:

$$\text{FAR} = \frac{FP}{FP + TN}$$

(2) False Reject Rate (FRR): the percentage of users who have been authorized but incorrectly rejected as invalid users. the formula for calculating FRR is as follows:

$$\text{FRR} = \frac{FN}{FN + TP}$$

(3) Equal Error Rate EER: EER is the equilibrium point of FAR=FRR in the FAR-FRR curve, the smaller the ERR, the better the performance of the algorithm. The formula for EER

is as follows:

$$\text{ERR} = \text{mean}（\text{FAR}，\ \text{FRR}）$$

(4) Accuracy: The number of correct predictions calculated by the classification model. The formula for calculating the accuracy is as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

(5) The ROC (Receiver Operating Characteristic) curve is a commonly used metric for evaluating the performance of a system's matching algorithm. In the field of finger vein recognition, a commonly used ROC curve is the FAR-FRR curve. This curve demonstrates the relationship between the False Accept Rate (FAR) and the False Reject Rate (FRR) with the change of matching score thresholds, thus reflecting the equilibrium relationship between the FRR and FAR of the recognition algorithm at different thresholds. The schematic diagram of the ROC curve is shown below.

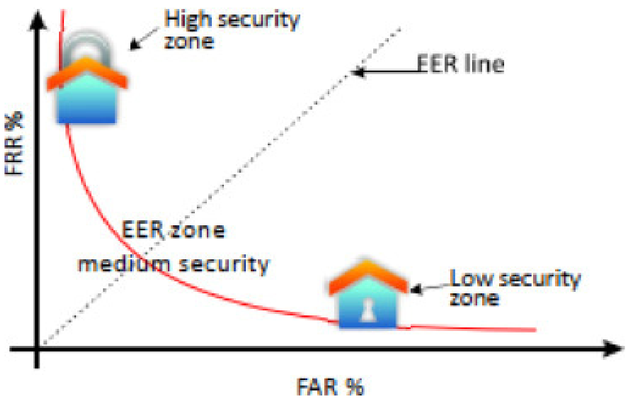

Figure 3. ROC curve

6. Summarizing and Looking Forward

This paper reviews the previous related literature on vein recognition and provides an overview of feature extraction research for finger vein recognition. The relevant techniques and processes of finger vein recognition are introduced, and the commonly used datasets at home and abroad are organized and summarized. Under the framework of deep learning, relevant feature extraction algorithms are discussed in detail, and non-deep learning feature extraction algorithms are categorized into texture features, texture features, and detail point features, and the applications after the introduction of deep learning are highlighted, including models such as CNN, CNN variants, and Transformer. Finally, the evaluation indexes commonly used in the field of finger vein recognition are introduced.

With the continuous development of deep learning, a variety of algorithms and models have emerged in the field of image processing, which provide more options for finger vein recognition and promote the progress of biometrics. However, this development also faces some challenges. For example, low-quality images are still an important limiting factor for finger vein recognition performance. In addition, the limited number of samples in publicly available datasets limits the application of deep learning in finger vein recognition. In addition, there is still relatively little research on the fusion of traditional feature extraction algorithms with deep learning. Although finger vein recognition has shown good performance in research, its application scope is still relatively narrow. In the future, finger vein recognition feature extraction needs higher accuracy and rate. It also needs to increase its applicability in different application scenarios so as to expand its application scope in the market.

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