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Review

A Systematic Review of Finger Vein Recognition Techniques

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Abstract: Biometric identification is the study of physiological and behavioral attributes of an individual to overcome security problems. Finger vein recognition is a biometric technique used to analyze finger vein patterns of persons for proper authentication. This paper presents a detailed review on finger vein recognition algorithms. Such tools include image acquisition, preprocessing, feature extraction and matching methods to extract and analyze object patterns. In addition, we list some novel findings after the critical comparative analysis of the highlighted techniques. The comparative studies indicate that the accuracy of finger vein identification methods is up to the mark.

Keywords: biometrics; finger vein recognition; feature extraction; matching; performance analysis

1. Introduction

The ability to identify individual attributes in the smart recognition field is a global security concern [1]. In recent years, various algorithms have been developed to address the security problem, but there is still room for fast and efficient biometric recognition. Biometric recognition refers to an automatic recognition of individual properties acquired by their anatomic/behavioral characteristics. Several types of biometric techniques have been presented based on these anatomic/behavioral features such as fingerprint, palm print, hand veins, finger veins, palm veins, foot vein, iris, gait, DNA recognition, palates, voice recognition, facial expression, heartbeat, signature, body language, and face shape [2]. These biometric recognition approaches can be divided into two categories: (i) extrinsic biometric features (palm print, iris, fingerprint, face) and (ii) intrinsic biometric features (palm vein, hand vein, and finger vein) [3]. Extrinsic features are more visible and have more adverse factors as compared to the intrinsic features. For instance, the retinal surface is affected by the high intensity of light during extraction of iris features [4]. Similarly, the accuracy of face identification is also distorted due to brightness variance, style of facial, blockage of blood vein and pose [5]. Table 1 present the merits, defects and other characteristics of some typical extrinsic and intrinsic features.

Table 1. Characteristics of typical extrinsic and intrinsic features.

Biometric Technique	Level of Security	Major Advantage	Disadvantage	Cost	Sensor
Face	Normal	Remote capture	Lighting conditions	Low	Non-contact
Voice	Normal	Natural and convenient	Noise	Low	Non-contact
Fingerprint	Good	Widely applied	Skin	Low	Contact
Iris	Excellent	High accuracy	Glasses	High	Non-contact
Finger vein	Excellent	High security level	Disease	Low	Non-contact

In 2002, Kono [6]—a Japanese medical researcher—introduced finger vein recognition techniques. Since then, these techniques have been widely implemented in hundreds of cities in Japan, and other countries worldwide have developed finger vein identification systems [7]. The vein-based authentication system contains biometric pattern models for security and convenience for personal identification. The typical framework of the biometric finger vein recognition (FVR) system is presented in Figure 1. The vein is a part of intrinsic features, and is therefore difficult to duplicate and falsify. Finger veins are frequently captured using near-infrared (NIR) light (700–900 nm) in a trans-illumination manner [8]. Vein-based systems usually utilize various anatomic features like finger vein, hand vein, foot vein or palm vein for personal verification. Finger vein is preferable in that its imaging tool is smallest, and the fact that fingers have a larger number of veins than the palm and hand [5]. In addition, a every finger vein pattern is unique even for identical twins and exists only for live humans [9]. Most importantly, each finger vein pattern does not change during a lifetime [4].

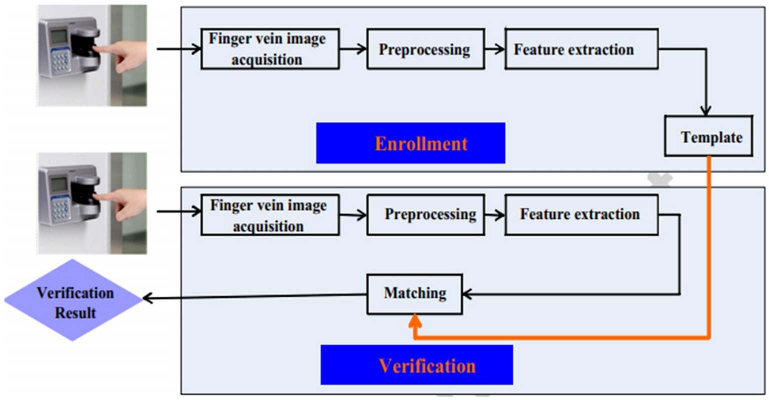

Figure 1. Typical framework for finger vein recognition [10].

It is considered that finger vein recognition is a challenging task because of low image contrast, uneven-illumination and temperature variations. Finger vein identification systems are also vulnerable to spoof attacks [4,8,11,12]; however, accuracy of personal verification is the most serious issue. Therefore, fast and efficient methods are still required for FVR.

The main objective of this study is to analyze the most recent techniques applied in finger vein identification. The rest of the paper is arranged as follows: Section 2 discusses various publicly available material commonly used in the finger vein identification systems. Section 3 highlights in detail existing finger vein recognition techniques, Section 4 provides the objective comparison of the reviewed conventional, machine learning and deep learning approaches and Section 5 discusses the prospects for finger vein systems. The conclusion is presented in Section 6.

2. Materials

There are many open finger vein databases such as SDUMLA-HMT [13], HKPU-FV [14], UTFV [15], MMCBNU_6000 [16], THU-FV [17], FV-USM [18] University developed their finger vein database called (HKPU-FV) [14], which consists of finger vein and low texture images. In 2010, Shandong University released one multimodal trait database SDUMLA-FV [13]. The third database UTFV [15] is presented by University of Twente. In the recent past, two finger vein databases, THU-FV [17] and MMCBU_6000 [16], were published by Tsinghua and Chunbuk Nation University respectively. All these public databases provide more than 100 subjects of finger veins, except UTFV database which provides 60 subjects. FV-USM was the infrared finger vein image dataset which was developed by University Sains Malaysia in 2013 [19]. In 2014, the VERA database was produced by the Idiap Research Institute in Martigny and Haute Ecole Specialisee de Suisse Occidentale in Sion, in Switzerland [20]. Some of the aforementioned databases may be well suited for one specific application and may not suit other applications. Table 2 illustrate the finger vein datasets.

Table 2. Detail of finger vein image datasets.

Database	Acquisition Method	No. of Subjects	No. of Images	No. of Fingers for Each Subject	No. of Images for Each Subject	Image Format	Size of Images
SDUMLA-FV [13]	Light transmission	106	3816	6 (both hands middle, index, ring)	6	bitmap	320 × 240 pxl
THU-FV [17]	Light transmission	220	440	1	1	bitmap	200 × 100 pxl
UTFV [15]	Light transmission	60	1440	6 (both hands middle, ring, index)	4	PNG, 8 Bit Gray Scale	672 × 380 pxl
HKPU-FV [14]	Light transmission	156	6264	3 (left hand middle, ring, index)	12/6 *	bitmap	513 × 256 pxl
MMCBNU_6000 [16]	Light transmission	100	6000	6 (both hands middle, ring, index)	10	bitmap	640 × 480 pxl
FV-USM [18]	Light transmission	123	5904	4 (both index fingers, both middle fingers)	6	bitmap	640 × 480 pxl
VERA [21]	Light transmission	110	440	2 (left index and right index)	2	PNG	665 × 250 pxl

* For the second imaging session, there were only 105 subjects turned up, so each of finger from these subjects has 6 images, but others each has 12 images.

3. Finger Vein Recognition (FVR)

Generally, FVR consists of image acquisition, preprocessing, feature extraction and matching methods. This section presents a detailed discussion on finger vein identification approaches related to the steps mentioned above. For ease of comprehension, the block diagram of the related literature is shown in Figure 2.

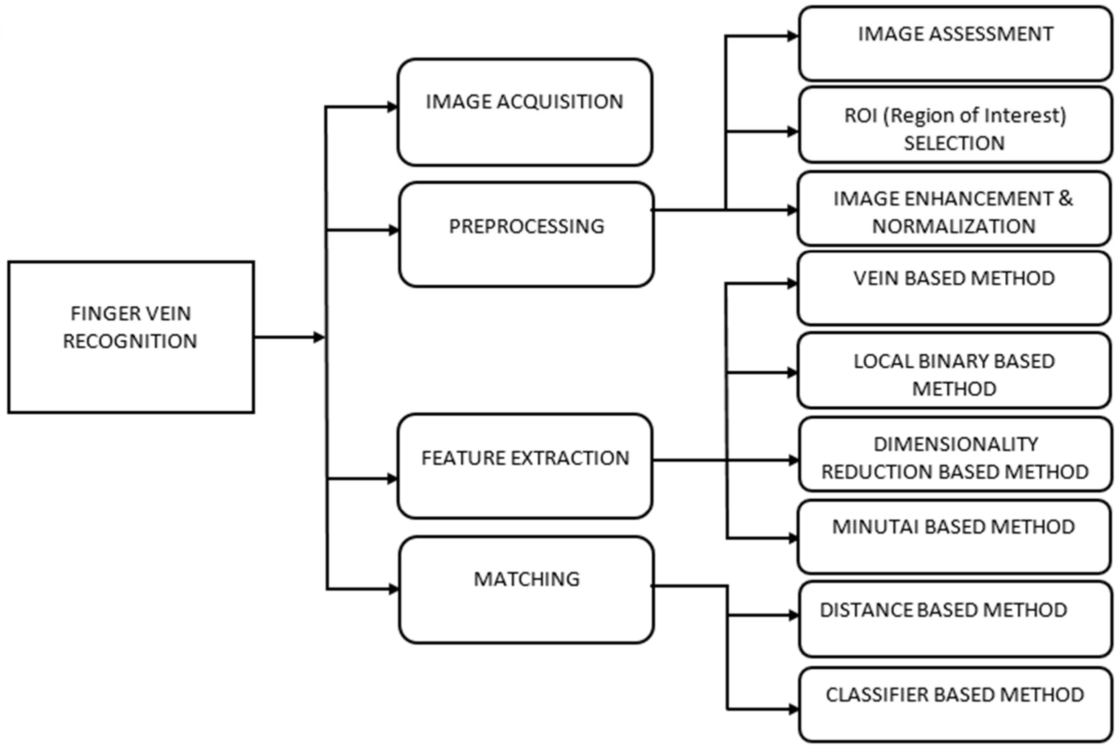

Figure 2. Block diagram of finger vein recognition techniques.

3.1. Image Acquisition

Image acquisition is the first basic step in FVR in which the finger vein image is captured by using NIR (near infra-red) light in the illumination transaction method. The acquisition device consists of an NIR assembly part for placement of the finger, and a charge-coupled device (CCD) preprocessor camera is then used to obtain an image of the finger vein [22,23]. The NIR light can pass through a finger but hemoglobin in the blood can absorb more NIR light than other tissues (such as bones and muscles) [9]. When the vein of a finger absorbs infrared light, the image of the finger vein can be acquired as a dark line. Figure 3 shows how the finger vein scanner works, and Figure 4 presents the finger vein scanner. NIR imaging is secure because it passes through the finger to capture the images [20]. Three methods are mainly used for finger vein image acquisition: light transmission method, light reflection method and two-way radiating method [24,25]. Among these methods, a high contrast image is captured using the transmission method, therefore most of finger vein imaging devices employ the light transmission method [26]. However, for optimization of the image acquisition device, there are always some problems, such as low contrast, translational and rotational variation and noise, which cannot be solved during the image capturing process, hence the next step—image preprocessing—which resolves these problems.

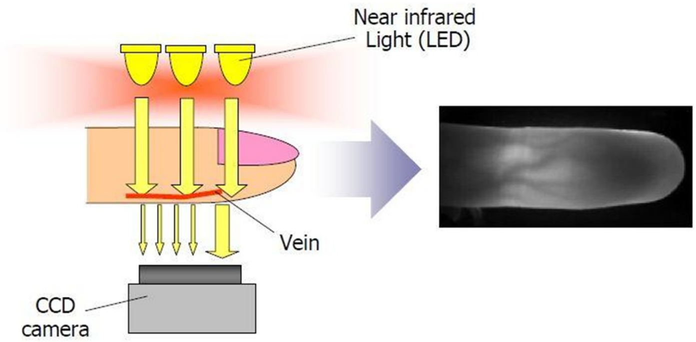

Figure 3. How a finger vein scanner works [27].

Figure 4. A finger vein scanner [28].

3.2. Preprocessing

Before the feature extraction step, the data from the image sensor device should be preprocessed. The objective of image preprocessing is to provide a robust Region of Interest (ROI) image for feature extraction. Good performance of a finger vein image depends on the finger vein image quality [29]. The finger vein image usually consists of noise, shades and low contrast. This is because of light fluctuation, a rotational and translational variation of the finger and also the performance of the capturing device. The preprocessing step is applied to relieve these problems. The three common preprocessing stages are (i) image quality assessment, (ii) region of interest (ROI) extraction, and (iii) normalization and enhancement.

3.2.1. Image Quality Assessment

Image assessment acts as the first sub-step of preprocessing. During this stage, quality of acquired image samples is examined to estimate the suitability for further processing. If the raw data of the required sample is not satisfactory then there are two options. One is to acquire the data again from the user and another option is to generate an exception which alerts the administrator to implement other suitable procedures [1]. Recently, several quality assessment schemes have been proposed to advance the performance of finger vein identification. To evaluate the quality of images, HSNR (signal to noise ratio based on the human visual system) evaluation index is proposed to simulate the properties of the human visual system [30]. Based on Radon transform, Qin et al. [31] proposed a new image quality assessment algorithm to enhance the performance of finger vein system, where the quality score was predicted from the curvature of corresponding Radon Space. A quality metric finger vein quality evaluation based on a hierarchical feature of the vein was presented, which was shown with better matching performance [32]. In order to reduce the authentication error rate, Nguyen et al. [33] measured the finger vein image quality by detecting number of vein points in the image. Yang et al. [13] estimated the quality of finger vein by combining image contrast, information capacity, and gradient, based on SVM, and filtered out the low-quality images. Peng et al. [34] used a triangular norm approach for performance improvement using attributes illustrated in Reference [35]. Zhou et al. [36] associated three local and two global level features based on SVR to determine the quality of the finger vein image, but the scores of training data need to be annotated manually in advance. To predict vein quality and also to reduce recognition error rate, Qin et al. [37] proposed a Deep Neural Network (DNN) for representation learning from the binary image, although it does not rely upon mean, energy and contrast features of the finger vein image; however it is complex in its application and requires more training data to train the deep neural network. Extracted stable and prominent features from a finger vein image can obviously upgrade the quality assessment of a vein image. Huang et al. [38] proposed a method based on information fusion of structure and texture that takes both the recognition strategy and feature extraction into account, which in turn enhances the recognition performance.

3.2.2. ROI Extraction

The second most important stage is ROI extraction. In finger vein images, there are undesirable regions (image background) and the valuable area (finger area) in the image. The valuable area is called ROI, and ROI extraction is the processing to localize and extract the finger area from the captured image and delete the image background [39]. Different approaches are used to segment the finger region from the captured image such as region-based method, thresholding, template method, and edge-based method [40]. Brindha et al. [39] extracted the ROI from the original image by using two morphological operations. Wang et al. [29] extracted the ROI from finger vein image by cutting the maximum inscribed rectangle of the finger vein image, and the original image was binarized using a selected threshold [29]. In Reference [41] the ROI was obtained from the original image by using Sobel operator. In References [42,43], the finger region was segmented by using sub window scheme.

Multiple image acquisitions are used in finger vein recognition system. Hence, different imaging devices using the ROI extraction method face challenges, such as gray level, image size variation, and background noise appearances in finger vein images, which affect the performance of the ROI extraction method. In order to address the sensor impact on finger vein images in a finger vein recognition system, Yang et al. [44] proposed a cross-sensor super-pixel-based ROI extraction method. In this work, the super-pixel segmentation method was conducted on the finger vein image and finger vein boundaries were tracked from the segmented image. One other issue in former ROI extraction approaches is that some important information is lost in cropped ROI. In order to solve the information loss problem, Wang [45] proposed a new ROI extraction method for finger vein images with fewer information losses by using modified sliding window method and outer rectangle method. The parameter used in the algorithm is also very important and they will influence the performance of the finger vein recognition systems. Zhang et al. [46] presented a parameter adjustment method in the preprocessing stage to select the filter in noise reduction and threshold in edge detection.

3.2.3. Normalization and Enhancement

Normalization is a process that normalizes the range of pixel intensity values in an image. After extracting the ROI, the finger vein image is normalized in order to accommodate geometric changes and to get consistent image size [47]. In addition, normalization in the preprocessing stage eliminates the diverse variation problems of the image [48].

Image enhancement is another key stage in the preprocessing phase. The basic goal of image enhancement is to advance the interpretable or knowledge of information in images for human viewers or to get the standard enhanced image from the unclear acquired image [29]. In finger vein recognition, image enhancement is required to get better matching performance. Enhancement of a finger vein image mainly focuses on contrast enhancement and noise removal. There are many enhancement techniques used to improve the image quality. Contrast limited adaptive histogram equalization (CLAHE) is one of the common enhancement approaches in finger vein recognition [48,49]. Additionally, some other enhancement algorithms have also presented good results [41,49–51]. Yang et al. [52] have employed Circular Gabor Filter (CGF) approach to improve finger vein images. Histogram equalization technique was employed by Liu and Song to enhance the gray level contrast in finger vein images [24]. Gaussian matching technique was proposed by Wang [29] to enhance finger vein image. Adaptive histogram equalization enhancement was implemented by Reference [10] to detect edges of vein significantly and enhanced the global contrast of input image. In References [5,25,31,48,53], Gabor filter technique was used to enhance finger vein images and remove noise from images. Zhang et al. applied CGF for image enhancement of finger vein [54]. Xie et al. proposed a normalization method for finger vein image enhancement using a guided filter-based single scale retinex (GFSSR) [48]. Moreover, some enhancement techniques were combined to enhance the finger vein image and reduce the noise. Pflug et al. employed adaptive non-local mean and non-linear diffusion method to enhance image and reduce noise [55]. Kayode et al. [19] combined Gabor filter and canny edge detector to enhance the finger vein image and remove noise.

3.3. Feature Extraction

Feature extraction represents one of the most crucial and major steps of FVR. During this step, the quantifiable property of the basic biometric trait is created, called the template, which is helpful for identifying the individual. For example, in a fingerprint biometric system [1], position and orientation of minutiae points in a fingerprint image is the key feature which needs to be different from another person. An efficient feature extraction technique is a step which enhances the precision of finger vein recognition. Numerous feature extraction techniques have been presented, and this paper discusses four groups of feature extraction methods, i.e., vein-based method, local binary-based method, dimensionality-based method and minutiae-based method.

3.3.1. Vein-Based Method

Gabor filtering is an impressive feature extraction technique in snatching texture characteristics from an image and is therefore employed in various pattern recognition applications i.e., finger print identification, hand vein identification and iris identification [47]. Gabor filtering is also valuable for finger vein extraction due to its directional acuteness, detecting oriented feature capability and fine tuning to a specific frequency. The General form of Gabor filtering can be represented as:

$$(x, y, f, \varphi) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[-\frac{1}{2}\left(\frac{x_{\varphi^2}}{\sigma_{x^2}} + \frac{y_{\varphi^2}}{\sigma_{y^2}}\right)\right] \cos(2\pi f x_\varphi) \tag{1}$$

Here, x, y represent the image x_φ and y_φ where φ represent the orientation and f show the frequency of a sinusoidal plane.

There are some Gabor filter-based FVR techniques. Kumar et al. [14] used multi-orientation for finger vein pattern extraction. Yang et al. proposed multi-channel Gabor filter and a bank of even-symmetric Gabor filter with eight orientations to get information about vein vessel [56,57]. In References [50,58], 2D Gabor filter was applied to extract direction texture and phase feature from finger vein image, and good recognition results were obtained. Xie et al. proposed guided Gabor filter method which obtained vein pattern without involving any segmentation process [59]. Multi-orientation Gabor filter was used for FVR in Reference [60]. Sapkale et al. [22], presented fractal dimension, lacunae extraction and Gabor filter algorithm for texture and edge feature extraction. In Reference [61], Gabor filter was applied to choose the characteristics texture extraction of vein images that capture the local orientation and the information of the frequencies of the vein network.

Repeated line tracking is also a vein pattern extraction technique that tracks vein patterns a particular number of times. Line tracking operation recognizes the local dark line (finger vein pattern) and executes pixel by pixel along black lines. If a black line is not detected, the new tracking point starts randomly at another position. In such a way, repeated line tracking operation tracks all the black lines in the image. Finally, a vein pattern of the finger is obtained. The repeated line tracking method has been proposed by Miura et al. [9] to obtain the finger vein pattern from an ambiguous image. However, the algorithm proposed in Reference [9] contains some drawbacks such as low robustness and complexity. Robustness and efficiency of the repeated line tracking algorithm relate to parameter p_{n0} described in Reference [62], p_{n0} is the point used to start the line tracking, to select the useful point for line tracking, and revise the parameter for finger vein image according to the width of vein for different images. To evaluate the locus space of finger vein, Liu et al. [62] presented a modified repeated line tracking (MRLT) on revised parameters which proved to be effective. However, such a proposed method lacks metric quantitative evaluation for image segmentation. To get a good result, the repeated line tracking method was combined with Gabor filter to extract features [63,64]. Repeated line tracking and Gabor filter methods were used to attain features from finger vein image and obtained a better result as compared to the separate result of both these techniques. Nonetheless, these algorithms are time consuming and complex. In multimodal biometric recognition system, repeated line tracking technique was also implemented to obtain feature extraction. In Reference [65], the repeated line tracking approach with feature-level fusion using fractional firefly (FFF) optimization was employed to extract features from finger knuckle and finger vein images.

Maximum curvature method is another excellent method to extract finger vein patterns. It utilizes the fact that vein patterns appear like a valley with high curvature in the cross-sectional profile. The curvature of finger vein is computed and only the centerlines of veins are saved. The centerlines are detected by searching for positions which have the locally maximal curvatures of a cross-sectional profile. Miura et al. proposed to use local maximum curvatures in cross-sectional profiles to extract vein pattern from the images with various widths and brightnesses [66].

The mathematical form of curvature, $k(z)$ as follows:

$$K(z) \ = \ \frac{d^2Pf(z)/dz^2}{\{1+(dPf(z)/dz)^2\}^{\frac{3}{2}}} \tag{2}$$

$Pf(z)$ represents a cross-sectional profile acquired from an image at any position and direction. The profile of $k(z)$ is classified into convex and concave. The local maximum of $k(z)$ is calculated at each concave area indicating center points of the veins. Score is calculated for each center position and all four direction are analyzed, and finally the image is obtained by selecting the maximum curvature points.

Tagkalakis et al. [67] also use maximum curvature point to obtain features from a captured finger vein image. However, the vein pattern produced in References [66,67] are uneven due to the fact that maximum curvature is estimated in only four directions (two diagonal, vertical and horizontal). Song et al. [68] proposed a mean curvature method which used geometrical properties of the intensity field to obtain vein pattern from unclear vein images in all direction. However, during the matching stage of algorithm, matched pixel ratio method was employed for binarized patterns that required whole finger vein pattern, which can expose the system to attacks on personal information. In finger vein verification, extracting a finger vein pattern from the infrared image is difficult. Choi et al. [69] proposed a feature extraction algorithm employing gradient normalization and principal curvature methods and obtained better performance than References [66,68]. In order to systematically differentiate between the individual finger vein samples, Yahya et al. [70] proposed maximum curvature and directional based features (MCDF) and discretization method to improve identification performance.

3.3.2. Local Binary-Based (LBP) Method

Local Binary Pattern is a local feature descriptor used to represent the finger vein local feature information. The LBP code may be described as an ordered set of binary values determined by comparing the gray value of a central pixel with its neighboring pixels. In Reference [71], the ordered set of binary values can be represented in a decimal form as shown below:

$$\mathrm{LBP}(x_c,\, y_c) \;=\; \sum_{n=0}^{7} S(i_n - i_c)2^n \tag{3}$$

where, i_n , i_c denotes the gray value of the central pixel $(x_c,\, y_c)$ and the gray values of the eight surrounding pixels, respectively.

Several approaches have been developed to extract a local feature of finger vein images. For example, Lee [71–73] used the locally based feature extraction scheme to remove the problem of irregular shading and the highly saturated area in the image, which greatly reduced the processing time and improved recognition. Rosdi et al. [74] introduced the local line binary pattern (LLBP) approach to extract features and achieved excellent results over previous methods [71,75]. LLPB method is a revised version of LBP (Local binary pattern), which extracts feature in both horizontal and vertical direction. Finger vein images have rich orientation information, and the line patterns obtained only from vertical and horizontal orientation may not have enough discrimination information for matching. To further enhance the discriminatory information, Yu et al. proposed polydirectional line pattern (PLLBP) [76] and generalized local line binary pattern (GLLBP) [77] methods, which extract line pattern at an arbitrary orientation. However, LLBP and PLLBP have low discriminatory information and a jumble of redundant information. Hence, Liu et al. advance a novel customized local line binary pattern (CLLBP) [78] approach to eliminate the information reduction, increase discriminatory information of local features and reduce the matching time of recognition system. Extraction of powerful feature greatly improves the performance of finger vein identification. For extracting powerful features, Xi et al. [79] introduced Pyramid histograms of gray, textures and orientation gradient (PFS-PHGTOG) technique by discriminating subset features from PHGTOG to reduce the verification error rate (EER). Translation and rotational variation of finger cause change of finger vein image which degrades performance of the FVR system. To deal with this difficulty, Wang [29] and Yang [80] proposed translational and rotational invariant feature extraction approach for FVR. A remarkable result is obtained in Reference [81]. A Multi-scale Sobel Angle Local Binary Pattern (MSALBP) novel feature extraction approach is presented for personal verification using finger texture pattern of five fingers. Xi [79] proposed feature extraction technique which outperforms the existing techniques. References [10,82] are finger vein identification technique which also used the local binary feature.

3.3.3. Dimensionality Reduction-Based Method

In dimensionality reduction-based method, finger vein image is transformed into a low dimensional space by dimension reduction, in which the discriminating information is kept and noises are discarded. Mostly feature extraction technique in this kind of method requires a training process to learn the transformation matrix, and a classifier is employed in the matching process. During image acquisition, the residual information is also obtained such as pose variation, shades of finger muscle and bone around the vein, which may affect the accuracy of the identification system. In order to remove these problems, Liu et al. [83] presented Orthogonal Neighborhood Preserving Projection (ONPP) manifold learning method for the first time to handle the pose variation problem in finger vein image and obtained 97.8% recognition rate. Due to the acquisition devices, torsion, translational and other deformation in the local area, the traditional approach achieved very low identification precision. Guan et al. [84] proposed a feature extraction method named Bi-directional Weighted Modular B2DPCA (BWMB2DPCA), which obtained a better result than the traditional techniques. The BWMB2DPCA method shortened the size of image feature matrix, which also decreased the recognition accuracy as different feature vectors effect identification efficiency. Additionally, the experimental result of BWMB2DPCA was not conclusive because the eigenvectors of column are ignored.

Therefore, method B2DPCA (BWMB2DPCA) in Reference [84] was proposed to the feature matrix Z = ^{T} as follows

$$\left\{ \begin{array}{c} Z = B_W{}^T A X_w \\ Z = (B \times diag(\lambda \times 1, \lambda \times 2, \lambda \times 3, \ldots, \lambda \times d))^T A\ (X \times diag\ (\lambda \times 1, \lambda \times 2, \lambda \times 3, \ldots, \lambda \times d)) \end{array} \right\} \tag{4}$$

where w shows the weighted factor, λ represent the separate values of column or row directions. The eigenvalue normalized formula is as follows

$$\lambda_i' = \frac{\lambda_i - \lambda_{min}}{\lambda_{max} - \lambda_{min}}\ i\ =\ 1,\ 2,\ \ldots,\ t, \ldots d \tag{5}$$

where λ_{max} and λ_{min} represent the maximum and minimum eigenvalue of the column and row direction.

However, B2DPCA in Reference [84] cannot extract the best discriminative features. Wu in [85,86] presented the PCA method with different machine learning classifier which extracted the most distinguished feature. Furthermore, the method in References [85,86] greatly reduces the computational cost, removes noise and enhances identification accuracy. Yang et al. [87] proposed (2D)^2 PCA method for feature extraction, which is more effective than the method in Reference [86] and B2DPCA. The dimension of the feature is considered very important; the system consumes more time if the dimension of the feature vector is high. However, if the dimension of the feature vector is low, the system might ignore some useful information. To resolve this issue, Haijian et al. [88] used optimal dimensional kernel feature reduction technique (KPCA) to keep the balance between accuracy and speed. In addition, due to some factors such as horizontal displacement, lights, and temperature, the vein image has some degree of nonlinear distributive properties. You et al. [89] employed B2DPCA and KMMC algorithm both to extract the nonlinear feature and outperform the algorithms in References [90,91].

3.3.4. Minutiae Point-Based Method

The point where the ridge lines end or fork is defined as a minutiae point. Minutiae points refer to the terminal point and bifurcation point of blood vessels, and are one kind of important feature of a finger vein image. Minutiae points are used in finger vein recognition, and such methods are already used in fingerprint recognition technique [92–95]. Mantrao et al. [96] presented a minutiae-based point feature extraction and matching approach which greatly improved the performance of the identification system. Aziz et al. [97] extracted minutiae points of finger vein by combining two methods, namely maximum curvature points and fingerprint application method. Prabhakar et al. [98] used endpoints and bifurcation points to eliminate false minutiae and make the identification more precise.

3.4. Matching

The matching technique is the last step of recognition to decide whether an input image is genuine or an imposter for one enrolled image, in which a matching score is generated. A matching score measures the likeness between the enrolled template and the input image. Two types of matching techniques are used, i.e., distance-based matching and classifier-based matching. Conventional finger vein identification approach uses the distance-based matching technique, while by machine learning techniques finger vein recognition can employ classifier-based matching technique. Classifier-based matching techniques were employed by References [29,49,61,65,85,86,99,100] for finger vein recognition systems.

Table 3 summarizes the conventional finger vein recognition approaches, and Table 4 shows the machine learning algorithms-based FVR methods. The image preprocessing methods, feature extraction methods and matching methods are all involved.

Table 3. Traditional (conventional) method of finger vein recognition.

Method of Preprocessing	Method of Feature Extraction	Method of Matching	References
Region of interest (ROI) extraction Filters combination to remove salt-and-pepper and Gaussian noise Image segmentation and denoising Extraction of vein and normalization method	Two direction weighted (2D)2LDA	-	[101]
ROI Detection image enhancement size normalization	ONPP-Manifold learning	Manifold distance method for recogntion	[83]
Segmentation of vein ROI Interphalangeal joint prior	Steerable filter	Nearest neighbor (NN) method	[52]
-	BWMB2DPCA	Nearest neighbor (NN) method	[84]
Modified Gaussian high-pass filter	Local line binary pattern	Hamming distance	[74]
Elimination of background Removal of noise Enhancement of finger vein image Brightness Normalization Size	Dynamic thresholding edian filter Morphological operation Vein location and direction coding	Template matching	[102]
Gaussian high-pass filter	Binarization local binary pattern	Hamming distance	[73]
Image gray processing ROI extraction normalization	Directional Code	Matching	[103]
Image gray processing ROI extraction Normalization (size and gray) method	Personalized best bit map (PBBM)	Matching	[104]
Histogram equalization Bucolic interpolation	Fractal dimension Wavelet transform	Wavelet transformation Energy feature	[105]
ROI extraction CLAHE	Linear Kernel Entropy Component analysis (KECA)	Euclidian distance	[106]
Anisotropic diffusion method Non-scatter transmission maps Gabor wavelet	Directional filtering method	Phase only correlation strategy	[107]
ROI extraction Enhancement Normalization size	Local line binary pattern	PWM-LLBP	[82]
Edge detection ROI Extraction Smoothing filter	Personalized best bit map (PBBM)	Cross-correlation matching	[108]

Table 3. *Cont.*

Method of Preprocessing	Method of Feature Extraction	Method of Matching	References
ROI Extraction	(HCGR) Histogram of competitive Gabor response	Matching	[109]
ROI Extraction Brightness normalization Minimization of the Mumford–Shah Model	Morphological dilation docal entropy thresholding Morphological filtering	Template matching	[110]
Region of interest extraction Multiscale matched filtering Line tracking	Variational approach	Sum of square differences	[111]
ROI Extraction Image enhancement	Fractal dimension Lacunae Gabor filter	Difference compared with threshold value	[46]
Denoising Image enhancement	Local binary pattern	Hamming distance	[20]
ROI extraction Binarization Thinning	MCDF		[70]
ROI Localization Image enhancement	Uniform optimal uniform rotation invariant LBP descriptor	Histogram intersection method	[112]
Binarized ROI Thinned Gabor filter	Minutiae-based extraction	Euclidian distance	[24]
Image denoising ROI localization Image enhancements	LLBP PLLBP	Histogram intersection	[76]
ROI extractions	GLLPB	Soft power metric	[77]
Size normalization ROI Extraction Gray normalization	CLLBP	Matching score	[78]

Table 4. Traditional Machine learning approaches for finger vein recognition.

Preprocessing Method	Feature Extraction Method	Matching Method	Reference
ROI extraction, image resize	PCA, DCA	SVM and ANFIS	[86]
ROI extraction, image resize	PCA	ANFIS (neuro-fuzzy system)	[85]
ROI extraction, median filter, histogram equalization	Morphological operation, maximum curvature points	MLP	[113]
Gaussian matched filter	LBPV	Global matching, SVM	[29]
Gabor filtering	Global thresholding, Gabor filter	SVM	[61]
ROI extraction, image resize	Convolutional neural network	Convolutional neural network	[100]
ROI extraction, normalization	Image contrast, gradient in spatial domain, Gabor feature, information capacity and entropy	SVR	[36]
Normalization, filtering, resizing	Grid-based location, feature-level fusion by FFF, optimization	K-SVM	[65]

4. Performance Analysis

We can see the main steps of the finger vein system are stable, but they have different types of method. Performance evaluation is an important way to recognize whether these algorithms are good or bad. In this section, first the benchmarks in the evaluation of FVR performance are listed, and then the performance of various FVR techniques was inputted to a non-matching template in the dataset [114]. Receiver Operating Characteristic curve (ROC) intuitively represents the balance between False Accept Rate (FAR) and False Reject Rate (FRR). The threshold is used to make a decision on the matching algorithm. If the threshold is reduced, FAR or false match rate (FMR) increased and FRR or False Non-Match Rate (FNMR) decreased. Similarly, the higher threshold increases the FRR or FNMR and decreases the FAR or FMR. Equal error rate (EER) value can be simply attained from Receiver Operating Curve (ROC). The lower the EER, the better the system works. Fail to enroll (FTE) rate indicates the proportion of users that cannot be successfully enrolled in a finger vein recognition system, and Fail to acquire (FTA) or Fail to capture (FTC) is the error in which the finger vein biometric sensor cannot capture the sample [1].

4.1. Conventional Finger Vein Recognition Method

Conventional finger vein approaches were less robust to noise and misalignment than machine learning approaches; therefore, image preprocessing methods were usually applied ahead of feature extraction and matching to overcome the above-mentioned problems. Numerous conventional finger vein identification methods have been developed, but some methods [73,76,78,83] have achieved remarkable development. In 2010, Lie et al. [83] proposed a finger vein verification approach, and obtained accuracy of 97.8% for identification. In term of accuracy, polydirectional local line binary pattern algorithm attained 99.21% accuracy on a dataset of 1902 images [76]. Moreover, in terms of equal error rate, conventional finger vein technique also achieved some tremendous achievements. The method proposed in References [77,78] brings about very low equal error rate of 0.61 and 0.055 on 100 and 156 subject's databases respectively. Most of the conventional finger vein recognition techniques show remarkable performance in terms of accuracy and equal error rate; however the total computational cost of the conventional finger vein algorithm is much too high [73,74,77]. Table 5 demonstrates the performance of typical conventional FVR techniques in aspect of accuracy, EER, FAR, FRR, Correct Classification Rate (CCR).

4.2. Traditional Machine Learning Finger Vein Recognition Methods

Some machine learning techniques (e.g., SVM, neural network and fuzzy logic) have been used in the feature extraction and matching stage of biometrics. These kinds of techniques have also proved to be efficient for feature extraction, matching and enhancing the performance of the FVR method. In most FVR techniques, machine learning classifier-based methods were employed during the matching stage of FVR. However, conventional finger vein approaches employ distance-based methods during the matching stage. Accuracy rate of almost all the proposed machine learning finger vein algorithms is close to 100% [61,85,86,105,115]. Table 6 lists the existing literature on traditional machine learning techniques-related finger vein recognition.

Table 5. Performance of some conventional finger vein recognition technique.

Method	Total Images	Subject	Resolution of Image	Image Format	Performance Measure	References
ONPP-Manifold learning	11,480	164	Not reported	Not reported	EER = 0.8	[83]
BWMB2DPCA	660	Not Reported	Not reported	Not reported	Accuracy = 97.7%	[84]
Steerable filter	1000	100	70 × 170 pixels	Not reported	CCR = 98.8%, FAR = 1.32	[52]
Two directional weighted $(2D)^2$LDA	660	Not Reported	80 × 200 pixels	Not reported	Accuracy = 94.69%	[101]
Binarization Local binary pattern Local derivative pattern	2400	30	640 × 480 pixels	Not reported	Binarization EER = 0.38, Processing Time = 30.6 ms LBP EER = 0.21, 44.7 ms LDP EER = 0.13, 112.5 ms	[73]
Location and direction Coding (LDC)	440	220	90 × 40 pixels	Not reported	EER = 0.44	[113]
LLBP	2040	51	192 × 64 pixels	Not reported	EER = 1.78, Processing Time = 37.5 ms	[74]
Linear kernal entropy Component analysis (KECA)	2040	204	Not reported	Not reported	Accuracy = 98%	[106]
Personalized best bit map (PBBM)	1484	106	96 × 64 pixels	Not reported	EER = 0.0038	[104]
Fractional dimension wavelet transform	6000	100	Not reported	Not reported	EER = 0.07	[105]
Local directional code	4080	34	96 × 64 pixels	24-bit color image	LDC-00 = 0.0116 LDC-45 = 0.0102	[103]
Directional filtering method	9000	100	100 × 180 pixels	8-bit gray image	EER = 0.0462	[116]
Personal weight maps	1360	34	96 × 64 pixels	Not reported	EER = 0.0056	[82]
Identification based on pattern created by finger vein	3600	100	320 × 240 pixels	BMP	EER = 27.56, GAR = 100, FAR = 0	[108]
Histogram of competitive Gabor responses (HCGR)	6000	100	64 × 128 pixels	BMP	EER = 0.671	[109]
PLLBP	1902	Not Reported	48 × 128 pixels	Not reported	Accuracy = 99.21%	[76]
GLLBP	6000	100	64 × 128 pixels	BMP	EER = 0.61, and Processing Time = 392.1 ms	[77]
Variational approach	2520	105	Not reported	Not reported	EER = 4.47	[111]
Maximum curvature	-	200	Not reported	Not reported	FAR = 0, FRR = 1.00	[67]
Spectral minutiae representation (SMR)	5000	125	Not reported	Not reported	EER = 20	[50]
Radom forest regression method on efficient local binary pattern	6000	100	640 × 480 pixels	Not reported	EER = 0.35, CCR = 99.65%	[99]
Super-pixel context feature (SPCF)	PolyU = 1872 SDUMLA = 636	PolyU = 156 SDUMLA = 106	96 × 64 pixels	BMP	PolyU EER = 0.0075 SDUMLA EER = 0.0697	[117]
Curvature in Radon space	PolyU = 2520 NTU = 680	PolyU = 105 NTU = 85	186 × 71 pixels	Not reported	PolyU EER = 0.48 NTU EER = 0.69	[3]
Scale-invariant feature transform	2000	100	460 × 680 pixels	Not reported	EER = 1.086	[118]
CLLBP	1872	156	96 × 64 pixels	Not reported	EER = 0.055	[78]

Table 6. Finger vein recognition performance using traditional machine learning techniques.

Machine Learning Approach	Total Number of Images	Subjects	Resolution of Image	Image Format	Performance Measure	Reference
SVM	100	10	20 × 20 pixels	Not reported	Accuracy = 98.00% Processing time = 0.15 s	[86]
ANFIS (neuro-fuzzy system)	100	10	130 × 130 pixels	Not reported	Accuracy = 99.00% Processing time = 45 s	[85]
SVM	Not reported	Not reported	Not reported	Not reported	Training data = 95.00% Test data = 93.00%	[113]
SVM	800	10	Not reported	Not reported	CR of Index = 90.00% CR of Ring = 96.00% CR of Middle = 90.0% CR of Little = 79.00% Index EER = 5.6 Ring EER = 6.5 Middle EER = 8.5 Little EER = 11.9	[29]
SVM	PKU(V2) = 200 PKU(V4) = 160	PKU(V2) = 20 PKU(V4) = 20	Not reported	Not reported	PKU(V2) Accuracy = 98.75% PKU(V4) Accuracy = 95%	[61]
SVR	1872	105	Not reported	BMP	EER = 4.88	[36]
Multi-SVM with FFF	1000	100	320 × 240 pixels	BMP	Accuracy = 96.00% EER = 0.35, FAR = 5, FRR = 5 Processing time = 5.1 s	[65]
Weighted K-nearest centroid neighbor (WKNCN)	2040	204	Not reported	Not reported	Accuracy = 99.7%	[119]
Multi-SVM	612	17	320 × 240 pixels	BMP	EER = 0.52 Accuracy = 94%	[51]
SVM	FV-SDU = 3816 FVUSM = 2952	SDU = 106 USM = 123	SDU = 320 × 240 pixels USM = 100 × 300 pixels	BMP	FV-SDU EER = 0.0359 FV-USM EER = 0.0038	[120]
Feature component-based extreme learning machines (FC-ELP)	1000	100	Not reported	BMP	Correct classification rate CCR = 99.53% Computational time = 0.87 ms	[115]

4.3. Finger Vein Recognition Using Deep Learning Methods

Deep Learning is a form of machine learning which include multiple layers of learning algorithms. This empowers the deep learning method to learn hierarchical representation/feature from data. Therefore, deep learning has replaced the conventional feature extraction approach in various domains involving computer vision, speech and natural language processing. Due to its strong capability with feature representation, researchers have brought deep learning in to the biometric field. In recent studies, several deep learning models are built on various datasets. However, deep learning has also been successfully applied to the field of FVR. Razdi et al. [100] used the deep learning approach for the first time in the field of FVR and accuracy of 100% was obtained on 50 subject datasets. Inspired by the recent advancement of deep learning algorithms in various research domains, Qin et al. [121] proposed a deep learning model for finger vein verification and achieved error rates of 2.70 and 1.42 on two different databases, respectively. Experimental results of Reference [121] outperform some traditional conventional finger vein recognition approaches. Moreover, Qin et al. [122] have successfully applied a deep learning algorithm to assess the quality of finger vein image and have achieved higher identification accuracy with respect to current traditional state-of-the-art image quality assessment. In Reference [123], a deep convolutional neural network (DCNN) with hard mining finger verification method was proposed which achieved better performance than commercial finger vein verification methods. This method [123] also accelerates the whole training process. The large template size requires a huge amount of storage space. Convolutional neural network (CNN) and supervised discrete hashing finger vein identification method [124] was proposed to overcome this problem, which reduce the template size by up to 250 bytes (2000 bits) and also increases the matching speed. Traditional finger vein identification methods are exposed to hackers because the template used by the system is in the form of bare data. Lie et al. [125] proposed a secure efficient and revocable finger vein template using deep learning and random projection, namely FVR-DLRP. Furthermore, most of the conventional finger vein recognition techniques have a misalignment and shading problem. In addition, conventional approaches require complex and complicated preprocessing and feature extraction, steps which need much more processing time and effort. To alleviate these problems, Hyung et al. [126] proposed a robust deep CNN model and an error rate of 0.396 was attained on a good quality database. Moreover, Gesi et al. [127] applied a convolutional neural network (CNN) finger vein recognition method and achieved almost 100% accuracy, obtaining a very low error rate of 0.21. Due to relatively small databases of finger vein, the training requirement to train deep neural network is a challenge. To address this problem, Fang et al. [128] proposed a lightweight deep learning framework, which resolved the lack of training data issue through the use of a similarity measure network. Table 7 demonstrates the performance analysis of some recent deep learning approaches in finger vein recognition.

Table 7. Finger vein recognition performance using deep learning methods.

Method	Total Number of Images	Subject	Resolution of Image	Image Format	Performance Measure	Reference
Fully convolutional network (FCN)	HKPU = 2520 USM = 5904	HKPU = 105 USM = 123	39 × 146 pixels 50 × 150 pixels	BMP	HKPU EER = 2.70 USM EER = 1.42	[121]
Patch-DNN+P-SVM	Database A = 5904 Database B = 2520	Not reported	640 × 480 pixels 256 × 513 pixels	BMP	High- and low-quality image accuracy on Database A = 71.01%, 73.57% High- and low-quality image accuracy on Database B = 87.08%,86.36%	[122]
Normalization +DCNN-HM	DS1 = 5000	Not reported	384 × 512 pixels	BMP	DS1 EER = 0.42 Total execution time = 19.27 ms	[123]
CNN with SDH	6264	156	Not reported	Not reported	EER = 0.0977 Reduced template Size = 250 bytes	[124]
CNN	4800	64	376 × 328 pixels	Not reported	Accuracys= 99.4% EER = 0.21	[127]
CNN	500	50	55 × 67 pixels	Not reported	Accuracy = 100.00%, total processing time = 0.15 s	[100]
DNN+P-SVM	Database A = 2520 Database B = 5904	Database A = 105 Database B = 123	50 × 240 pixels 80 × 240 pixels	BMP	EER of high- and low-quality image on Database A = 88.99% and 88.18% EER of high- and low-quality image on Database B = 74.98% and 70.07%	[37]
CNN (Deep learning)	Good-Quality Database = 1200	20	Not reported	BMP	On Good-Quality Database EER = 0.396	[126]
Two channel network learning	MMCBNU_6000 = 6000 SDUMLA = 3816	100 106	640 × 480 pixels 64 × 128 pixels	BMP	EER = 0.10 EER = 0.47	[128]

4.4. Spoofing Attack (Presentation Attack) in Finger Vein Recognition

Biometric systems are vulnerable to different kinds of attacks that may be broadly classified into two types [129]: (1) Direct attack or spoofing or presentation attack: Biometric materials are presented directly to device (sensor) in this attack. (2) Indirect attack: Part of biometric system is attacked through malware or virus. In biometric systems, the direct attack or presentation attack is of high interest because of the security evaluation in biometric systems. Finger vein recognition previously had a good spoofing resistance as compared to other biometric modalities, but recent literature has shown that FVR devices are vulnerable to spoof attack [129,130]. In 2007, Matsumoto deceive a system using a synthetic artifact, which was the first attempt to spoof a finger vein image to the best of our knowledge [12]. If spoofing of fixed finger vein (using a printed material with registered finger vein) are applied to identify the finger vein database, then the success rate to mislead FVR system is above 80% (FAR $\geq$ 80%) [25]. Nowadays, study on finger vein identification is the most popular technique. Several traditional handcrafted, machine learning algorithms are proposed to detect the presentation attack in finger vein image [12,129,131]. In 2013, a textured based conventional presentation attack detection (PAD) method was proposed using Fourier Spectral Energy Ratio and Discrete Wavelet Transform (FSER-DWT) [132]. However, the result was not satisfactory even on a small database of 33 subjects. In the recent past, five traditional PAD methods have been proposed at the International Conference on Biometrics (ICB) 2015 [130], including Monogenic scale space (MSS), binarized statistical image features (BSIF), residual local binary pattern (RLBP), Fourier spectral bandwidth energy (FSBE) and Weber local descriptor (LPQ-WLD). However, none of them achieved 100% detection accuracy on both cropped and full image datasets. Some other conventional PAD methods—Windowed-dynamic mode decomposition (W-DMD) [129] and Steerable Pyramids [133]—also have not obtained 100% detection accuracy on any dataset. The reason for not achieving high accuracy is the feature extractor they used; these traditional PAD methods employ handcrafted feature extractor. To remove any limitation of feature extraction in presentation attack approaches, Nguyen et al. [131] presented transfer learning convolutional neural network (CNN) with PCA and SVM. The proposed method achieved 100% detection accuracy on two large dataset Istituto Dalle Molle di Intelligenza Artificiale Percettiva (IDIAP) [130] and ISPR [132] including both cropped and full versions of images. To the best of our knowledge, it was the first attempt to detect a presentation attack using a deep learning framework. Moreover, Raghavendra et al. [134] also employed transferable deep convolutional neural network to PAD technique and obtained low attack presentation classification error rate (APCER) of 0.4% and bona fide presentation classification error rate (BPCER) of 0%. Traditional handcrafted methods are not robust enough to detect presentation attacks in finger vein recognition systems because of the high computational cost, large processing time and use of small databases in those conventional methods. In addition, the detection accuracy is also limited due to the use of handcraft feature extractor. However, a spoofing countermeasure using deep learning method can greatly enhance the performance of the PAD algorithm. Moreover, with a deep learning framework we can process a huge amount of data with lower computation cost. Below, Table 8 summarizes the proposed PAD methods.

Table 8. Existing spoofing attack methods.

Methods	Total Number of Images	Subject	Resolution of Image	Image Format	Performance Measure	References
FSER-DWT	Live images = 3330 Fake images = 2520	33	640 × 480 pixels	Not reported	EER = 1.476	[132]
MSS	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150	PNG	Half Total Error Rate (HTER) on full image and cropped image = 0.00% and 1.25%	[130]
BSIF	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150	PNG	HTER on full image and cropped image = 4.00% and 2.75%	[130]
RLBP	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150		HTER on cropped image = 0.00%	[130]
FSBE	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150	PNG	HTER on full image and cropped image = 0.00% and 20.50%	[130]
LPQ-WLD	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150	PNG	HTER on full image = 0.00%	[130]
W-DMD	*Idiap* database total images including real and fake = 880	110	Full image = 665 × 250 pixels, Croppped image = 565 × 150	PNG	EER on full and cropped image = 0.08% and 1.59%	[129]
Steerable pyramids	T-Image = 300	100	100 × 300 pixels	Not reported	Average Classification Error rate (ACER) = 2.4%	[133]
Total variation LBP	SCUT database total images including real and fake = 7200 Idiap database total images including real and fake = 880	100 110	Not reported	Not reported	APCER, BPCER and ACER on both database and also on full and cropped images = 0.00%	[12]
Transfer learning CNN with PCA and SVM	ISPR database total images including real and fake = 7560 Idiap database total images including real and fake = 880	7 110	Not reported	Not reported	APCER, BPCER and ACER on both database and also full and cropped image = 0.00%	[129]
Transferable deep convolutional neural network	FVVPA database = 300 instance FVIPA database = 300 instance	Not reported	Not reported	Not reported	APCER = 0.4% BPCER = 0.00%	[134]

4.5. Impact of Deep Learning in Finger Vein Recognition

Deep learning approaches have shown excellent development in FVR and various other research domains in terms of performance. Recent literature demonstrates that deep learning approaches have been successfully applied and enhance finger vein recognition methods. Feature extraction is one of the main steps in FVR. Deep learning approaches are robust to learn features directly from raw pixels, without the need for handcrafted descriptors, which greatly improves matching performance [122]. However, in conventional approaches handcrafted descriptors (Curvature, Gabor filter, Radon transform, Information capacity, etc.) are employed to extract features from finger vein images [49,52,135]. In addition, introducing deep learning to finger vein recognition can reduce the total processing time of recognition. In contrast, conventional finger vein identification requires much computation time to process different steps of finger vein recognition [127]. Personal accuracy is still a serious issue in finger vein algorithm. Conventional finger vein recognition technique needs complex preprocessing, with much effort needed to remove noise, extract and enhance the features before performing distance-based matching method. In these cases, however, a small correction can decrease recognition accuracy [100]. However, a deep learning approach does not need over-complex preprocessing and image processing. Moreover, deep learning methods are robust to noise and misalignment problems [100]. Although the dataset for finger vein recognition is small, the performance of deep learning finger vein recognition is remarkable. Deep learning finger vein identification method performance can be enhanced by employing large datasets, so there is a need for a large finger vein image dataset. Furthermore, applying deep learning methods to Presentation Attack Detection (PAD) approaches can also enhance the detection performance of presentation attack of finger vein image [134]. Moreover, template size of finger vein requires more memory space. Therefore, most of the conventional methods are proposed to reduce template size but none of them perform well enough. To resolve this, the CNN deep learning method with supervised discrete hashing method [124] are proposed, which perform very well to reduce the template size to 2000 bits. Furthermore, the methods speed up the matching process of finger vein technique.

5. Discussion and Future Prospects

In this paper, we review all the processing steps of FVR: image acquisition, preprocessing, feature extraction and matching. Moreover, in Section 4 we also discuss the performance of conventional, machine learning and deep learning algorithms in the FVR domain.

Although deep learning FVR methods are recognized as highly efficient, there are some problems which still need to be solved. The first problem is related to the first step of image preprocessing ROI extraction method of finger vein recognition methods. Yang et al. [44] used a super-pixel-based boundary detection method for ROI extraction, which is robust towards image variation, such as gray level and background noise to a limited extent. However, the experiment demonstrates that the super-pixel-based extraction method does not perfectly select the tracking point to detect the finger boundary. Moreover, in most of the ROI extraction method there is a problem of vein information loss. Hence, there is a need for a robust ROI extraction method to overcome the problem of information loss and improve the performance of finger vein recognition. Additionally, common factors also affecting the quality of the image are image blurring, non-uniform illumination, low contrast, temperature, humidity, gender, thickness of fat etc. As a result, degraded performance is still the main problem for finger vein recognition systems. Many conventional image quality evaluation, image enhancement and restoration methods have been developed to overcome these image quality problems. These methods enhance the finger vein image to some extent; however little attention has been given to factors of finger tissue (fat, tissue, muscle, water, etc.) which result in poor quality of finger vein image. This is still an open issue; an acceptable level of recognition performance has not yet been achieved. Therefore, more powerful deep learning image quality methods are still needed to deal with the quality of image.

The second challenge is related to the image acquisition device, the quality of pixel affected by the aging of the sensor [77]. If the sensor of the device is used for a long time it will affect image quality, which finally affects the performance of the FVR system.

The third challenging problem is related to spoofing attacks, as with other biometric recognition approaches. FVR systems are also vulnerable to presentation attacks from printed vein images. As a result, presentation attack detection (PAD) is the most popular subject in finger vein recognition systems research in recent years. Newer spoof finger vein recognition methods are researched in References [12,129,130,134], which greatly reduce spoofing attacks. However, finger vein presentation attack detection is still the most challenging task that needs to be addressed to improve the reliability of the finger vein biometric. In most spoof finger vein detection systems, two texture-based [12,129] and liveness-based [12] algorithms are employed. Both of these PAD algorithms face setbacks. The first concerns the liveness-based PAD method; liveness detection is an important defense against spoofing. To protect the FVR system from spoofing attack, liveness detection is now very efficient. In Reference [132], Fourier and wavelet transform are employed to detect fake finger vein images. Furthermore, Deng et al. [12] used pulse detection for liveness detection against presentation attack. Liveness detection algorithms show remarkable results in PAD methods. However, there are some deficiencies, detection was too strict, and only preliminary studies have been performed. Therefore, the liveness-based PAD method is still an open problem in PAD techniques. The second concerns the texture-based PAD algorithm. Qiu et al. [12] employ noise and blurriness which improves the discriminative power. Moreover, the texture-based PAD algorithms perform well on small databases. However, on large databases there is some scope for performance improvement. In addition, there is also a need to use more discriminative features as criteria for PAD techniques. Overall, there is a need to collect more data of real and presentation attacks to simulate all the possible cases of the PAD problem, in order to make the system resistant to the various possible presentation attack methods. Because of the above-mentioned problem, presentation attack detection is a challenging task.

The fourth challenge is related to the size of the existing finger vein database. Most of the conventional recognition methods work well on small databases, but there is need for large datasets to check the performance of the recognition methods. Furthermore, performance of deep learning approaches will be further enhanced on large-scale finger vein datasets.

The above problems have been partially solved, and finger vein recognition systems require considerable advances in techniques for the improvement of the method. As mentioned in Section 4.5, traditional finger vein recognition methods involve complex preprocessing (ROI extraction, image quality evaluation, image enhancement and normalization), handcrafted feature extraction and distance-based matching methods. Moreover, the performance of conventional FVR was also affected on a large dataset. Therefore, conventional finger vein identification approaches are found less robust and computationally expensive in finger vein identification. By contrast, introducing deep learning in preprocessing, feature extraction and matching stage of FVR can reduce the total processing time of recognition, improve the quality of images, and offer better capability to extract desirable features directly from finger vein image. Moreover, it also provides accurate matching that can significantly advance the state-of-the-art FVR methods. Additionally, performance of deep learning algorithms can be improved by incorporating a maximum number of layers to achieve much deeper networks, and these can then be tested on a large amount of images. In addition to the deeper networks, the performance of PAD methods could improve with large datasets. Clearly, it is a better choice to employ deep learning algorithm to texture and liveness-based PAD methods in order to get significant results. Although, the existing datasets of finger vein are limited, data samples to train deep models can be replicated using a similarity measure network. Finally, deep learning is recognized as a revolutionary mechanism for real-time finger vein recognition.

6. Conclusions

This paper provided a comprehensive review on conventional, machine learning and deep learning-based finger vein recognition approaches. Algorithms were assessed in the key recognition steps of image acquisition, preprocessing, feature extraction and matching. In image acquisition, the light transmission method was considered to be the best for capturing the high-quality image. In image preprocessing, ROI extraction methods and image enhancement methods were reviewed. In addition, the conventional feature extraction methods were classified into four groups (i.e., vein-based method, local binary-based method, dimensionality-based method and minutiae-based method) and introduced in detail. For the matching stage, the distance-based matching methods and classifier-based matching methods were both exampled. Furthermore, we compared conventional and recently developed deep learning finger vein identification methods. However, deep learning methods showed significant improvement over traditional finger vein recognition techniques.

The paper presented the most recent research advancements in the field of FVR during the past decade, despite the challenges that need to be resolved. In particular, during image acquisition, a good image acquisition device is needed to improve the quality of finger vein image. A large-scale database is needed; in fact, this will be useful in the evaluation of all kinds of FVR techniques. Moreover, a high recognition spoof detection finger vein identification method is needed to identify spoof attacks. Furthermore, machine learning approaches play an important role in finger vein recognition. Introducing deep learning approaches into FVR has the potential to enhance the recognition performance in a broad sense.

In conclusion, the authors expect this work to be a useful starting point for new approaches, and a common ground for a wide range of benefits in the area of finger vein authentication and identification.

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