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Finger Vein Recognition Techniques: A Comprehensive Review

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Abstract

This paper discusses a comprehensive review of the previous research in the field of the finger vein recognition system with a focus on finger vein enhancements and features extraction advances and shortcomings. It starts with a general introduction of the biometric system followed by detailed descriptions on finger vein identification, and its architecture archival of it, which includes image acquisition, preprocessing of the image, feature extraction, and vein matching. This study focuses on related work proposed by previous researchers, issues in the field that originated from the related work, and a discussion of each of the issues associated and the proposed solutions to each of them. Next a comprehensive discussion on the advances and shortcomings of the existing techniques based on the qualities, capturing device, database, and feature of that quality is presented. Accurate comparisons between existing techniques are presented as tables to make it easy for new researchers to come up with advances and drawbacks of each technique without spending time on all existing research in this area.

Keywords

vein recognition system, finger vein, biometric system, vein identification, vein matching.

1.Introduction

The biometric system has been known as a tool that can fulfil the obligation for critical security applications. Finger vein is among the existing biometric traits, which have the most stable and use effectively for Biometric Identification Systems (BISs) [1-4]. Currently, biometric application technologies are applied in forensics, most especially in the identification of criminal and prison security. Similarly, biometrics has the capability to remain extensively approved for the very wide scope of national purposes such as voter and driver registration, national identification, customs and immigration systems, physical access control, and banking security. These technologies have been made possible by explosive advances in computing power and have been made necessary by the near general interconnection of computers around the world [10].The typical existing biometric features are DNA, finger print, iris, retina, facial themogrm, hand vein, face, signature, finger vein, voice.

However, every biometrics authentication systems have its own shortcomings based on the qualities, capturing device, database, and feature of that quality [11-14]. To solve the inadequacies of existing based biometric systems, research into finger vein identification comes to the limelight. The beginning of finger vein can be traced back to the year of 2000 when a Japanese medical researcher introduced biometric finger vein trait for identification systems [17]. Since then, finger vein has attracted a lot of researchers' attention in other countries worldwide to develop finger vein identification systems because of its merits [22]. Finger vein is the vein patterns or the networks of blood tissue under the skin of a finger. The vein that contains deoxygenated blood absorb the Near Infra-Red (NIR) light thus appearing darker than the surrounding background in the vein map [23]. Despite that, finger vein can only be obtained in a living person, it is so unique for every individual, including identical twins [26, 27]. Hence, vein patterns are obscured and are not easily be replicated [20].

This paper is centered on the review of related literature in the field of finger vein identification. The paper begins with a brief introduction about biometric technologies, its definition and the processes included in human identification by biometrics. Based on the observations by the author through the rigorous analysis of previous studies, the decision to use NIR finger vein images was finally chosen. NIR images was chosen because it is hard to fake the finger vein that reside inside the internal tissues of human finger [28]. The author focuses on the methods used in finger vein identification for preprocessing, feature extraction, and classification. The subsequent aspect of the paper is dedicated to finger vein identification. First, the definition of the finger vein is presented. The related works, including a detailed description and analysis of the current state of the finger vein identification research as well as the methods used in preprocessing, feature extraction, and matching classification for each proposed work is presented. The previous studies were classified based on the feature extraction categories and is summarized. Based on the literature presented, it is found that the methods used for preprocessing and feature extraction for finger vein identification do not provide the optimal solution to the problem in hand. These previous methods suffer from five problems as follows: First, some of them are tested under small database and hence the acquired accuracy is unreliable. Second, the performance metric on image after pre-processing did not used to know the image quality before the features are extracted. Third, some of the methods are complicated and used fusion score level of multimodal trait at the feature extraction processing stage. For instance, combining fingerprint feature with finger vein feature Fourth, some of the methods are complicated and they don’t improve the accuracy significantly. Fifth, the feature extraction methods extract either local or global method and there is no single method that extracted both important kinds of data.

This paper is structured as follows. In Section 2, the background information required for a better understanding of biometric system presented in this paper is discussed. In Section 3, the related studies on Finger Vein Identification are presented. So, at the end of this section, Review of Existing Databases is expressed. In section4, Discussion on Related Finger Vein Recognition Works are described in detail. Finally, the general conclusion of this paper is explained in section 5.

Fingerprint biometrics appears to be popular in human identification systems. However, its privacy cannot be granted as it can be spoofed and forged. In identification and information security application, vein technology offers many merits in biometrics such as generality and distinctiveness. As human age increases, the vein pattern does not change, which means it is static in nature. In addition, sickness, surgery, and epidermis do not change the body vein pattern to cause conflict over two people's personal identification. Finger vein biometric trait is increasingly being used nowadays because it overcomes the problem of creating complex passwords and the user has one less thing to remember, their biometric trait (vein) is always with them (Sharma et al., 2014).

Despite extensive research in the finger vein identification system, there are still several aspects of this area that still crave for lots of research studies. The system includes various phases of operation such as image acquisition, enhancement, feature extraction, and matching.

Research shows that image enhancement and feature extraction are the most known challenging processes in finger vein image processing (Yang and Shi, 2012) and even in finger vein identification systems (Podgantwar and Raut, 2013). In previous years, image enhancement and its feature extraction image methods have been created and enhanced to conquer the challenges of images. Enhancement and feature extraction of the finger vein refers to the removal of the unwanted object, increasing the contrast between ridges to identify and obtain information that represents the individual through the vein.

Despite several previous works on finger vein identification systems, issues on finger vein image enhancement and feature extraction are still challenging the system. Efforts and research to improve the contrast level and denoise the mixed noise in image enhancement and feature extraction have not been adequately investigated. Therefore, the finger vein image enhancement and feature extraction's advances and shortcomings along with presenting a comprehensive discussion on this area are to be solved in this study.

2. Biometric System

A biometric system is a system that allows the recognition of a certain characteristic of an individual using mathematical algorithms and biometric data. Figure 1 shows the general step of processes in biometrics system. The process begins with data collection from the users who will ultimately make use of the system. The data collected undergo the pre-processing, which is the second stage. The third step is feature extraction, used to select the most discriminating features from the original data, and the last step in the system is matching the image with the templates in the database.

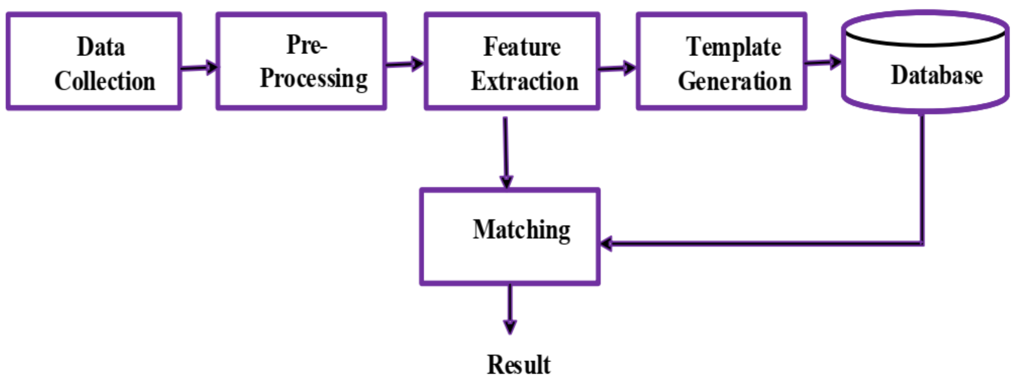


Figure 1.The composition of biometrics system

In the past years, many biometrics systems have been implemented with some limitations. For instance, it is established that about 2% of the targeted population find it difficult to scan their fingerprints and getting good quality fingerprint images from manual workers [29]. Likewise, face biometric recognition encounters difficulties such as noise, variations in pose and illumination [30], while iris and retina-based biometrics are inconvenient for users [14]. Besides, the uniqueness, as well as permanence of several behavioral features put forward in the literature, in the form of signature and gait, are weak [13]. Conversely, the finger vein has many benefits over other biometric traits. Apart from its location under the skin, it provides various kinds of features and wider area than a fingerprint. It is also discriminating and permanent in nature. In addition, the finger vein can be included easily as part of multimodal biometrics system, which is convenient for users. Table 1 compares different biometrics modalities based on device capturing, security, cost, speed, and image size, which comprises the requirement for a biometric. The speed deal with rapidity at which the system works and provide the result, for example, false accepted rate and false rejected rate; Cost of the system characteristic fees that enable the system to work; and while the Image size is for storage capacity to store each trait. On the other hand, Security level reflects the ability of the system to detect spoof attacks easily [31, 32].

Table 1. Comparison of Biometric Technologies [31, 32]

Biometrics	Device	Security	Cost	Speed	Image size
Face	Light camera	Medium	Medium	Slow	Large
Palm print	Scan	Medium	Medium	Medium	Medium
Iris	Radial	High	High	Medium	Large
Voice	Microphone	Medium	Low	Fast	Small
Hand geometry	IR camera	Low	Medium	Medium	Medium
Fingerprint	Ink print	Medium	Low	Medium	Small
Finger vein	NIR camera	High	Low	Fast	Small

However, a biometric system operates in either verification mode or identification mode, depending on the context of application [33].

2.1. Enrolment

A biometric system starts with the enrolment module. This module records persons into the biometric system database with a biometric sensor reader (charge- coupled device camera) firstly scans the person’s biometric trait to create its digital depiction. The system, however, does a proper examination to make sure that successive stages can process the acquired sample. The acquired sample generates a compact called a template, which can be stored in the biometric system to a central database or on a smart card provided by the individual [33, 34]. Figure 2 displays the biometric enrolment process.

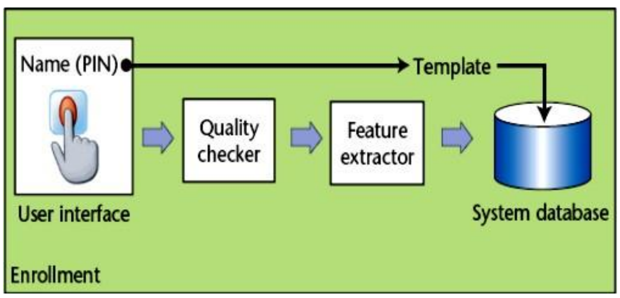


Figure 2. Biometric enrolment process [34]

2.2. Verification

The first biometric system mode is known as verification mode, which involves matching the subject biometrics data with a template of their names to adopt if the requested identity by individuals is true or false. It is always painstaking to be “one-to-one” (1:1) matching. Only one subject needs to be compared to the sample template out of the millions of reference templates. Hence, the result of the biometric verification systems (BVS) takes less than a second to operate with a match or no match decision. This type of mode is usually used for positive recognition with the ambition to avoid several people from using the same identity [33, 35, 36]. Figure 3 shows the verification biometric mode.

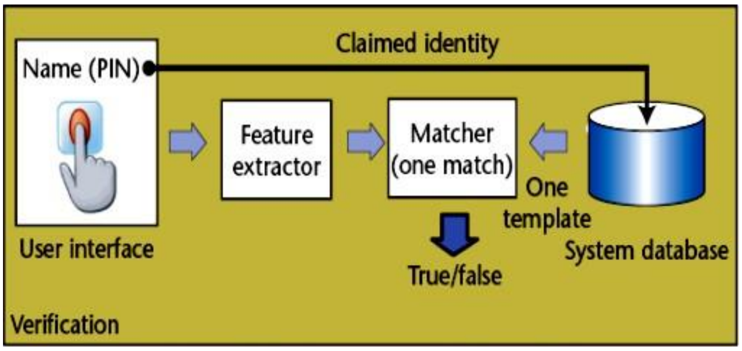


Figure 3. Verification biometric mode [33]

2.3.Identification

The second biometric system mode is called identification, which makes a comparison of data between individual biometrics and the database to find their identities. In this mode, recognition of an individual by the system was established from a match after searching the whole template database. The system will conduct a one-to-many (1:N) comparison for individual’s identity establishment, which gives output as genuine or impostor [33, 37]. Figure 4 shows the identification biometric mode.

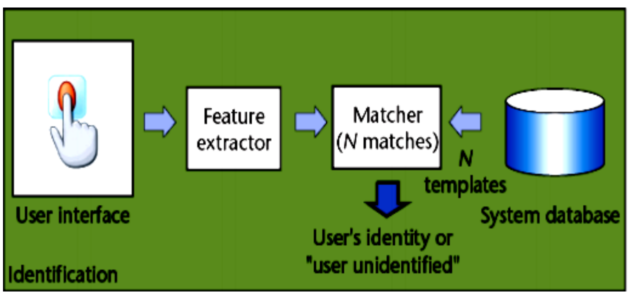


Figure 4. Identification biometric mode [33]

3. Related studies on Finger Vein Identification

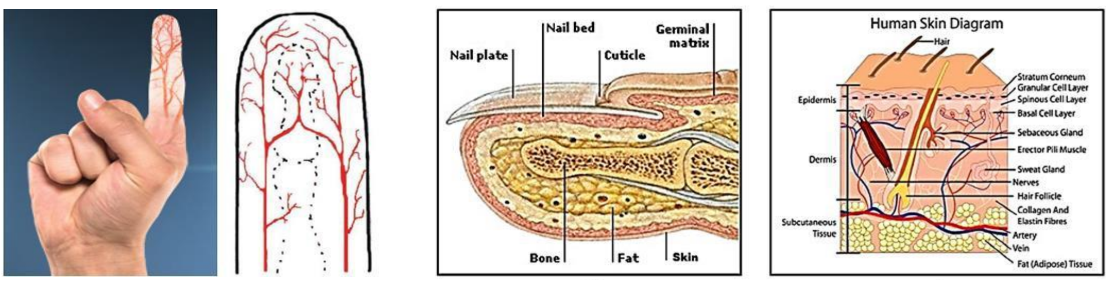
3.1. Finger Vein Identification

Finger vein identification has certain properties, which makes it an interesting research area in the field of biometrics recognition that uses pattern identification methods to identify individual and verify their identity.

3.1.1. Finger Vein Feature

Finger vein is the vein patterns or the networks of blood tissue under the skin of a finger. Research revealed that individual vein patterns are different from one another, even among twins. All fingers contain tissues (vein) and organ, which are capable of absorbing Near Infra-Red (NIR) light various absorptivity. The vein that contains deoxygenated blood absorb the NIR light, thus appear darker than the surrounding background in the vein map [23]. Hence, the finger vein images refer to the images taken under NIR light. Finger vein patterns offer better advantages among other biometric traits [5, 27, 38]. Figure 5 shows the finger vein under the near infra-red light with many of its components.

Unlike other biometric traits, finger vein is difficult to be spoofed [28, 39]. Literature shows that fingerprint system can easily be spoofed when the user moulds his fake finger image through the pressing of a finger on easy absorbing material like wax, dental impression to create fingerprint impression [40]. Face spoofing also has what is known as “copy attack”. Face recognition system spoof could be through the circumventing of the face recognition systems, stealing or sharing social image websites and social networking websites downloaded by an attacker to fool a face recognition system [41]. Literature also mentioned that iris spoofing attacks could be photo attacks, contact-lens attacks or artificial-eye attacks [42].



(a) (b)

Figure 5.Cross-section anatomy of finger vein under near Infra-red light [23]; (a) Human finger (b) Finger cross-session under human skin

Apart from spoofing, identification using finger vein offers certain key advantages compared to other biometrics recognition technologies in the sense that it is more accurate with lower false rejection rate (FRR) and lower false accepted rate (FAR). It is also less invasive in the sense that it does not entail the subject to place his finger in contact with the scanning surface of the scanner machine. Thus, there are no hygiene disputes associated with finger vein scanning. Another advantage is that it does not require the subject to touch the scanning surface of the device. Thus, it does not leave any latent prints behind. In additional to this, wet or dry weather does not affect it since it is sub-dermal, and age has no effect on it, which means that the enrolment can be used for the whole lifetime of the subject [43]. Figure 6 depicts the vein pattern of the finger.

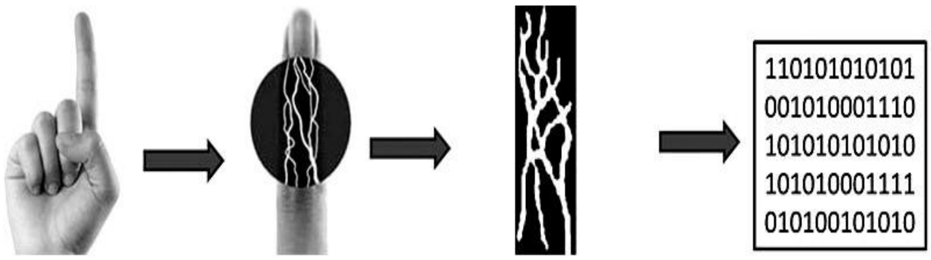


Figure 6. Structure of finger vein pattern [44]

3.1.2. General Model of Finger Vein Identification

A finger vein identification scheme includes two main phases as shown in Figure 7. The first phase is registration, also known as enrolment. The second phase is identification, also known as matching. In the phase of enrolment, individual images are collected and passed across the preprocessing and feature extraction stages, then saved as templates in the database. In the identification phase, the user’s image is captured then preprocessed. The preprocessing procedure is used to identify the interest region to be used in the later procedures. This stage also consists of image alignment and enhancement. The extracted discriminating features are then matched with the database of templates to decide the user identity in identification mode, or to verify the user identity in the identification mode [27]. However, Charged Coupled Device (CCD) camera acquisition device is used in the finger vein images collection. The next sections discuss the procedures and methods used in each method, high point the benefits, and drawbacks of each of them, starting with the operation of finger vein image acquisition.

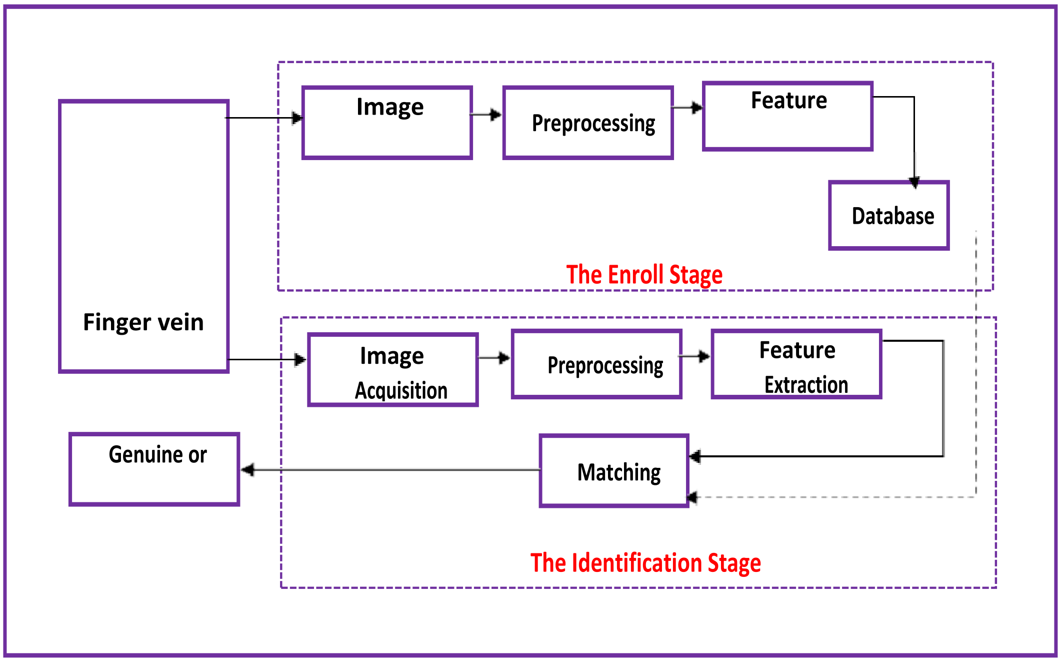


Figure 7. The model of finger vein identification

3.2. Finger Vein Image Acquisition

Initially, Hashimoto [38] introduced three approaches leading to the acquisition of vein pattern image: light reflection, light transmission, and side lighting. These methods used infra-red (IR) light but are distinguished by the placement of a finger or infra-red light. Later in 2012, the light transmission was reviewed to have the bottom light transmission in addition to the existing methods of finger vein acquisition. Detail descriptions of each method are discussed in the following sub-sections.

3.2.1. Light Reflection Method

Light reflection method captures vein pattern using infra-red (IR) light. In this method, the IR is positioned sideways of the CCD image sensor, and the finger is laid in anterior of the sensor as illustrated in Figure 8. Usually, this method is not adopted in the vein of palm, palm-dorsa or wrist capturing because the size of these areas is large, IR is unable to penetrate it. Therefore, light-reflection is claimed to be the best capturing method, and its ability to be in a compressed mode (a small device for the final product) give this method advantages over other methods. However, the contrast is low because the light can only penetrate up to 1 mm of the skin depth. Hence, advanced image processing method is essential because the tiny size of the vein and other parts make it difficult to section, mainly for the thin vein [38, 45].

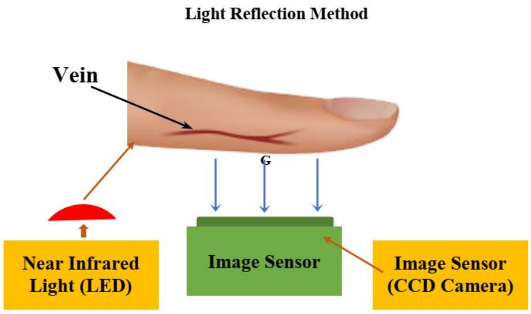


Figure 8. Light reflection method

3.2.2. Light Transmission Method

This is different from light reflection. The IR light in this method is placed opposite the CCD sensor and finger is placed in between as shown in Figure 9. The principle is, the sensor will capture the IR light that is transmitted through the finger. Although it seems more reliable in capturing the vein pattern, not all parts can be used and only parts with suitable thickness can be used [38].

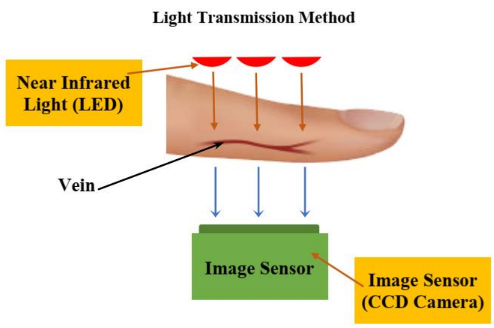


Figure 9. Light transmission method

3.2.3. Side Lighting

Side lighting method was introduced by Hashimoto [38]. In this method, the IR light is placed at both sides of the finger (Figure 10) with the idea that the light will penetrate through fingers, scatters, and passed the signals to the sensor to capture the image of the vein. This approach has proven to give a better and sharp image contrast. The end devices might be bigger than the light reflection device but smaller than the light transmission.

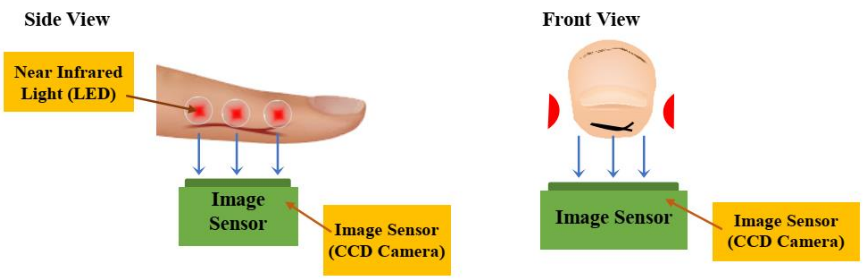


Figure 10. Side lighting method

3.2.4. Bottom Light Transmission

This method has been reviewed by Vallah [46] as the fourth approach in capturing vein image. Vallah [46] mentioned that this approach was introduced by Himaga [47] to overcome the limitation in terms of mobility. This method placed the camera and the sensor (IR-LED light) on the base of the device. The approach is almost like the light reflection approach, but the finger must touch the LED screen. Once the sensor senses the finger, the light will be projected and propagated inside the finger, making the capturing vein pattern to be similar with the side lightning approach. The process is shown in Figure 11.

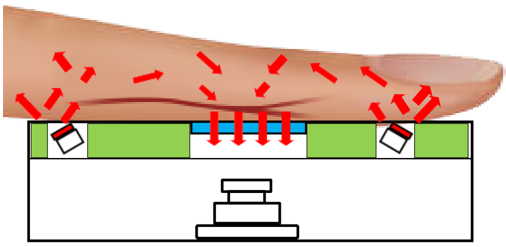


Figure 11. Bottom Light Transmission

Having explained in detail, the finger vein image acquisition through the various four approaches, the advantages and disadvantages of each method are presented in Table 2 for easy comparison.

Table 2. Comparison of finger vein capturing methods for image acquisition

Methods	Advantages	Disadvantages
Light Reflection	i. Sharp contrast after optimizing ii. Low cost iii. Low power	High quality requirement for NIR sources and components
Light Transmission	Sharp contrast	Inhomogeneity in images with contrast differences between regions
Side Lighting (Hybrid)	Higher definition and contrast than images obtained by reflection	Complicated and High cost
Bottom Light Transmission	Higher definition like side lighting Can be made to mobile Low cost	-

Various elements can affect the image quality of human finger vein: fatness, thickness and individuals' skin color, finger position, capturing of image background, and efficiency of the image capturing machine [48]. However, for image capturing control, no standard measure is available. Thus, the presence of low-quality captured images in definite numbers is unavoidable. Hence, finger vein images with low-quality can be categorized into four forms as shown in Table 3.

Table 3. Categories of low-quality finger vein image

Problem	Description
Blurry image [49]	the vein patterns that contain little contrast
Askew image [50]	the vein images with a definite grade of deformation
Dim image [51]	the captured images with a dim or black portion
Bright image [52, 53]	the existence of sunny portion in the images

Finger vein images that are low in quality can lead to a gloomy identification and may significantly cause a slow pre-processing and complex feature extraction.

The capturing method is used to develop the finger vein reader, which is a biometric machine. This machine is designed to capture the patterns of finger vein of an individual. It contains no less than one optical imaging unit and a digital signal processor, which is used in capturing finger vein patterns as biometric features [54]. The scanner for finger vein reader is displayed in Figure 12.

Figure 12. Typical finger vein readers

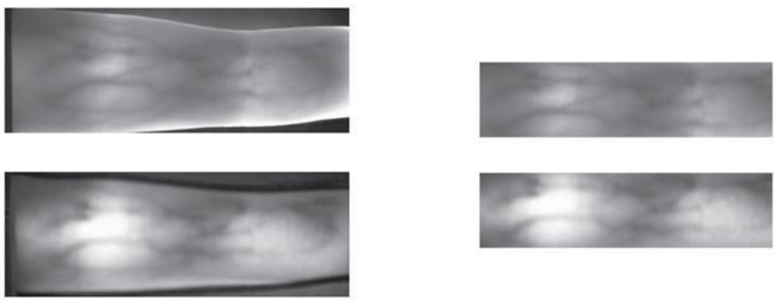
3.3. Image Preprocessing

Preprocessing functions in image processing include those actions or preparations that are usually essential prior to the main data examination and extraction of information. It is used to improve the deficiency such as low contrast and noise in the image. In this case, image enhancement is applied in a preprocessing step. The steps include image restoration, cropping of the region of interest (ROI), and image enhancement. Many algorithms are implemented to produce and align the ROI. A commonly used method is the simple mask filter, which is the Lee-Region detection [55].

The processing of an image is a general way to measure image quality. The importance of image quality metric can be viewed from three perspectives. First, to monitor the quality image for quality control systems. Second, to benchmark the image processing systems and algorithms. Finally, to optimize the algorithms and parameters setting when inserted in the image processing system [56, 57]. It is on this basis that finger vein image has to be processed because a good performance of a finger vein image depends on the finger vein image quality [58].

3.3.1. Image Restoration

Image restoration is the elimination or reduction of known degradations in an image. This includes de-distorting of image corrupted by shortcomings of a reader machine or its background through noise filtering and improvement of geometric distortion or non-linearity due to the sensor. However, before the image enhancement, finger vein must be cropped to remove unwanted portions. Figure 13 shows the pictorial example of the input image, before and after cropping.



(a) (b)

Figure 13. Finger Vein Image Cropping [59] (a). Image before Cropping (b). Image after Cropping

3.3.2. Image Segmentation of ROI

Segmentation of location or region of interest (ROI) is a very good aspect of operation in the preprocessing of a finger vein identification system. In finger vein context, ROI is the portion of the finger that contains many networks of vein pattern. The reason of extracting ROI is based on the determination of the portion of the image that is good for vein feature extraction. This portion is preserved for further processing while the non-useful information around the image is removed. The important way in extracting ROI is to make ROI as part of the entire images of finger vein from the dataset and provide enough features of finger vein for extraction. The computational complexity can be sufficiently brought down if correct extraction ROI of finger vein image is known. This might enhance the efficiency of the finger vein recognition system. Hence, ROI extraction performs a very serious operation in finger vein identification-based systems.

Few algorithms exist for the extraction of ROI vein in the finger. Rosdi and his co-researchers [60] made use of the fixed-size window base to crop out a certain portion of the finger in the finger vein image. The method is sensitive to displacement of the finger and is not accessible to be used by askew finger vein images. In their own cases, Yang and Li [61] and Yang and Shi [62] offered an ROI localization method that was based on the physiological structure of human fingers. Though, the issue of displacement of the finger can be resolved, the method is not accessible for askew finger images. Hence, before using the available method of ROI extraction, it is very necessary that askew finger vein images must be corrected at the first stage. ROI extracted through an edge detector was done by Kumar and Zhou [15] after he performed the rotational alignment. However, the method refused to harvest the ROI area from finger vein images, causing the operation of an image to have more background than the vein portion.

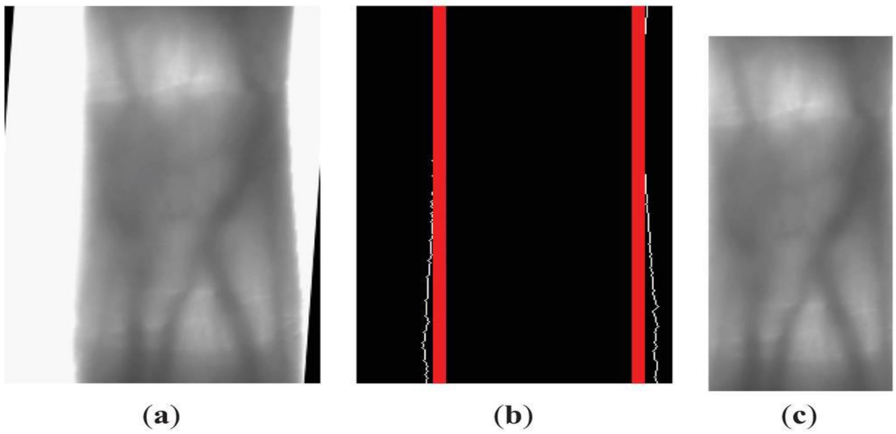


Figure 14. The measurement of the ROI [63]; (a) ROI in actual stature. (b) Finger image edge using internal lines. (c) ROI of a finger vein image

3.3.3. Image Enhancement

Image enhancement is an important operation part of image processing that aid in improving the visibility of any part of the image for further analysis by an operator or a system [64]. In the case of digital image enhancement method, there are many combinations of sets that can improve the appearance of image performance. There are suitable choices of a method that is seriously affected by the imaging modality, assignment at hand, and observing situations. A common instance of enhancement occurs when there is an increase in the contrast of an image and the removal of noise which then makes it better. It should be noted that enhancement shows a very important role in image processing. Hence, using a suitable enhancement method can improve the value of degraded images.

However, many works have been done in image enhancement area. For instance, Arun and his co-researchers [65] in their work proposed that a better result of image enhancement can be achieved by using Adaptive histogram equalization. The work was taken as uncompleted as the blurry form could still be noticed in the images. The brightness, background information, and contrast of the image is poor. The entire image is dark in tone caused by alpha rooting. Also, there is a loss of the clouds that was noticeable in the case of histogram equalization. In addition, Agaian et al. [66] proposed that global histogram equalization is the common enhancement method without the need for transformation. This method alters the image spatial histogram to make a close semblance of the distribution. Thus, it is noticeable that Histogram equalization has drawbacks of being poorly fit in holding local detail because of its global treatment of the image. However, the equalization method might over enhance the image and cause the losing of quality visual and intensity scale undesirably. Tang et al. [67] stated that global histogram equalization can regulate histogram into local setting to estimate unvarying dissemination. In this case, global histogram alteration gives images equal sections; hence, regularly produces a lowly local presentation in terms of feature protection. Thus, many algorithms have been suggested to improve the local image enhancement setting. From the study of histogram method, it can be concluded that the vibrant scope of the vein image is not very much distributed along each pixel [68-70].

Whenever the vein image is being captured with an image sensor, the light intensity adds a background to it, which is called noise. Noise is unwanted information which may lead to changes in the quality of the image quality. It degrades the image. The removal of noise or denoising and keeping the edges of the image is the act of image enhancement. The common noises in vein images are Salt- and-pepper noise and Gaussian noise. Median filter and Wiener filter (Gaussian filter) are good in removing Salt-and-pepper noise and Gaussian noise respectively [71]. Difference of Gaussian-Histogram Equalization (DoG-HE) was proposed by Kang et al. [72]. This method is used to improve the clearness and contrast vein image. Median filter has often been applied to remove burrs and reduce the unwanted flaws in image. This noise is generally eliminated based on the amount of noise in the vein image [73-75]. However, the Median filter cannot remove Gaussian noise from the vein image that contains both Salt-and-pepper noise and Gaussian noise. Recently, some researcher has work in this area where the Median filter is applied first followed by the Wiener filter. This is a serial operation for vein image enhancement [76, 77]. The finger vein image degradation is now a serious task for finger vein identification in the sense that the degraded vein cannot be effectively used. So far now, many researchers have been working on finger vein image enhancement [5, 7, 26, 60, 78]. The development of existing vein enhancement methods in finger vein identification had worked to a certain extent, but the methods still need to be improved because the effective vein feature extraction method depends on the quality of the vein enhanced. Table 4 shows some researcher proposed methods for the vein enhancement.

Table 4. Previous research on image enhancement and quality evaluation

References	**Name of Method**	**Enhancement Methods**		**Limitations**
		Single-Based	**Multiple-Based**	
[48]	Elliptic high pass filter	√		Treated single noise
[79]	Non-Subsampled Directional Filter bank (NSDFB), Frangi filtering	√		Treated single noise
[80]	Median filter	√		Treated single noise
[78]	Modified Gaussian high-pass filter	√		Treated single noise
[81]	Gaussian filter Elliptic high	√		Treated single noise
[15]	Histogram Equalization	√		Treated single noise
[82]	Gabor filters	√		Treated single noise
[83]	Histogram Equalization	√		Treated single noise
[84]	Median filter and Winner filter Gray linear transformation Niblack method	√		Treated single noise
[85]	Median filter Contrast Limited Adaptive Histogram Equalization (CLAHE) Gabor filter	√		Treated single noise
[86]	Fusion of Gabor filter and Retinex filter		√	Treated single noise
[87]	Multiscale matched filtering	√		Treated single noise
[88]	Support Vector Regression (SVR)	√		Treated single noise
[89]	Histogram equalization	√		Treated single noise
[90]	Interval type- 2 fuzzy set	√		Treated single noise
[91]	Gabor filter and Canny edge detector		√	Treated single noise
[92]	Image layer separation (ILS). Gaussian blur	√		Treated single noise

Table 4 shows the previous methods used in vein image enhancement, which is either single-based (contains one filter method) or multiple-based (contains more than one filter methods). Many of these methods are not evaluated after enhancement, and few are only used visual evaluation method. The methods were only applied to single noise image, which forms the limitation.

3.4. Feature Extraction

Feature extraction is the conversion of the involved image into a selected feature. The feature sets collected from the involved image are used as information to carry out the preferred task; this is against using the whole image captured. Thus, feature extraction can make use of an algorithm to identify and separate a certain portion of an image. This permits processing of digital images to detect the regions that are of visual interest. These listed features in image feature extraction include the mean, energy, entropy, singular value decomposition (SVD) and variance. The mean is a feature that gives recognition about the general brightness of an image. The variance is a feature that relates to the texture of an image. Higher variances are features originated from the high frequency of image texture regions. The energy component states the gray level supply of an image. The entropy is a feature that measures the number of bits that are required to code the image data for the analysis. The methods for features extraction in finger vein identification area can be divided into four groups: vein pattern-based methods, dimensionality reduction-based methods, local binary pattern-based methods, and texture-based methods. A brief review of the methods used in each category is given in the following sub-sections.

3.4.1. Vein Pattern-Based Methods

In these methods, segmentation of the vein patterns is considered first, while matching uses the geometrical shape or topological structure of vein pattern. Repeated Line Tracking [5, 6], Maximum Curvature [7-9], Gabor [15, 16], Mean Curvature [18], Region Growth [19-21], and Modified Repeated Line Tracking [24, 25] are typical methods used in this group. The common methods used in vein pattern-based feature extraction are described in Table 5.

Table 5. Descriptions on some typical vein pattern-based feature extraction methods

Method	Descriptions	Reference
Repeated Line Tracking	The vein in the image is traced to randomly select seed (directions chosen from predefined probability). The process is repeatedly done until	[5, 6]
Maximum Curvature	Image extraction by detecting its center line	[7-9]
Gabor	A linear filter used for edge detection by transforming the image into the frequency domain	[15, 16]
Mean Curvature	Image segmentation using the mean of the surface curvatures in all directions It can quantify the degree of likeness to a ridge or valley	[18]
Region Growth	This is running the region growing operator on the different seeds with emphasizes continuity and symmetry of valleys in the cross-sectional profile.	[19-21]
Modified Repeated Line Tracking	Find the image locus based on the revised parameters	[24, 25]

3.4.2. Dimensionality Reduction-Based Methods

This category is subspace learning methods such as Principal Component Analysis (PCA) [93], Linear Discriminant Analysis (LDA) [94] which extract the global features from the finger vein and ignore the local features; (2D)2PCA [21, 95], and manifold learning [96]. Meanwhile, Local Projection Pattern (LPP) extracts the local line features and ignores the global features. However, both local line and global features are important for recognition and they affect the accuracy level. Classifiers like neural network and k-nearest neighbor are used in matching for these methods. In large- scale applications, it is not preferable to use dimensionality reduction-based methods because transformation matrix learning could be difficult to quite numbers of users [20].

3.4.3. Local Binary Pattern-based Methods

This category of the method is based on the local area, and the features extraction is in binary formation. They are local binary pattern (LBP) [78, 97], the local line binary pattern (LLBP) [60], the personalized best bit maps (PBBM) [98], personalized weight maps (PWM) [52], and the local directional code (LDC) [99]. Derivation of the local binary code is made by comparing the gray level of the current pixel and its neighbors in the case of LBP and LLBP. The binary codes stability is further explored in PPBM and PWM and matched using the stable binary codes. Most of these methods adopt the use of hamming distance (HD) for the measurement in the similarity of enrolled and input binary vein features.

3.4.4. Texture-Shape Descriptor Methods

Shape descriptors are grouped into contour-based and region-based methods. This grouping considers whether shape features are removed from the contour or from the entire shape section. Shape descriptors are additionally grouped into structural (local) and global descriptors. If the shape is characterized by bits or regions, it is structural and if the shape is characterized by the whole region, it is global. Another grouping arranges the shape description into spatial and transforms domain methods, which is dependent on the use of coordinate estimations or applying a transformation of the shape. Figure 15 shows the shape representation and description methods.

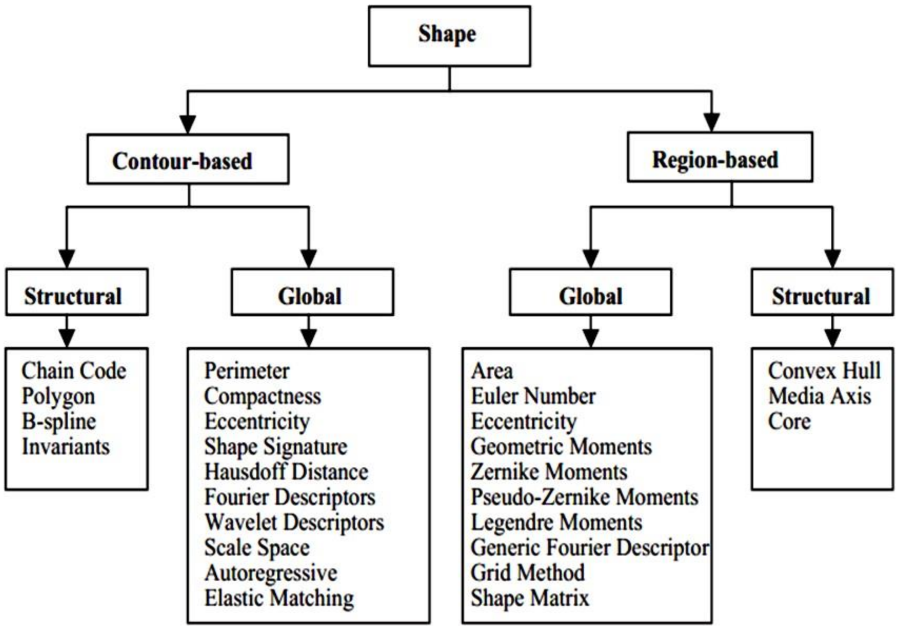


Figure 15. Shape representation and description methods [100]

Contour-based methods extract the boundary information, but in many applications, at times, the boundary information is not always available. In addition, Contour-based methods are sensitive to noise and variations because of small parts of shapes involved and interior contents of some of the applications have more importance. In other words, Region-based approaches reflect all the pixels within the shape region as against the boundary information used in the contour-based approaches. Thus, uses of region-based methods are more robust and applicable in general applications. The composition of Contour-based shape descriptors comprises Fourier descriptor [101, 102], wavelet descriptors [100, 103] and curvature scale space (CSS) [104, 105]. Region- based shape descriptors include moment invariants [106, 107] and Zernike moments [108, 109].

The clear and stable line shape patterns of the finger veins image encouraged researchers to treat it as a texture image and to extract texture features as local ridges and valleys from the finger vein image. Many works have been proposed in the literature based on texture features. The most used methods are wavelet transform and Gabor filter. Others are Discrete Wavelet Transform (DWT) [110], Discrete Fourier Transform (DFT), and Discrete Wavelet Packet Transform (DWPT) [111].

Park [112] combined both the local features of Local Binary Pattern (LBP) and the global feature information for finger vein recognition using Wavelet transform. Support vector machine (SVM) was used to combine the two score values from the LBP and Wavelet transform. A custom database of 4,000 finger vein images from 10 images of each 8 fingers (apart from both hands' thumbs) from 50 people. The evaluation was expressed in an equal error rate (EER), which was 0.011%.

Gayathri and Ramamoorthy [113] proposed feature level fusion for palmprint authentication of an individual. The three features correlation, energy, and homogeneity are fused together, and tested on 125 publicly available palmprint database of Hong Kong Polytechnic University using nearest neighbor classifier. The experimental results realize recognition rate was 98.4%, which performed better than using a single feature.

Mohd et al. [114] on their research combined Finger Vein Recognition based on BLPOC and finger Geometry Recognition based on WCCD at Score-Level Fusion. This fusion was tested on Non-public database collection from 123 volunteers and recognition performance was expressed in equal error rate (EER), which was 1.78%. with a processing time of 24.22ms.

3.5. Matching

The decision-making stage in the finger vein identification process is the matching stage. In this stage, the features extracted from a pattern are comparable to those of the enrolment set. This decides if the entry image is original or fake for registered image to produce a matching score (the similarity between the registered template and the entry image). There are twofold categories of matching methods, namely; classifier-based matching and distance-based matching [115]. The distance-based matching method is exploited by conventional finger vein identification approach, and while classifier-based matching method is use for machine learning finger vein identification. Thus, classifier-based matching will try to categorise the pattern that will lead to the generation of hypotheses, and not as a unique solution [116].

Generally, classification is achieved based on features such as minutiae [117], local line binary pattern [60], SIFT [60], soft biometrics [20], statistical measures [118], machine learning [96], correlation (or template) based methods [15], and hybrid algorithms [112].

The uses of minutiae feature for classification commonly indicates finger vein images low-quality performance, which consists of several fake and limited genuine minutiae. Likewise, fewer amount of accurate and typical SIFT key-points can damage the enactment of classification. Also, because of the pose variation of the finger, using such width of the phalangeal joint soft biometric trait [20] or finger geometry [119] is not productive for classification. In addition, the statistical measures of feature extraction such as local moments for classification, is unproductive due to the less discrimination of statistical features. Classification via machine learning methods needs a massive quantity of training data that can reflect some of the likely distortions, but it is always impossible [96]. Even if the genuine veins are lost or the fake veins are presented, the use of correlation or template-based matching can give an accurate result. It removes strong distortion within image registration; hence, it can be described as classification based on strong registration. The similarity score is computed by using registered images. Thus, features for registration are such as vein structure [15] and vein skeleton [120]. However, finger poses [63] can decline the correlation or template-based classification performance.

K-nearest neighbor (kNN) classifier is one of the most well-known supervised learning algorithms in pattern classification, which employed by some researchers. Many researchers claimed that using K-nearest neighbor (kNN) classifier has several benefits such as intuitiveness, effectiveness, competitive, and simplicity performance of classification in several domains [121]. However, KNN works with a distance-based metric for the evaluation of the comparison level between the feature vector of the input pattern and the tested template(s).

Gongping Yang et al. [21] proposed feature extraction of finger veins using a 2D PCA method and KNN classifier for classification of everyone. Furthermore, they adopted to solve the class-imbalance problem using the SMOTE technology. A custom database of 80 individuals' index fingers of the right hand from 18 finger vein images was used. Table 6 summarizes the matching methods in finger vein identification schemes. The scheme illustrates the various image preprocessing methods, methods of feature extraction, and matching methods.

Table 6. Finger vein matching methods

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	
			Distance-Based	Classifier-Based
[96]	ROI Detection image enhancement size normalization	ONPP-Manifold learning	Manifold distance	
[122]	Non	BWMB2DPCA	Nearest neighbor	
[78]	Gaussian high-pass filter	Binarization local binary pattern	Hamming distance	
[60]	Modified Gaussian high-pass filter	Local line binary pattern	Hamming distance	
[93]	ROI extraction, image resize	PCA		ANFIS (neuro-fuzzy system)
[94]	ROI extraction, image resize	PCA, DCA		SVM and ANFIS
[26]	Elimination of background Removal of noise Enhancement of finger vein image Brightness Normalization Size	Dynamic thresholding Median filter Morphological operation Vein location and direction coding	Template matching	
[123]	ROI extraction, median filter, histogram equalization	Morphological operation, maximum curvature points		MLP
[58]	Gaussian matched filter	LBPV		Global matching, SVM
[99]	Image gray processing ROI extraction, normalization	Directional Code	Template matching	

Table 6. Finger vein matching methods (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	
			Distance-Based	Classifier - Based
[95]	Image gray processing ROI extraction Normalization (size and gray) metho	Personalized best bit map (PBBM)	Template matching	
[124]	Histogram equalization Bucolic interpolation	Fractal dimension Wavelet transform	Wavelet transformation Energy feature	
[125]	ROI extraction CLAHE	Linear Kernel Entropy Component analysis (KECA)	Euclidian distance	
[70]	Binarized ROI Thinned Gabor filter	Minutiae-based extraction	Euclidian distance	
[126]	Image denoising ROI localization Image enhancements	LLBP PLLBP	Histogram intersection	
[63]	ROI extraction Enhancement Normalization size	Local line binary pattern	PWM-LLBP	
[16]	Gabor filtering	Global thresholding, Gabor filter		SVM
[127]	ROI extractions	GLLPB	Soft power metric	

Table 6. Finger vein matching methods (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	
			Distance-Based	**Classifier-Based**
[53]	Anisotropic diffusion method Non-scatter transmission maps Gabor wavelet	Directional filtering method	Phase-only correlation strategy	
[128]	Edge detection ROI Extraction Smoothing filter	Personalized best bit map (PBBM)	Cross-correlation matching	
[129]	ROI Extraction (HCGR) Histogram of competitive Gabor response Matching	Histogram of competitive Gabor response (HCGR)	Template matching	
[87]	Region of interest extraction Multiscale matched filtering Line tracking	Variational approach	Sum of square differences	
[88]	ROI extraction, normalization	Image contrast, the gradient in spatial domain, Gabor feature, information capacity and entropy		SVR
[130]	ROI Localization Image enhancement	Uniform optimal uniform rotation invariant LBP descriptor	Histogram intersection method	

Table 6. Finger vein matching methods (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	
			Distance-Based	**Classifier-Based**
[75]	Sobel operator	Multi-directional finding method	Modified Hausdorff distance	
[131]	Normalization, filtering, resizing	Grid-based location, feature-level fusion by FFF, optimization		K-SVM
[132]	ROI extraction, image resize	Convolutional neural network		Convolutional neural network
[133]	Size normalization ROI Extraction Gray normalization	CLLBP	Matching score	
[134]	ROI Extraction Image enhancement	Fractal dimension Lacunae Gabor filter	Difference compared with threshold value	
[135]	mini-ROI	three convolutions layers		Two channel network learning

3.6. Review of Existing Databases

For each finger vein identification method, the database is prepared prior to feature extraction. The scope of the database is depending on the number of participants and samples of each participant. A demonstrative database consists of samples collected from males, females, and diverse ethnic groups [136], adults and children in diverse ages, etc. It is essential that minimum of two samples of vein images are mandatory to be captured for individual partaker, in which one is for enrolment, and the second for evaluating the algorithm used [17]. Table 7 shows the numbers of the finger vein databases that were in use over some years for finger vein identification both in the research arena and the field of industry. The table contains some of publicly available databases, the size of the image and year each of the database was made. All the mentioned databases in the table were captured by the transmission method excluding CFVD that was gotten via reflection method [137].

Human hand contains five fingers, which are the thumb, index, middle, ring, and pinky. Therefore, ten (10) fingers were made up of both right and left hands. Thus, Table 7 captured all fingers of two hands except the thumb and pinky (little) fingers because they are respectively thicker and shorter in length to be captured compares with other three fingers [126]. Also, the near-infrared light finds it difficult to pass through the thick skin of thumb finger, which is possible for it to fail in capturing the vein configuration. Besides, placing the thumbs on the capturing device was difficult because of the device's structure, which is unstable to capture images appropriate for enrolment and identification [38]. Right finger index, middle, and ring, are represented as Ri,m,r while left finger index, middle, and ring, are represented as Li,m,r

Table 7. Review of Existing Finger Vein Databases

Databases	Public Available	Subjects	Fingers Per Subject	Session	Acq. Per Session	Images	Image Size	Device	Year	EER (%)
Hitachi Res. Lab. [138]	No	2,673	$L_{i,m}$ $R_{i,m}$	1	11	117, 612	Unknown	TS-EE3F1	2004	0.0
Int. Biom. Group [47]	No	650	$L_{i,m}$ $R_{i,m}$	2	2-9	28, 600	Unknown	TS-EE3F1	2006	0.5
Hitachi-Kyushu [54]	No	506	R_{i}	1	2	1,012	Unknown	TS-EE3F1	2007	0.0
PKU v.2,3,4 [139]	Yes	5,208	$L_{i,l}$ $R_{i,l}$	1	5	50,700	512 × 384	Proto PKU	2008	1.2
GUC45 [140]	No	45	10	12	2	10,800	512 × 240	Proto GUC	2009	0.7
SDUMLA-HMT [141]	Yes	106	$L_{i,m,r}$,$R_{i,m,r}$	1	6	3,816	320 × 240	Proto Wuhan Univ	2011	-
HKPU [15]	Yes	156	$L_{i,m}$ $R_{i,m}$	2	6	6,264	513 × 256	Proto HKPU	2011	0.6
UTFVP [142]	Yes	60	$L_{i,m,r}$,$R_{i,m,r}$	1	4	1,440	672 × 380	Proto Twente Univ	2013	0.4
MMC BNU6000 [126]	Yes	100	$L_{i,m,r}$,$R_{i,m,r}$	1	10	6,000	640 × 480	Proto Chonobuk Univ	2013	-
CFVD [143]	Yes	13	$L_{i,m,r}$,$R_{i,m,r}$	2	51	1,345	640 × 480	Proto Shandong Univ	2013	-
Shandong Univ [99]	No	34	$L_{i,m}$ $R_{i,m}$	2	20 -10	4,080	320 × 240	Proto Whuan Univ	2013	1.1
FV-USM [114]	Yes	123	$L_{i,m,r}$,$R_{i,m,r}$	2	6	5,904	640 × 480	Proto Sains Univ	2013	7.01

key:

R – Right Hand, **L** – Left Hand. **i –** Index finger, **m –** middle finger, **r –** ring finger, **l –** little finger

Proto – Laboratory-Made Prototype **EER –** Equal Error Rate

4. Discussion on Related Finger Vein Recognition Works

The related works in the field is discussed in this section to provide an appropriate background to the issues of finger vein identification. The main stages of the finger vein scheme are unwavering, but they contain various forms of method.

For a decade, many works have been committed for finger vein image enhancement [7, 60]. There is image enhancement [65], which is based on Adaptive histogram equalization. The work was taken as uncompleted as the blurry form could still be noticed in the images. The brightness, background information, and contrast of the image is poor. Alpha rooting rendered the entire image in a dark tone. Also, there is a loss of the clouds that was noticeable in the case of histogram equalization. From the study of histogram method, it can be concluded that the dynamic scope of the vein image is not very much distributed along each pixel [68-70].

The common noises in vein images are Salt-and-pepper noise and Gaussian noise. Gupta and Kaushik [71], indeed applied the Median filter and Wiener filter (Gaussian filter) to remove these noises separately. However, they never consider a situation where the image will contain both gaussian noise and salt-and-pepper noise as mixed noise. are good at removing Salt-and-pepper noise and Gaussian noise respectively.

Likewise, Wang et al. [144] offered an extra stable and trustworthy human recognition machine with biometrics technology operational inserted in the user's electronics tools. This system presented finger vein identification with higher security and dependability than other identification tools, but its procedure contains feature extraction via radon changing and singular quantity disintegration and classifies action in a normalized distance measure.

Liu and Song [70] suggested a real-time embedded finger-vein recognition system for authentication on mobile devices. This system was applied on a DSP platform equipped with finger-vein recognition algorithm. To validate one input finger-vein sample and achieved an equal error rate of 0.07 percent on a database of 100 subjects, it took the system about 0.8 seconds. The findings from this system showed that the finger-vein recognition system is capable of authentication on mobile devices. However, the system was not implemented on the PC system to know its accuracy and throughput. The 100 subjects are also low compared to technology growth rate in the present age.

A research on a finger vein identification mechanism using minutiae features with spurious minutiae removal mechanism was offered by Prabhakar and Thomas [85]. They effectively removed a sum of false minutiae points, but their work did not further explain contrast enhancement and feature extraction. Hence, the identification system was not justified.

Yang et al. [20] developed three frameworks to conduct the combination of the width measurement and finger vein pattern i.e. the fusion frame work, the filter frame work, and the hybrid framework. The stability of soft biometric trait extracted directly from images cannot be explored further, as the measurement of a soft biometric trait depends on the scale of the image, which is related to the image acquisition device. Open finger vein database was used to test the method. It produced an equal error rate (EER) of 8.08% and matching rate of 76.87% accuracy. In Kumar and Zhou [15], a Gabor method was used to extract finger vein patterns, and fused finger vein and finger texture together. Yang et al. [20] proposed to use the width of the phalangeal joint as a soft biometric trait to enhance the recognition accuracy for finger vein. Although, they have solved some problems in their works but there still a lot of key problems remain unsolved. For example, the acquisition of the high-quality image, the high recognition rate, and the large-scale applications.

Song et al. [18] proposed a new finger-vein verification system based on the mean curvature. This system treated the intensity surface of an image as a geometrical object. Thus, their method treated vein patterns as sets of points with negative mean curvature to be determined as a valley-like structure. Matched Pixel Ratio (MPR) was used at the matching stage for evaluation of their system. In Huang et al. [139], the finger vein features were extracted using a wide line detector. Based on the proposed line detector, the authors aimed to obtain a more precise width of vein information.

A novel a multi-scale matched filter was proposed by Gupta and Gupta [87], which deal with the noise arisen due to non-uniform illumination, low local contrast, hair and skin texture. The performance of the method was tested with a public database of 3132 unconstrained finger vein images obtained from 156 subjects, and it has an equal error rate (EER) of 4.447%.

Table 8 summarizes the finger vein identification performance. Performance assessment is a very important way to know if the methods used need to be improved or not since the major stages of the finger vein scheme are constant [145]. The systems are measured through Receiver Operating Characteristic curve (ROC), which signifies the equilibrium between False Accept Rate (FAR) and False Reject Rate (FRR). The matching algorithm uses the threshold to decide. Thus, if the threshold is reduced, FAR or false match rate (FMR) increased and FRR or False Non-Match Rate (FNMR) decreased. Likewise, Equal error rate (EER) value can be attained from Receiver Operating Curve (ROC). The lower the EER, the better the system works. An accurate timeline of Finger vein identification and matching methods is presented in Figure 16.

Table 8. Finger vein identification Performance Measure

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	Performance Measure		Remark
				Accuracy (%)	EER	
[96]	ROI Detection image enhancement size normalization	ONPP-Manifold learning	Manifold distance		0.8	Private Dataset
[122]	Non	BWMB2DPCA	Nearest neighbor	97.7		Private Dataset
[78]	Gaussian high-pass filter	Binarization local binary pattern	Hamming distance		0.38	Private Dataset
[60]	Modified Gaussian high-pass filter	Local line binary pattern	Hamming distance		1.78	Private Dataset
[93]	ROI extraction, image resize	PCA	ANFIS (neuro-fuzzy system)	99		Private Dataset
[94]	ROI extraction, image resize	PCA, DCA	SVM and ANFIS	98		Private Dataset
[26]	Elimination of background Removal of noise Enhancement of finger vein image Brightness Normalization Size	Dynamic thresholding Median filter Morphological operation Vein location and direction coding	Template matching			
[123]	ROI extraction, median filter, histogram equalization	Morphological operation, maximum curvature points	MLP			

Table 8. Finger vein identification Performance Measure (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	Performance Measure		Remark
				Accuracy (%)	EER	
[58]	Gaussian matched filter	LBPV	Global matching, SVM	90.0	5.6	Private Dataset
[95]	Image gray processing ROI extraction Normalization (size and gray) metho	Personalized best bit map (PBBM)	Template matching		0.0038	Private Dataset
[124]	Histogram equalization Bucolic interpolation	Fractal dimension Wavelet transform	Wavelet transformation Energy feature		0.07	Private Dataset
[125]	ROI extraction CLAHE	Linear Kernel Entropy Component analysis (KECA)	Euclidian distance	98.0		Private Dataset
[70]	Binarized ROI Thinned Gabor filter	Minutiae-based extraction	Euclidian distance			
[146]	Image denoising ROI localization Image enhancements	LLBP PLLBP	Histogram intersection	99.2		Private Dataset

Table 8. Finger vein identification Performance Measure (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	Performance Measure		Remark
				Accuracy (%)	EER	
[63]	ROI extraction Enhancement Normalization size	Local line binary pattern	PWM-LLBP	99.67		Private Dataset
[16]	Gabor filtering	Global thresholding, Gabor filter	SVM	95.0		PKU Dataset
[127]	ROI extractions	GLLPB	Soft power metric		0.61	Private Dataset
[53]	Anisotropic diffusion method Non-scatter transmission maps Gabor wavelet	Directional filtering method	Phase only correlation strategy			
[128]	Edge detection ROI Extraction Smoothing filter	Personalized best bit map (PBBM)	Cross-correlation matching		0.0038	Private Dataset
[129]	ROI Extraction (HCGR) Histogram of competitive Gabor response Matching	Histogram of competitive Gabor response (HCGR)	Matching		0.671	Private Dataset

Table 8. Finger vein identification Performance Measure (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	Performance Measure		Remark
				Accuracy (%)	EER	
[87]	Region of interest extraction Multiscale matched filtering Line tracking	Variational approach	Sum of square differences		4.47	Private Dataset
[88]	ROI extraction, normalization	Image contrast, gradient in spatial domain, Gabor feature, information capacity and entropy	SVR		4.88	HKPU Dataset
[130]	ROI Localization Image enhancement	Uniform optimal uniform rotation invariant LBP descriptor	Histogram intersection method	99.65	9.35	Private Dataset
[75]	Sobel operator	multi-directional finding method	Modified Hausdorff distance	97.14		Private Dataset
[131]	Normalization, filtering, resizing	Grid-based location, feature-level fusion by FFF, optimization	K-SVM	96	0.35	Private Dataset

Table 8. Finger vein identification Performance Measure (continued)

Reference	Preprocessing Method	Feature Extraction Method	Matching Methods	Performance Measure		Remark
				Accuracy (%)	EER	
[132]	ROI extraction, image resize	Convolutional neural network	Convolutional neural network			
[133]	Size normalization ROI Extraction Gray normalization	CLLBP	Matching score		0.055	Private Dataset
[134]	ROI Extraction Image enhancement	Fractal dimension Lacunae Gabor filter	Difference compared with threshold value		0.03	Private Dataset
[135]	mini-ROI	three convolutions layers	Two channel network learning		0.10 0.47	MMCBNU_6000 SDUMLA
[147]	mini-ROI	three convolutions layers	Convolutional neural network			Private Dataset
[148]	ROI Extraction Image enhancement	convolutions layers	4 CNN model			Private Dataset
[149]	ROI Extraction Image enhancement	convolutions layers	CNN and k-NN		0.06	Private Dataset
[150]	ROI Extraction Image enhancement	convolutions layers	three convolutions layers and two fully linked layers comprise the CNN model (FCL)		0.05	FV-USM

[151]	ROI Extraction Image enhancement	convolutions layers	Adaptive K-nearest Centroid Neighbor (Ak-NCN)		0.64	FV-USM
[152]	ROI Extraction Image enhancement		Texture Descriptors		0.07	Private Dataset
[153]	ROI Extraction Image enhancement	Xception model based on depth-wise separable	convolutional neural network		0.08	Private Dataset

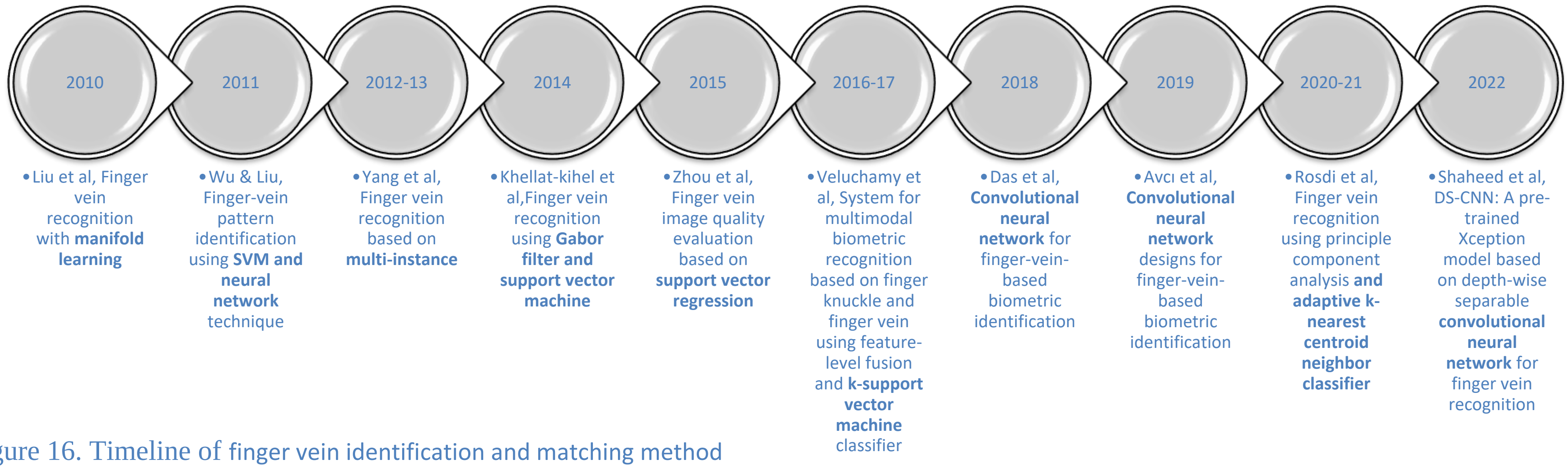


Figure 16. Timeline of finger vein identification and matching method

In [96], the authors use Manifold Learning to identify finger vein. This approach has the benefit of a high recognition rate due to the feature's small dimensions, a reduction that changes the picture from a higher to a smaller dimension. The disadvantage of this approach is that global features are highly dependent on parameters like location, occlusion, distortion, and lighting and are hence unsuitable for extraction as vein finger features.

In [93] , [94] and [123], neural network and SVM methods have been used to identify finger vein. In [93] is used ANFIS (neuro-fuzzy system) .In [94], is used PCA and Linear Discriminant Analysis (LDA), as well as matching through SVM and an Adaptive Neuro Fuzzy Inference System (ANFIS). It only works in an environment with controlled background noise, some images are damaged due to poor lighting, observation angle, and other parameters.

In the papers [58] and [95], conventional recognition have been used to identify finger vein, such as multi-instance and LBP. In 2012, it is worth noting that Harsha and Subashini [124] are presented a novel finger-vein recognition system for authenticated on teller machine. Also, Liu and Song are presented a real-time finger-vein recognition system for mobile devices [70].

Khellat-kihel and e al. [16], is used information capacity, a gradient in the spatial domain, entropy with image, contrast and Gabor feature and matching by Support Vector Regression (SVR) for finger vein recognition(machine learning methods).. The disadvantage of this method, focus on integrating and creating an ROI in the venous system. It is a multimodal scheme as many biometric systems. Zhou and et al In [88], feature extraction methods are image contrast, gradient in spatial domain, Gabor feature, information capacity and entropy. Support vector regression (SVR) is matching method (machine learning methods). Veluchamy and Karlmarx [131], are used Location on a grid, feature-level fusion by Fractional Firefly (FFF) and matching by K-Means Support Vector Regression (K-SVM) for multimodal biometric recognition (machine learning methods). In this paper, Various objective functions are required to be developed to find the ideal weight score and to improve results.

Liu and et al. [133] , are used Gray and size normalization with ROI extraction, Customized Local Line Binary Pattern (CLLBP) and matching score for finger vein recognition. Since it only deals with the acquisition system's image improvement direction, it needs to be central to this plan.

In [147] is presented Convolutional neural network for finger-vein-based biometric identification. In this paper is used five convolutional layers, three max pooling layers, one SoftMax layer, and one ReLu layer with contrast-limited adaptive histogram equalization make up the Convolutional Neural Network (CNN) Model (CLAH). The disadvantage of this approach is that cannot be used on photos of non-trained classes’ finger veins.

Also, Avcı and et al. [148] are presented Convolutional neural network designs for finger-vein-based biometric identification. Data augmentation may be used to enhance training samples for four datasets using non-publicly available data to reduce over customization of the CNN designs.

Zhao et al. [150], are used three convolutional layers, three max pooling layers, and two fully linked layers comprise the CNN model (FCL) for finger vein recognition. The suggested system is not robust, and you should improve the performance accuracy. Second, the details of this model should be enhanced and supplemented with the loss function in trials to enable comparison of comparable performance and study of the benefits and drawbacks of each loss function

Rosdi and et al. [151], are discussed analyses of the principal components and an Adaptive K-Nearest Centroid Neighbour Classifer for finger vein recognition. As an upgrade to the kNCN classifer, an Adaptive Centroid Closer Neighbor (akNCN) is presented. In the two experiments at akNCN. .v1 and akNCN.v2 The accuracy was 85.64 and there was no improvement in accuracy but the time difference was up to 5,153 seconds for v2 while it was 6,321 for v1. The proposed classifer achieves little classifcation accuracy compared to the original kNCN being compared. On Asaha, on the other hand, a lot of information is neglected. This method reduces the size of the training data and removes templates.

5. Conclusion

This paper presents an overview of the literature regarding finger vein and acquisition devices. This study also reviews several types of image enhancement, feature extraction methods, and related finger vein identification work.

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