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Vein Feature Extraction Techniques for Biometric Identifications: A Survey

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Abstract: Privacy of personal information and security in Financial Transactions are serious concern in the modern world today. In this regards many sophisticated systems are available but biometrics remains the most reliable of them all. Vein pattern extraction has emerged as a promising biometric modality due to its unique characteristics, such as being internal, invisible, and highly complex. This paper presents a comprehensive review of vein pattern extraction methods for biometric applications, and also focusing on low-cost and portable Image acquisition through near-infrared (NIR) imaging and it's pre-processing. The review covers various stages of vein pattern extraction, which includes Image acquisition, pre-processing and feature extraction. Finally, it concludes with a discussion on potential future research directions to further enhance the accuracy and reliability of vein pattern extraction for biometric applications.

***Keywords**: Biometric, Identification, Vein Feature Extractions, NIR Imaging System*

1. INTRODUCTION

Vein Pattern based Biometrics (also known as Vascular Biometrics) is a cutting-edge technology in the field of biometric identification. Unlike traditional biometric modalities such as fingerprints or iris scans, which rely on external features, vascular biometrics utilizes the unique patterns of veins within the human body for identification purposes. This innovative approach offers several advantages, including non-invasiveness, enhanced security, accuracy, and resistance to spoofing. Biometrics are usually classified into two different types: (1) physiological biometrics, which are based on physical characteristics and (2) behavioral biometrics, which are based on patterns of behavior [1]. Each type of biometric has its own advantages, limitations, and applications, and the choice of biometric modality depends on factors such as security requirements, user acceptance, and deployment environment.

Vascular biometrics (finger, hand, and wrist vein recognition) exhibits several advantages over other biometric modalities (fingerprint and face/palm print recognition) [2].

- Vascular Biometrics provides contactless image sensing, as the Image Acquisition camera is not coming in direct contact with the human hand
- As the Vascular Biometrics are based on NIR imaging it is expected to be insensitive to skin surface condition (i.e dirt, dryness, lotion) and abrasion (scars, cuts).
- As only the vessels are visible in the infrared region, Vascular Biometrics systems acts as more robust systems against forgeries (Presentation attacks).
- Real-time vessel detection is also possible through NIR video acquisition and relevant video analysis.

In addition to the above mentioned advantages, finger/hand vein imaging system has certain drawbacks. Mainly with the quality of the acquired image, a high-quality IR camera must be required with the illuminating source having optimum intensity [3]. Enhancing the accuracy and efficiency of recognition is the main problem faced by biometric systems. The comparison of various characteristics of different biometric modalities is described below [3,4,5].

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Table 1: The comparison of different Biometric methods based on various characteristics [3,4,5].

Biometric Trait	Accuracy	Size of Template	Cost	Performance	Stability	Security Level	Commercial Use
Finger Print	Medium	Small	Low	Medium	Low	Low	High
Facial Recognition		Large	High	Medium	Low	Low	Medium
Iris Scan	High	Small	High	High	Medium	Medium	Medium
Voice Recognition	Low	Small	Medium	Medium	Low	Low	Low
Finger Vein	High	Medium	Medium	High	High	High	Low
Hand/Palm Geometry	High	Small	Medium	Medium	Medium	Medium	Medium

Principle: Near Infra-Red (Nir) Imaging

In traditional medical practices, vascular images are obtained through X-ray and ultrasonic scanning. Although these techniques have the capability to generate high-resolution images of blood vessels, they entail an invasive approach necessitating the injection of agents into the blood vessels. This invasive approach makes these techniques unsuitable for general purpose biometric applications. Thus, acquiring the vein patterns through non-invasive and cost-effective way is the key challenge in vascular biometrics [6]. Under normal visible light conditions, the visibility of human vein patterns beneath the skin is very low. However, this can be resolved by using Near-Infrared (NIR) imaging techniques [6].

NIR can penetrate into the biological tissue up to 3mm of depth and more IR radiation is getting absorbed by the reduced hemoglobin in venous blood [7]. Therefore by transmitting the IR radiation of a designated wavelength toward the targeted body area, an IR camera can capture the vein image and the vein appears darker than the surrounding tissue in the acquired image [6].

2. Literature Survey: Various Algorithms for Feature Extraction in Image

N Miura et al. [8] proposed the method that uses the repeating line tracking algorithm that starts from different positions to extracts the finger-vein pattern from the Infrared images. After identifying the local dark lines, line tracking is carried out by moving pixel by pixel along the lines. An additional tracking operation begins at a different location if a dark line cannot be seen. By carrying out these local line tracking operations repeatedly, it is possible to track every one of the image's dark lines.

Beng, T et al. [9] the authors propose a method that involves creating a pattern map (PM) from the finger vein image, followed by applying principal component analysis (PCA) for feature extraction in the proposed biometric verification system, while back-propagation (BP) networks and adaptive neuro-fuzzy inference systems (ANFIS) are used for pattern classification. The integration of PM and PCA effectively enhances the performance of system, making it a promising approach for biometric authentication.

Zhongbo, Z et al. [10] proposed an advanced technique for finger-vein identification by combining multiscale feature extraction using the Curvelet transform with a Local Inter-connection Structure Neural Network (LISNN) to process the multiscale features extracted by the Curvelet transform. The integration of Curvelet-based feature extraction with LISNN provides a powerful approach to finger-vein identification.

Choi, J et al. [11] proposed a method for finger-vein patterns extraction by utilizing Gradient normalization (GN), Principal curvature techniques and Binarization. Gradient normalization helps in reducing the effects of varying lighting conditions and noise, thus enhancing the visibility of vein patterns and creates a uniform background, making the vein patterns more prominent. Principal curvature which is created from Eigen values captures the intrinsic geometrical properties of the vein patterns, highlighting the curved features of the veins.

Liu, Z et al. [12] introduces a method that leverages manifold learning techniques to improve the accuracy and efficiency of biometric identification systems. The method uses Orthogonal Neighborhood Preserving Projections (ONPP) for feature extraction and dimensionality reduction that preserves the local neighborhood structure of high-dimensional data in a lower-dimensional space.

Guan, F et al. [13] used Bi-Directional Weighted Modular Block-Based Two-Dimensional Principal Component Analysis (B2DPCA) technique, this method operates in a bi-directional manner, considering both horizontal and vertical directions of the image data. B2DPCA is used to extract principal features from modular blocks assigned with different weight based on their significance of the finger-vein images. The modular and weighted strategies enhance the method's ability to handle variations in finger-vein images caused by factors such as uneven IR lighting, rotation, and translation.

Lee et al. [14] proposes the method that utilizes Weighted Local Binary Pattern (WLBP) codes combined with a Support Vector Machine (SVM) classifier to improve the accuracy and robustness of the systems. WLBP is an extension of the Local Binary Pattern (LBP) technique; weights are assigned to the LBP to emphasize the most significant features, which are used for texture analysis. SVM classifier learns to distinguish between different individuals based on their unique finger-vein patterns.

Song, W et al. [15] used the Mean curvature technique (MCT) to detect and enhance the vein patterns in finger-vein images. It captures the curvature of the vein structures, highlighting the prominent features while suppressing noise and irrelevant details. The mean curvature-based approach improves the clarity and distinctiveness of the extracted vein patterns, leading to higher verification accuracy.

Park et al. [16] proposed the method that enhances the accuracy of finger-vein recognition by combining Gabor Wavelet and LBP to extract global and local features respectively from vein image. The method also uses the SVM classifier that effectively handles the high-dimensional feature space and provides robust classification performance.

Chen et al. [17] proposes a finger vein image recognition method based on Tri-Value Template Fuzzy Matching. It involves creating templates from finger vein images and applying fuzzy logic to handle variations and uncertainties in the matching process. The finger vein images are segmented using predefine threshold value into three areas: the subject area, the fuzzy area and the background area, then after subject area and fuzzy area used for matching. The matching process accommodates variations in vein patterns due to factors such as uneven lighting conditions, orientation, and image quality.

Ushapriya et al. [18] uses Radon transform in addition to PCA for feature extraction. In that instance, PCA is used to each projection matrix after the features are obtained using the Radon projections of an image of a finger vein in various orientations.

Dong et al. [19] presented the transformation of Weighted Symmetric Local Graph Structure (W-SLGS) into Multi-Oriented W-SLGS (MOW-SLGS). Similar to the SLGS, this technique compares the pixel values for a variety of angles in both clockwise and counterclockwise directions. From the resulting feature vectors, the maximum value is selected as the feature of the target pixel, and the pixel's weight is determined based on the distance between the pixels.

Lu et al. [20] introduced the Generalized Local Line Binary Pattern (GLLBP) algorithm for vein feature extraction; this technique captures local texture and line information from finger vein images. The extracted features are encoded into binary patterns, which are then used to create a feature vector for each finger vein image.

Yang et al. [21] used 2D- Principal Component Analysis $(2D)^2$PCA and metric learning techniques. $(2D)^2$PCA is a variant of the traditional PCA, specifically designed for two-dimensional image data. $(2D)^2$PCA is applied to the preprocessed images to extract essential features while reducing dimensionality, while metric learning step enhances the ability to distinguish between different individuals by optimizing the feature space for better separability.

Damavandinejadmonfared et al. [22] tested the effectiveness of a neural network with different numbers of training and testing images for each subject using PCA, KPCA, and KECA.

You et al. [23] combines two methods: Two-Dimensional Principal Component Analysis $(2D)^2$PCA with Kernel Maximum Margin Criterion (KMMC) to enhance the accuracy and reliability of biometric systems. $(2D)^2$PCA is a feature extraction technique that operates directly on two-dimensional image matrices, preserving the spatial information of finger vein images. KMMC is a technique used to improve the discriminative power of the extracted features by maximizing the margin between different classes in a higher-dimensional feature space.

Liu et al. [24] uses Singular Value Decomposition (SVD) algorithm for vein recognition. SVD is a mathematical technique used to decompose a matrix into its singular values and corresponding vectors; this method is applied to finger vein images to extract significant features that are used for matching minutiae points. The matching method focuses on comparing these minutiae points to determine the similarity between different finger vein patterns.

Nivas et al. [25] uses the Repeated Line Tracking (RLT) algorithm during the feature extraction phase of the finger-vein recognition process. The algorithm starts by detecting initial line-like structures in the preprocessed image, which represent potential vein patterns. It tracks these lines by following the intensity changes in the image, iteratively confirming and enhancing the detected vein patterns. The process is repeated multiple times to ensure robustness, capturing even faint and unclear vein lines. The final output is a set of enhanced vein patterns that can be reliably used for matching against a database.

Liu et al. [26] introduces a Modified Repeated Line Tracking (MRLT) algorithm tailored for finger-vein segmentation. The modified approach addresses issues such as faint or broken vein lines, ensuring a more complete and accurate segmentation.

Kalaimathi, P et al. [27] introduces the Gradient Boosted Feature (GBF) Algorithm a novel approach for the extraction and authentication of finger-vein patterns. The Sobel Filter is used to highlights the edges of vein patterns by calculating the gradient of the image intensity at each pixel, thus making the vein patterns more distinct and easier to process in subsequent steps.

Babu et al. [28] proposes a sophisticated method for extracting features from finger-vein patterns utilizing Gabor Filters, which are effective in capturing texture information and edge details at multiple orientations and scales. To filter out unwanted regions, they have used Gabor Filter with specific orientation and convolved them with the enhanced image. After that the morphological operation are performed to further enhance the quality of the vein pattern.

3. Description of Vein Pattern Detection System

NIR based Vein Imaging system works in different phases: Image Data collection, Image Pre-processing, Vein Pattern Extraction, Pattern matching [6].

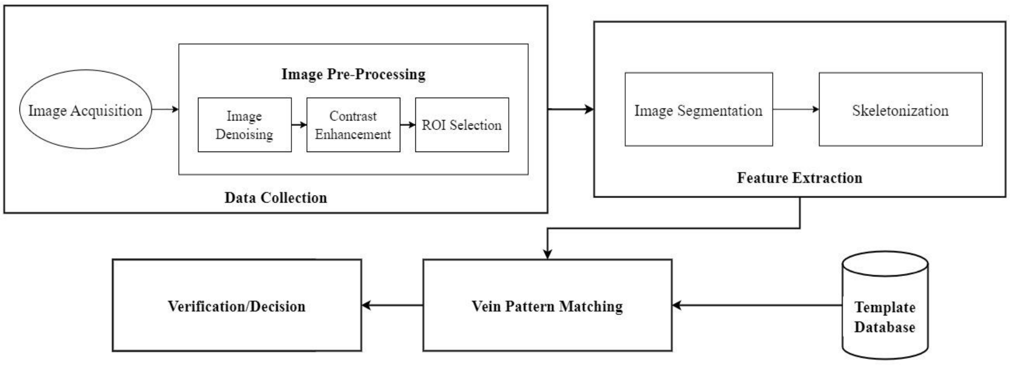

Fig. 1: Vein pattern detection and verification system model

A. Image Acquisition

An Image acquisition module mainly consists of three parts: A Near Infrared LED light source, NIR filter and CCD camera to capture the IR image. As shown in fig. 2, an array of Infrared LEDs is used as NIR light source that illuminates the backside of the finger/palm. In order to get the proper contrast between veins and the surrounding tissue the light source should provide the perfect illumination in the IR spectrum (wavelength round 850 nm). The IR-sensitive CCD camera captures the transmitted infrared IR light from the Finger's skin surface. Since veins absorb more infrared light compared to surrounding tissue, they appear darker or more prominent in the captured image. NIR filter is used before the CCD camera to avoid the interference of ambient light from the environment.

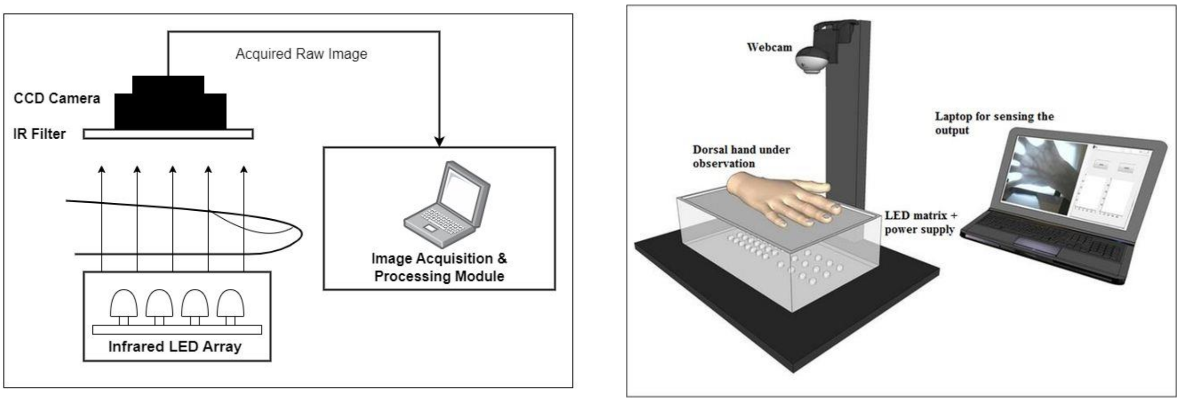

Fig. 2: System setup of Vein Image Acquisition Module [29]

B. Image Processing

The vein images captured by CCD camera is in RGB format and that must be converted in to grey scale image for faster processing in further stages compared to colored image [30]. After the acquisition of raw vein images various image pre-processing algorithms i.e. image denoising, contrast enhancement and ROI selection must be implemented on it through software module (MATLAB). Since the CCD camera captures images in real-time, they often contain noise, such as salt and pepper noise. To eliminate this noise and reveal the underlying information, smoothing, or image denoising, is performed using a Median Filter. The median filter, a non-linear filter, substitutes each pixel with the median value of its neighboring pixels. Following to this various Image Enhancement techniques i.e. sharpening and contrast adjustments are done so, that the veins appears darker and can be easily discriminated with the surrounding tissue [3, 29]. In addition to conventional image processing techniques, a number of highly sophisticated techniques are now used on images in order to extract the best information possible and maximize the overall image quality.

The crucial step in image pre-processing is image segmentation, which transforms the representation of a digital image into more meaningful and easily readable elements such as pixels, boundaries, and contours as shown in the fig.3.

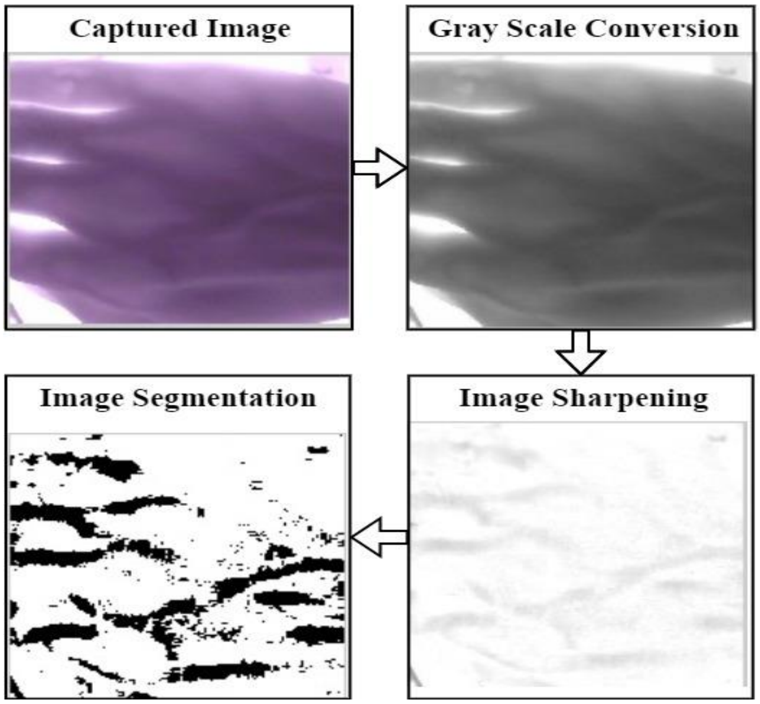

Fig. 3: Implementation of various Image Processing algorithms on Captured RGB Image

The system needs to separate only the vein pattern from the captured image; otherwise, it serves no purpose. Various algorithms have been proposed to study this pattern exclusively, which will further help in verification process.

Among the many methods of image segmentation, image thresholding is the most suitable for this application. Thresholding divides each pixel of the image into two parts based on a threshold parameter. If the intensity is greater than that parameter, the pixels are assigned to one particular class; otherwise, they are assigned to another class.

C. Image Verification(Matching)

Pattern verification or matching in the biometrics systems is the final stage in which the features extracted from the pre-processed image is matched with the stored templates in the database. This can be done using multiple algorithms like (i) Correlation based matching in which measuring the correlation between the new image and the stored templates. (ii) Distance Metrics Method in which by calculating the distance between feature points in the new image and the templates and (iii) Machine Learning Techniques using classifiers such as support vector machines (SVM) or neural networks to perform the matching based on the extracted features.

4. COMPARITIVE ANALYSIS OF THE FEATURE EXTRACTION ALGORITHMS

Vein recognition is a biometric technology that identifies individuals based on the unique vein patterns. There are several approaches to vein recognition, as there are multiple methods and parameters which can be used for Feature Extraction. Broadly Feature Extraction Algorithms can be divided in three categories: Local Binary Based Algorithm, Vein Pattern Based Algorithm and Dimensionality Reduction Based Algorithm. Normally the performance of the Feature Extraction Methods are evaluated according to Equal Error Rate (EER) and Recognition Rate (RR).

A. Local Binary Based Algorithm:

The Extracted Features are presented in Binary format in this method. There are various techniques that comes under this category i.e. Local Binary Pattern (LBP), LLBP, Local Directional Code (LDC), Personalized Weight Maps (PWM), PBBM etc.

B. Vein Pattern Based Algorithm:

In this Method, after the image acquisition several pre-processing task i.e. image enhancement, segmentation etc. are done, then after various geometric shapes are used for verification or matching purpose. Some of the feature extraction methods lies in this category are: Principal Curvature [11], Mean Curvature [15], Gabor [28], repeated line tracking (RLT) [25] and modified repeated line tracking (MRLT).

C. Dimensionality Reduction Based Algorithm:

Dimensionality reduction techniques are essential tools in feature extraction that helps in reducing the dimensions of the image from higher to lower dimensions. The most common dimensionality reduction techniques are: PCA [9, 18], $(2D)^2$PCA [21, 23], LDA. These methods uses neural networks and machine learning.

Sr. No.	Key Features/ Algorithm used	Category Type	Advantages/EER/RR
1	Principal Curvature, Gradient Normalization and Binarization [11]	Vein Pattern Based	EER=036%, Unaffected by vein thickness or brightness
2	Mean Curvature [15]	Vein Pattern Based	EER=0.25%, Pattern extraction in unclear vein images
3	Repeated Line Tracking [25]	Vein Pattern Based	EER=0.145%
4	Gabor [28]	Vein Pattern Based	EER=065%, captures local orientation and frequency
5	Modified Repeated Line Tracking (MRLT)	Vein Pattern Based	NA
6	PCA [9]	Dimensionality Reduction Based	RR=99%
7	Manifold Learning [12]	Dimensionality Reduction Based	RR=97.8% and EER=0.8%
8	$(2D)^2$PCA [21]	Dimensionality Reduction Based	RR=99.17%
9	LDA	Dimensionality Reduction Based	RR=98%
10	Use of NN for local feature	Local Binary Based	EER=0.128%

	extraction [10]		
11	Weighted LBP [14]	Local Binary Based	EER=0.0049%
12	Combination of LBP and Wavelet transformation [16]	Local Binary Based	EER=0.011%
13	Combination of LBP and LDP [17]	Local Binary Based	EER=0.89%
14	MOW-SLGS [19]	Local Binary Based	RR=96%

Table 2: The comparison of various Algorithms based on their advantages [1, 3].

5. Conclusion

In this comprehensive survey various feature extraction methods used for the Vascular Biometric applications are presented. The importance of vein biometrics stems from their inherent advantages, such as high uniqueness, invisible, complex patterns, and resistance to spoofing, making them a robust choice for secure identification systems. We have also presented various prerequisite steps of feature extractions such as image acquisition and image processing. We have presented the review of traditional vein pattern based feature extraction methods i.e. mean curvature, Gabor filters etc. to the advanced machine learning approaches i.e. support vector machines (SVM) and principal component analysis (PCA) with comparative analysis. The presented system is most reliable and secure compared to other biometric modalities, despite having some shortcomings.

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