Kolivand, H, Akintoye, KA, Asadianfam, S and Rahim, MS

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Improved methods for finger vein identification using composite Median-Wiener filter and hierarchical centroid features extraction

Hoshang Kolivand[1] • Kayode Akinlekan Akintoye[2] • Shiva Asadianfam[1,3,4] • Mohd Shafry Rahim[2]

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Abstract

Finger vein patterns contain highly discriminative characteristics, which are difficult to be forged due to residing underneath the skin. Several pieces of research have been carried out in this field but there is still an unresolved issue when data capturing and processing is of low quality. Low-quality data have caused errors in the feature extraction process and reduced identification performance rate in finger vein identification. The objective of this paper is to address this issue by presenting two methods, a new image enhancement, and a feature extraction method. The image enhancement, Composite Median-Wiener (CMW) filter, improves image quality and preserves the edges. Moreover, the feature extraction method, Hierarchical Centroid Feature Method (HCM), is fused with the statistical pixel-based distribution feature method at the feature-level fusion to improve the performance of finger vein identification. These methods were evaluated on public SDUMLA-HMT and FV-USM finger vein databases. Each database was divided into training and testing sets. The average result of the experiments conducted was taken to ensure the accuracy of the measurements. The k-Nearest Neighbor classifier with city block distance to match the features was implemented. Both these methods produced accuracy as high as 97.64% for identification rate and 1.11% of equal error rate (EER) for measures verification rate. These showed that the accuracy of the proposed finger vein identification method is higher than the existing methods. The results have proven that the CMW filter and HCM have significantly improved the accuracy of finger vein identification.

Keywords Biometric system · Finger vein identification · Composite Median-Wiener · Feature extraction · Hierarchical Centroid Feature Method

✉ Shiva Asadianfam
sh_asadianfam@yahoo.com

Extended author information available on the last page of the article

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1 Introduction

Biometric via physiological attributes (fingerprint, dorsal vein, finger vein, and facial) or behavioral characters (signature, speech, and handwriting), refers to the science of validating and authenticating the identity of a person for automatic recognition [38, 50, 53]. Law enforcement agencies were the first to adopt biometric systems in the 1970s to investigate criminals through fingerprint recognition [18, 19]. However, with the current biometric technologies advancement, in parallel with the growth of threats in information security, biometric application systems have proliferated into the physical and logical access control domains [2, 48]. This kind of system gains attraction because the cost of biometric capture machines is low [28, 35, 61].

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 problems to be solved in this study can be described as follows: (a) Having a dataset of finger vein images corrupted by many characteristics of noises simultaneously with Gaussian noise and Impulse noise form mixed noise [14, 36]. The challenges are to increase the contrast level, divide the image into regions using neighborhood contrast intensity in order to get an exact localization of the region and employ different methods to filter the pixels in regions from noise. Based on this challenge, several issues are required to answer for a possible solution. It is discovered that many existing image enhancement methods are limited to increasing the contrast level and filtering [43]. Also, it has been studied that satisfactory filtering cannot be obtained using a single filter method [5, 24]. Hence, the main challenge is the development of an improved image enhancement method to be used in removing the mixed noise. (b) The next issue is related to the feature extraction methods, which are the fundamental components of finger vein identification systems. Various methods to extract the local and global features from finger vein images have been developed for a finger vein identification system. Extraction of local features are mainly using minutiae points, repeated line tracking and the maximum curvature method, which were found very difficult to produce enough information about finger vein images [46]. Also, some methods extract local and global features with complexity, which makes them so impractical for real-life applications [16]. Compared to a single extraction type of feature, the fusion of many features of extraction can improve the performance of the finger vein identification system [6]. Therefore, it was found that the areas for a combination of multiple features in the feature extraction stage for the finger vein identification system need to be explored more [49].

Besides the features extraction, the combination of classifier and metric distance employed has a significant effect on similarity matching between the query and the data images, which affects the performance of the system [41]. Enhancement of finger vein images is the procedure of extracting Region of Interest (ROI) and improving the image quality, out of a reduced input image quality [51]. ROI refers to a discrete section of the image that detects some specific objects extracted from the image [27, 37, 58].

The contributions of this research are:

- Proposing an image enhancement method that removes the mixed noise and improves the contrast in the finger vein images.

- Enhancing the feature extraction method based on texture and structural features that improve the similar matching between the query and data images in order to improve the accuracy of the identification scheme for the noisy finger vein images.
- Optimizing finger vein identification (FVI) based on the supervised learning algorithm (SLA).

The organization of this paper is as follows: In Section 2, a review of previous studies related to finger vein identification is investigated. In Section 3, the methodology of research is presented in detail. In Section 4, the qualitative and quantitative experimental results are described. Finally, in Section 5, a general conclusion is drawn.

2 Literature review

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 [55] and even in finger vein identification systems [31]. 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. Enhancement of finger vein images is the procedure of extracting Region of Interest (ROI) and improving the image quality, out of a reduced input image quality [51]. ROI refers to a discrete section of the image that detects some specific objects extracted from the image [27, 37, 58].

Working with finger vein images has anonymities such as noise, blurred, and low contrast in some vein tissues. Noise is unwanted information added to an original finger vein image, which reduces the image quality [33, 58]. Noise in finger vein images has several origins. The photoelectronic during finger vein capturing caused the Gaussian noise due to the thermal motion of the electron. Likewise, an unstable network caused impulse noise known as Salt-and-pepper noise during the transmission of the image [17]. When an image is corrupted by several feature noises simultaneously such as a combination of Gaussian and impulse noise on an image, it is known as mixed noise, which is common in finger vein images [1, 16, 42, 54].

The feature extraction process in the finger vein is performed to find a subset of features to ensure either the maximum effectiveness of identification or the efficiency of the process (by minimizing the number of features) or both. Many features can be extracted from the image properties. These features can be categorized into five sets: image characteristics-based features, statistical calculation-based features, a region of pixels-based features, the boundary of segmented region-based features, and image textures-based features [12]. Nevertheless, the type of features depends mainly on the state of images employed in the identification. Finger vein images are in various states of low image contrast, an uneven-illumination, scale variation, hair and skin texture, which occurred as a result of noise. It is worth noting that feature extraction for finger vein using the methods referred to in this paragraph still needs more image enhancement to improve the accuracy level performance of the finger vein identification scheme. In this context, the scheme is the method of attaining finger vein images to identify individuals accurately.

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 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 [40].

Datta et al. [11] presented a novel technique to detect caries lesions using isophote concepts. Early detection of caries lesions prevents the spreading of infection. Dental x-ray images have a poor intensity which results in difficulties in finding the exact affected area at a glance. They addressed the issue by employing a traditional handcrafted method as deep learning methods were not suitable due to a lack of training set available.

Table 1 shows the previous methods used in vein image enhancement, which are either single-based or multiple-based. The methods were only applied to single noise images, which forms the limitation.

3 Research methodology

The operational framework shows the overall processes required to achieve the aim of this research and it includes the research design of the proposed scheme of the study. This research proposes a general framework as seen in Fig. 1. The framework of this research consists of three main phases, which are preprocessing, feature extraction, and matching. Each phase is described in separate sections. The operational framework of this study is shown in Table 2.

3.1 Proposed image enhancement framework (preprocessing)

In finger vein identification, the feature extraction depends on the quality of image enhanced. The proposed research suggests composite filter method to achieve image enhancement

Table 1 Previous research on image enhancement and quality evaluation

References	Name of Method	Enhancement Methods		Limitations
		Single-Based	Multiple-Based	
[16]	Multiscale matched filtering	√		Treated single noise
[42]	Gabor filters	√		Treated single noise
[30]	Elliptic high pass filter	√		Treated single noise
[56]	Median filter	√		Treated single noise
[52]	Gaussian filter Elliptic high	√		Treated single noise
[44]	Fusion of Gabor filter and Retinex filter		√	Treated single noise
[13]	Interval type- 2 fuzzy set	√		Treated single noise
[3]	Gabor filter and Canny edge detector		√	Treated single noise

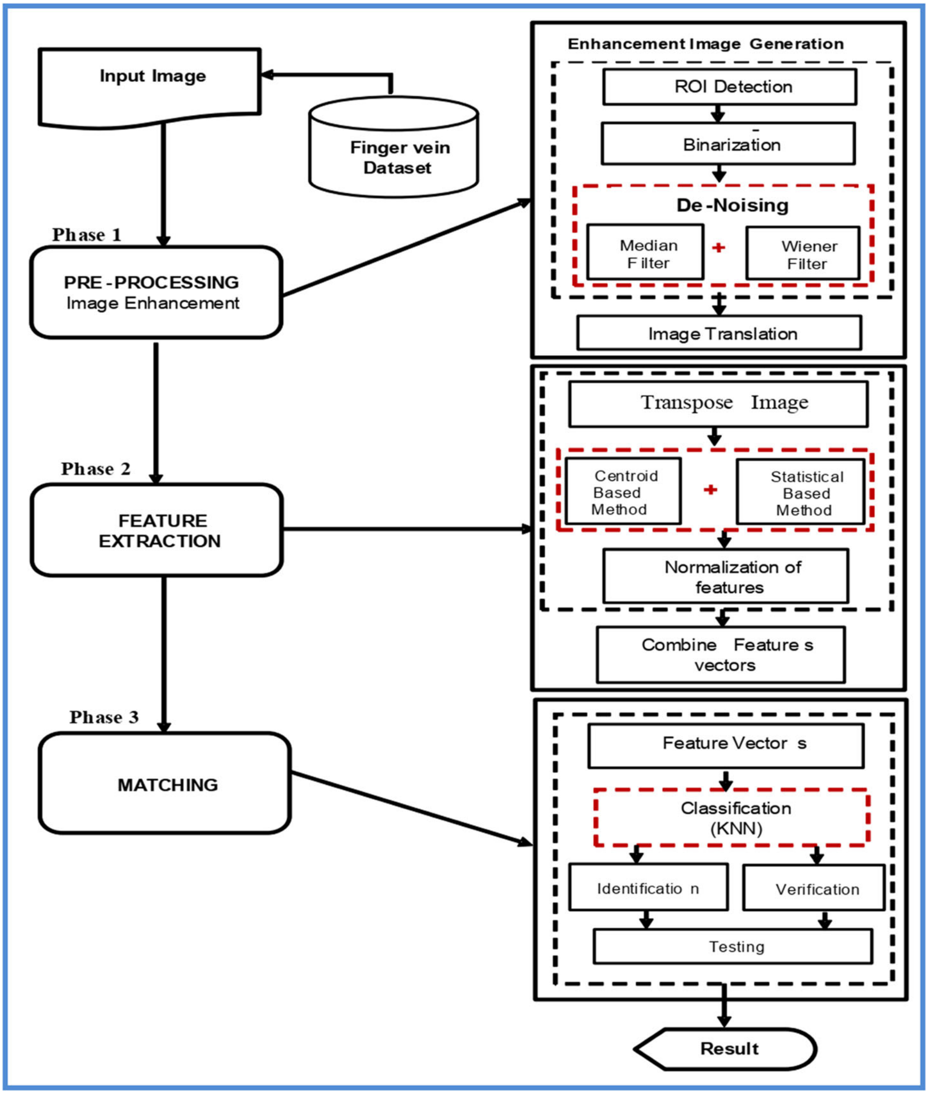

Fig. 1 Proposed framework

scheme. Therefore, several points have been considered in the proposed contrast enhancement stage, such as region of interest (ROI) detection, binarization for segmentation, and denoising the image using Composite Median- Wiener (CMW) filter.

3.1.1 Region of interest detection

Location of region of interest (ROI) idea in image enhancement is to extract the interest region from a finger vein sample that can solely represent the vein pattern. This is used to improve the visibility of the vein patterns. For the finger region detection, an existing simple localization-based ROI extraction algorithm is used. Algorithm 1 illustrates the algorithm of region of interest detection.

Table 2 Operational framework

Main Phases	Research Question	Objective	Methodology	Performance Measurement	Results Comparison
1	How can noisy finger vein images be improved to ensure better performance for finger vein identification?	**To propose** an image enhancement method that removes the noise and improve the contrast in the linger vein images.	Detecting Region of Interest (ROD of the image using Mask Filter Binarized the ROI for segmentation, Enhancing the vein segment using Composite Median-Wiener Filter Method	- visualization - peak signal-to-noise ratio (PSNR)	Proposed method with existing methods
2	What representations or features extracted from finger vein image are most appropriate to reflect the uniqueness of person?	**To enhance** the feature extraction method based on texture and structural features that could improve the similarity matching between the query and data images in order to improve the performance of the identification scheme for the noisy finger vein images.	Fusing Hierarchical Centroid Feature with other statistical pixel-based distribution features using Combined Feature Extraction Method (CFM) at feature-level fusion.	-Computation time -Accuracy	Comparison with other feature extraction methods and their results in term of identification and verification performance.
3	Are the optimized features extracted from the finger vein be efficient for identification and verification tasks?	**To optimize** finger vein identification (FYI) based on the supervised learning algorithm (SLA).	Performing matching on feature vector using k-Nearest Neighbor (kNN) classifier with City block distance metric	-Mean value -Standard deviation -Confident interval -Identification rate -Average Equal Error Rate (EER)	Comparison with variation value of kNN classifier with different distance metrics

Algorithm 1. Region of interest detection algorithm

Input: Gray Finger vein (FV) image
Output: Finger vein region and edges
Parameter: mask_height; mask_width
Begin
For each image do

i. Read-in FV image
ii. determine lower half starting point of image
iii. construct mask for filtering
iv. filtering image with mask (using both upper part & lower part)
v. filling region in-between upper and lower edges
vi. save finger edges
vii. show the original, detected region and edges

End for
End

3.1.2 Binarization

The digital finger vein images are normally maneuvered and characterized as a grayscale image. In such a manner, the binarization algorithm has been applied to utilize a variety of threshold esteems**.** The proposed algorithm contains four classes of pixel reaches to changes over the grayscale image to a binary image. The output image replaces all pixels in the input image with luminance greater than the level with the value 1 (black) and replaces all other pixels with the value 0 (white). The four specific levels are in the range [0,1]. This range is with respect to the signal levels likely for the image's class. The proposed algorithm for binarization is in algorithm 2.

Algorithm 2. Binarization algorithm

Input: Gray Finger vein (FV) image I
Output: white and black binary image I
Parameter: f(I, j) for pixel gray-level value, T for threshold level value
Begin
For each image do

i. Read-in FV image with gray levels of pixels[i,….j]
ii. Compute histogran and average of intensity distribution of image I
iii. Test for threshold, T at interval of gray-level average value
iv. Update the image I
v. show the orignal image I, binarized image I

End for
End

3.1.3 Remove unwanted objects

The binarized image may contain numerous items which are not wanted for our calculation. The goal of this step is to analyze the associated segments considering geometric properties (zone and measurement) and afterward expel the superfluous items. The unwanted objects in the finger vein image are the noises. The photoelectronic during finger vein capturing cause the Gaussian noise and impulse cause Salt-and-pepper noise during transmission of the image or due to bit errors. Wiener filter is well known for removing Gaussian noise, and the Median filter is used in removing Salt-and-pepper noise. The proposed composite image filter method was applied to remove all the connected unwanted objects (mixed noise) that contain in the image and produce another binary image. The composite image filter method is chosen based on the simplicity operation to remove any noise (without knowing the source) at low processing time.

3.1.4 Composite image filtering

Composite filter (CF) refers to the process of fusion two or more filters of distinct types [34]. Thus, composite image filter is the fusion of multiple image filters for enhancement of image with mixed noises. Figure 2 shows the general concept of CF framework where y_l, y_m, and y_h are the input signal low-pass, medium-pass, and high-pass respectively. G'_l, G'_m, and G'_h are the low- pass complement, medium-pass complement, and high-pass complement respectively, while y_{fl}, y_{fm}, y_{fh}, and y_{fc} are the output functions of low-pass, medium- pass, high-pass, and composite respectively. Every CF contains at least two parallel tracks with at least one auxiliary filter and at least one complementary filter element in the sequence. However, each auxiliary filter element has an integral form, which is sequentially fused with its complementary filter element to create a proper CF component. Table 3 describes the variable notations in the concept of CF and Fig. 2 shows a two-element and three-element form of the composite filters concept.

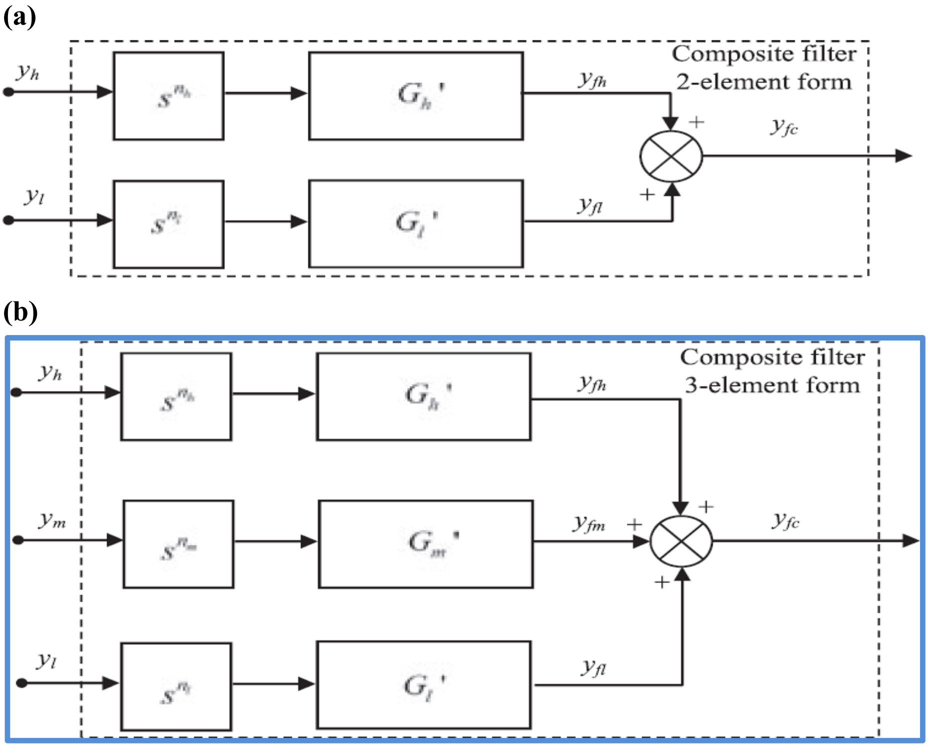

Fig. 2 Composite filters concept: **a** two-element form **b** three-element form

Table 3 Descriptions of CF variable notations

Notation	Meaning
yh	Input high-pass signal
yl	Input low-pass signal
ςnh	High-pass transform order variable
ςnl	Low-pass transform order variable
G'h	High-pass Complement (High-pass transfer function)
G'l	Low-pass Complement (Low-pass transfer function)
yfh	Output high-pass signal
yfl	Output low-pass signal
yfc	Output composite signal

The two-element CF shown in Fig. 2a is determined by the match of signals [*yh, yl*] such that the subscripts *h* and *l* denote the highest and lowest derivative information, respectively. The composite signal, *yfc*, is the result, which is a filtered evaluation of a certain input signal or a consistent unmeasured signal. Hence, for the situation of a two-element CF, the complementary element is essential to be fulfilled. In this study, a new composite image filter method has been proposed, which shares the advantages of the mask filter method for locating the region of interest and fusion of median and Wiener filters for enhancement of vein image. The next section explains the steps taken in developing the composite image filter for this research work using a 2-element form of CF, the complementary element is essential to be fulfilled.

$$G_h^{'} + G_l^{'} = 1 \tag{1}$$

Likewise, the three-element CF is exhibited in Fig. 2b, the input signals are [y_h, y_m, y_l], such that the subscript m denotes to intermediate derivative data. Hence, for this situation,

$$G_h^{'} + G_m^{'} + G_l^{'} = 1 \tag{2}$$

In this study, a new composite image filter method has been proposed, which shares the advantages of the mask filter method for locating the region of interest and fusion of median and wiener filters for enhancement of vein image. The next section explains the steps taken in developing the composite image filter for this research work using a 2-element form of CF concept.

3.1.5 Composite Median-Wiener

Composite Median-Wiener (CMW) filter method is suitable for image enhancement. CMW filter design is based on the 2-element from the concept of the composite filter is contained in Fig. 2 because it involved two different filters. The proposed CMW filter is the fusion of a linear model filter and a non-linear filter to make up for the inadequacies of each model by fusing the properties of the two models to make a single model filter. The proposed CMW filter need not have (prior) knowledge if the finger vein image has Gaussian noise, Salt-and-pepper noise, or has both noises. Based on its properties, it removes any noise and preserves the images in enhancement processing. Figure 3 illustrates the proposed structure of the CMW filter method and the process is described in the following section.

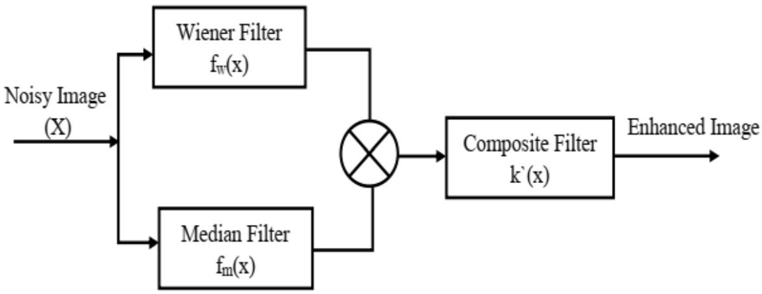

Fig. 3 Proposed structure of the CMW filter

3.1.6 CMW filtering development

The development of CMW filter takes the concept of two-element CF as shown in Figs. 2a and 3, which contain the combination of the Median (non-linear) filter and Wiener (linear) filter. The properties of these linear and non-linear filters contain a single filter of CMW filter for enhancement of finger vein image such that it is free from any form of noise and sharpens the edge of the image.

The target image X is assumed to be corrupted by mixed noise, and the filter is designed to denoise and adjust the contrast of the image. The proposed composite is modeled based on Fig. 3 as follows:

$$K^{l}(x) = f_{w}(f_{m}(x)) \tag{3}$$

where x is the image input signal, $k^1(x)$ is the proposed composite image filter, f_w is the Wiener filter function and f_m is the Median filter function.

In general, where i = 1,2, 3….m; j = 1,2, 3…. n; such that m = n = 3,5,7 neighbor, then, matrix X becomes:

$$X = \begin{bmatrix} x_{11} & \dots & x_{1n} \\ \dots & x_{ij} & \dots \\ x_{m1} & \dots & x_{mn} \end{bmatrix} \tag{4}$$

For every point selected in the neighboring pixel of (3 × 3) image, apply Median filter (f_m) on x_{ij} in matrix X of Eq. 4.

Thus,

$$\widehat{x}_{ij} = f_{m}(x) \tag{5}$$

$$Order\left(\widehat{x}\right) = \widehat{x}_{11} < \dots < \widehat{x}_{i-1,j-1} < \widehat{x}_{ij} < \widehat{x}_{i+1,j+1} < \dots < \widehat{x}_{mn} \tag{6}$$

By applying Weiner filter (f_w) on $\widehat{x}_{ij}$ in matrix X of Eq. 4, then Eq. 3 is achieved (Detail of Algorithm 3). The proposed algorithm for CMW filter is illustrated in Algorithm 3.

Algorithm 3. Composite image enhancement filter

Input: Noisy gray finger vein (FV) image
Output: Enhanced black and white binary image
Parameter: $f(I, j)$ for pixel gray-level value, T for threshold level value
Begin
For each image do
i. Read-in FV image with gray levels of pixels [i…. j]
ii. Getting region of interest of the image using mask filtering
iii. Segment the image by binarization method
iv. Using Gamma Corrector to improve the image contrast
v. Rem: Enhance the new binary image using CMW filtering
vi. Set neighborhood value of mxn (3x3) matrices
vii. Set noise variance, v $(0 < v < 1)$
viii. For each pixel (x) do
a. Compute median filter (fm) of xij based on the neighboring pixels using $x_{ij}=f_m(x)$
b. Compute kij' value of the neighboring pixels on new pixel, xij using Weiner filter fw
ix. End for
x. Show the original image I, enhanced image I
End for
End

3.2 Feature extraction

This section discusses the methods used in the study by giving details of the procedures performed to build the research design of the proposed scheme presented in Fig. 4. To improve the finger vein identification scheme, combined hierarchical centroid features and statistical pixel features are utilized. It is necessary to combine several sources of information at the feature extraction stage to improve the identification performance [4]. The combined feature extraction method (CFM) fused hierarchical centroid, vertical and horizontal pixel features produced from HCM and PDM respectively to test the performance of the identification scheme. The feature extracted from each of the images in the dataset is to produce a distinct set of features for the classifier to make a decision. Figure 4 shows the block chart of the research design for feature extraction.

3.2.1 Enhanced Hierarchical Centroid Features Extraction Method (HCM)

Image decomposition in the domain of the pixel is considered in this method by using a kd-tree algorithm. Thus, information about centroid coordinates is extracted such that the length of a descriptor is $2 \times (2d - 2)$, and d is the process depth of the features extraction. Figure 5 shows the design of HCM using level 3 of kd-tree decomposition to extract the features at the centers of gravity of the image.

In HCM, the processed image, enhanced finger vein image is binarized cropped to pixels of size 165×480. The method is applied to obtain characteristics that allow the descriptor to get an image and computes the x-coordinate of the center of mass. The subdivided image calls

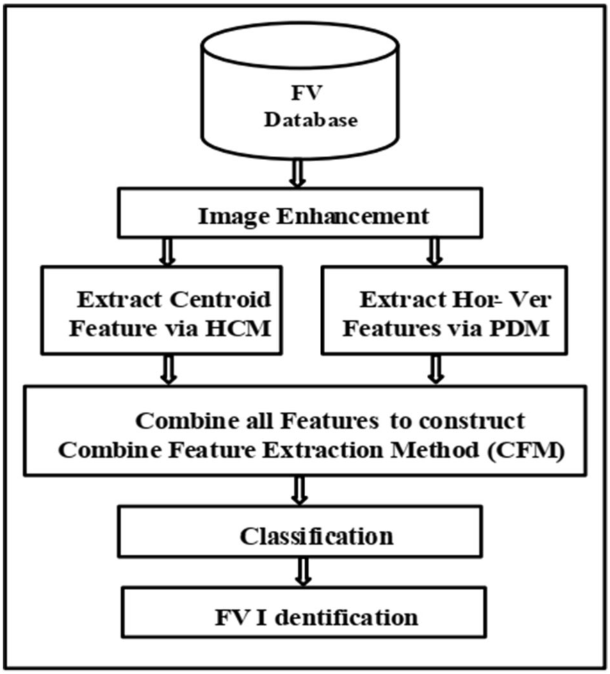

Fig. 4 Research Design for Feature Extraction

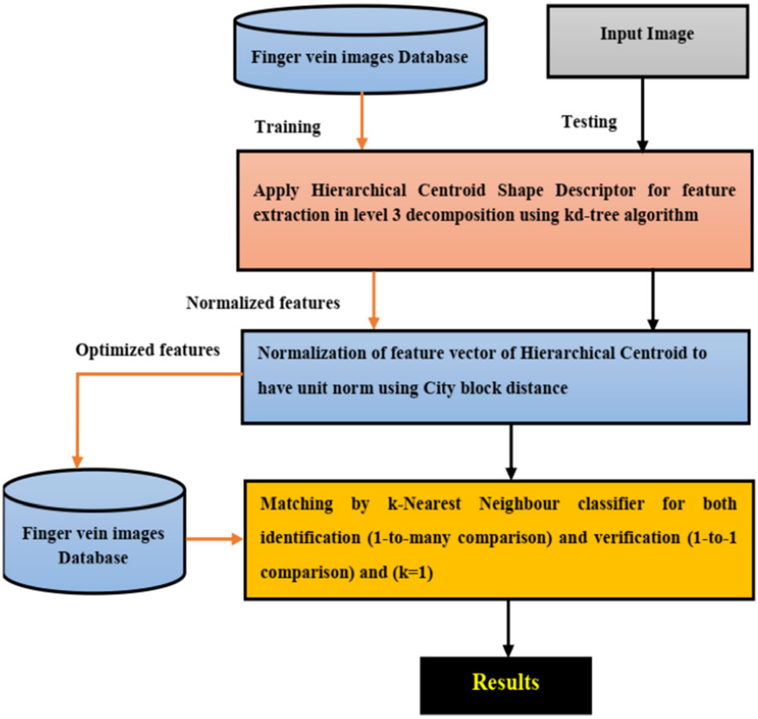

Fig. 5 Design of Enhanced Hierarchical Centroid Features Extraction Method (HCM)

itself recursively on the transpose of each of the two sub-images. The coordinate values are computed in relation to the whole image and returned. The transposed image and the two subsequent vectors are concatenated based on descriptor evaluation to balance the representation. Algorithm 4 shows the algorithm procedure of Hierarchical Centroid feature extraction method.

Enhanced Hierarchical Centroid (HC) is a new geometric shape feature in finger vein image domain, which captured the global and local characteristics of the finger vein image. In this research, the depth d of the descriptor length 2 × (2d − 2) is set to value 7 because of its highest accuracy performance value at the experimental level. The result of the variation value of d, which determines the length of feature vectors is shown in the experimental result in the next section. The feature vectors are normalized in order to gather information from multiple sources with many features, which give the best representation of the domain.

Let I be the M × N binary image with foreground I_f and background I_b, the HCM is built as follows:

Algorithm 4. Enhanced Hierarchical Centroid Feature Extraction

Input: Binary of Enhanced Finger vein (FV) Image,
Output: Hierarchical Centroid feature vectors
Begin:
For each image do
i. Read-in binary Image, *I*
ii. Compute the binary image to transposed image I^T
iii. Mark the transposed Image with minus sign
iv. Apply the descriptor, which includes Normalization
v. Compute where $m10$, $m01$ and $m00$ respectively represent x-axis, y-axis, and Ifg.
Hence, centroid (x_C, y_C) of a vein image denoted by centers of gravity, G (x, y) can be calculated as:

Then, the digital image raw moment's M_{pq} containing pixel intensities I(i, j) are computed as:

$$X_c = \frac{\sum_{i,j} i \times g(i,j)}{\sum_{i,j} g(i,j)} \qquad y_c = \frac{\sum_{i,j} j \times g(i,j)}{\sum_{i,j} g(i,j)}$$

$$m_{pq} = \sum_{i=0}^{M} \sum_{j=0}^{N} i^p j^q I(i,j)$$

i. Recursively divide the mage in 2 sub-images depend on centers of gravity to the chosen decomposition depth *(d = 7)*
ii. Normalizing the obtained vector for the interval of -0.5 to 0.5. *(Point 0 links to the centroid of the left part of the image and the positives define the right side of the tree decomposition).*
iii. Concatenate the extracted features from the image *I* and I^T
iv. Return the features vector
End for
End

The vector acquired via the kd-tree decomposition for the prior procedure is denoted as:

$$V = \left(x_0^0, y_0^1, y_1^1, x_0^2, x_1^2, x_2^2, x_3^2, y_0^3, y_1^3, \ldots, y_7^3\right) \tag{7}$$

where x_0 denotes the root level coordinate V^n_m. The *m*th y coordinate at level n and X^n_m the *m*th x coordinate at level n.

At the root level, a centroid C (x^0_0, y^0_0) is computed from the entire binary image, but only its x_c coordinate is captured ($x_c = x^0_0$) and the image is divided into two parts by the line $x = x^0_0$. Then, at level 1, two centroids are calculated from each divided part and their y_c coordinates are captured ($y_{c1} = y^1$ and $y_{c2} = y^1_1$). This process is performed recursively as the depth of decomposition is changing.

3.2.2 Enhanced Statistical Pixel Distribution-Based Feature Extraction methods (PDM)

The method combines the object pixel features of the image along both horizontal and vertical to form feature vectors. The parameter values that obtain the best identification rate for each singular method were used. The experimental design for Double feature types (Horizontal-Vertical) is shown in Fig. 6. Algorithm 5 shows the algorithm for obtaining the feature vectors for horizontal-vertical bar pixel features using PDM.

In this method, two extraction features (horizontal span and vertical span) are used. The method is adopted to bring distinctive features depending on the object pixel distribution. The method extracts two categories of features, which are the horizontal span feature and the vertical span feature. The first feature, horizontal span, performs very well in producing 19

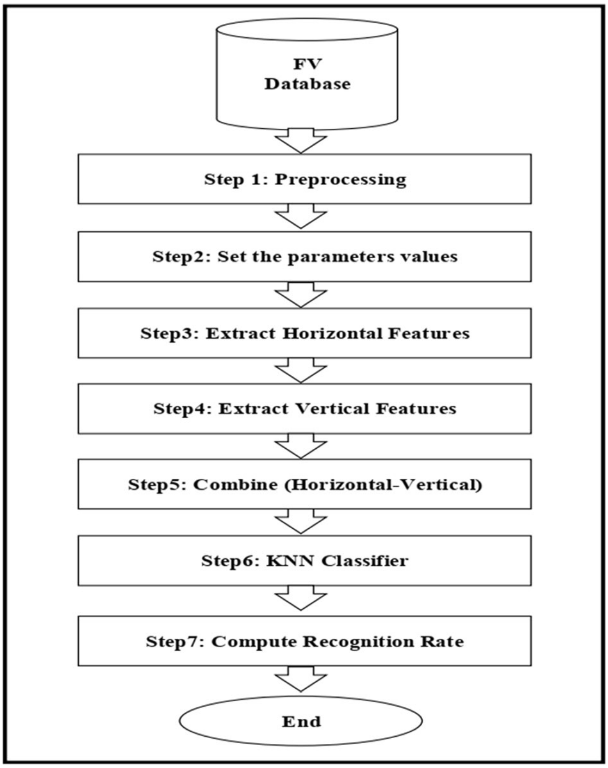

Fig. 6 Design of Enhanced Statistical Pixel Distribution Based Features Method (PDM)

feature vectors while the second feature, vertical span, performs well in producing 48 feature vectors. This feature extraction method is applied to each image in the dataset to acquire a separate set of features.

Algorithm 5. Horizontal-Vertical pixel features extraction

Input: Binary of Enhanced Finger vein (FV) Image, *I*
Output: FV Feature Vectors
Begin:

For each image do

i. Read-in binary Image, *I*

ii. Segment the whole image into many horizontal bars

a. Extract the black pixel in the image as features

b. Normalized the extracted features

c. Store the normalized features as Hor_vector

iii. Segment the whole image into many vertical bars

a. Extract the black pixel in the image as features

b. Normalized the extracted features

c. Store the normalized features as Ver_vector

iv. Combine steps ii(c) and iii(c) to make Hor_Ver Vector

v. Display Hor_Ver Vector

End for
End

3.2.3 Combined feature extraction method

This method is proposed to bring distinctive features extracted from all the methods together. The combining of several features at the feature extraction stage overcomes the weakness of using the method separately because many features provide more information than a single feature. In this section, two feature extraction methods were combined, which are the hierarchical centroid features extraction method (HCM) and the enhanced statistical pixel distribution-based features method (PDM). Therefore, the two methods were fused to develop the combined feature extraction method (CFM). The combined feature extraction methods used in this work are adapted from [6] where a new geometrical feature called Width-Centroid Contour Distance (WCCD) was produced from the fusion of finger width (W) feature and Centroid Contour Distance (CCD) feature. The design for this combined feature extraction method has already been presented in Fig. 4, and Algorithm 6 shows its algorithm procedure.

Algorithm 6. Features extraction using CFM

Input: Binary of Enhanced Finger vein (FV) Image, *I*
Output: FV Feature Vectors
Begin:

For each image do
\\ Feature of each image Read-in binary Image, *I* Resizing the binary Image, *I*
Compute HCT features (HC 252 features) Compute PDT features (Hor 19 features) Compute PDT features (Ver 48 features)
\\ Normalization of features
Normalize every feature by the utmost value of individual features
\\ Feature concatenation
Combine all the features into a single vector
End for
End

3.3 Matching

The proposed finger vein identification scheme works in identification and verification modes. The degree of matching between the extracted vein features list of the input image and the stored templates is compared using the classifier-based matching method. Thus, K-Nearest Neighbor classifier with three different distance metrics was used in testing the three feature extraction methods for different feature dimension lengths. A set of 3180 data samples was used for training while a set of 636 data samples was used for testing. K-Nearest Neighbor classifiers method was used as a single classifier with the three distances measurement, namely; Euclidean distance, City block distance and Cosine distance on the three enhanced feature methods (HCM, PDM, and CFM) to calculate the matching score.

4 Evaluation and comparison

The combined Feature Extraction Method (CFM) combined the previous two methods Hierarchical Centroid Based Feature Extraction Method (HCM) and Statistical Pixel Distribution-Based Feature Extraction Method (PDM). This combination provides a sturdy base to overcome the weaknesses of both methods. Moreover, the utilization of the nearest neighbor classifier served in reducing the computational time while preserving a reliable performance. This chapter gives the process of parameter tuning for the nearest neighbor classifier used throughout this research to complete the elements of the proposed scheme. All experiments were conducted on the finger vein identification scheme implemented in MATLAB 2015b.

4.1 Data sets

The research used the quantitative method only, which is limited to two public databases of finger vein images, namely:

A. SDUMLA-HMT finger vein image database, which was created at Wuhan University. The database contains 106*6*6, which is 3816 finger vein samples collected from 106 subjects and all images were saved with "bmp" format of 320 × 240 pixels' size, and hence 0.85G bytes is the total size of this finger vein database.

B. FV-USM finger vein image dataset, which was created by Universiti Sains Malaysia. It was collected from 123 participants, which consist of 83 males and 40 females from staff and students. The 5904 total images from 492 finger classes were obtained. The captured finger images have spatial and depth resolution of 640 × 480 and 256 Gy levels, separately.

4.2 Analysis on image enhancement methods

This section extensively explains the experiments conducted to prove that the proposed method in finger vein image enhancement. Public SDUMLA-HMT finger vein database images are used in this experiment, which contains 3816 images of the index, middle, and ring of both left hand and right hand. Although, there are not many image quality assessment methods for finger vein images [10]. Assessments methods of image quality are common in fingerprint images [8, 21], iris images [32], and single-frame video images [26]. On this basis, there are two classes of image quality assessment that were employed in this work. They are human visualization, and mathematically defined measures, which is the peak signal-to-noise ratio (PSNR). The assessment of image quality is very important as it influences the accuracy of the identification system. Thus, finger vein image quality is the determinant of the effectiveness of the finger vein identification scheme. Figure 7 shows the implementation of

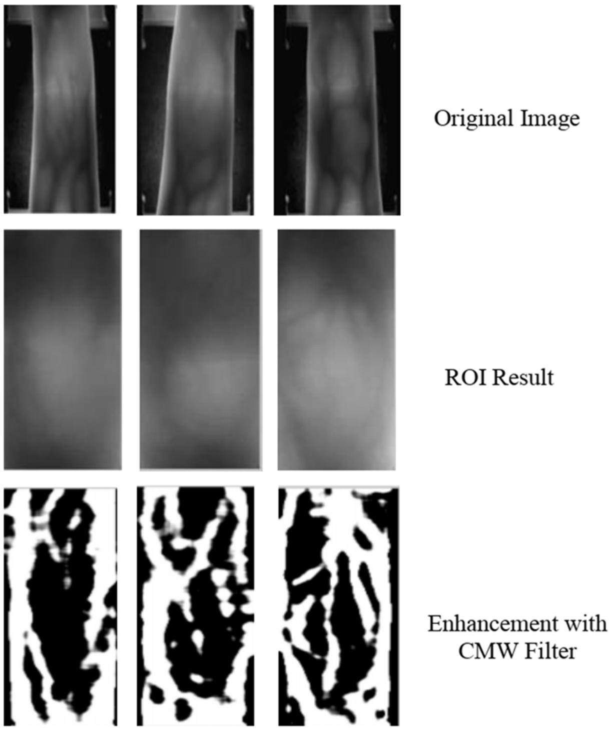

Fig. 7 Finger vein image enhancement

CMW filter on a noisy finger vein image. In Fig. 7, the original image, ROI result and enhancement with CMW filter are displayed.

4.2.1 Human visualization

The visual results of filters on SDUMLA-HMT finger vein images are shown in Fig. 8. Figure 8a–f shows the original FV image, followed by the results of filtered images when adopting the Median filter [57], Wiener filter [47], Beniwal and Singh [7] and Liu [25] hybrid serial Medial Wiener filter, and interchange the hybrid serial Wiener Median filter, and the proposed, Composite Median-Wiener (CMW) filter respectively. The human visual observed that the proposed. CMW filter image results superseded other filtered image results in the sense that there are no traces of noise. The contrast is clear, and the edges of the image are preserved.

4.2.2 Analysis of the peak signal-to-noise ratio

The peak signal-to-noise ratio (PSNR) and mean square error (MSE) are mathematically defined measures. The PSNR is generally utilized for image quality measurement. PSNR and MSE are interrelated such that the higher the PSNR and the lower the MSE, the better the contrast and quality of the image become. The reason for using PSNR is its simplicity of implementation. PSNR operates in such a way, that it shows a low signal-to-noise value if the image is influenced by intense noise; thus, the image quality is poor. The signal-to-noise ratio is described as Eq. 8:

$$PSNR = 10\ log_{10}^{\frac{L^2}{MSE}} \tag{8}$$

where L, is the dynamic range of permissible pixel forces. For instance, an 8-bit of each pixel image has L = 28–1 = 255, and MSE is the mean square error, which can be computed as Eq. 9:

$$MSE(x,y) = \frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2 \tag{9}$$

MSE is the cumulative mean square error between the original image, x and the filtered image, y [60].

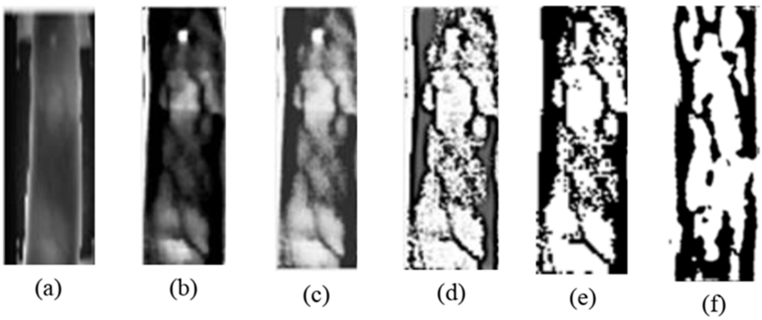

Fig. 8 Human Visual Comparisons in finger-vein images enhancement. **a** Original images. **b** Wiener filter **c** Median filter **d** Serial Wiener filter to Median filter **e** Serial Medial filter to Wiener filter **f** Composite Median-Wiener filter

The evaluation framework for comparing the enhanced image result of CMW filter with other filters to remove Mixed noise (Gaussian noise and Salt-and-pepper noise) of high-quality contrast and image edges preservation is shown in Fig. 9.

Table 4 shows PSNR iteration mean values of CMW filter and other image enhancement filtering techniques as applied on noisy finger vein images from five subjects. Subject 1 from the index finger type have the highest PSNR mean values of 27.75 for CMW filter compared to other filtering methods.

The Spreadsheet of the Microsoft Excel software package was used in explaining Table 4 for each finger type. The explanations are shown in Fig. 10a–c.

Figure 10a shows the comparison of CMW filter with other filtering methods on the right index finger with five subjects and the mean value of five iterations of each subject. The mean value iteration of subject 1 shows that the result of the enhanced image using Wiener filter has the least PSNR value of 23.8401 following the value of 25.5717 from the application of the Median filter. The serial application of the Wiener filter followed by the Median filter has a value of 27.0100, while the serial application of the Median filter followed by Wiener filter has a value of 27.1780. The proposed method, Composite Median-Wiener (CMW) filter has the highest PSNR mean value of 27.7503, which shows that the image quality using this method is the best finger vein image enhancement method in furtherance to finger vein identification system. Figure 10a shows the highest PSNR mean value for subject 1 for the image using CMW filter; hence, CMW filter method is the best image enhancement method compared to other filtering methods.

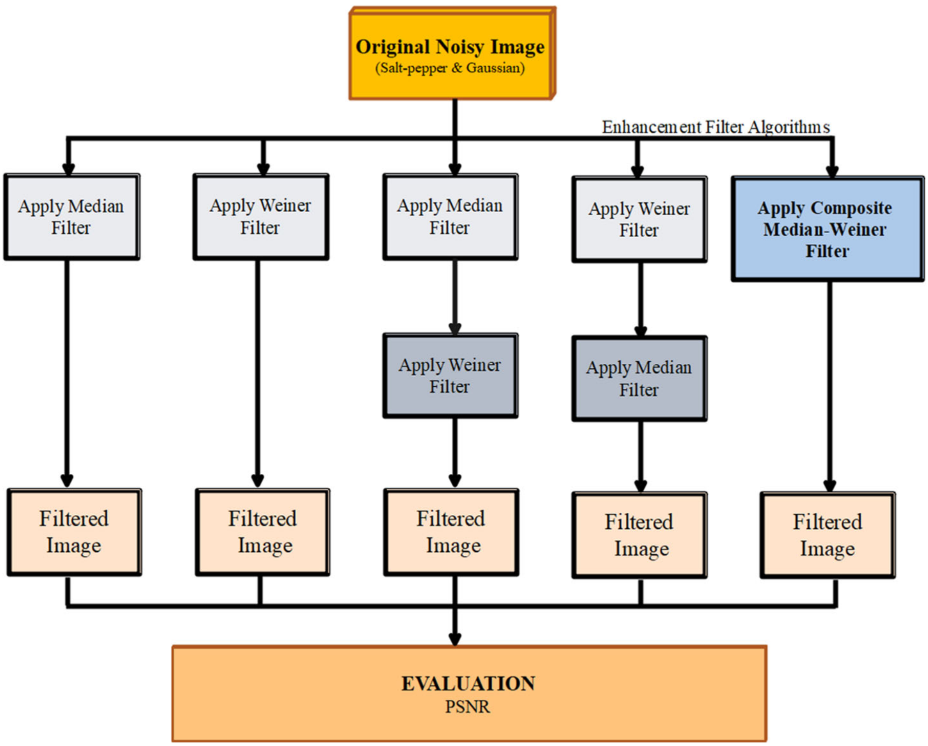

Fig. 9 Propose framework for evaluation of CMW filter

Table 4 PSNR values of CMW Filter and other Filtering Methods on SDUMLA-HMT finger vein database images

Fingers	Subjects	Noisy Image	Median Filter	Wiener Filter	Median>Wiener Filter	Wiener > Median Filter	CMW Filter
Index	1	19.3177	25.5717	23.8401	27.1780	27.0100	27.7503
	2	16.1104	22.2447	21.7217	24.6321	24.2862	25.0031
	3	13.7337	19.8519	19.1713	21.8538	21.4905	22.9771
	4	17.3008	25.4203	20.8741	27.1100	26.8961	27.3767
	5	15.1913	22.1916	20.2091	24.3696	24.3696	25.0171
Middle	1	13.3034	19.7689	18.5399	21.7692	21.2358	22.7709
	2	16.1060	25.2442	19.6662	26.7909	26.7054	27.0028
	3	14.4781	21.9494	19.2973	23.9910	23.8640	24.7158
	4	12.8767	19.5165	17.9617	21.4505	20.8333	22.5664
	5	15.0897	25.0122	18.7916	26.4979	26.2213	26.9097
Ring	1	13.8562	21.8297	18.5617	23.8698	23.4493	24.7660
	2	12.5075	19.3960	17.5324	21.3318	20.5113	22.5650
	3	14.2645	24.5776	18.2382	25.9907	25.4527	26.4951
	4	13.3230	21.4991	18.0764	23.4737	22.8962	24.3895
	5	12.1557	19.0878	17.1204	20.9369	20.0614	22.2445

Figure 10b takes the processing steps of Fig. 10a such that it shows the comparison of CMW filter with other filtering methods on the right middle finger with five subjects and the mean value of five iterations of each subject. Subject 1 shows that the result of the enhanced image using Wiener filter has the least PSNR value of 18.5399 followed by the value of 19.7689 from the application of the Median filter. The serial application of Wiener filter followed by the Median filter has a value of 21.2358, while the serial application of the Median filter next to Wiener filter which has a value of 21.7692. The proposed method, Composite Median-Wiener (CMW) filter has the highest PSNR mean value of 22.7709, which shows that the image quality of this method is the best finger vein image enhancement method further to finger vein identification. Figure 10b also shows that each of the subject images using CMW filter contains the highest PSNR value; hence, CMW filter method is the best image enhancement method compared to other filtering methods.

Figure 10c takes the processing steps of Fig. 10a and b such that it shows the comparison of CMW filter with other filtering methods on the right ring finger with five (5) iterations. Iteration 1 shows that the result of the enhanced image using Wiener filter has the least PSNR value of 18.5617 followed by the value of 21.8297 from the application of the Median filter. The serial application of the Wiener filter followed by Median filter has the value of 23.4493, while the serial application of the Median filter was next to Wiener filter with a value of 23.8698. The proposed method, Composite Median-Wiener (CMW) filter has the highest PSNR value of 24.7660, which shows that the image quality of this method is the best finger vein image enhancement method further to finger vein recognition system. The chart shows at each of the iterations that the image result using CMW filter contains the highest PSNR value, hence, CMW filter method is the best image enhancement method compared to other filtering methods.

4.3 Results of HCM, PDM and CFM on SDUMLA-HMT and FV-USM databases

In all experiments, the identification performance is evaluated based on identification percentage and Equal Error Rate (EER). The EER is the error rate when the False Acceptance Rate

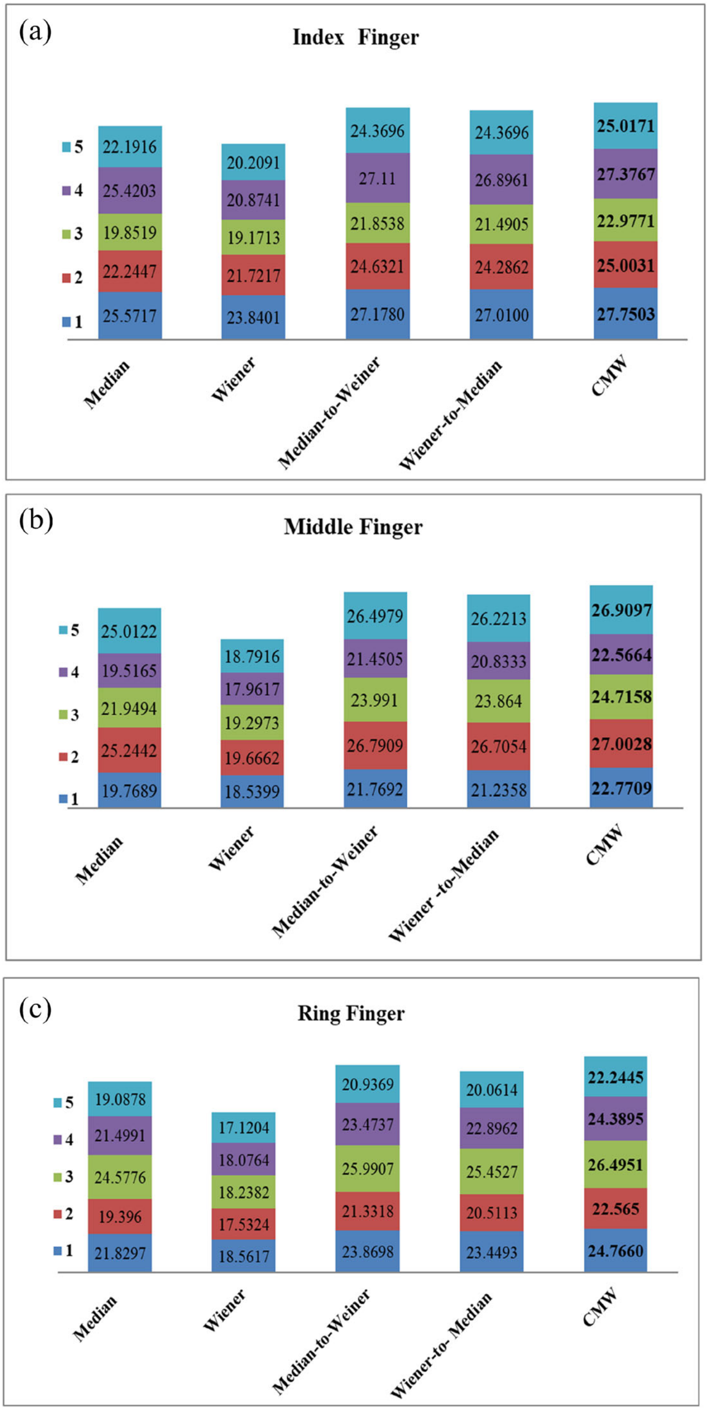

Fig. 10 The comparison of CMW Filter with other Filtering Methods on right **a** index, **b** middle **c** ring finger using PSNR value

(FAR) and False Rejection Rate (FRR) are equal. FAR is the error rate of imposter matching cases, which are misclassified into authentic classes, while FRR is the error of misclassified authentic testing cases into imposter classes.

Identification accuracy is computed for each rank from 1 to the total number of the dataset in the database as:

$$IR = \frac{\#genuine\ acceptance}{\#total\ identification\ attempts} \tag{10}$$

Verification rate is taken as False Rejection Rate (FRR), thus, it is computed as:

$$VR = \frac{\#genuine\ acceptance}{\#genuine\ \ attempts} \tag{11}$$

Combined Feature Extraction Methods (CFM) declares the highest average identification value with the smallest standard deviation and EER value, which assure the stability of the method. Figure 11a and b show the identification rate of each method on right and left fingers based on SDUMLA-HMT database.

On the other hand, Fig. 11a and b presents the identification average rate and the standard deviation of HCM, PDM, and CFM for evaluating both right-hand and left-hand fingers based on SDUMLA-HMT finger vein database, which is the major database used in this study. The purpose is to compare the identification rate performance of both hands (right and left) fingers.

However, in this experiment, it is worth noticing that the right-hand index finger and the left-hand index finger have the highest value identification and verification in all three (3) methods. Thus, two fingers can be combined in finger vein identification scheme. In addition, CFM showed significant performance on SDUMLA-HMT finger vein database. Also, Fig. 12a and b show the verification rate of each method on right and left fingers based on SDUMLA-HMT database.

Figures 11a and b and 12a and b present in overall the average identification rate and the standard deviation, and average verification rate (EER) respectively of the Combined Feature Extraction Method (CFM) and other methods (HCM and PDM) for evaluating both right hand and left-hand fingers based on SDUMLA-HMT finger vein database. A total of 1908 (106 × 3 × 6) images from 636 fingers are involved in each hand for 1272 images for the training set and 636 for the testing set.

Table 5 shows the identification rate and Verification rate (EER rate) result of CFM on SDUMLA-HMT and FV-USM finger vein database.

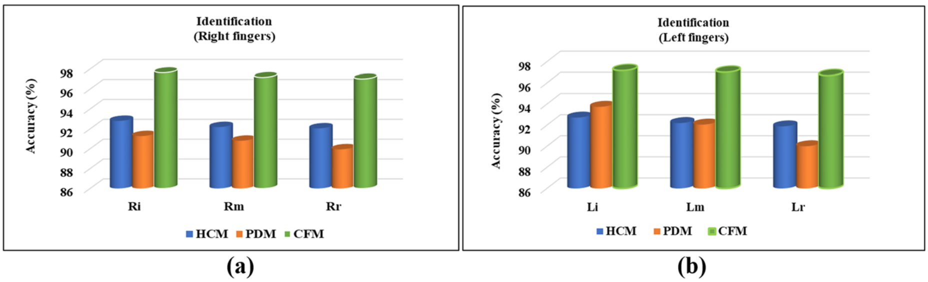

Fig. 11 Identification rate of each method over each captured **a** right finger, **b** left finger based on SDUMLA-HMT database

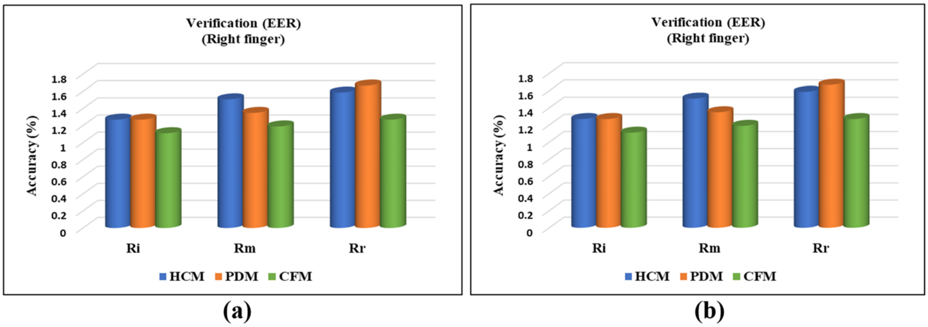

Fig. 12 Verification rate (EER) of each method over each captured **a** right finger, **b** left finger based on SDUMLA-HMT database

Figure 13 shows that the CFM has a higher identification performance of 97.94% on SDUMLA-HMT finger vein database than FV-USM database with 90.24%. Also, the verification rate of SDUMLA-HMT finger vein database is 1.11% while FV-USM database is 4.91%. It shows that the finger vein lines are clearer in SDUMLA-HMT database than in FV-USM database even though FV-USM database has more classes (subjects) than SDUMLA-HMT database.

4.4 Image quality assessment

The peak signal-to-noise ratio (PSNR) is used to measure the quality of the image enhanced. The highest value of other filter methods is compared with the proposed method, CMW filter for image enhancement of high-quality contrast and image edges preservation. Table 6 shows that the proposed composite image filter has PSNR values of 27.7503, 27.0028, and 26.495 for fingers index, middle, and ring respectively. These PSNR values are shown the most promising quality contrast enhancement results compared to existing methods. Hence, the proposed method was used throughout this research work. Also, Table 6 shows that the index finger is distinguished for the highest quality of finger vein image enhancement when compared to the other two (middle and ring) finger types because of its highest PSNR value.

4.5 Stability and statistical significance of the proposed method

The proposed finger vein identification scheme based on Combined Feature Extraction Method (CFM) is tested six (6) times over a total of 3816 finger-vein images from 106 different persons. The 636 images are used for testing parameter setting and the remaining 3180 images are used for evaluating the performance of the proposed FVI.

Table 5 Identification rate and Verification rate (EER rate) result of CFM on SDUMLA-HMT and FV-USM finger vein database

Database	Identification Rate (%)	Verification Rate (EER)
SDUMLA-HMT	97.64	1.11
FV-USM	90.24	4.91

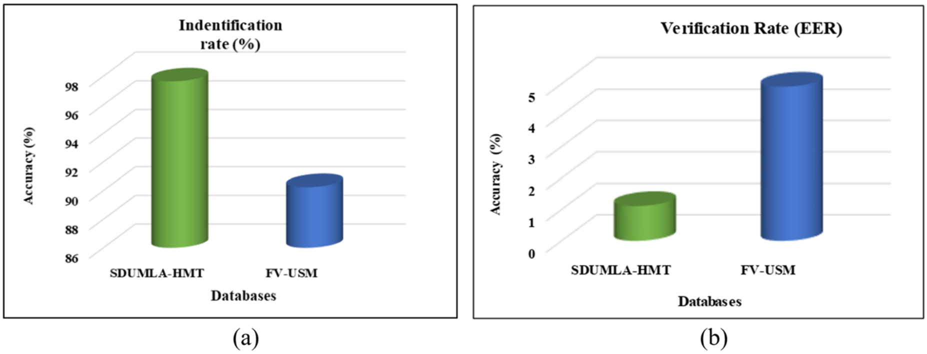

Fig. 13 Illustrate the performance of CFM using SDUMLA-HMT and FV- USM finger vein databases **a** Average identification rate **b** Verification rate (average EER)

In feature extraction and combination, singular, double, and triple feature types are constructed. The improvement in every type has been traced. For the singular feature type (Hierarchical Centroid), one method to extract a feature from a finger vein image has been conducted. To validate the effectiveness of every method, parameter values have been tuned to produce the best identification rate 92.80% with 252 features after normalization of the testing set 636 images. Enhanced Hierarchical Centroid Based Feature Extraction Method (HCM) is used to produce a singular feature type. For double feature types, the two methods have been combined and evaluated. In the horizontal span method, the parameter value number of horizontal bars (NHB) has 19 features. Similarly, the number of vertical span methods has a parameter value (NVB) of the 48 features. The combined 48 features, which were extracted from the finger vein image produced an identification rate of 93.74% at the testing set 636 images. Enhanced Statistical Pixel Distribution-Based Feature Extraction Method (PDM) is used to produce double feature types.

In triple feature types, two methods at a time have been combined. The triple feature types are hierarchical centroid, horizontal span, and vertical span, which produced 319 features and an identification rate of 97.64% at the testing set 636 images. This means there is an improvement in triple feature types compared to double feature types. The combined Feature Extraction Method (CFM) is used to produce triple feature types. Tables 7 and 8 give results of the average identification rate and the standard deviation, and the average verification rate (average EER) respectively, to test the stability and the statistical significance of each design

Table 6 Enhanced image quality assessment

Methods	Author	PSNR		
		Index Finger	Middle Finger	Ring Finger
Median Filter	Yang et al., [57]	25.5717	25.2442	24.5776
Wiener Filter	Sim et al., [47]	23.8401	19.6662	18.7916
Hybrid MW	Beniwal and Singh [7]	27.1780	26.7909	25.9907
Hybrid WM	Liu [25]	27.0100	26.7054	25.4527
Composite MW	Proposed	27.7503	27.0028	26.4951

Table 7 Identification rate of CFM compare with HCM and PDM using SDUMLA-HMT database

Methods	Average (%)	Standard Deviation	Confidence Interval
HCM	92.80	1.76	[91.39, 94.21]
PDM	93.74	2.95	[91.39, 96.09]
CFM	97.64	1.39	[96.53, 98.75]

Table 8 EER rate of CFM compare with HCM and PDM using SDUMLA- HMT database

Methods	Average (%)
HCM	1.19
PDM	1.26
CFM	1.11

for the feature extraction methods used in this work. The methods are Hierarchical Centroid Based Feature Extraction Method (HCM), Statistical Pixel Distribution-Based Feature Extraction Method (PDM), and Combined Feature Extraction Method (CFM). The highest average value in each method from the right and left hand with the index, middle, and ring fingers is considered for the evaluation.

Figure 14a and b show the analysis results in respect of identification rate and EER rate of CFM compare with HCM and PDM. As indicated in Tables 7, 8, and Fig. 14a and b, CFM features clearly outperform the other feature extraction methods for SDUMLA-HMT database in the identification and verification modes. Confidence intervals for CFM are tighter than other methods. CFM reports the smallest standard deviation with the highest average value which assures the stability of the method. It is worth noting that the leading performance of the CFM is clearer in the identification trials than in verification trials. This confirms the strength of the method since in the identification the comparison is between the input image and all other templates in the database. Hence, it is more prone to be affected by variations in the database, unlike verification where the matching is only with one template in the database.

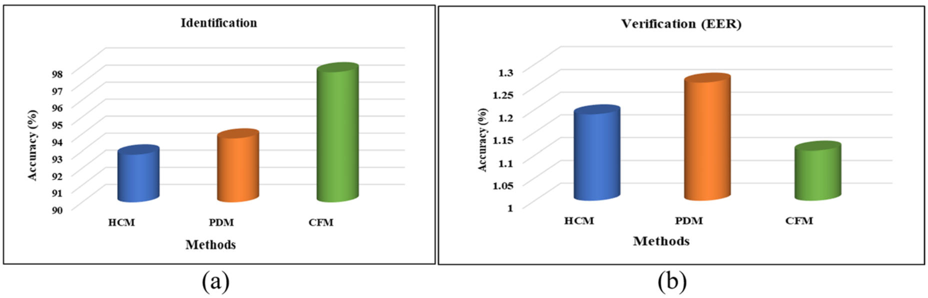

Fig. 14 **a** Confidence intervals over average identification rate, **b** Average EER for each method by SDUMLA-HMT database

4.6 Evaluation of the proposed method using classifier-based matching

The extraction of features of the methods used throughout this study is compared with the classification performance of the metric-learning-based method. In this study, k-Nearest Neighbor (KNN) is employed for classification. K-Nearest Neighbor is a non-parametric learning algorithm with a simple effective method of classification. For the experiments here, k is set to 1 because of its simplicity as the nearest neighbor algorithm [29]. KNN classifier is based on the training set and test set. Thus, it uses a distance function to calculate the distance between the training image and the test image. To tune the distance parameter of the nearest neighbor classifier the following steps are taken. Firstly, feature extraction by methods is carried out for the finger vein images and the feature vector for each image is stored in the feature's matrix. The features are normalized to have a unit norm for each feature vector, and the data are divided into training and testing sets. Finally, the feature matrix is fed to the nearest neighbor classifier, and it is tested for the three metric distances, which are Euclidean distance, City block distance, and Cosine distance. Table 9 indicates the average value of KNN classifier with different metric distances for finger vein identification matching score. The table also indicates the features extracted and their dimensions, and the three methods used in this study, which are Hierarchical Centroid Based Feature Extraction Method (HCM), Statistical Pixel Distribution- Based Feature Extraction Method (PDM), and Combined Feature Extraction Method (CFM). The features are *hc* - hierarchical centroid, *hs* - horizontal span, and vs - vertical span.

The experimental results presented in Table 9 were conducted based on SDUMLA-HMT finger vein database with a total number of 3816 images from 106 different individuals. 3180 images are set for training and the remaining 636 images are for testing. The training samples from each individual are regarded as the positive class and a center point for each class is constructed. Five images were chosen randomly for training purposes. The experiment is performed five times for each distance, and the average values are then taken for these measurements. The comparative performance analysis of the experimental results is shown in Fig. 15.

Figure 15 shows the performance analysis made with the use of KNN and three different distance metrics. The performance is measured in the identification accuracy rate. From the figure, combining multiple features of the biometric finger vein trait gives the highest report. Regarding performance accuracy, it is clear from the figure that City block distance outperforms other distance metrics in all the methods. This shows that the City block distance metric increases the performance of the k-nearest neighbor algorithm.

4.7 Comparison of the proposed with existing methods for finger vein identification

This section presents the results obtained in this work and compares it with other methods of the same database.

Table 9 Identification rate based on KNN classifier with distance metrics

Methods	Features	Feature Dimension	Identification Rate (%)		
			Cosine	Euclidean	City block
HCM	*hc*	252	88.58	89.95	92.80
DPM	*hs,* vs	67	90.17	91.83	93.74
CFM	*hc, hs,* vs	319	96.50	96.88	97.64

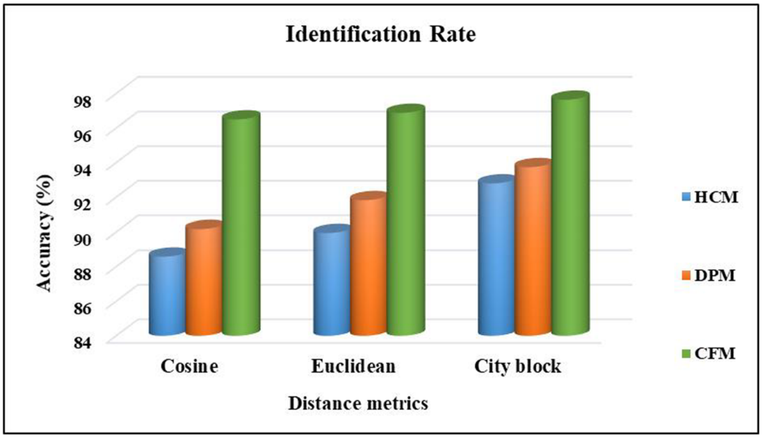

Fig. 15 Comparative identification rate of Cosine, Euclidean and City block distance

4.7.1 Comparison of the proposed with existing methods based on SDUMLA- HMT finger vein database

Table 10 presents the identification accuracy levels for other methods in comparison with the proposed method for finger vein identification by the same SDUMLA-HMT finger vein database. The methods are Rotated Wavelet Filter (RWF) with the extraction of two features [22], Haar Wavelet Transform (HWT) with the extraction of one feature [39], a combination of Zernike Moments (ZM) and Wide Line Detector (WL) with the extraction of two features [59], Shrikhande and Fadewar [45] extracted two features through Discrete Wavelet Packet Transform (DWPT) method. The finger vein skeleton was extracted by the minutiae point extraction method called Skeleton Network (SN) [9], while the combination of the Discrete Wavelet Transform (DWT) method and Rotated Wavelet Filter (RWF) extracted two type features [46]. To evaluate the proposed method and existing methods for the finger vein identification scheme, two measurements are required, the identification accuracy percentage and equal error rate for verification percentage. Table 9 presents the analysis of accuracy levels of the proposed CFM and other methods reported in the literature for the same SDUMLA-HMT finger vein database.

Figure 16 shows the evaluation of the proposed method in comparison with other methods.

Table 10 Comparison of Identification rate between the proposed method and other previous proposed methods

Methods	No of features extracted	Database fingers × samples per each	Identification Rate (%)
RWF [22]	2	636×6 images	63.68
HWT [39]	1	636×6 images	92.90
ZM+WL [59]	2	636×6 images	87.48
DWPT [45]	2	360×6 images	92.33
SN [9]	1	100×5 images	91.81
DWT+RWF [46]	2	636×6 images	93.67
CFM (Proposed)	3	636×6 images	97.64

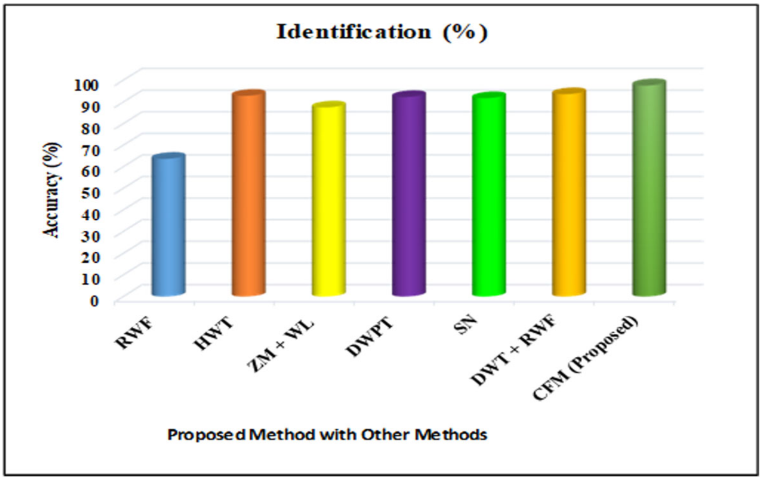

Fig. 16 Comparison of the proposed method with other methods for finger vein identification based on SDUMLA-HMT database

4.7.2 Comparison of the proposed with existing methods based on FV-USM finger vein database

In this section, the proposed method is compared with other methods based on FV-USM database and their EER results are summarized in Table 11. The other methods include LLBP - Local Line Binary Pattern [37] with 15.7%, LBP - Local Binary Pattern [23] with 27.42%, CCD - Centroid Contour Distance [15] with 10.43%, W - Width [20] with 9.53% and WCCD - Width-Centroid Contour Distance [6] with 7.01%.

All the methods used in Table 11 was based on the same FV-USM database and the performance was evaluated in term of equal error rate (EER), which measured the verification rate. Hence, Fig. 17 compared the proposed method with other methods.

Figure 17 shows the proposed method (CFM), which combines three features, Hierarchical Centroid, horizontal span, and vertical span have the lowest equal error rate (EER) of 4.91% the measured verification rate outperforms other methods in term of identification accuracy. WCCD, which is a combination of two features - W (Width) and CCD (Centroid Contour Distance) has EER of 7.01%, and it shows better accuracy performance for finger vein identification. Local Binary Pattern (LBP) with a single feature has the highest EER of 27.42%, which shows the least performance for finger vein identification in Fig. 17. Thus, integration of multiple features produces better identification results, which is a result of the extraction of several information from finger vein, which represents the person.

Table 11 Comparison of EER rate between the proposed method and other previously proposed methods

#	Methods	No of features extracted	EER (%)
1	LLBP [37]	1	15.7
2	LBP [23]	1	27.42
3	CCD [15]	1	10.43
4	W [20]	1	9.53
5	WCCD [6]	2	7.01
6	CFM (Proposed)	3	4.91

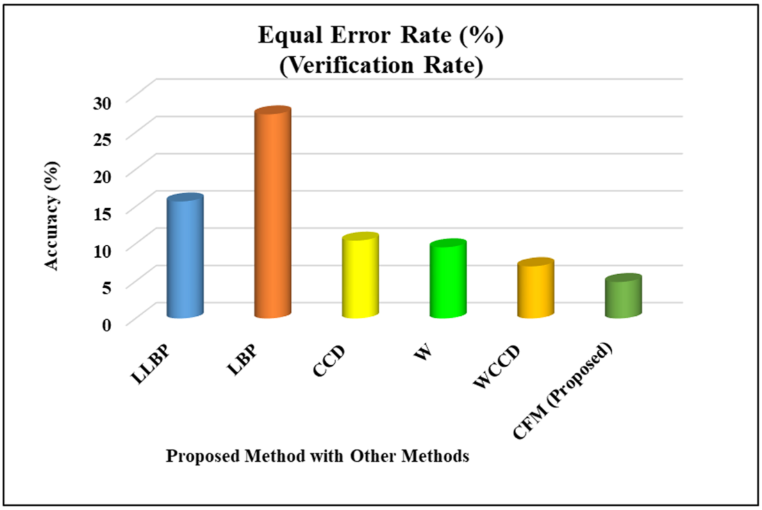

Fig. 17 Comparison of the proposed method with other methods for finger vein identification based on FV-USM database

5 Conclusion

Throughout this study, comprehensive explanations have been justified on the improvement of image enhancement, feature extraction method, and matching measurement. The enhancement method prepared the quality image for finger vein feature extraction to improve the human identification performance. The proposed feature extraction method is simple and has low computational complexity. City block distance was adopted for k-nearest neighbor (KNN) classifier based on its better accuracy compared to other distances for evaluation metrics, which showed that the proposed method significantly improved the identification accuracy. The method was tested on finger vein public databases and it showed a high accuracy rate of 97.64% for measuring identification performance and an equal error rate (EER) for measuring verification rate of 1.11%. Some directions recommended for future work have been highlighted for possible application and enhancement of the proposed scheme. Additionally, exploring other classifiers and investigating other multi- classifiers methods may lead to a better identification rate. Another research interest area is creating a benchmark dataset for finger vein images processing research, which can provide a strong platform to make a comparison and improve the research work. One more strategy may include the area of feature selection methods.

Declarations

Conflict of interest We certify that there is no actual or potential conflict of interest in relation to this article.

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Affiliations

Hoshang Kolivand[1] • **Kayode Akinlekan Akintoye**[2] • **Shiva Asadianfam**[1,3,4] • **Mohd Shafry Rahim**[2]

Hoshang Kolivand
h.kolivand@ljmu.ac.uk

Kayode Akinlekan Akintoye
A.akin@live.utm.my

Mohd Shafry Rahim
Shafry@utm.my

1 Department of Computer Science, Liverpool John Moores University, Liverpool L3 3AF, UK

2 MAGICX (Media and Games Innovation Centre of Excellence), Institute of Human Centred Engineering, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia

3 Faculty of Electrical & Computer Engineering, Qom University of Technology, Qom, Iran

4 Department of Computer Engineering, Qom Branch, Islamic Azad University, Qom, Iran