Hand Vein Pattern Enhancement using Advanced Fusion Decision

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***Abstract*—Amidst the numerous biometric modalities, the hand vein recognition has been famous for its high accuracy and stability. The idea of our proposed method is to extract new features from the hand vein, such as; vein direction, its length and combined veins that are considered to be a unique feature for the hand vein of each particular person. This images exposed to filtering techniques, in addition to using enhancement approaches and segmentation processes. This was followed by dividing this study into two parts: the first part used a traditional Pixel by Pixel method to test the processed images. On the other hand, the second part (which is the proposed method of this study) used the "Modified Hough transformation", which is the novelty of the proposed method, to extract the structural features; vein lengths and its angles based on the studied images. Fusion between these structural features and brightness indicator (white pixels) has been followed to be considered as new features for vein image then to be classified. The brightness indicator has been calculated based on the study of number of white pixels before and after Hough transformation. These techniques were applied to a total number of 600 images collected from 100 individuals belonging to a diverse demography of age groups. Finally, matching experiments were implemented for both parts, and the results obtained revealed that the second part yielded 99.5% accuracy compared to 98.5% reaching by traditional method.**

Keywords*—*Hand vein, Pixel by Pixel, Modified Hough transformation.

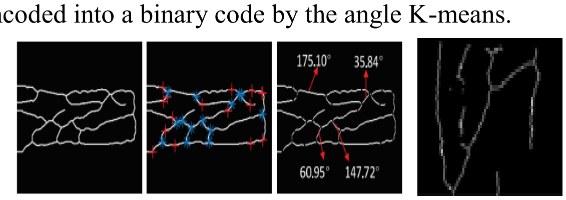
I. Introduction

Biometric systems use either a person's physical characteristics (such as; fingerprints, retinas or veins); or behavioral characteristics (such as; voice, keystroke, Signature or typing rhythm) with the aim of determining their identity or confirming that they are truly who they claim themselves to be [1-5]. Each person's biometric data are incredibly unique. They're simple to obtain, non-intrusive, and time invariant, and are very easily distinguishable from humans without the need for extensive specialized training [6-7]. Hand vein recognition, which is one of the biometric data collection methods, is more advantageous when compared to other biometric identification methods such as fingerprint, retina, face… etc. Many biometric traits, including as fingerprints, retina, face and veins, have been in use for a long time [8]. As a result, hand vein patterns are implemented and preferred in comparison to other public biometric features because they are located beneath the skin and are invisible to the human eye. Furthermore, the vascular patterns in the dorsal of each hand are distinct from one another. It is worth noting that, only a live body can capture the image of a hand vein pattern[9-10], Hand vein recognition is performed using NIR (Near-infrared) LEDs and a camera capturing the veins' acquisition. Since the obtained images have noise varying in rotation and translation; it is imperical that the input image made by the camera are pre-processed using characteristic processes [11]. To function, the system makes use of the vascular system. In human physiology, the lungs oxygenate the haemoglobin in the blood, which is subsequently sent to the body's tissues by the arteries. The deoxidized haemoglobin returns to the heart through the veins after the oxygen is released into the tissues. It's worth noting that the rate of absorption differs between the two forms of haemoglobin [12]. Due to the particular absorption of infrared radiation in blood vessels, the hand vein system can identify only veins, not arteries, which is critical for the system's optimal operation. Vein patterns are sufficiently diverse amongst people, according to several previous research [13], and they are also stable and unaffected by ageing. Blood vein patterns differ from person to person, even between twins.

The most significant advantages for finger vein and hand vein:

1. Its features cannot be lost or forgotten.
2. Its features are difficult to copy, share or distribute.
3. They require the presence of the authenticated person at the exact time and authentication point[11].

A new strategy is employed to improve the hand vein recognition system due to the near similarity between finger vein structure and that of the hand vein as represented in "Fig.1". In "Fig. 1" (a) [15] vein patterns were extracted from finger vein. Each vein segment's angle is identified and represented as a feature for indexing by the elliptical direction map, which is then encoded into a binary code by the angle K-means.



(a) (b)

Fig. 1. (a) Vein direction detection (b) Hand vein thinned image

By considering this similarity and taking the advantage of extracting both the vein direction and its length to generate unique features for each person's hand vein and using the Hough transformation, high accuracy was yielded.

II. Theoretical Background

The last decades witnessed rapid development in vein recognition studies. Ramsoful, P., & Khan, M. H. M. [16] used three methods of feature extraction and representation techniques; Pixel by Pixel, Hough Lines Transform and Directional Coding Method. These three techniques were applied on 500 images, and Mahalanobis Distance and Correlation Percentage were used for matching. The results showed that the Pixel by Pixel technique is the most effective feature extraction method, with a False Rejection Rate of 0.03 %. Hough Lines transform was implemented by Sree, V. K., & Rao, P. S. [17] to extract the features of query and database images. They used the K-Nearest neighbor Search to obtain the optimum match between the query image and database. While, morphological techniques were used to extract the vein patterns. Noise reduction filters were used to enhance the vein patterns obtaining 96.25% accuracy.

Moving on to Belean et al. [18], who employed a trained multi-layer perceptron neural network to extract vein vessel patterns from the same person's hand picture samples and classify them. Huang et al. [19] investigated a new process that combined holistic and local analysis, which was then hierarchically combined with an analysis extracted from the surface modality of a reputable texture operator, Local Binary Patterns, Binary Coding, and a graph for decision-making by Factored Graph Matching.The results yielded were greater than the results obtained through the Pixel By Pixel method found in other works, proving its efficacy and superiority.

Chuang [20] suggested a local feature-based vein modelling approach based on minutiae features from skeleton pictures. Chuang's goal was to figure out which regions and traits were the most discriminative for identification.When comparing this method with six other existing verification algorithms, it is obvious that its performance is the best attained. Wang and Zheng [21] used the standard scale-invariant feature transform to improve the scale factor, the extreme searching neighbourhood structure, and the matching threshold for cross-device hand vein recognition, achieving an average recognition rate of 88.5%. Deep learning-based algorithms are also used to recognise dorsal hand veins. To extract vein features, Wan et al. [22] trained Reference-Caffe-Net, Alex-Net, and VGG-Net. They were able to get a recognition accuracy of over 99% in the end. However, the main problem faced with these methods is its high time complexity.

Recently, Norah A. Al-johania and Lamiaa A. Elrefaei [23] conducted a study that automatically learns how to extract features from original images without the need for pre-processing. They divided their study into two approaches: the first approach uses pre-trained CNN models (AlexNet, VGG16 and VGG19) to extract features from 'fc6','fc7' and 'fc8' layers, followed by Error-Correcting Output Codes with Support Vector Machine and K-Nearest Neighbor algorithms as classifiers. The second approach is to employ transfer learning with CNN (AlexNet, VGG16, and VGG19) models for feature extraction and classification. The experiment conducted under the second approach yielded the best recognition accuracy result for all models.

III. DATA AND METHODOLOGY

Most hand vein biometrics systems use high-level architecture modules for image collecting, pre-processing, feature extraction, and classification stage. In this current study, we implemented an additional fusion among the new extracted features (structural features) and brightness indicator of the studied images. "Fig. 2" below presents the proposed hand dorsal veins recognition model of the input images.

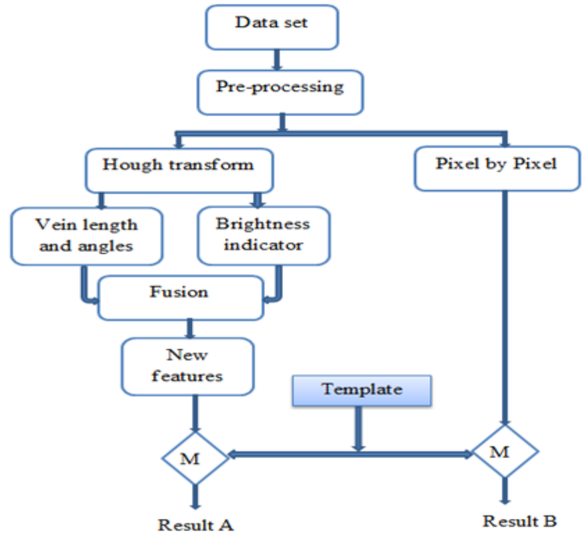


Fig. 2. Proposed technique

A. Image acquisition

The hardware arrangement for this study's proposed technique is as follows:

- Tohama IR camera.
- Easycap connector connecting the IR camera to the user interface used.
- The Assembly box containing the hands of the person in "Fig. 3".

Fig. 3. Experimental setup of hand vein infrared image acquisition system.

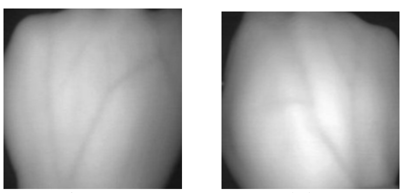
The method used in this study employed a newly designed box for the Image Acquisition stage. This box is used to restrain a person's hand; it can be used on either the right or left hand. The box includes a slot at its top, where the IR camera could be placed. There is also a front slot for the person's hand. Additionally, the box has a tube connecting its sides and a ring is installed around the tube in a specific location to avoid any significant rotation or translation of the person's hand. It also contains a support before the tube and after the slot, through which the person enters his or her hand to keep the hand upright. The hardware setup proposed by this new model is displayed in Fig 3. It consists of a Tohama IR camera sensitive to the near infrared spectrum. This IR camera is connected to the laptop via the USB cable. There is also an Easycap connector connecting the IR camera to the user interface and the box containing the hands of the person.

The hand is placed along the tube inside the box to ensure that it is in the same position every time it enters the box. There is also a support to ensure there is no rotation of the hand. This makes image recognition easier by removing the need for preprocessing activities like as rotation and translation correction. The images are then sent to a computer and recorded in a database for further processing.The resolution of the image used is 720 x 480 pixels.

In order to evaluate the produced system's performance, creating a hand vein database containing 100 registered persons are the first step. For each person in the database, three different acquisitions from each hand (two images to train / learning and one image to test for every hand) are needed at different times, so six images(three for left and three for right hand) were captured for each person. Each person's hand is treated as a separate user for the purposes of testing. Thus, the 100 registered persons represent a database of 600 different templates, as shown in “Table I”. A sample hand vein image from the dataset of the study is displayed in “Fig. 4” representing a female hand.

TABLE I. HAND VEIN DATABASE

Image/ Database	Involved of the data base	Out of data base
All images	600	50
Training	400	--
Testing	200	50



Left Right

Fig. 4. Hand vein image from our data

B. Preprocessing

The pre-processing stage in this model begins with converting the acquired image into a grayscale image. This is followed by extracting the Region of Interest (ROI) of the images through converting the image into a binary image and creating a mask. Binarization is segmenting the image into two levels: object (hand region) and background. The segmentation substage's technique is an iterative approach for calculating and determining an effective threshold for segmenting the image into two different parts: hand and background. "Fig. 5" shows an example of the ROI that was extracted.

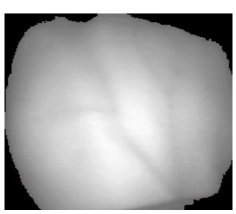


Fig. 5. Extracted ROI

Enhancing the contrast of the image using Histogram Equalization is the step that follows. This technique is used to adjust the image intensities in order to enhance its contrast by increasing it. The intensities are better dispersed on the histogram as a result of this adjustment, allowing areas of lower local contrast to obtain a higher contrast. This is achieved using histogram equalisation, which effectively spreads out the most frequent intensity values, as displayed in “Fig. 6”.

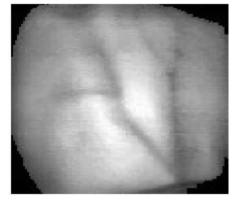


Fig. 6. Image after Histogram equalization

C. Smoothing and noise reduction

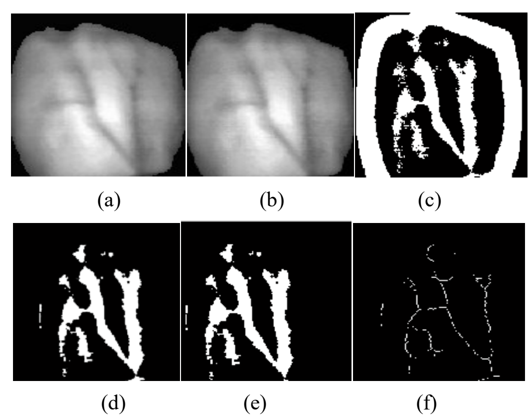
This stage is conducted using a Median Filter, which is applied to smooth the contrasted image.

D. Post-processing

This stage was used to process the image after segmentation in order to eliminate the effect of unwanted elements like noise and improve the shape of the vein pattern by cleaning the Gaps and Pores. In order to improve the geometry of the veins, the vein picture must also be recreated. The following procedures were taken to accomplish this:

- removing noisy little objects from the image, as well as areas of the background that were mistakenly identified as veins;
- Removing protrusions;
- Objects' contours (veins) are smoothed out;
- resolving the issue of regions with a mixture of white and black pixels;
- Removing small holes, and;
- Preventing vein breaking in the necks and thin portions of veins.

The filtered image is segmented using a local adaptive threshold. Using the Median Filter and another Gaussian Filter, the noise in the thresholded image is removed once again. Finally, morphological methods such as erosion and dilation are applied to the filtered image to obtain a thinned image, as shown in "Fig. 7".



(a) (b) (c)

(d) (e) (f)

Fig. 7. (a) Median Filtered, (b) Gaussian Filter, (c) Thresholded Masked, (d) Thresholded Median Filter Image, (e) Thresholded Gaussian Filter Image and (f) thinning image.

IV. FEATURE EXTRACTION AND MATCHING OF HAND VEIN PATTERNS

Two algorithms have been used in this section. The traditional pixel by pixel, and the proposed algorithm based on HT to extract structural features fusioned with brightness indicator[14].

A. *Pixel-By-Pixel methodology*

In this method, each pixel in the hand vein image is compared to the pixels of the image template (after finding the thinned image). This method is to superimpose two vein projections on each other comparing them pixel wise. It was not necessary to rotate the subject's image to align it with the template image as the hand had a fixed position inside the assembly box. The number of nonzero matrix elements of both the test image and the database images are compared together. As a result, the matching output ratio is either Yes (indicating that the two images are of the same pattern) or No (indicating that the two images are not of the same pattern).

On the Pixel by Pixel methodology, the Correlation Percentage method is employed as the matching technique. The percentage of white pixels that overlap between the test image and the template image is compared to the minimal number of white pixels in the two matched images. In the matrix elements zeros represent the black background, while ones represent the white pixels (Vein pattern) of the binary image. The feature extraction matrix contains 480x720 elements as final image size, which are reshaped into an array, indicating that the matrix elements are taken column-wise into a ($345600x1$) logical array to determine the highest percentage of correlation between two images of hand veins as in "(1), (2) ".

$$\mathrm{Correlation}\left(\mathrm{T_x}, \mathrm{T_y}, \theta\right) = \frac{\mathrm{forall}_{\mathrm{Tx,Ty},\theta}(|\mathrm{X} \bullet \mathrm{T}| * 100)}{\min(|\mathrm{X}|, |\mathrm{T}|)} \quad (1)$$

$$\mathrm{Maxcorrelation} = \max\left(\mathrm{Correlation}(\mathrm{T\_x}, \mathrm{T\_y}, \theta)\right) \quad (2)$$

The overlapped white pixels between the two comparison images determine whether an individual is successfully recognized or not. A predefined threshold validates or refuses the matching. The threshold used in the implementation below shows that the user is considered a mismatch by (70%). A pair of pixels is considered a mismatch when two corresponding pixels are from different categories.

B. *Hough transformation methodology*

This study used Hough Transform to identify straight lines in an image. The algorithm applied enabled us to determine the lengths of veins together with the angles between the vein and horizontal lines as our proposed features. The outputs revealed that the Hough space matrix and their peaks represent potential straight lines found in the studied image. To identify potential straight lines, the equation(3) has been applied as shown in "Fig. 8".

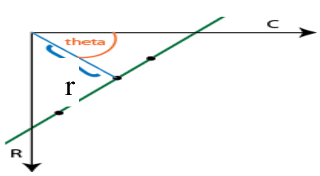


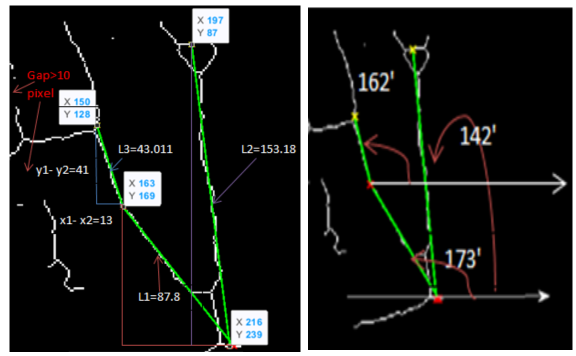
Fig. 8. Straight line calculation via using HT

$$\mathrm{r} = \mathrm{x}\cos(\theta) + \mathrm{y}\sin(\theta) \quad (3)$$

Where: For each (xi, yi) point on this line, the perpendicular distance between the origin and the line is denoted by r and the orientation of r is denoted by θ . The range of θ is $-\pi/2 \leq \theta \leq \pi/2$ with a step-size determined by the Theta resolution (radians) parameter. To find the angle of each line with x-axis given by:

$$\text{angle} = \pi - \theta \quad (4)$$

In the proposed approach, Hough transformation can detect straight lines in a thinned vein image. It defines these lines and separates the features in the vein image; offering extremes of the spotted lines as output and discovering the angle of the lines about x-axes. This is done through determining certain threshold for vein lengths (minimum 30 connected pixels) and space (maximum 10 pixels) extracting the studied lengths and angles. Extracting these features, allowed us to compare between the captured image and the template image. "Fig. 9" shows an example of the discovered lines within the image's veins after using this method.



(a) (b)

Fig. 9. (a) Start and end points of each line together with its length (b) Calculated angles between the vein and horizontal axis.

By calculating the vein lengths l_i via below "(5),".

$$l_i = \sqrt{(x_{2i} - x_{1i})^{\,2} + (y_{2i} - y_{1i})^{\,2}} \quad (5)$$

Where (x_1, y_1) and (x_2, y_2) are start and end point of each straight line and i is the numbers of straight line in the vein image As example :

$$l_1 = \sqrt{(216 - 163)^{\,2} + (169 - 239)^{\,2}} = 87.8$$

$$l_2 = \sqrt{(216 - 197)^{\,2} + (239 - 87)^{\,2}} = 153.18$$

$$l_3 = \sqrt{(150 - 163)^{\,2} + (128 - 169)^{\,2}} = 43.011$$

and $\theta_1 = 173^{\circ}, \theta_2 = 142^{\circ}, \theta_3 = 162^{\circ}$

By applying Hough Transformation on vein images, we extract the start and end points of each line in the image; then we calculate the vein lengths (as $l_1, l_2, l_3, \ldots \ldots l_i$) and angles between veins and horizontal lines. Based on the collected data set, every image has different number of lines / veins. Thus, we identified three lines only from the captured image (right / left) together with their attached angles to be analyzed, so that every image will have three vein lengths(l_1, l_2, l_3) and three angles($\theta_1, \theta_2, \theta_3$).

V. FUSION DECISION

After having the new calculated features of studied images, an additional parameter has been added (number of white pixels) which reflect the average brightness indicator of image. By merging this parameter together with the previous collected features, there are seven unique features for every hand that can be used in classification step.

- Weighted Euclidean distance Method.

The classifying method used for the Hough transformation unique feature (Angle, Length and number of white pixels) is the weighted Euclidean distance. It is used to classify the unique feature of vein image awaiting recognition according to the features in the database. When the distance between these features is the shortest, they are regarded to be of the same class. The following is the formula:

$$w(k) = \sum[(f_{iw} - f_{iw}^{k})^{2}/(\delta_{iw}^{k})^{2}] \quad (6)$$

The number of i geometrical structural features of the input vein is $\boldsymbol{f_{iw}}$; $\boldsymbol{f_{iw}^{k}}$ is the number of i feature of the number of k-hand vein and $\boldsymbol{\delta_{iw}^{k}}$ is the number of i feature standard deviation of the number of k-hand vein. The distances between the input hand veins and the database hand veins are measured one by one. The input hand vein is recognised as the number of k-class if the distance between the number of k classes in the database is the shortest.

- Classification

Weighted Euclidean distance has been used to evaluate fusion technique between structural feature and brightness indicator. By getting the minimum distance between the two studied images (captured and template), the decision can be taken either by matching the two images or not. And used correlation to evaluate pixel by pixel technique.

VI. EXPERIMENTAL RESULTS

The results of the performed algorithms (Pixel by pixel, fusion between structural features and brightness indicator) after using the collected data for 600 images will be discussed below. Biometric performance measurements were employed to evaluate the system's performance.

- Analysis and Evaluation

The Receiver operating characteristic curve (ROC) displays the False acceptance rate (FAR) against the Genuine acceptance rate (GAR) (or 1 - False rejection rate (FRR) to assess the performance of the established biometric system. The Equal Error Rate (EER), defined as the error rate when the FAR and the FRR are equal, is also used to assess performance.

Where:

FAR: stands for the likelihood of an impostor gaining access.

$$\text{FAR} = \frac{number\ of\ impostor\ attempt\ accpted}{\text{total}\ number\ impostor\ attempt} \quad (7)$$

FRR: the likelihood of a genuine user's access attempt failing.

$$\text{FRR} = \frac{number\ of\ \text{genuine}\ attempt\ \ rejected}{\text{total}\ number\ \text{genuine}\ attempt} \quad (8)$$

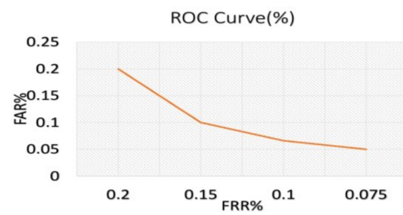
GAR: is the probability of an authorized person is successfully accepted.

$$\text{GAR} = \frac{number\ of\ \text{genuine}\ attempt\ accepted}{\text{total}\ number\ \text{genuine}\ attempt} \quad (9)$$

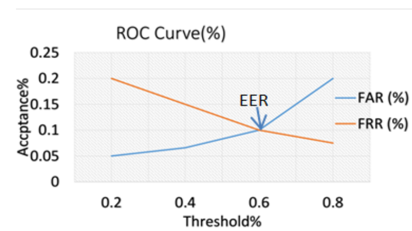
The system's performance was evaluated using the above-mentioned database, with a ROI size of 480x720 and features retrieved using the pixel-by-pixel methodology, with a 98.5 % accuracy. "Table III" and "Fig. 10" show the FAR, FRR, and GAR findings achieved using the proposed technique.

TABLE III. OUTCOME OF THE PIXEL BY PIXEL METHODOLOGY

Number of Images	FAR (%)	FRR (%)	GAR (%)
10	0.200	0.200	0.800
20	0.100	0.150	0.850
30	0.066	0.1	0.9
40	0.050	0.075	0.925
200		0.015	0.985



(a)



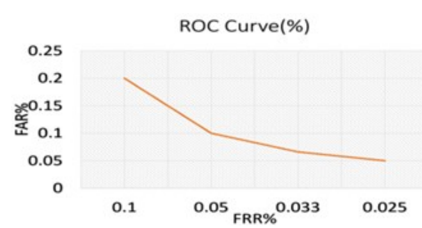
(b)

Fig. 10. (a, b) ROC curve for Pixel by Pixel Method.

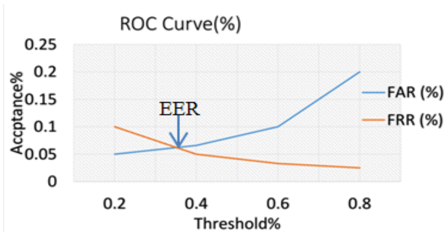
The features were extracted with the modified Hough transformation method scoring an accuracy of 99.5%. "Table IV" and "Fig. 11" show the FAR, FRR, and GAR findings achieved using the proposed technique.

TABLE IV. OUTCOME OF THE MODIFIED HOUGH TRASFORMATION METHODOLOGY

Number of Images	FAR (%)	FRR (%)	GAR (%)
10	0.200	0.100	0.900
20	0.100	0.050	0.950
30	0.066	0.033	0.967
40	0.050	0.025	0.975
200		0.005	0.995



(a)



(b)

Fig. 11. (a, b) ROC curve for Hough Line Transform

VII. CONCLUSION

This study has used the hand vein patterns to identify individuals employing a low cost system. The used system is composed of a black box with an arm to fix the hand together with a camera to capture images connected to the PC. A collection of advanced image processing techniques have been applied to 600 collected images (There are six images per person in this data collection for 100 people of various ages and genders (three for the right hand and three for the left)). The study used the assembled data under two different scenarios: the first is to compare the tested image to the stored ones via pixel by pixel technique, it gave an accuracy 98.5%, FAR is 0.05%, FRR is 0.015% . Where as, the second is to use modified Hough transform to extract structural features fusioned with brightness indicator to collect a group of new features used in match process. Three lengths, together with three angles have been extracted from every image together with the number of white pixels. Based on the extracted features, the tested images have been classified via Euclidean distance. It gave an accuracy 99.5%, FAR is 0.05%, FRR is 0.005%. It has been observed that our proposed technique based on Hough transform yielded higher performance compared to the first one "pixel by pixel" as shown in "Table V".

TABLE V. HAND VEIN RECOGNITION SYSTEM VS. PROPOSED SYSTEM

Ref #	Feature	Matching	System Results
Ramsoful, P., & Khan, M. H. M. [14] 2013	Hough Line Transform	Mahalanobis Distance	FAR=0.01%
	Pixel by Pixel	Correlation	FAR=0.03%
	Directional Coding	--	FAR=high
Sree, V. K., & Rao, P. S. [15] 2014	Hough transformation	KNN	FAR=20% FRR=3.75% Ac= 96.25%
Belean et. Al. [17] 2017	Hough transformation	SPMA k1 =0.76	EER= 1.67%
		NNA k2 =0.81	EER= 0.83%
Proposed method	Pixel-by-pixel	Correlation	FAR = 0.05%, FRR= 0.015% EER= 0.6%
	Hough transformation	Angle, Length and Weighted Euclidean	FAR=0.05% FRR= 0.005% EER= 0.35%

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