Hand Vein-based Multimodal Biometric Recognition

S. Bharathi[1], R. Sudhakar[1], Valentina E Balas[2]

[1]Department of Electronics and Communication Engineering, Dr.Mahalingam College of Engineering and Technology, Pollachi -642 003, Tamilnadu, India
E-mail: sbharathi@drmcet.ac.in, hod_ece@drmcet.ac.in

[2]Department of Automatics and Applied Software, Aurel Vlaicu University of Arad, 77 B-dul Revolutiei, 310130 Arad, Romania
E-mail: valentina.balas@uav.ro

Abstract: Multi-modal biometric recognition utilizes more than one modality for recognition of a person, when compared to the single modality with the help of enhanced security. The vascular patterns are one of the physiological biometrics and internal feature of the body, hence, it cannot be easily cracked, falsified or spoofed. This paper proposes a novel approach for biometric recognition, using finger vein, palm vein and dorsal vein of the hand. Our proposed method utilizes both the Shearlet transform and Scale-invariant feature transform to extract features from the hand vein images. The extracted features in the form of coefficients are stored in the data base. Then the matching is done between the coefficients of the input test images and the features stored in the data base using distance measure and finally the fusion is carried out using the maximum likelihood ratio technique. This approach was tested on standard data bases of finger vein, palm vein and dorsal vein images of hands. The proposed method provides a maximum accuracy of 94%, with a reduction in false acceptance and false rejection rates, illustrating the efficiency of the technique compared to other current methods.

Keywords: hand vein; shearlet transform; scale-invariant feature transform; multi-modal biometric recognition; maximum likelihood-based fusion

1 Introduction

Biometrics has many advantages over conventional safety measures such as Non-repudiation, Accuracy, Screening and Security. Nowadays, biometric recognition is a familiar and reliable way to authenticate the identity of a person through physical measurements of unique human characteristics or behavior. A physiological characteristic is a distinctive personal traits, such as fingerprint, palm print, hand vein, iris pattern and many more [1]. Signature, gait and keystrokes are some of the behavioral characteristics. Biometric technology provides assurance of a trouble-free, safe technique to make an exceedingly precise authentication of a person [2, 3]. Alternate symbols of distinctiveness like passwords and identity cards have the vulnerability of being easily misplaced, shared or stolen. Passwords may also be easily cracked by means of social engineering and dictionary attacks [4, 5] and offer negligible protection. As biometric techniques make it a precondition for the client to be physically present during validation, it serves as a deterrent against the possibility of clients emerging with false refutation claims at a later stage [6].

The excellence of a biometric technique is assessed by means of its inherent competence. Regardless, even the finest biometrics, of our modern age is haunted by many problems, several of them innate in the technology itself. Multi-biometrics is a comparatively novel method to conquer these obstacles by means of manifold models of a solitary biometric trait, known as, multi-sample biometrics or models of multiple biometric traits called multi-source or multi-modal biometrics [7, 8]. Multi-biometric techniques are capable of diminishing several of the constraints of uni-biometric methods, as the diverse biometric sources generally compensate for the inborn constraints of the supplementary sources [9]. The significant objective of multi-biometrics, is to scale up the accuracy of detection over a specific technique by synthesizing the outcomes of several traits, sensors or algorithms. In multi-modal biometrics, selection of true modality is a demanding task in the identification of a person. The personal recognition by means of hand vein has, nowadays, attracted the ever-increasing enthusiasm of investigators because of its superior biometric traits over other modalities [10, 11, 12].

In multimodal biometric recognition systems, the fusion [13] of various traits can be carried out at different levels, such as sensor level, feature level, [14, 15] score level [16, 17] and decision level [18]. Score level blending is the most desirable factor in multimodal biometric systems in view of the fact that matching scores encompass ample data to distinguish between true and false cases and they are comparatively easy to access. This facilitates trouble-free amalgamation of data gathered from specific modalities, by means of score level synthesis, making it realistic and reasonable. The amalgamation procedure can be carried out using the approaches like transformation-based, classifier-based and density-based at the score level. Scores from multiple matchers are treated as a feature vector and a classifier is constructed to discriminate genuine and impostor scores in a classifier based fusion. The density-based approach [19] has the advantage that it directly achieves optimal performance at any desired operating point, provided the score densities are estimated accurately.

Herein, the proposed technique, employs Shearlet transformation and Scale-invariant Feature Transformation (SIFT) to obtain feature coefficients from hand vein images and a maximum likelihood ratio-based fusion, at the score level. The rest of the paper is organized as follows: A brief review of research related to the proposed technique is presented in Section 2. The proposed technique is presented in Section 3. The detailed experimental results and discussion are given in Section 4 and the concluding remarks are provided at the end.

2 Background of the Research Work

A multimodal biometric recognition based on finger images was discussed in [20].The local binary patterns algorithm was used to extract features and match for the fingerprints and finger veins, while the oriented FAST and Rotated BRIEF algorithm was applied for knuckle prints. Finally, score-level fusion was performed on the matching results from the above three finger biometrics. In [21], a multimodal biometric recognition using iris and facial images was discussed. Contourlet transform and two dimensional principal component analyses were used here to extract the iris features and the facial features respectively, and a feature vector was formed by the combination of the iris and facial features. A fixed random matrix was used here, to improve the recognition efficiency. The excellence of sum rule-based and support vector machine based score level fusion were deliberated in [22]. Three biometric characteristics were taken into consideration, for the purpose of the investigation, including fingerprints, faces, and finger veins. Authors have formulated vigorous normalization systems, such as, diminution of high-scores effect normalization which has been obtained from min-max normalization technique.

Shubhangi Sapkal [23] have smartly developed a novel level synthesis method to fine tune population coverage and scale down spoofing, that possess the quality of flexibility to error forbearance of various mono-modal biometric techniques. This method was intended as an access management system necessitating the enhanced safety in permitting access to significant data. Poh, N. [24] have proficiently proposed a technique to mechanically validate the uniqueness of an individual by way of biometrics, employing face and fingerprint. They established the fact that the superior performing fusion algorithms were those that make the utmost use of the mechanically mined biometric trait quality calculated with a view to detect the utmost possible biometric mechanism from which the query biometric data was obtained.

Recently, personal identification by means of hand veins has attained progressively more research attention. Hand vein recognition has been deliberated in [25], based on the statistical processing of the hand vein patterns. The hand vein database has been collected under practical conditions and subjected to go through different procedures. Here a combination of geometric and appearance-based techniques were used for feature extraction and distance metrics for recognition. A bank of Gabor filters was used for feature extraction [26] of finger vein images, from which finger vein codes were generated using the local and global features of the vein. Nearest cosine classifier was used for classification and fusion was carried out at the decision level. In [27], Palm-dorsal vein recognition method based on histogram of local Gabor phase XOR Pattern has been suggested. They have used chi-square distance measure for recognition. The modified two directional two-dimensional linear discriminant analysis was proposed by Lee [28] for personal verification approach using palm vein patterns. A minimum distance classifier was used here for identification.

From these discussions, it is clear that the vein based biometrics provide improved security and it cannot be easily spoofed or falsified. Hence, in our proposed system, we have used hand vein biometrics, such as, finger vein, palm vein and dorsal vein of the hand, for multimodal biometric recognition.

3 Proposed Method

Biometric recognition has the advantage of being reliable and secure for authentication purposes. Multi-biometrics uses more than one trait and overcomes the draw backs of using single modality. It improves security, but choosing the right modality and techniques involved, is of utmost importance. Finger vein, palm vein and dorsal vein of the hand are used here as the biometric modalities. The proposed technique employs Shearlet transform [29] and SIFT [30] for feature extraction and the fusion is carried out using maximum likelihood ratio-based technique. The block diagram of the proposed technique is given in Fig. 1.

3.1 Formation of feature set

In order to generate the required feature set, the input vein images of hands are transformed using Shearlet transform and Scale-invariant feature transform.

3.1.1 Shearlet Transformation

The Shearlet is an affine system with a single generating mother Shearlet function parameterized by a scaling, shear, and translation parameter. The Shearlet transform thus overcomes this drawback while retaining most aspects of the mathematical framework of wavelets. Shearlet has the properties that the associated system forms an affine system and the transform can be regarded as matrix coefficients of a unitary representation of a special group.

Shearlet can be represented as:

$$\Psi_{a,s,t}(x) = a^{-3/4}\Psi((D_{a,s}{}^{-1}(x-t)), \quad where \quad D_{a,s} = [a,-a^{1/2}s;0,a^{1/2}] \qquad (1)$$

Where, a is a scaling parameter, s is a shear parameter and t is a translation parameter.

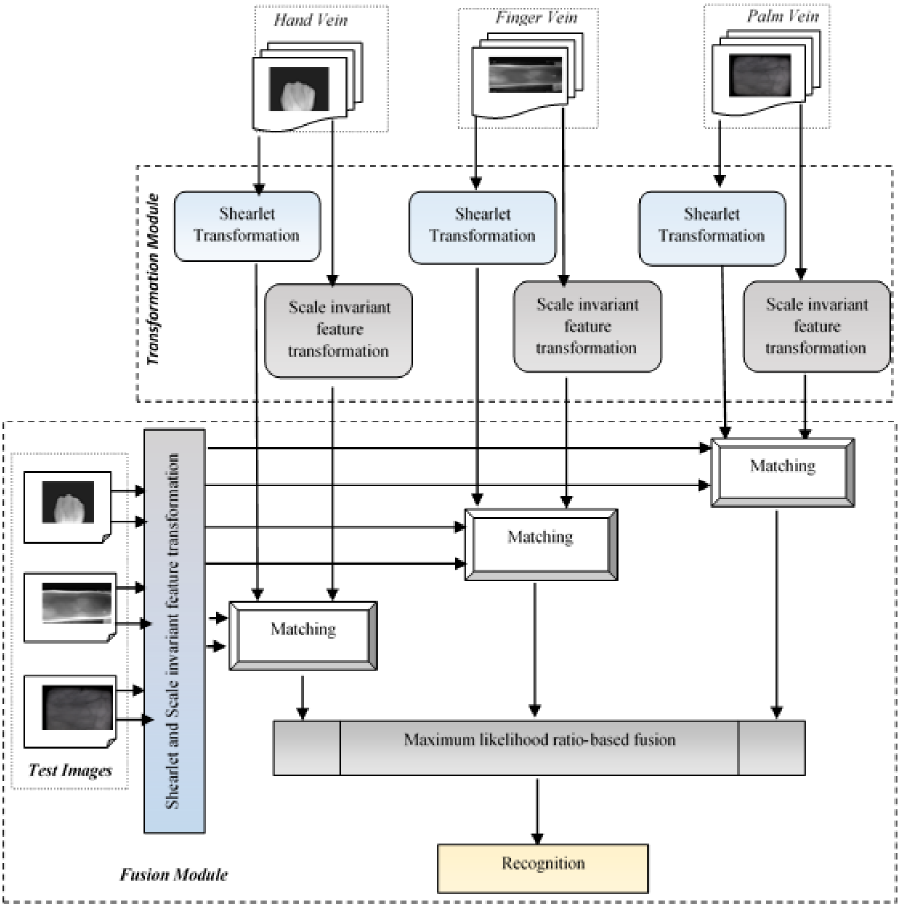

Figure 1

Block diagram of the proposed recognition technique

The mother Shearlet function Ψ is defined as:

$$\Psi(\xi_1,\xi_2)=\Psi_1(\xi_1)\Psi_2\left(\frac{\xi_2}{\xi_1}\right) \tag{2}$$

Where, Ψ_1 is a wavelet and Ψ_2 is a bump function.

The associated continuous Shearlet transform depends on the scaling, shear and translation parameters and is defined by

$$ST\left[f(a,s,t)\right]=\left\langle f,\Psi_{a,s,t}\right\rangle \tag{3}$$

This transform can also be regarded as matrix coefficients of the unitary representation:

$$\sigma(a,s,t)(\Psi)(x) = \Psi_{a,s,t}(x) = a^{-3/4}\Psi\left(D_{a,s}{}^{-1}(x-t)\right) \tag{4}$$

Let the input hand vein, finger vein and palm vein images be represented as

$$H = \{h_1, h_2, h_3, ..., h_n\}, D = \{d_1, d_2, d_3, ..., d_n\} \;\; and \\ P = \{p_1, p_2, p_3, ..., p_n\} \tag{5}$$

Here, n is the number of images. Then the Shearlet transformed hand vein, finger vein and palm vein images can be represented by

$$SH = \{sh_1, sh_2, sh_3, ..., sh_n\},\; SD = \{sd_1, sd_2, sd_3, ...sd_n\} \;\; and \\ SP = \{sp_1, sp_2, sp_3, ...sp_n\} \tag{6}$$

3.1.2 Scale-Invariant Feature Transformation

Scale-invariant feature transform (SIFT) is a step by step procedure to identify and delineate the local features in images. There are mainly four steps involved in SIFT algorithm namely scale space extrema detection, key point localization, orientation assignment, key point descriptor and key point matching.

Scale-space extrema detection is employed to detect larger corners using larger windows. Here, Laplacian of Gaussian (LoG) is found for the image with various scaling parameter values (θ). LoG acts as a blob detector which detects blobs in various sizes. As LoG is a little costly, SIFT algorithm uses Difference of Gaussians which is an approximation of LoG. Difference of Gaussian (DoG) is obtained as the difference of Gaussian blurring of an image with two different θ and $k\theta$. Once this DoG is found, images are searched for local extrema over scale and space.

Once potential key points locations are found, they have to be refined to get more accurate results in the key point localization. If the intensity at this extrema is less than a threshold value, it is rejected so as to eliminate low contrast key points. Similarly, edge threshold is used to remove low edge key points. These processes would rise to retain of strong interest points.

The SIFT transformed images of hand vein, finger vein and palm vein images can be represented by

$$FH = \{ fh_1, fh_2, fh_3, ..., fh_n\},\; FD = \{ fd_1, fd_2, fd_3, ... fd_n\} \;\; and \\ FP = \{ fp_1, fp_2, fp_3, ... fp_n\} \tag{7}$$

3.2 Maximum Likelihood Ratio-based Fusion and Recognition

The feature set obtained from the transformations are matched and fused for recognition. Initially, images of hand vein, finger vein and palm vein are transformed using the above transforms and stored in the database. The database (DB) would consist of both the Shearlet and the SIFT transformed images:

$$DB = \{SH, SD, SP, FH, FD, FP\} \tag{8}$$

Where,

$$SH = \{sh_1, sh_2, sh_3, ..., sh_n\}, SD = \{sd_1, sd_2, sd_3, ..., sd_n\},$$
$$SP = \{sp_1, sp_2, sp_3, ..., sp_n\}, FH = \{fh_1, fh_2, fh_3, ..., fh_n\}$$
$$FD = \{fd_1, fd_2, fd_3, ..., fd_n\} \text{ and } FP = \{fp_1, fp_2, fp_3, ..., fp_n\}$$

Subsequently, the matching score is compared to the test input images

and those in the database. The test images are represented by:

$$T = \{h_{test}, d_{test}, p_{test}\} \tag{9}$$

The transformed images are represented as:

$$T^* = \{sh_{test}, sd_{test}, sp_{test}, fh_{test}, fd_{test}, fp_{test}\} \tag{10}$$

These features are compared with those in the database using the Euclidean distance measure which gives the matching score. If the Euclidean distance between the test image and that of the data base image is less than the threshold set, then the images are said to be in a matched condition. Suppose the Euclidean distance between images Im_1 *and* Im_2 is represented by *dis* and the threshold set is represented as d_{thr}, then,

if dis $< d_{thr}$ *, then* Im_1 *and* Im_2 are in matched condition (11)

Each of the images are matched with the database image and then matching scores of all images are discovered. After the matching process, a fusion process is carried out with the use of maximum likelihood ratio based fusion. It is basically a density based score fusion which requires explicit estimation of genuine and impostor match score densities. Each comparison of the test image with that in the database would yield a matching score and for the fusion process each of the matching scores are taken into consideration. It is supposed that total of *m* matching is carried out, to get the matching score vector given by

$$SV = \{sv_1, sv_2, ..., sv_m\} \tag{12}$$

Let the conditional joint densities of the M match scores for the genuine and impostor classes be represented by *Ge(sv) and Ip(sv)*. The respective class of genuine or impostor is assigned by analyzing the score vector and Gaussian mixture model is employed for finding out the score densities.

Let the M-variant Gaussian density be represented as $g(sv;\mu,c)$, where μ is the mean vector and c is the covariance matrix.

The estimates obtained can be represented as $\hat{Ge}(sv)$ and $\hat{Ip}(sv)$. Then the maximum likelihood ratio is given by:

$$L(sv) = \frac{\hat{Ge}(sv)}{\hat{Ip}(sv)} \tag{13}$$

The matching score vector sv is assigned to genuine class, if $L(sv) >$ decision threshold or assigned to impostor class, if $L(sv) \leq$ decision threshold. The decision threshold is determined based on the specified False acceptance rate (FAR).

4 Results and Discussion

The experimental results of the proposed method for vein based biometric recognition are discussed here. The evaluation metrics employed here are accuracy, FAR (False Acceptance Rate) and FRR (False Rejection Rate).

FAR is the measure of the likelihood that a biometric security system will incorrectly accept an access attempt by an unauthorized user. FAR typically is stated as the ratio of the number of false acceptances divided by the number of identification attempts.

FRR is the measure of the likelihood that the biometric security system will incorrectly reject an access attempt by an authorized user. FRR typically is stated as the ratio of the number of false rejections divided by the number of identification attempts.

The database utilized for our experimentation is taken from the standard data bases [31, 32, 33] for hand vein, palm vein and finger vein images. The experimental results at various stages of hand vein, palm vein and finger vein images are given in Figure 2.

(a) (b) (c)

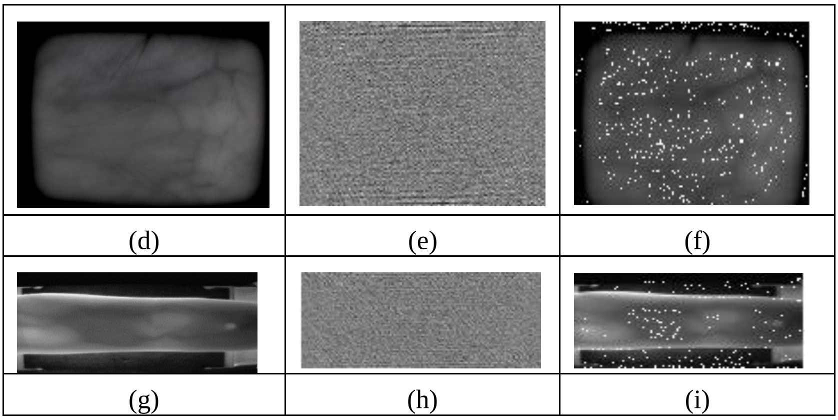

Figure 2

Images at various stages (a) Input dorsal hand vein image (b) Shearlet transformed dorsal vein image (c) Scale-invariant feature transformed dorsal vein image (d) Input palm vein image (e) Shearlet transformed palm vein image (f) Scale-invariant feature transformed palm vein image (g) Input finger vein image (h) Shearlet transformed finger vein image (i) Scale-invariant feature transformed finger vein image

4.1 Performance Analysis

The performance of the proposed technique is evaluated using metrics of FAR, FRR and accuracy. The values are taken for each modality of hand vein images such as dorsal vein, finger vein and palm vein. The evaluation metrics is also taken for feature one (when Shearlet transform is only performed), feature two (when SIFT transform is only performed) and product (when the fusion is carried out using product rule). The analysis is carried out and they are illustrated in the graphs separately.

The performance graph of FAR, FRR, FAR-FRR, ROC and Accuracy is plotted in Figures 3 to 7. Here, initially the experimental analysis is carried out with the hand vein features, which are extracted by using the shearlet and SIFT transforms separately. Then the analysis is performed with the vein features (extracted by using both shearlet and SIFT) fused at the score level using product rule. Finally, the above results are compared with our proposed technique. In Figure 3, we have obtained FAR with good performance for which, the threshold is above 0.3. From the graph shown in Figure 4, FRR of the proposed method attained lower value compared with the product rule based fusion at the score level. FRR-FAR curve obtained are shown in Figure 5 and the lines meet at a score threshold of 0.4 when FRR-FAR values were below 0.1 and this indicates improved performance of the proposed system.

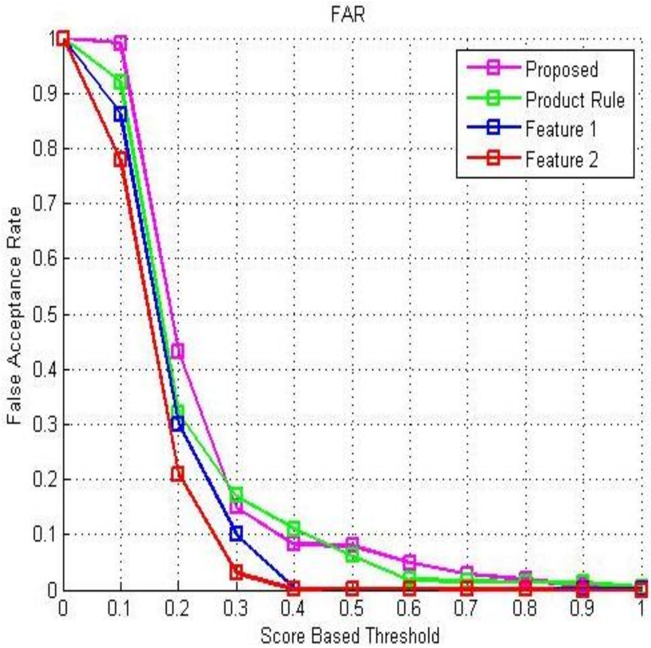

Figure 3
Plot of FAR

The accuracy graph (Figure 6) is plotted by varying score based threshold, in the range of zero to one (0-1). For each threshold value set, we can see that our proposed technique has achieved a higher accuracy. Here, we found that our proposed technique provides low FAR, FRR and high accuracy of 94%. Also, we observed that from the Receiver operating characteristics (Figure 7), the proposed technique achieved a low Equal error rate (EER) of 0.04, in comparison with other techniques.

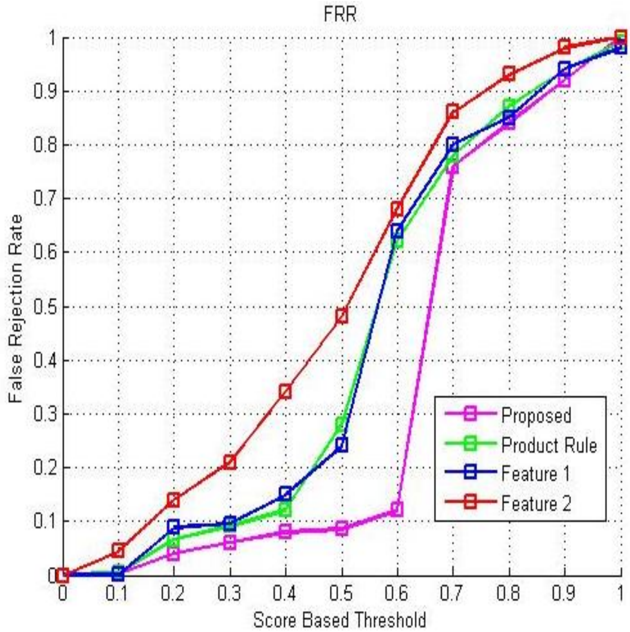

Figure 4
Plot of FRR

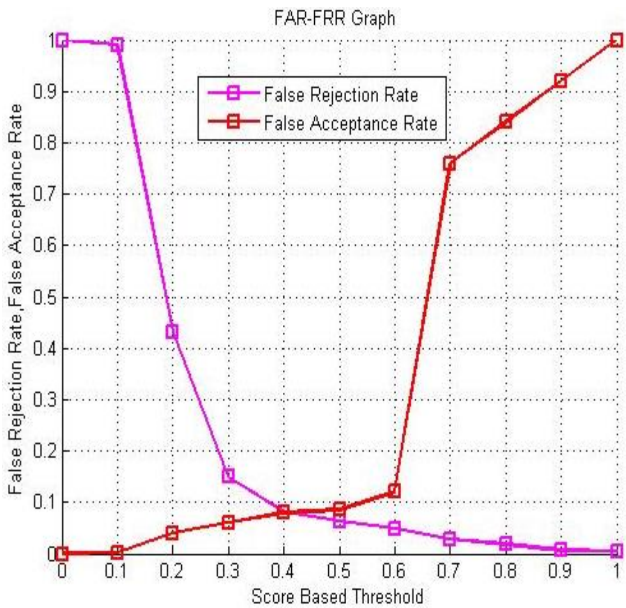

Figure 5
Plot of FAR-FRR

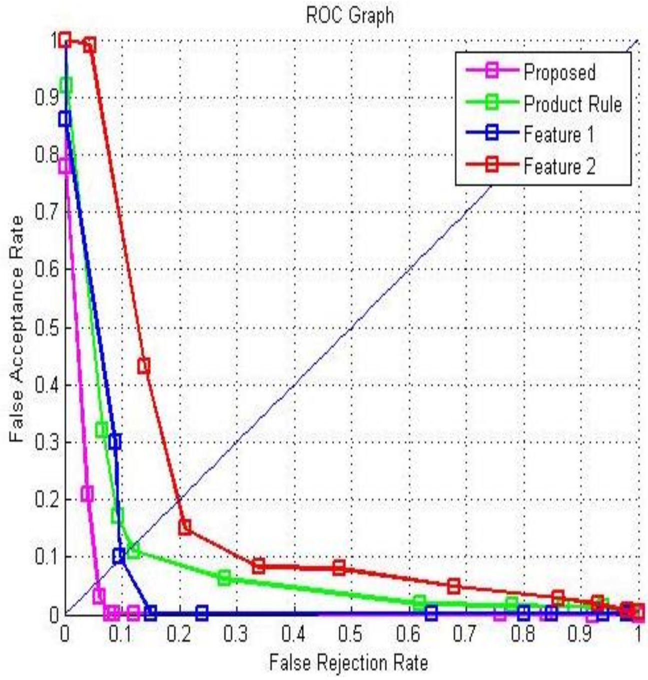

Figure 6
Plot of ROC

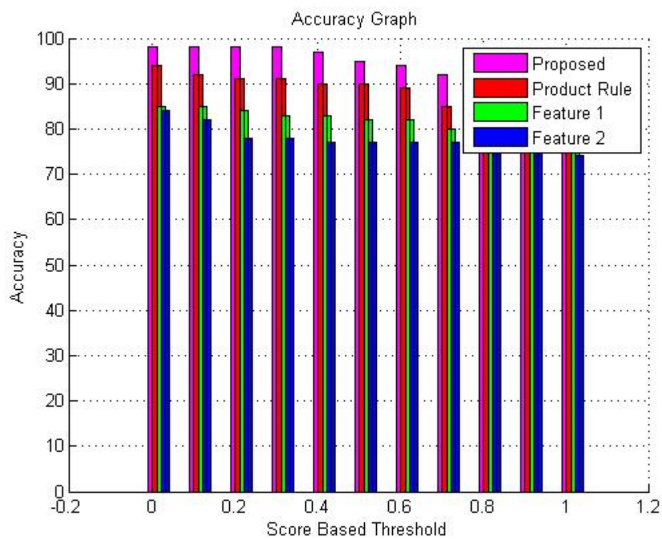

Figure 7
Plot of Accuracy

Table 1
Comparative analysis of related work on vein based biometric recognition

Author	**Biometric features**	**Methodology**	**Imaging**	**Data base**	**Performance**
Lin, C.L., and Fan, K.C [34]	Palm-dorsa vein	Multi resolution analysis and combination	Thermal imaging	32 users	FAR = 1.5 FRR = 3.5 EER = 3.75
Kumar, A., and Prathyusha, K.V [35]	Hand vein and knuckle shape	Matching vein triangulation and shape features	Near IR imaging	100 users	FAR = 1.14 FRR = 1.14
Raghavendra, R., Imran, M., Rao, A., and Kumar, G.H [36]	Hand vein and palm print images	Log Gabor transform	Near IR imaging	50 users	FAR = 7.4, FRR = 4.8
		Non-standard mask			FAR = 2.8, FRR = 1.4
Ferrer, M.A., Morales, A., Travieso, C.M. and Alonso, J.B [37]	Hand geometry, palm and finger textures, dorsal hand vein	Simple Sum rule	Near IR imaging	50 users	FAR = 0.01, FRR = 0.01, EER = 0.01
Yuksel, A., and Akarun, L [38]	Hand vein	ICA 1, ICA2, LEM and NMF	Near IR imaging	100 users	EER =5.4, 7.24,7.64 and 9.17
Proposed method	Dorsal hand vein, palm vein and finger vein	Maximum likelihood	Near IR imaging	100 users	FAR = 0.04, FRR = 0.05, EER = 0.04

4.2 Comparative Analysis

The comparative analysis of the related work on vein based authentication is given in Table 1. All the results presented in this table are in terms of Equal error rate (EER), FAR and FRR. EER is defined as a point, at which, FAR is equal to FRR. The lower the values of EER, the better the performance of the system, but it varies according to the imaging technique, type of biometric trait, methodologies used for feature extraction, method and type of fusion of these features and number of users in the data base.

Conclusions

In this work, a novel multi-modal biometric recognition was presented, using only the vein biometric traits present in the hand. Here, we used the finger vein, palm vein and dorsal vein biometric traits of the hand. Shearlet Transform and Shift Invariant Feature Transform (SIFT) were used for feature extraction and the fusion was carried out using the maximum likelihood ratio method at the score level. All the biometric traits used here are the vascular patterns of the body so it cannot be spoofed and the trait, provides a better security, compared to other kinds of multi-modal biometric systems. The proposed system is evaluated using the parameters of accuracy, FAR and FRR. The experimental results show improved performance of the system, when compared with other current techniques, indicating the effectiveness of our proposed technique. This technique provides the highest accuracy of 94% and minimum FAR and FRR.

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