IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.8, Issue.5, May 2020 E-ISSN: 2347-2693

An Efficient Feature Selection scheme based on Genetic Algorithm for Finger Vein Recognition

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DOI: https://doi.org/10.26438/ijcse/v8i5.715 | Available online at: www.ijcseonline.org

Received: 06/May/2020, Accepted: 18/May/2020, Published: 31/May/2020

Abstract— Any Biometric system comprises five modules which are data acquisition, Pre-processing, feature extraction, matching and decision. Finger vein is another biometric innovation that contends with other ground-breaking biometrics modalities, for example, the face, palm print, fingerprint, iris and voice. Finger vein recognition is a biometric method used to analyze finger vein patterns of people for appropriate verification. The feature extraction module is very important in a biometric system. The extracted features perhaps include irrelevant and redundant features that can drive to the retreat of the performance of the biometric system. To solve this problem, an efficient feature selection scheme based on the Genetic Algorithm (GA) for Finger vein recognition is proposed. While feature extraction the work was divided into four scenarios based on the full feature, Principal Components Analysis (PCA) method for feature reduction, a hybrid of GA and PCA for feature reduction and selection, and GA for feature selection. The proposed method tested on two standard finger vein biometrics databases (SDUMLA-HMT and UTFV). The experimental results show that the proposed method gives the best results with high accuracy reached to 99.95% and 99.89595%.

Keywords— Finger-Vein, Biometrics, Genetic Algorithm, Feature Extraction, Gabor Filter, PCA, Correlation Coefficients, FAR, FRR.

I. INTRODUCTION

The capability to recognize individual characteristics in the intelligent identification is a security matter [1]. In recent years, a lot of algorithms have been developed to address the security issues, but there is still a place for fast and efficient biometric recognition. Biometric recognition refers to the automatic recognition of individual properties captured by their anatomic/behavioral characteristics. Several types of biometric techniques have been produced based on these physiological/behavioral traits such as face, fingerprint, palmprint, hand veins, finger veins, palm veins, iris, foot vein, DNA, gait recognition, signature, voice recognition, facial expression, heartbeat, palates, and body language [2,3]. These biometric recognition techniques can be divided into two categories: (i) extrinsic biometric traits (palm print, iris, fingerprint, face) and (ii) intrinsic biometric traits (palm vein, hand vein, and finger vein) [4,5]. Extrinsic traits are more visible than the intrinsic trait and have more adverse factors. For example, the retinal surface is affected by the high intensity of light through the extraction of iris features [6]. Similarly, the accuracy of face identification is also disfigured due to brightness variance, style of facial, blockage of blood vein and pose [7]. Table 1 presents the advantages, disadvantages, security level, and other characteristics of some typical extrinsic and intrinsic traits. In 2002, Kono [8]-a Japanese medical researcher-introduced finger vein recognition methods. Since then, these methods have been largely implemented in hundreds of cities in Japan, and other countries worldwide have developed finger vein recognition systems [9]. The vein-based identification system has biometric pattern models for security and convenience for personal authentication. The typical scheme of the biometric finger vein recognition (FVR) system is presented in Figure 1. The vein is a part of intrinsic traits and is therefore difficult to replicate and falsify. Finger veins are generally captured by using near-infrared (NIR) light (700–900 nm) in a trans-illumination manner [10]. Vein-based systems frequently utilize various physiological traits like finger vein, hand vein, foot vein or palm vein for personal identification/verification. Finger vein is preferable in that its imaging tool is smallest, and that fingers have a larger number of veins than the palm and hand [7]. In addition, every finger vein pattern is unique even for identical twins and exists only for live humans [11]. Most substantially, each finger vein pattern does not change during a lifetime [6].

Table 1. Extrinsic and Intrinsic features Characteristics.

BIOMETRIC TRAITS	SECURITY LEVEL	ADVANTAGES	DISADVANTAGES	COST	SENSOR
Fingerprint	Good	Widely applied	Skin	Low	Contact
Voice	Normal	Natural and convenient	Noise	Low	Non-contact
Face	Normal	Remote capture	Lighting conditions	Low	Non-contact
Iris	Excellent	High accuracy	Glasses	High	Non-contact
Finger vein	Excellent	High security level	Disease	Low	Non-contact

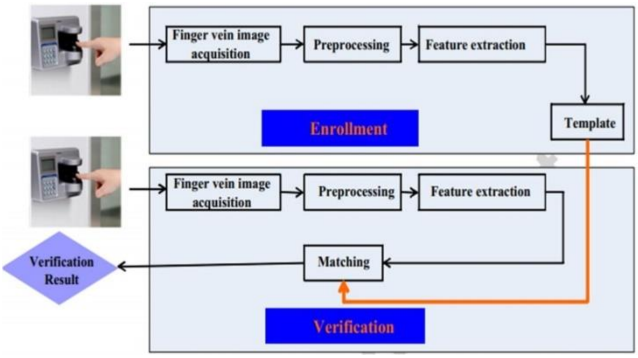


Figure 1. Typical framework for finger vein recognition [12].

We consider it that finger vein recognition is a challenging task because of uneven-illumination, low image contrast, and temperature variations. Finger vein identification systems are also vulnerable to spoofing attacks [6,10,13,14]; however, the most serious issue is the accuracy of personal verification. Thus, FVR still requires fast and efficient methods. In any biometric system, the feature extraction module is very important module. The extracted features maybe contain irrelevant and redundant features that can lead to the dimensionality curse problem, and also may lead to degradation of the performance of the biometric system. To solve this problem, there are two solutions feature reduction and feature selection [10,15]. First, feature reduction is a technique that allows producing a new feature vector from the origin feature space in order to increase the representativeness of the features by keeping the most important eigenvectors. The most widely methods that are used in biometric systems are Principal Component Analysis (PCA) [16,17], Kernel Linear Discriminant Analysis (KLDA) [10], and Linear Discriminant Analysis (LDA) [16,17]. Second, feature selection is method that finds the most important and relevant features assigning a particular objective function to be optimized. The most popular approaches that used in feature selection are Sequential Backward Selection (SBS), Sequential Forward Selection (SFS), Sequential Floating Forward Selection (SFFS). All these approaches start processing with an initial subset and sequentially remove/add the feature one by one that locally optimizes the objective function. But there are some problems with these approaches like time-consuming, exhaustive searches are costly and hard to implementing. To solve these problems, Intelligent techniques using artificial intelligence concepts have been proposed. For instance, the Genetic Algorithm (GA) [18,19] that has been used for feature selection and feature level fusion of fingerprint and iris. Particle Swarm Optimisation (PSO) [10,20,21] was used for feature level fusion of face and palmprint. These approaches have given promising results that motivate as to apply one of them on a unimodal biometric system. In this work, finger vein biometric architecture is proposed with an efficient feature selection based on GA. This paper organised as follow, Section I contains the introduction of finger vein recognition based on GA as feature selection scheme. In Section II a literature review of a finger vein biometric system is presented. The proposed method is presented in section III. In Section IV the results that obtained from applying the proposed method on finger vein biometric and comparison with previous studies, all features, PCA, and hybrid GA+PCA is presented. In Section V conclusion and some of future works are drawn up.

II. RELATED WORK

In this section, previous works in finger vein are presented. For example, a mobile device on real-time embedded finger vein recognition method authentication is suggested [22]. The structure is established on the DSP platform and set up with a novel finger vein authentication algorithm. While Peng et al. [23] proposed noise removal, Region of Interest (ROI), and Gray Scale Normalization as three pre-processing functions. For feature extraction, Gabor Filter is used with 8 directions and 5 scales, then SIFT features are used to equalize the outcome of images rotation and shift impact. In addition, Khalil-Hani et al. [24] suggested protection in networking and communication systems with the help of the strongest biometric finger vein system. They used the Genetic Algorithm (GA) to fine-tune the image processing factors in a finger vein biometric FPGA based method. Khellat-Kihel et al. [25] proposed a finger authentication method by using Support Vector Machine (SVM) based on a supervised training algorithm. Song et al. [26] introduced the mean curvature method, that analysis the valley like pattern with negative mean curvatures and gets the vein images as a geometric shape. Liu et al. [27] suggested the system that is stout adequate next to noise and deformation. In recognition, ONPP is used for various education and point to various programs is demoralized for tasting vein image cataloging. Lee et al. [28] proposed the latest vein recognition method of finger vein pattern using a weighted Local Binary Pattern (LBP) and (SVM). The holistic codes are taken out by the LBP method except for a vein detection process. Guan et al. [29] suggested the feature of Wavelet Transform (WT), Horizontal and Vertical Two-Dimensional Principal Component Analysis (2D 2PCA). Yang et al. [30]

proposed structured individual authentication to come up to using Location and Direction Coding (LCD) and finger vein location. Hong and Qubo [31] suggested a new optical finding method that was proposed to sing the near-infrared finger pattern capturing method. The vein pattern-based extraction method on the maximum curvature mechanism was realized. Hashimoto [32] suggested the technology and applications of finger vein authentication. From individual recognition, the finger vein is the latest biometric authentication technique. Japan's monetary foundation uses the latest; secure technology because the vein pattern is unique for the individual.

III. METHODOLOGY

Every biometric system is consisted of Five modules: Data Acquisition Module, Pre-processing Module, Feature Extraction Module, Matching Module, and Decision Module. Figure 2, shows all the five modules in our method.

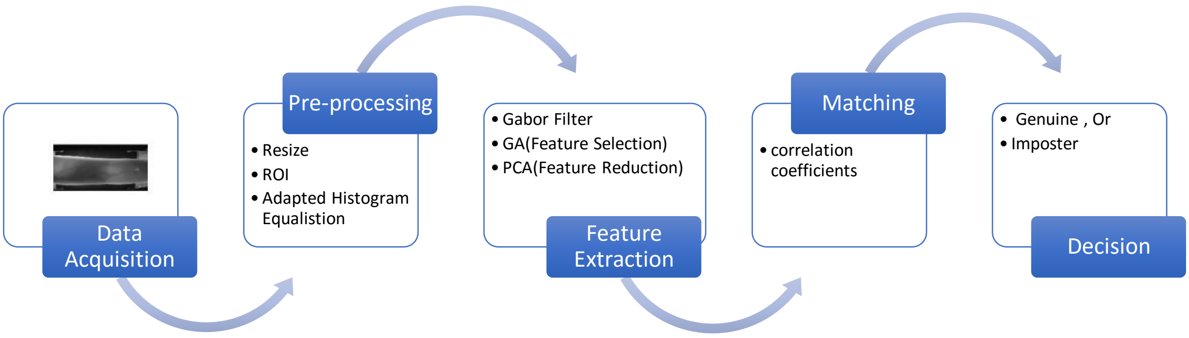


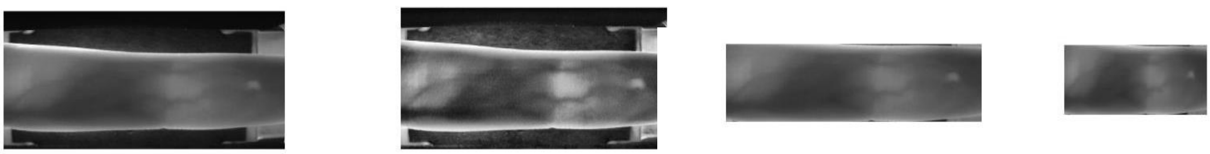
Figure. 2. The proposed method

A. Data Acquisition Module

There are many open finger vein databases, in this paper, two standard databases are used. SDUMLA-HMT [33] and UTFV [34]. In 2010, Shandong University released one multimodal trait database SDUMLA-FV [33]. The second database UTFV [34] is presented by the University of Twente.

B. Pre-processing Module

In this module, for improving the recognition rate the input finger vein image must be enhanced. In this paper, there are three main steps: First, Region of Interest (ROI) is used by Lee et al. [4], Second, Adapted Histogram Equalisation (AHE) is implemented to improve the finger vein image quality image and last, the finger vein is resized into the dimension of [200 200]. Figure 3, illustrates this module.



a. Original Image b. Enhanced Image c. ROI Image d. Resized Image

Figure 3.Finger vein Pre-processing Module

C. Feature Extraction Module

In this module, extraction the features from the enhanced finger vein input image by using one of the feature extraction methods. In this work, Gabor Filter is used for extracting the features, and the number of extracted features is so large. This led to one of the widest problems is called Dimensional curse, to solve this problem a genetic algorithm is proposed in order to select the most important and relevant features. Gabor wavelets (filters) have a frequency and orientation representations comparable to those of the human view system and they have been found to be particularly appropriate for texture, representation, and discrimination [35]. Gabor filters have been widely used in pattern analysis applications [15,22,36,37]. Among the advantage of Gabor filters: Its invariance to illumination, rotation, scale, and translation. In the spatial domain, a two-dimensional Gabor filter is modulated by a complex sinusoidal plane wave, defined as described in formula (1).

$$G(x,y) = \frac{f^2}{\pi} \exp\left(\frac{-x'^2 + \gamma^2 y'^2}{2\delta^2}\right) \exp(j2\pi f x' + \emptyset) \quad (1)$$

$$x' = x\cos\theta + y\sin\theta \quad (2)$$

$$y' = -x\sin\theta + y\cos\theta \quad (3)$$

Where f is the frequency of the sinusoidal factor, φ is the phase offset, θ means the orientation of the normal to the parallel stripes of a Gabor filter function, δ is the standard deviation of the Gaussian envelope and γ is the spatial aspect ratio which specifies the ellipticity of the support of the Gabor function. The Gabor filter used in our work employs 32 Gabor filters in 4 scales and 8 orientation. To reduce the computation cost due to the size of the resulting Gabor filter. We down-sample the features images resulting from the Gabor filter. The size of the output feature vector is the size of the re-sized finger-vein biometric image which is (128 ∗ 128) multiplied by the number of scales and orientations (4 ∗ 8) divided by the row and column down-sampling factors which is (6 ∗ 6). So, the size of the feature vector is 8192. Figure 4 illustrates the finger-vein biometrics feature extraction using Gabor filters.

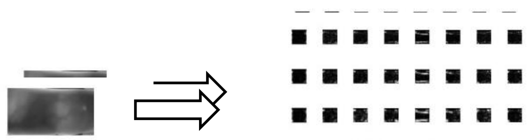


Figure. 4 Gabor filters on finger-vein sample

Genetic Algorithm (GA) is evolutionary algorithms, it is an adaptive heuristic search algorithm based on selection and genetics invented by Holland [38, 39]. They represent an intelligent utilization of a random search used to solve optimization problems. GA is among the most powerful meta-heuristics used to solve (0/1) problems. The GA algorithm general steps are presented in algorithm 1:

Algorithm 1 Genetic Algorithm

```
Input: inS = (x1, x2, . . ., xn, y): Database.
Where, x1,x2,..,xn are the features and y is the label
Popu:Popualtion
Psize: Population size.
Clen: Chromosome length.
Pc: Crossover probability.
Pm: Mutation probability.
T: Number of iterations.
Output: The Best fitness and optimal feature subset OFS
1: Initialize algorithm parameters.(table 3)
2: Load database inS.
// Data Normalization
3:inSn =norm(inS)
4: loop i =1 to Psize do
5: loop j =1 to Clen do
// Initialize the Population
6:      Popu(i, j) = rand>0.5
7: endloop (j)
8: endloop (i)
9: loop i =1 to Psize do
10:     Subset = inSn(:, findall(Popu(i, :) ==1))
11: endloop (i)
// initialization of iteration
12: it = 0
13: While it <= T
14:         loop i =1 to Psize do
//calculate fitness of individual by SVM.
15:             Fitvalue(i) = fit1(Popu(i))
16:             sort(Fitvalue(i))
17:         endloop (i)
//elitist preservation is applied
18:         Popu = Elit(Popu)
19:         Popu=crossover(Popu,Pc)
20:         Popu =mutation(Popu,Pm)
21:         NewPop = Popu
22:         it = it + 1
23: end_While_loop(13)
//The Best individual in the first place
24: BFS = inS(:, Find(NewPop(1, :) ==1))
25: return The Best fitness and the best feature subset
```

Chromosome Represent*:* In this type of problems, a string (0/1) digits are used. A (0/1) digit represents a feature, values 1 and 0 meaning selected and unselected, respectively. Objective function*:* The recognition rate (Accuracy) is the term of evaluating the performance of a biometric system, which is given by the formula of equation (4).

$$Accuracy = 100 - \left(\frac{FAR+FRR}{2}\right) \quad (4)$$

Where: FAR is the False Acceptance Rate that indicates the rate of an imposter is falsely accepted as genuine person which is given by equation (5),

$$FAR = \frac{No.of\ imposters\ falsely\ accepted}{total\ No.of\ imposters} \quad (5)$$

and FRR is the False Reject Rate that a genuine person is falsely rejected as an imposter which is given by equation (6),

$$FRR = \frac{No.of\ genuines\ falsely\ rejected}{total\ No.of\ genuins} \quad (6)$$

So, in this work our objective function represents the accuracy of the biometrics system as defined in the formula (5).

$$Fobj\ =\ SVM(Pop) \quad (7)$$

Principle Component Analysis (PCA) is widely used in biometric systems and it is proven its efficiency [16,17,40]. PCA is used for reducing the dimensions of the data matrix by determining the directions, and the corresponding strengths, of variation in the data [41]. PCA is computing the eigenvectors and eigenvalues of the covariance matrix of the data. Keeping only a few eigenvectors corresponding to the largest eigenvalues. In this work, PCA is used as a sub-module in feature extraction module for reducing the feature vector size of the extracted features.

D. MATCHING MODULE

In this paper, the Correlation Coefficients (CC) is used to measure the similarity between the input finger vein image and the templates collected during the enrollment phase.

Formula (6) shows how to calculate CC [42] between two templates.

$$\rho(A, B) = \frac{1}{N-1} \sum_{i=1}^{N} \left(\frac{\overline{A_i - \mu_A}}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right) \quad (8)$$

where μ_A and σ_A are the mean and standard deviation of A, respectively, and μ_B and $\boldsymbol{\sigma_B}$ are the mean and standard deviation of B.

E. Decision Module

In this module, the decision of acceptance or reject of a person depends on the threshold τ. The latter is calculated by the analysis of the matching score between the templates enrolled in the system and fixed based on a different trial of the biometric system. For example, if the score greater/less than the , the decision will be accepted or rejected.

IV. RESULTS AND DISCUSSION

In this section, the proposed method is verified by applying it on two different types of finger vein databases. The verification process divided to two sections: numerical results and graphical results. The proposed method is compared to the full feature system, PCA for feature reduction, GA+PCA for feature reduction and selection, and some of the previous work.

A. Databases

There are many open finger vein databases, in this paper two standard databases are used. SDUMLA-HMT [33] and UTFV [34]. In 2010, Shandong University released one multimodal trait database SDUMLA-FV [33]. The second database UTFV [34] is produced by the University of Twente. Table 2 illustrate the finger vein datasets.

Table 2. Finger vein databases in details.

Database	SDUMLA-FV	UTFV
Subjects	100	100
Total images	600	800
Finger vein per subject	1	1
Images per Finger vein	6	8
Image type	bitmap	bitmap
Image size	320 × 240 pxl	672 × 380 pxl

B. GA Parameters

Table 3 shows the parameters control of the proposed GA based on different tests of the proposed method.

Table 3 The parameters control of the GA

Size of Population	50
Generations	50
Method of Selection	Rank
Crossover Probability (Pc)	0.9
Mutation Probability (Pm)	0.1

C. Numerical Results and Discussion

In this work, four scenarios are performed. Full feature system, PCA for feature reduction, GA for feature selection, and the hybrid of PCA+ GA for feature reduction and selection. The numerical results are presented in Tables 4, and 5 regarding to feature vector size, FAR, FRR, and Accuracy. From the tables, the proposed method gives a good performance that is reducing the size of the feature vector and increasing the accuracy. The hybrid of GA and PCA reduced the size of a feature vector much better than GA. However, the accuracy of the proposed GA based method is better than the hybrid of the GA + PCA. From the reported results, we can say that the proposed method improves the performance of the biometric system and grants reducing the feature size. However, the hybrid of the GA and PCA reduces the feature size, but performing the biometrics system is less than the proposed GA based method. We can deduct that the PCA reduces the feature size very well but cannot increase the performance of the biometrics system very well compared to the proposed GA based feature selection because PCA transforms the feature vector into another feature space and this transformation can be unsuitable for features. In table 6, the proposed method compared with other unimodal and multimodal biometric systems. The proposed method is using only finger vein images. The finger vein image provides lowest FAR and FRR of 0.02722 and 0.07785, respectively. The accuracy of the proposed method is 99.94746% when compared with the biometric system proposed by Rattani et al. [43] which is 96.66%. Again, by considering the EER, the proposed method provides a lowest value of 0.0.052535 when compared with the biometric system using speech modality, fingerprint, and face biometrics proposed by Lau et al. [44] which is 0.31. Hence, the biometric system using only veins traits provides better performance than the other biometric systems. Table 6 shows the detailed comparative analysis of the related work on biometric authentication. All the results showed in this table are in terms of FAR, FRR, and accuracy. The lower values of FAR and FRR means better the performance of the system, but it varies depending on the type of biometric traits and the imaging resolution, methodology of enhancement, and a number of users in the database.

Table 4. Performance evaluation of the proposed approach on SDUMLA-FV

APPROACH	FEATURE SIZE	FAR (%)	FRR (%)	ACCURACY (%)
FULL FEATURE	8192	0.12697	0.440714	99.71616
PCA	4440	0.034836	0.531071	99.71705
GA	**4000**	**0.039433**	**0.168667**	**99.89595**
GA+PCA	2050	0.029192	0.078214	99.9463

Table 5. Performance evaluation of the proposed approach on

APPROACH	FEATURE SIZE	FAR (%)	FRR (%)	ACCURACY (%)
FULL FEATURE	8192	0.057026	0.610667	99.66615
PCA	4501	0.051925	0.616667	99.6657
GA	**4500**	**0.027222**	**0.077857**	**99.94746**
GA+PCA	2250	0.040191	0.161333	99.89924

UTFV

The performance curves of all features, PCA method, the proposed GA for feature selection and GA+PCA hybrid are shown in Figures 5,6,7 and 8 on SDUMLA-FV database and figures 9,10,11 and 12 on UTFV database. The figures below show four different charts (FAR vs FRR), EER, Accuracy and (GAR vs FAR). The proposed method shows high performance compared to the other architectures. Also, the figures show that the PCA and all features so close, and the proposed method and the hybrid GA+PCA are closed to each other.

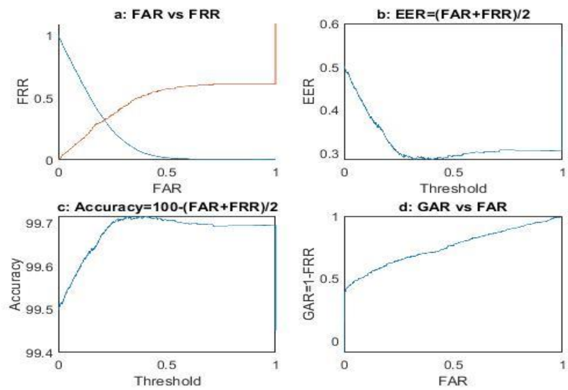


Figure. 5. The performance of all features on SDUMLA-FV

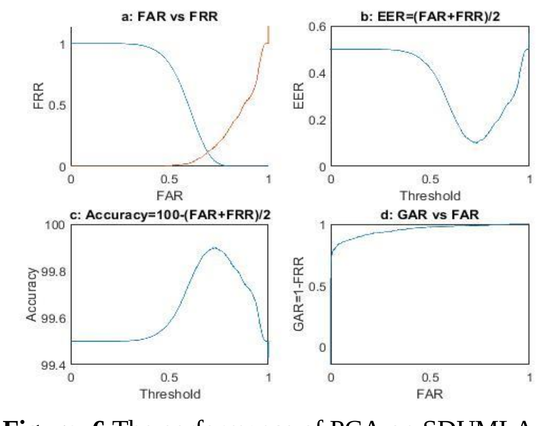


Figure. 6 The performance of PCA on SDUMLA-FV

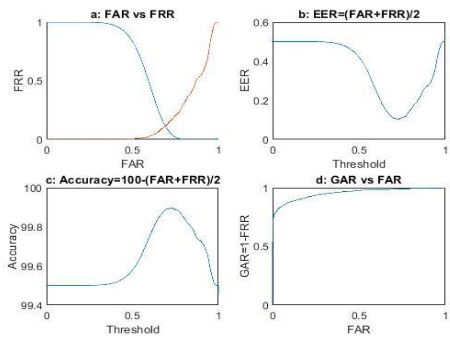


Figure. 7 The performance of GA on SDUMLA-FV

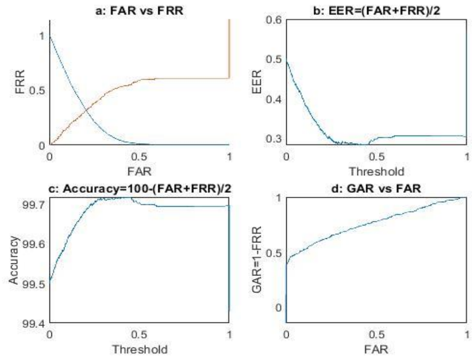


Figure. 8 The performance of GA+PCA on SDUMLA-FV

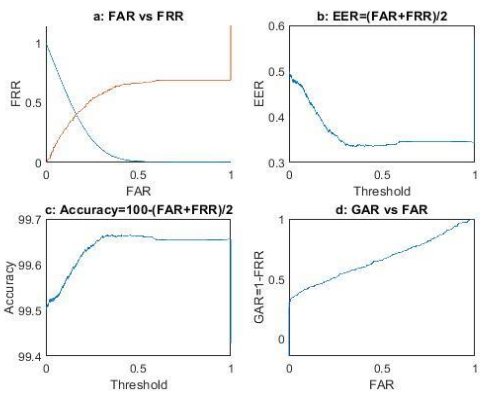


Figure. 9 The performance of all features on UTFV

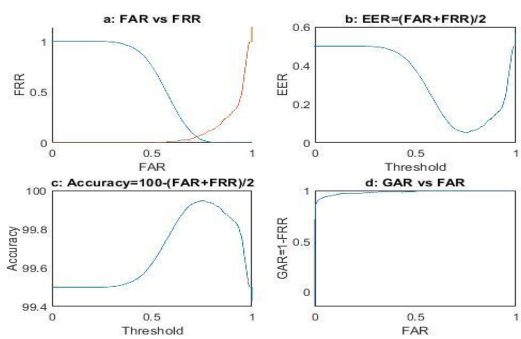


Figure. 10 The performance of PCA on UTFV

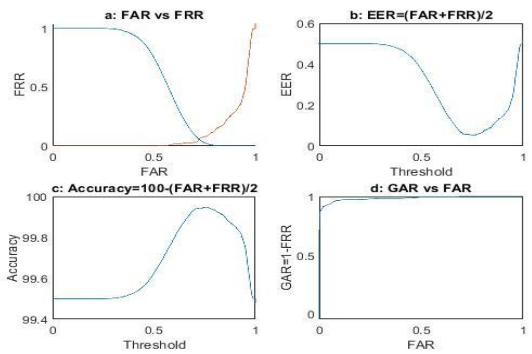


Figure. 11 The performance of GA on UTFV

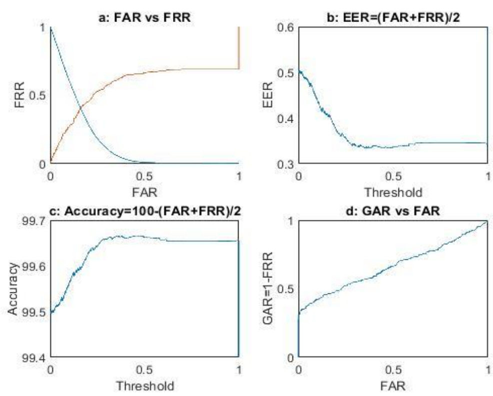


Figure. 12 The performance of GA+PCA on UTFV [34]
Figure. 12 The performance of PCA+GA on UTFV

Table 6 The proposed method compared with related work on vein-based authentication

Ref.	traits	Methodology	Users	Evaluation
[45]	Fingerprint and Iris	Hamming distance matching	50	FAR =0, FRR= 5.7
[46]	Hand dorsal vein	Lanczos algorithm and Cholesky decomposition	200	FAR=1.0 FRR=2.0
[47]	knuckle shape and Hand vein	shape features and Matching vein triangulation	100	FAR = 1.14 FRR = 1.14
[48]	dorsa vein and Palm vein	Combination and Multi-resolution analysis	32	FAR = 1.5 FRR = 3.5
[43]	Fingerprint and face	minutiae matching, Scale invariant feature transform features (SIFT)	400	FAR=4.95 FRR=1.12 Accuracy= 96.66%
[49]	Finger vein and Palm vein	gradient-based line detection method, 2D Gabor filter	100	FAR=0.1 FRR=0 Accuracy= 99.5 %
[50]	Finger vein	DSP processor	70	FAR=1.26 FRR=2.61
[51]	Fingerprint and finger vein	Supervised local-preserving canonical correlation analysis method (SLPCCAM)	640	FAR=1.35 FRR=0
[52]	Finger shape and finger vein	Finger vein network extraction algorithm	250	FAR=2.25
Proposed method	**finger vein SDUMLA-HMT**	**Lee ROI, AHE, Gabor filter, Correlation Coefficients**	**100**	**FAR=0.039433 FRR=0.168667 Accuracy=99.89595**
	finger vein UTFV		**100**	**FAR=0.02722 FRR=0.07785 Accuracy=99.94746**

V. CONCLUSION

In this work, five modules of finger-vein biometric are presented. The system used a genetic algorithm to select the most important features for the finger vein biometric recognition system. This work is divided into four scenarios like full-feature system, PCA for feature reduction, GA for feature selection and PCA+GA for feature reduction and selection. In the case of first scenario Full-feature system is resulted in FAR equals 0.057026, FRR equals 0.61066 and 99.666 Accuracy. The second scenario PCA is resulted in FAR equals 0.051925, FRR equals 0.616667 and 99.6657Accuracy. The third scenario GA is resulted in FAR equals 0.027222, FRR equals 0.077857 and 99.94746 Accuracy. Finally, the fourth scenario PCA+GA is resulted in FAR equals 0.040191, FRR equals 0.161333 and 99.89924 Accuracy. It is concluded that GA is applied on SDUMLA-HMT and UTFV databases is achieved best results compared with the other scenarios. For future work, there are two expansions of the current work of planning. First, developing a feature-level fusion of multibiometric system, for example, finger vein, and palm vein traits. Second, applying other recent meta-heuristics or other parameters for the genetic algorithm.

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