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Combinational Rule based Multimodal biometric System using Face and Fingerprint

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Abstract In recent years, biometrics has played a vital role in protecting a user's privacy and enabling secure authentication. Multimodal security, comprised of identity cards with attached unique passwords are used for authenticating the genuine or imposter person, however it is not a perfect security framework. Biometric traits are unique to each and every individual and hence proved to be very secure. This paper proposed a hybrid approach by combining cascaded and fusion based multimodal biometric framework using fingerprint and face traits. The fingerprint and face features are extracted using minutiae feature extraction algorithm and principal component analysis (PCA) algorithm respectively. The hybrid approach is applied on a self -built database of around 450 fingerprints and 450 face images. The performance of the proposed hybrid system is determined using False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER) and Accuracy evaluation parameters. The unimodal system of fingerprint and face at Level I and Level II yields an accuracy of 100% at threshold value of 0.42 and 0.54 respectively. The multimodal system at Level III delivers an accuracy rate of 98.45%, 99.2%, 97.85% and 99.5% at threshold value of 0.75, 0.60, 0.30 and 0.60 in sum-level fusion, product-level fusion, min-level fusion and max-level fusion schemes respectively.

Keywords: Principal Component Analysis; false acceptance rates; false rejection rate; equal error rate; accuracy; cascaded based system; fusion based systems.

1. Introduction

Distinguishing between genuine and fake identity is the most discussed research problem in today's information loaded world. In today's automated system which decides the acceptance of an individual based on its identity, it is a daunting task to identify the parameters which can be used to verify the genuineness of an individual. Different security techniques are designed to make life task easier. For instance, ID cards are used for verification but this concept failed due to its vulnerability to unsafe hands. Personal Identification Numbers are used to login into the system but it can be easily spied. Multimodal biometric system[1] provides an alternative when a person cannot be authenticated due to noisy sensor data, illumination problems and susceptibility to spoof attacks.[2, 3] A person has several physical features to be used for authentication but the prominent ones are: face, palm print, iris, fingerprint and finger veins. Among behavioral features, voice, signature and walk pattern. However, all security systems have some weakness. In palm print, principle lines faded with age. In finger veins, accurate authentication is not possible after death as blood circulation stops in blood vessels. Therefore, it is very difficult to develop a biometric system which can give its best performance under constraint conditions. Biometric systems operate in two modes: verification and validation. In verification mode, extracted biometric template is matched with individual's stored biometric template in database. Hence, it is one to one matching process. In validation mode, an occupied biometric trait is compared with all the stored biometric templates in biometric database. Hence, it is one to many matching process. Based on functionality, biometric systems can be utilized under three given scenarios: (i) Unimodal systems (ii) Multimodal systems (iii) Serial or cascading systems. Many security systems have already been developed and are undergoing using multimodal fusion technique to increase the performance and robustness against fraudulent and spoofing attacks. Here, fusion is performed on different multiple traits at different levels which exhibits some limitations[4], all available biometrics are necessary to be fused, thus the verification time increases and the complexity of system increases. Hence, a combination of cascaded and multimodal based system can be a good trade –off between performance, complexity and verification time.

The working of biometric system generally goes through five phases[1] including data collection phase which captures biometric data using different sensors; preprocessing phase which extracts region of interest; feature extraction phase that extracted features vectors containing highest volume of feature information; matching phase which gives matching scores and decision phase which provides the solution as accepted or not rejected.

In last decade, the human authentication problem research area have utilized fingerprint and face traits to a great extent due to their easy availability. Till date, researchers have worked a lot in biometric systems and provide various solutions for authentication related problems. Singh *et al*.[5] provides a comprehensive review of multimodal biometric traits, possible scenarios of fusion and matching possibilities of various biometric traits. The research discusses the quality of data used for authentication and using biometric identifiers for biometric fusion. Ross and Jain[6] address the challenges of fusing biometric information at score level. They experimented on three traits: face, fingerprint and hand geometry. Results shows that sum rule method delivers better performance than decision tree and linear discriminant classifiers. P. Sharma and K. Singh[7] uses fingerprint and face for fusion and applying fuzzy logic at decision level. This multimodal approach gives higher accuracy as compared to other fusion methods. M. Ghayoumi[8] gives a comprehensive review of different fusion techniques and their applications along with various integration strategies to combine information. The paper discussed the challenges and solutions for different fusion schemes used in multimodal fusion system. W.K. Fatt *et al*.[9] proposed a new multimodal biometric system using face and fingerprint. The face features are extracted using local binary patterns (LBP) and crossing number technique (CN) is used for extracting ridge endings and bifurcations of fingerprint. The system yields an accuracy rate of 98.1% for sum-level fusion scheme. S. Almas *et al*.[10] extracted the fingerprint features using minutiae matching and face features using Gabor filter approach along with extraction of face features using PCA. The fusion is performed at score level and matching is performed using Euclidean distance. The overall accuracy rate of system is 97%. U. Gawande *et al*.[11] gives a new fusion algorithm that uses Mahalanobis distance metric to fuse biometric features. The study evaluated prominent biometric parameters like FAR and FRR through various SVM techniques such as Poly SVM and RBF SVM. M. Hanmandlu *et al*.[12] present a general approach for fusion of matching scores at score level of multiple biometric traits using triangular norms (t-norms). The proposed method provides good performance and outperforms various score level normalization rules (min, mean and sum). Then scores are fused using sum, product and weighted sum rules. The experimental results clearly shows that performance of weighted sum rule is far better than sum and product fusion rule. A. Lumini and L. Nanni[13] analyzes different techniques to fuse information extracted from various biometric traits. The study provides significant overview of different system architectures related to combination of biometric systems: both unimodal and multimodal. Various performance indicators and existing benchmarks are also discussed thoroughly. A. Kumar and A. Kumar[14] uses Ant Colony Optimization approach for choosing metrics such as decision threshold for delivering better performance during deployment of various biometric systems.

In this paper, we propose a novel hybrid authentication approach that combines both cascading and multimodal biometric based approaches. The person presents his/her fingerprint for authentication as an input to the system. In case of either acceptance or rejection, the person is liable to present his face for input, thus assuring additional security to the system and also ensuring that genuine person, who has skin problems like irritations, bruises etc. should not be denied entry to the system. Further, the decision at two levels will be fused together to further approve the user authentication. Minutiae based feature extraction technique is chosen for fingerprint. PCA is used for feature extracting features from face. The system have three decision levels: Level I, Level II and Level III. At Level I, the decision regarding fingerprint matching is taken. At Level II, the Eigen vectors of face are extracted and then matched with stored template to generate face matching decision. At Level III, the two former decisions will be fused to approve or disapprove the entry to the system. Four possible scenarios and their outcomes will be analyzed in this biometric system: (i) If Level I fails and Level II succeed, then fusion of the matching scores at both levels will be done to authenticate user. (ii) If Level I succeed and Level II fails, then fusion of the matching scores will be done to authenticate the user. (iii) If both Level I and Level II succeed, then fusion of the matching scores will be done to authenticate the user. (iv) If both Level I and Level II fails, then user will be denied access to the system.

The novel feature of this system is that cascading and fusion goes side by side to ensure better balancing between verification and time complexity. Additionally, the genuine entry will not be denied on the basis of its first biometric authentication. Also, the cascading followed by fusion will increase security requirements to the system. The fusion is accomplished at score level to allow or reject the entry to the system. The proposed scheme is presented as shown in Fig. 1.

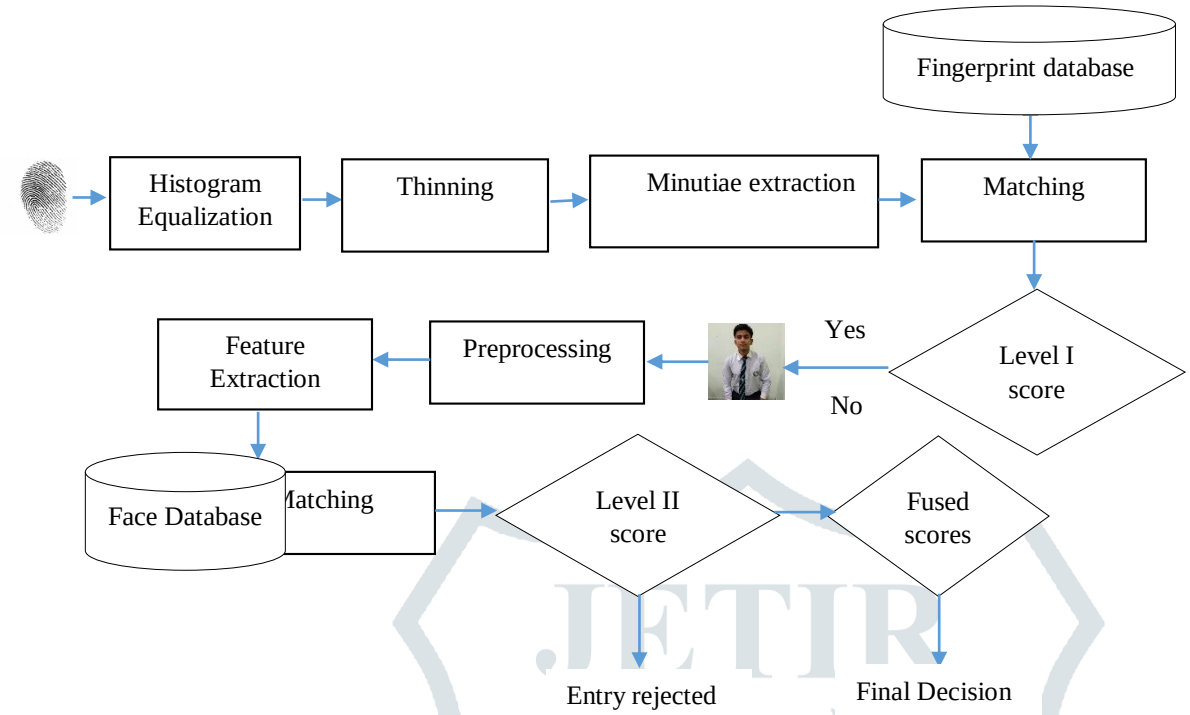

Fig.1 Proposed Multimodal Biometric Cascaded System

The paper is organized as follows: Sec. 2 explains the feature extraction methodology used for fingerprint biometric trait. Sec. 3 described the PCA algorithm which is used for extracting eigen vectors from face preprocessed template. The database collection and experimental results are described in Sec. 4. Finally, Sec. 5 has been devoted to drawing conclusion.

2. Fingerprint Recognition System

The fingerprint surface has two visible patterns: ridges and valleys. The physical structure of ridges and valleys will determine the authenticity of a person. Image acquition is performed using HD quality camera for better processing of image details. Generally, the fingerprint recognition comprises of three steps: (i) image enhancement (ii) thinning (iii) feature extraction.

2.1 Image enhancement

In image enhancement step, the histogram equalization technique is used to increase the contrast between ridges and valleys as shown in Fig. 2. It is accomplished by distributing the most frequent intensity value of pixels throughout the image. More the number of pixels in an image area, more will be brightness. After histogram equalization, binarization technique is performed where gray scale image is converted into black and white image. A threshold value of gray scale image is fixed and pixels are compared to this threshold value. If the pixel value is greater than threshold, then pixel is converted into white. If the pixel value is smaller than threshold, then pixel is converted into black.

2.1 (a) Original Image

2.1 (b) Histogram Equalized Image

2.3 (c) Binarized Image

Fig. 2. Images showing histogram process and binarization

2.2 Thinning

Thinning is a technique which is used for eliminating foreground pixels from binary images. This morphological operation will decrease the thickness of pixel value to one as shown in Fig. 3. Thinning operation is useful in several applications especially skeletonization. This operation erodes boundaries of foreground objects to maximum extent. However, it does not affect the pixels at the end of lines.

2.2 (a) Binarized Image 2.2 (b) Thinned Image

Fig. 3. Thinning process

2.3 Feature extraction

In feature extraction, minutiae features are extracted from resulted pre-processed image (see Fig.3). Minutiae point s are endpoints of ridge bifurcations and ridge endings. There are many methods for feature extraction such as crossing number, adaptive flow orientation-based extraction etc. One method which is used in this study is crossing number (CN) method. In this method, the minutiae points are extracted by comparing each ridge pixel with eight neighborhood pixels. The formulae for CN method is given in Eq.1:

$$CN = \frac{1}{2} \sum_{m=1}^{8} V_m - V_{m-1} + 1 \quad (1)$$

where V_m is the value of pixel at index m. When ridge pixel is equal to 1, then it is true minutiae point. If ridge pixel is equal to 3, then also it is true minutiae point. When ridge pixel is equal to other value than 1 and 3, then there is false minutiae point. In matching phase, the stored minutiae points in database is matched with inputted image minutiae points. The sets of extracted minutiae features are matched using Euclidean distance. This formula is used to calculate the distance between two data points in a plane. This algorithm is much less computationally complex when performing distance measurement between pair of scalar data points.

Let $U = (m_{u_1}, m_{u_2}, \ldots\ldots\ldots, m_{u_m})$ represents the extracted minutiae feature vector of the stored fingerprint template in database. Let $V = (m_{v_1}, m_{v_2}, \ldots\ldots\ldots, m_{v_m})$ represents the extracted minutiae feature of the query fingerprint input for matching, where $m_i = (p, q, \theta)$, p q and θ are spatial coordinates and orientation of each minutiae point respectively.

Matching of two minutiae points is successful if both satisfies the given geometric distance D_g and angle difference D_α as shown in Eq. (2) and Eq. (3).

$$D_g \left(m_{u_i}, m_{v_j}\right) = \sqrt{(x_{u_i} - x_{v_i})^2 + (y_{u_i} - y_{v_i})^2} < c_d \quad (2)$$

$$D_\alpha \left(m_{u_i}, m_{v_j}\right) = \min(\,(\theta_{u_i} - \theta_{v_i}), 360 - (\theta_{u_i} - \theta_{v_i})\,) < c_\alpha \quad (3)$$

where c_d and c_α is the permissible difference between two minutiae points. The computation of similarity score is based on the given formulae given in Eq. (4).

$$Finger_{score} = \sqrt{\frac{{N_m}^2}{N_u \times N_v}} \quad (4)$$

where N_m is the matched minutiae pairs and N_u and N_m represent minutiae points in fingerprint image stored in database and input fingerprint image respectively. The matching score generated between database template and query image is passed as input to the decision module. Prior matching, a threshold score value is decided to allow user entry or rejection to the system. This value is called preset decision threshold. If the $Finger_{score}$ is greater or equal to preset decision threshold, then user authentication is done at Level I and score will be forwarded for score level fusion with face query image. Even if comparison with decision threshold fails, the $Finger_{score}$ will be subjected to fuse with face image score for full authentication.

3. Face Recognition System

Face is the most widely used human trait in today's biometric research industry. We use principle component analysis (PCA) for extracting face features. PCA transforms the original image into training set of eigen vectors. These are also called eigen faces. Then eigen faces when combined together forms an approximation of original image which is subjected to PCA. Hence, PCA reduces the large dimensionality of input image space into smaller image space by eliminating less informative eigen faces. The steps involved in PCA algorithm are described as a series of Eq. (5) – Eq. (9).

Step 1: Database Acquition

The set S is created containing M vectors of face images. These vectors are represented by τ. The face images are numbered as $I_1, I_2, I_3, \dots \dots I_M$. Each image is converted into a vector of size $MN \times 1$. The face images are set to size of $N \times N$.

$$S = \{\tau_1, \tau_2, \dots \dots . \tau_n\} \quad (5)$$

Step 2: Calculation of Mean

The mean image Ψ is calculated as,

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \tau_n \quad (6)$$

where τ_n is the image vectors of data images.

Step 3: Subtraction of Mean from Original Image

The mean image is subtracted from input image and is stored in Φ

$$\Phi_i = \tau_i - \Psi \quad (7)$$

Step 4: Calculation of covariance matrix (CM)

$$CM = \frac{1}{M} \sum_{n=1}^{M} \Phi_M \Phi_M^T = BB^T \quad (8)$$

$$B = \{\Phi_1, \Phi_2, \Phi_3, \dots \dots ., \Phi_n\} \quad (9)$$

Step 5: Calculation of eigenvectors and eigenvalues of the covariance matrix and select ion of principal components

In this step, for each human face M, the eigen vectors u_i and eigen values λ_i are calculated. Each eigen vector has its associated eigen value. From M face images, M eigen vectors and corresponding eigen values are generated. From M eigen vectors, only those M' eigen vectors are selected which have highest eigen value based on predefined threshold. Eigen vectors with lower eigen values are omitted as they specify least part of characteristic features of face. After M' eigen faces are determined, the training phase of the algorithm is finished.

The reason behind using PCA is that it reduces the dimensionality of large data sets while keeping the required variation as possible. PCA algorithm creates new variables called principal components which possess dominant information in an image of a dataset. In addition to the low-dimensional sample representation, it provides a synchronized low-dimensional representation of the variables.

4. Experimental Results

Matlab version R-2017a is used to implement this cascaded based multimodal fusion system. Experiments are performed on a self – built database of 300 individuals. The age of the individuals varies from 18 to 27 years of age with different face texture and fingerprint properties. The hardware configuration used is Windows 10 Home with 2.29GHz processor and 4GB RAM. The scores produced by different fusion methods may belong to different numerical range. Normalization is a technique that transforms different numerical values into same numerical range. In this study, min- max normalization method is used for normalization as it robust and efficient.

4.1 Database Acquition

The database is divided in two categories: (i) Fingerprint database of total 450 images with each individual contributing 3 images. All fingerprint images are in .jpg form with resolution 380 × 370 pixels each. For testing, first image is stored as template in database and other 2 images are used for matching purpose. (ii) Face database has also total of 450 images with each individual contributing 3 images. All face images have resolution of 376 × 292 pixels each. The testing methodology is same as that of fingerprint. The face and corresponding fingerprint images of database are represented below in Fig. 4

Fig. 4. Sample images of face and fingerprint images in database

4.2 Results and Discussions

At Level I and Level II, the fingerprint image and face image of an individual is matched with the fingerprint template and face template stored in database. For testing, first image is selected as template and other two images are used for matching for both traits. Hence, total of 450 genuine scores and 450 imposter scores are generated. The performance of biometric recognition system is analyzed with three metrics: (i) FAR (ii) FRR (iii) Accuracy. FAR is the percentage of unauthorized users entering the system and FRR is the percentage of authorized users rejected by the system. The visual description of performance measurement is analyzed by using ROC (Receiver Operating Characteristic) at different threshold settings. ROC curve is the plotting of FAR against FRR for different threshold values. These threshold values are to be set by user for analyzing performance of biometric system. The equations of three metrics are described below:

$$FAR = \frac{imposter\ scores\ exceding\ threshold}{Total\ no\ of\ imposter\ scores} \quad (10)$$

$$FRR = \frac{genuine\ scores\ below\ threshold}{Total\ no\ of\ genuine\ scores} \quad (11)$$

$$Accuracy = 100 - (\frac{FAR+FRR}{2}) \quad (12)$$

As shown in Table.1 and Table.2, the first set of experiments have been analyzed at Level I and Level II on two unimodal biometric systems namely fingerprint and face biometric traits. At Level III, four multimodal fusion strategies are analyzed. The performance of four fusion methods presented in this study are min, max, OR and product. Tables 1 and 2 represents the experimental results of unimodal fingerprint recognition system and face recognition system at different thresholds. It is seen from Tables that at threshold value of 0.45 for fingerprint and 0.54 for face, the proposed system has 100 % accuracy rate with FAR and FRR values as 0%, respectively, for both fingerprint and face unimodal systems.

Table 1. Fingerprint Matching Threshold Results

Fingerprint Threshold	False Acceptance Rate	False Rejection Rate	Accuracy (%)
.15	0.8366	0	58
.18	0.7233	0	64
.21	0.5433	0	73
.24	0.41	0	80
.27	0.293	0	85
.30	0.226	0	89
.33	0.063	0	97
.36	0.040	0	98
.39	0.037	0	98
.42	0.0033	0	100
.45	0	0	100
.48	0	0.01	100
.51	0	0.033	98
.54	0	0.043	98
.57	0	0.05	98
.6	0	0.073	96
.63	0	0.113	94
.66	0	0.156	92
.69	0	0.176	91

.72	0	0.2	90
.75	0	0.33	84
.78	0	0.416	79
.81	0	0.62	69
.84	0	0.72	64
.87	0	0.79	61
.90	0	0.83	59

Table 2. Face Matching Threshold Results

Face Threshold	False Acceptance Rate	False Rejection Rate	Accuracy (%)
.15	0.80	0	60
.18	0.74	0	63
.21	0.68	0	66
.24	0.64	0	68
.27	0.456	0	77
.30	0.312	0	84
.33	0.236	0	88
.36	0.197	0	90
.39	0.168	0	92
.42	0.135	0	93
.45	0.096	0	95
.48	0.043	0	98
.51	0	0	100
.54	0	0	100
.57	0	0.243	88
.60	0	0.276	86
.63	0	0.323	84
.66	0	0.436	78
.69	0	0.466	77
.72	0	0.516	74
.75	0	0.576	71
.78	0	0.653	67
.81	0	0.713	64
.84	0	0.746	63
.87	0	0.81	60
.9	0	0.83	59

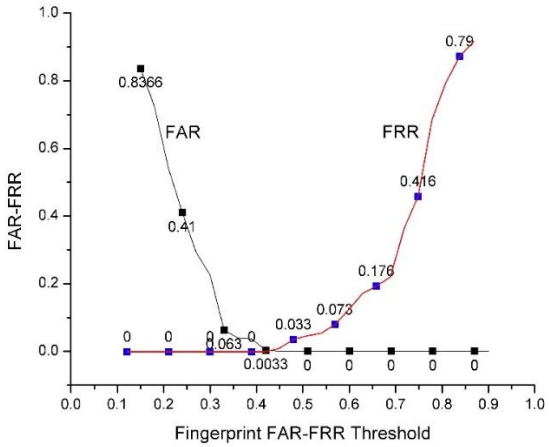

Fig. 5. FAR-FRR curve for unimodal fingerprint recognition system

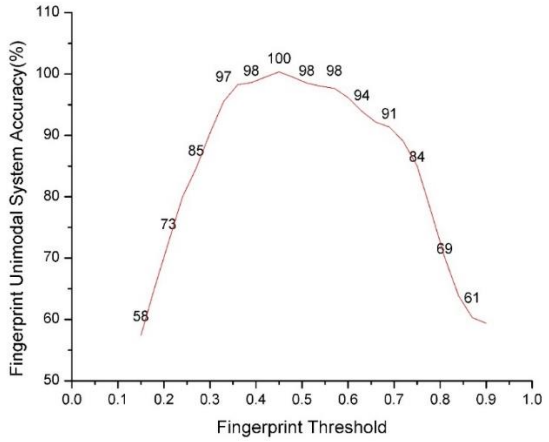

Fig. 6. Accuracy rate curve for unimodal fingerprint biometric system

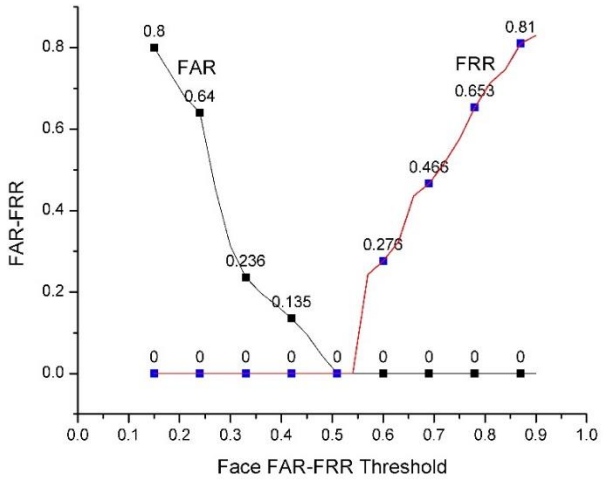

Fig. 7. FAR-FRR Curve for unimodal face recognition system

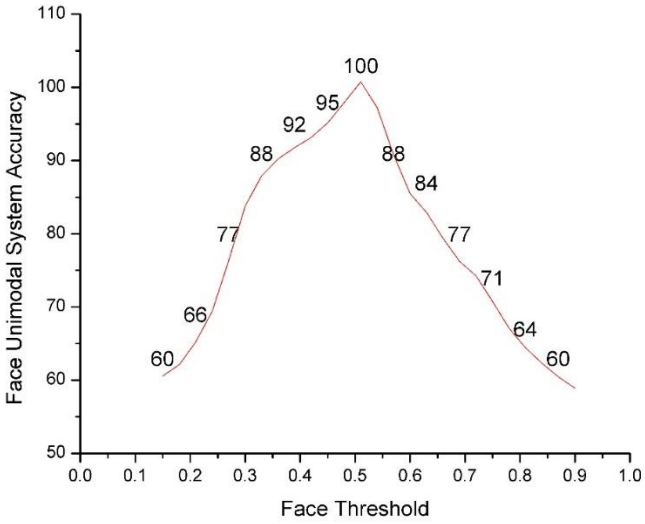

Fig. 8. Accuracy rate curve for unimodal face recognition system

From Fig. 5 and Fig. 7, it is clear that false identification rate and false rejection rate for unimodal biometric system at Level I and Level II is minimal and optimal. It is seen from Fig. 5 and Fig.7, the unimodal system of fingerprint and face delivers low Equal Error Rate(EER) of 0.42 and 0.54 which ensures a better recognition system. EER is the point at which both FAR and FRR are equal.

At Level III, experiments are performed using score level fusion methods on fingerprint and face to showcase their effects. As shown in Table 3, the sum level fusion method delivers a high recognition rate of 98.45% at threshold value of 0.75. The ROC curve represent the lesser EER (Equal Error Rate) as shown in Fig. 9.

Table 3. Sum Level Fusion Results

Sum Fusion Threshold	False Acceptance Rate	False Rejection Rate	Accuracy (%)
.15	80.3	0	59.85
.18	77.6	0	61.2
.21	74	0	63
.24	60	0	70
.27	58.6	0	70.7
.30	55	0	72.5
.33	50	0	75
.36	48	0	76
.39	44.3	0	77.85
.42	40.6	0	79.7
.45	35.2	0	82.4
.48	32.9	0	83.55
.51	29.8	0	85.1
.54	25.6	0	87.2
.57	23	0	88.5
.6	20	0	90
.63	12.6	0	93.7
0.66	10	0	95
0.69	6.7	0	96.65
0.72	3.9	0	98.05
0.75	1.5	1.6	98.45
0.78	0	9.8	95.1
0.81	0	12.6	93.7
0.84	0	20.6	89.7
0.87	0	32.9	83.55
0.9	0	96.3	51.85

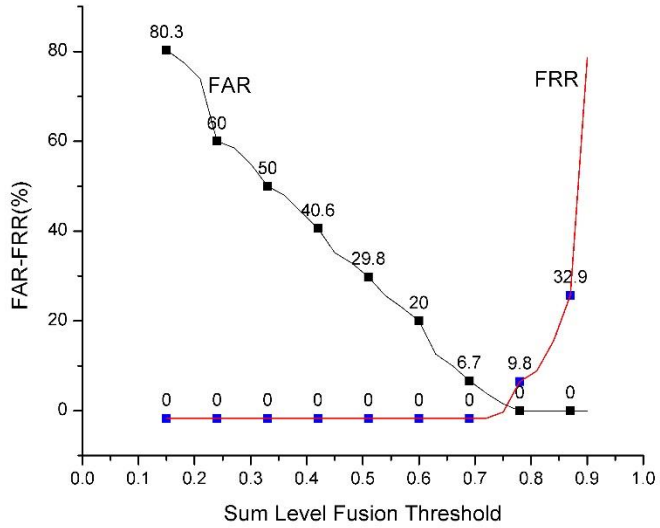

Fig. 9. FAR-FRR Curve of Sum Level Fusion Results

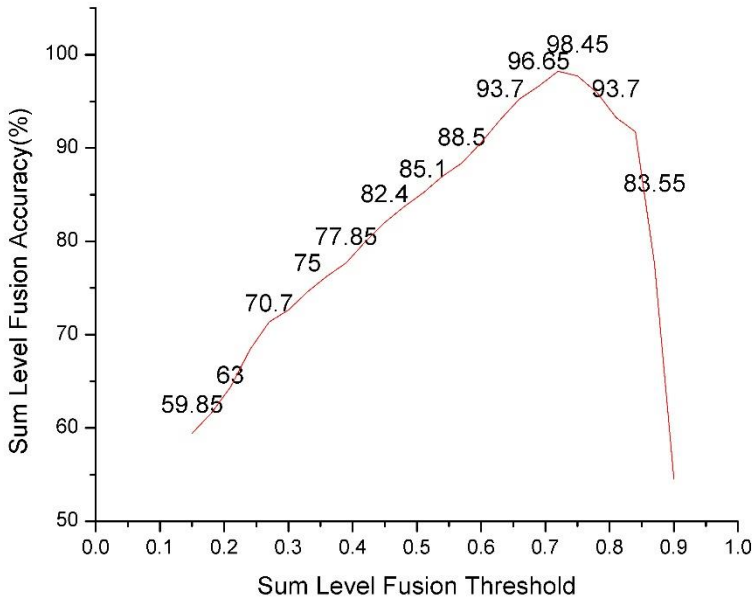

Fig. 10. Accuracy Curve of Sum Level Fusion Results

Table 4. Product Level Fusion Results

Product Fusion Threshold	False Acceptance Rate	False Rejection Rate	Accuracy
.1	97.5	0	51.25
.2	89.6	0	55.2
.3	65.2	0	67.4
.4	37.6	0	81.2
.5	12.1	0.4	93.75

.6	0.7	0.9	99.2
.7	0	56.4	97.6
.8	0	73.8	86.5
.9	0	91.2	73.2
1	0	99.7	50.15

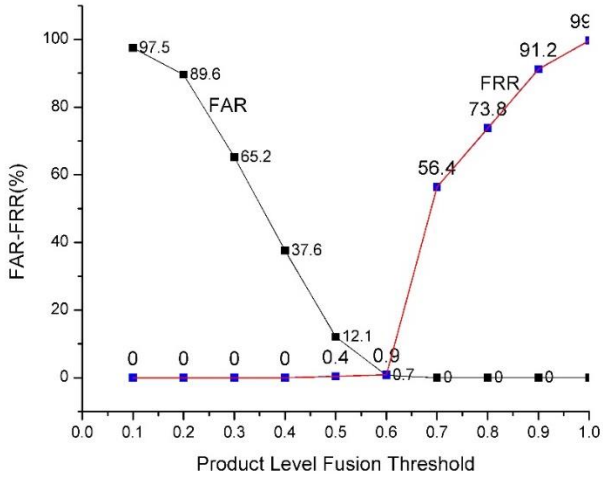

Fig.11. FAR-FRR Curve of Product Level Fusion Results

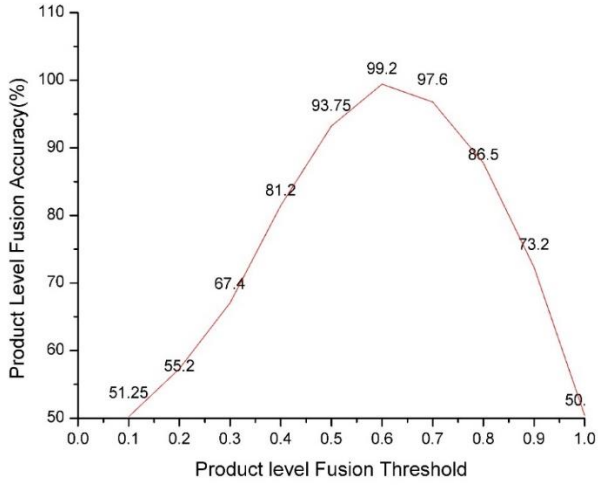

Fig.12. Accuracy Curve of Product Level Fusion Results

From Table 4, it is evident that product level fusion method delivers a higher recognition rate of 99.5% at FAR and FRR values of 0 and 1 respectively. As we can see, that product level fusion method outperforms sum level fusion method in terms of accuracy. The EER of sum level fusion and product level fusion is 0.75 and 0.6 which is relatively good for better recognition rate of biometric system. Table 5 introduces the performance analysis of min- fusion method on fingerprint and face biometric traits. The proposed method demonstrate the effectiveness and the advantages of min-fusion method based on score level fusion approaches since fingerprint and face biometric features are rich and suitable for fusion. The proposed fusion schemes delivers the recognition rate of 97.85% at FAR of 1% and FRR of 3.3%.

Table 5. Min- Level Fusion Results

Face Threshold	FAR	FRR	Accuracy
0.1	86.6	0	56.7
0.2	40.3	0	79.85
0.3	1	3.3	97.85
0.4	0	11.6	94.2
0.5	0	17.3	91.35
0.6	0	33.6	83.2
0.7	0	58.6	70.7
0.8	0	84.6	57.7
0.9	0	96	52
1	0	100	50

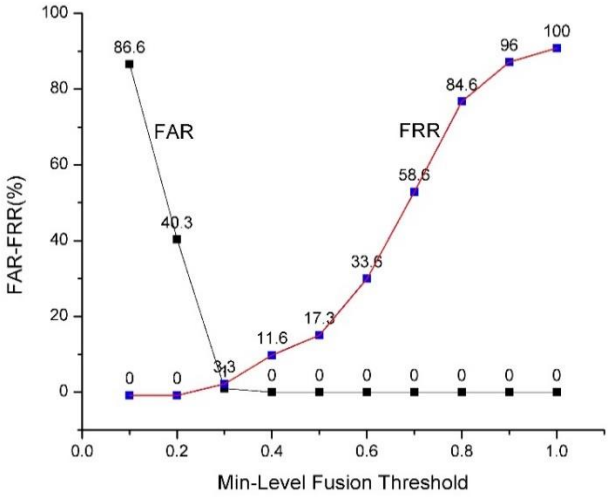

Fig.13. FAR-FRR Curve of Min- Level Fusion Results

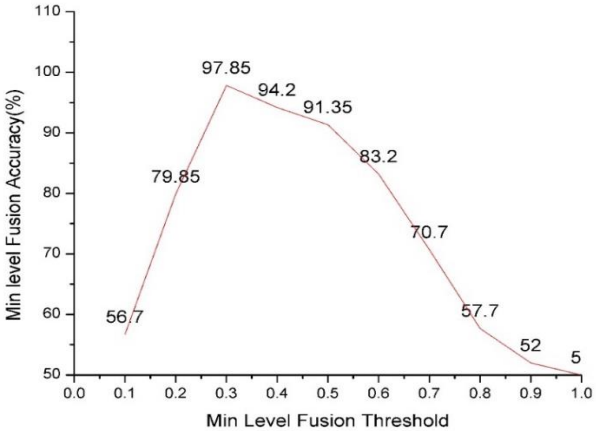

Fig.14. Accuracy Curve of Min- Level Fusion Results

Table 6 demonstrates the results of max-fusion method based on score level fusion technique. From the data, it is clear that the system achieved a significant accuracy rate of 99.5%. Also, the lower EER (Equal Error Rate) value shown in Fig. 15 justified the efficiency and advantage of this proposed cascaded- multimodal biometric system.

Table 6. Max- level Fusion Results

Max Fusion Threshold	FAR	FRR	Accuracy
0.1	98.6	0	50.7
0.2	85	0	57.5
0.3	45.6	0	77.2
0.4	15.6	0	92.2
0.5	2.6	0.3	98.55
0.6	0.6	0.4	99.5
0.7	0	9.3	95.35
0.8	0	37.6	81.2
0.9	0	68.3	65.85
1	0	97	51.5

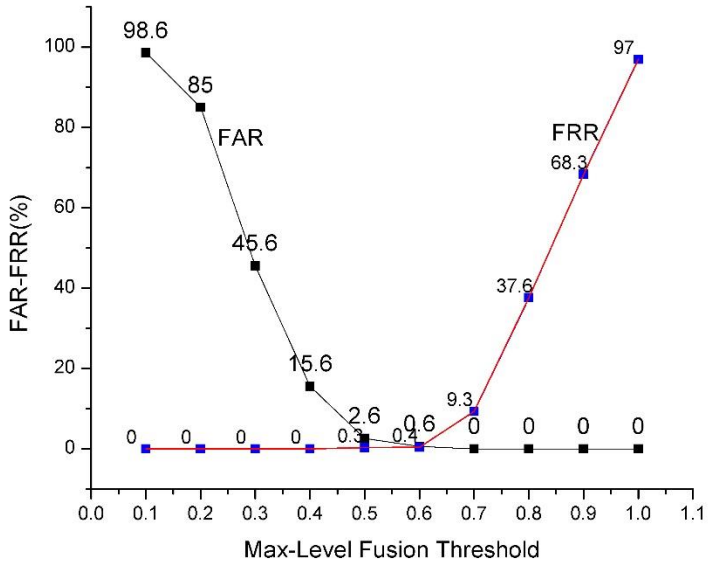

Fig.15. FAR-FRR Curve of Max - Level Fusion Results

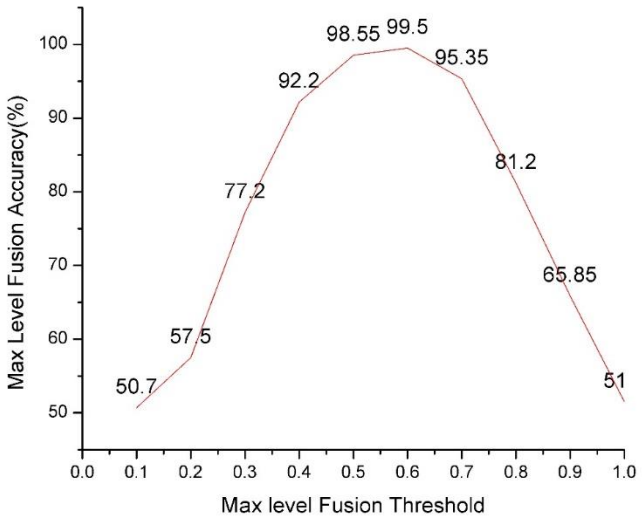

Fig.16. Accuracy Curve of Max- Level Fusion Results

The fusion schemes detailed in Table 3- Table 6 outputs different performance in terms of recognition rate. Table 7 combines all fusion schemes together to get the real view of biometric results. It is clear that among all fusion schemes product level fusion delivers the best performance with recognition rate of 99.2%. However, Max- level fusion scheme delivers 98.70% recognition rate but it has slightly upper FRR of 2%. This could be area of concern which can go for improvement. Both Sum-level fusion and Min-level fusion delivers the accuracy rate of 98.45% and 97.85% respectively but with increase in FAR and FRR.

Table 7. Comparative results of different fusion schemes

Fusion Techniques	Results			
	Threshold Rate	FAR Rate	FRR Rate	Accuracy Rate
Min- Level Fusion	30%	1%	3.3%	97.85%
Sum- Level Fusion	75%	1.5%	1.6%	98.45%
Max- Level Fusion	60%	0.6%	2%	98.70%
Product Level Fusion	60%	0.7%	0.9%	99.2%

Table 7 shows the comparative results of four score level fusion methods with FAR, FRR and accuracy rates. From the table, it is seen that product level fusion outperforms all other fusion techniques in terms of accuracy rate but with slightly higher FAR and FRR in comparison to max level fusion. The max level fusion method achieves the accuracy rate of 98.70%. Sum level fusion and min level fusion methods deliver the accuracy rate of 98.45% and 97.85% respectively. The min level fusion method has FAR and FRR of 1% and 3.3% which is slightly higher than all other fusion schemes.

5. Conclusion and Future Scope

This paper presents a hybrid approach for cascading and multimodal system using face and fingerprint biometrics. First of all, a thorough literature review is done on unimodal system and multimodal system using face and fingerprint biometric traits. The experiments are conducted on a self- built database of 900 images (450 images of fingerprint and 450 images of face). This 900 image sized database is large enough to determine the feasibility and performance of the proposed system. However, we are looking to enroll more users in our database so that more accurate performance of the system can be estimated. The proposed hybrid system uses PCA (Principal Component Analysis) and minutiae extraction as feature extraction techniques for face and fingerprint respectively. The experimental results carried out on a self-built database display a significant improvement in performance over other multimodal systems considered in the literature survey. Also, the proposed approach will serve as an encouragement for all those genuine users whom system denies the entry due to skin problems. Our

system will only deny the entry when decision at Level I and Level II are rejected. Also, one more outcome is that performance results vary when experiments are done on heterogeneous images particularly on self – collected database. Therefore, it is suggested for researchers to carry out experimental work on different databases rather than standard databases available on which enough research have already been done.

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