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Multimodal Biometrics System Design using Score Level Fusion Approach

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ABSTRACT: Despite substantial advances in recent years, there are still severe challenges like non-universality, noisy sensor data, Intra-class variations, Inter-class similarities, spoof attacks in obtaining reliable authentication through unimodal biometric systems. Multimodal biometrics based identification provide improved identification performance using biometric information obtained from multiple traits as compared to unimodal biometrics identification which relies on a single biometric trait of an individual. This research work proposes an efficient multimodal system using score level fusion which can be employed for security critical applications. In this paper the performance of score level fusion using sum rule has been evaluated. Proposed fusion approach integrates four biometric modalities: iris, fingerprint, face and signature. Normalization of scores is very important in score level fusion based multimodal biometrics. Proposed fusion approach performs score normalization using three methods z-score normalization, min–max normalization, and tanh-estimators normalization. A new efficient normalization has been proposed. Weighted sum rule based method has been employed for combination of these normalized scores. Experimental results on combining four biometric modalities are presented. With proposed score level fusion algorithm implementation we have got significant reduction in error rates. We have achieved interesting to point work with multimodal system as FAR=0% and FRR=1.66%.

Keywords: Multimodal biometrics, score level fusion, face, iris, fingerprint, signature, normalization.

Abbreviations: FAR, False Accept Rate, FRR, False Reject Rate, GAR, Genuine Accept Rate, EER, Equal Error Rate.

I. INTRODUCTION

Recently, biometric-based identification systems are becoming very popular for large number of identification applications. Biometrics system is defined as a pattern-recognition system. Biometric system identifies a person based on features derived from a specific characteristic or traits of the person [1]. Various Biometrics characteristics include face, fingerprints, iris, voice, retina, gait, signature, palm-print, ear, etc. Biometric systems which perform human identification using only one single trait (i.e., unimodal biometric systems) have various limitations like noisy data, non-universality, higher error rates, and spoof attacks [2]. Multimodal biometric systems can be designed to reduce these problems by using fused information extracted from various biometric sources [3]. Multimodal biometric system performs integration of information obtained from various biometric modalities. Various studies [7-11] has been presented for multimodal biometrics system by various researchers. These studies discussed that by using multimodal system performance of biometrics can be exceled. In a multimodal biometric system which relies on different biometric traits, fusion can be achieved at four different levels of abstraction. These four levels correspond to four modules of multimodal system [4]. Biometric information fusion can be done at the different levels such as sensor level, feature extraction level, matching score level, or decision level. feature level is somewhat complex and challenging because of inaccessibility or incompatibility of the feature sets obtained from different biometric modalities. Decision level fusion is less applied due to availability of limited amount of information. Score level is very commonly used because of easy access of scores. Different biometric matching modules generates a numerical value called match scores which is used as similarity measure between the features of query and stored template. In our research work we have designed multimodal biometrics system at score level with an aim to excel the identification performance. Match score values resulting from matchers may not be in the same range. So for combination of these scores they must be mapped into a common range. After that mapped scores can be fused together. In proposed score level fusion scores has been normalized using common methods as Z-score, Min-max, and tanh-estimators normalization [5, 6].

Score level can be applied to all types of biometric systems [41]. Score level fusion can be performed by using two approaches combination approach and classification approach. The combination approach consists of combining the scores to form a single score then using it to make the final decision, and the classification approach based on handling the subject as a problem of classification [4, 5]. Kamel Aizi *et al*., [43] has presented multibiometric fusion for the identification of persons using two modalities, the iris and the fingerprint at score level. Proposed work using k-means clustering method, for each modality, splits the score range into three zones of interest relevant to the proposed identification method. The fusion is then applied to the extracted regions using two approaches. The first one achieves the classification by the decision tree combined to the weighted sum (BCC), while the second approach is based on the fuzzy logic (BFL). Walia *et al.,* [42] has proposed a multimodal biometric system using three complementary traits namely iris, finger vein and fingerprint. For this, individual classifier performance has been optimized using evolutionary Backtracking Search Optimization Algorithm (BSA). The system exhibits optimal behavior under dynamic environment through boosting or suppression of concurrent classifiers and resolving conflicts among discordant classifiers.

Lot of researchers has carried out research on score level fusion approach. But still there is scope for improvement in performance of score level fusion based multimodal system. This research work proposes robust multimodal system. Objective of proposed research work is to design efficient and robust multimodal system at score level fusion using selected biometrics face, fingerprint, iris, signature. No other work has taken these four biometrics traits of an individual collectively. Proposed system can be employed for security of critical information or critical objects. As It relies on evidence presented by four biometrics traits of an individual, it is very difficult to forge all biometrics traits at the same time. This research work aims at reduction of various error rates such as false acceptance, false rejection, equal error rate, genuine accept rate

Proposed approach has presented modified normalization technique which was obtained from tanh normalization. The proposed normalization method is found more robust. These normalized scores has been further combined using weighted sum rule based approach. Proposed score level fusion method outperforms unimodal biometrics system.

This paper is organized as follows: Section II describes design of unimodal biometric systems for all four modalities face, iris, fingerprint and signature, Section III discusses basics Score level fusion. Section IV describes the proposed match score level fusion based approach for multimodal biometrics system which integrates scores obtained from unimodal biometrics system. In Section V Experimental setup and experimental results has been discussed. Section VI has presented conclusion of research work.

II. UNIMODAL BIOMETRICS SYSTEM

In this section we have discussed the design of the various unimdal systems and details of implementation. Proposed score level fusion approach have selected four biometric modalities as face, iris, fingerprint and signature. Face, iris and fingerprint are very commonly used while signature is only one modality used in all legal transaction for daily applications. Iris as biometrics provides an excellent identification performance. Also chosen biometrics characteristics have been employed in large scale for real time biometrics applications.

Proposed work have designed wavelet based feature extraction algorithm. Distinct and significant features from all biometric modalities are extracted using the discrete wavelet transform. For face, iris and signature modalities proposed algorithm uses detail coefficients obtained from wavelet decomposition. We have used approximation coefficients generated from wavelet decomposition for fingerprint modality. Using hamming classifier we have obtained scores from all four modalities.

Joshi *et al*., (2013) has presented DWT based feature extraction algorithm for signature modality Proposed system has used these DWT based features for signature representation [37]. Iris recognition system mainly consists of two important operations as iris pre-processing and feature extraction.

Iris pre-processing consists of iris segmentation, normalization and enhancement of iris image. Before feature extraction it is necessary to eliminate unwanted parts of iris image such as eyelid, eyelashes, pupil, and sclera. Firstly iris and pupil boundaries are identified. Simultaneously eyelids and eyelashes are separated. Iris features has been obtained from iris image and finally iris features are matched with iris features stored in the database. Using canny edge detection algorithm [13, 14] edge map of iris image has been obtained. Further Hough transform [16] is used for identifying exact location of pupil and iris boundary. This process results in boundary extraction of iris image. Eyelids and eyelashes in iris image cause performance degradation as they appear like noise. Next important step in iris segmentation is eyelids and eyelashes detection. Here Hough transform has been used for eyelids detection. Iris segmentation has been performed to obtain iris region of interest. Resulting iris region is mapped to fixed dimensions for making them in comparable form. Stretching of the iris caused due to pupil dilation from varying levels of illumination results into dimensional inconsistencies between eye. Daugman's rubber sheet model [12, 19, 20] is used for normalisation of iris regions. Histogram equalization of segmented iris images has been done for contrast enhancement.

We have performed decomposition of normalized iris pattern of size 100x402 pixels upto fifth level by using haar wavelet transform. Coefficients which are having redundant information are eliminated. Fourth level detail coefficients are very much identical to lower level detail coefficients. So we have selected fourth level detail coefficients as representative of information corresponding to all four levels. Fifth level is having unique textures and selected as a whole. Similarly Fourth and fifth level detail coefficients has been selected for representing significant information of normalized iris image. Proposed feature extraction algorithm employs combination of fourth and fifth level detail coefficients including horizontal, vertical and diagonal as a feature vector [18]. Resulting feature vector is of size 702 elements. Size of feature vector obtained has been reduced as compared to that of Daugman [12]. Proposed algorithm uses only lower part of iris which results into reduction of feature vector size as compared to that of daugman's approach where complete iris is considered. Further feature vector has been encoded into Boolean form which results into simple matching process. Template coding assigns value one to wavelet coefficients with value greater than 0 otherwise 0. Iris template matching has been performed using hamming distance.

We have designed and implemented wavelet based framework using log-gabor filter for fingerprint authentication. Proposed method consists of steps such as core point detection, ROI extraction, multilevel decomposition using haar wavelet, log-gabor encoding on wavelet coefficients. A Poincare has been employed for core point detection. Core point has been considered as the centre. During core detection step if two core points are obtained then core point with lower y value has been selected as centre of fingerprint. Fingerprint ROI has been extracted by cropping the fingerprint image with 128×128 size around the core point. Fingerprint ROI are decomposed up to fourth level of decomposition. After performing discrete wavelet transform decomposition it results in four components Approximate, Horizontal, Vertical, diagonal at each level. As the approximate sub band carries a large significant information of image energy, we have chosen third and fourth level approximation coefficient of fingerprint image. Proposed feature extraction algorithm is based on Log-Gabor filter implementation proposed by Masek [17]. Feature encoding was implemented by convolving approximation coefficient with Log Gabor wavelets by convolving wavelet coefficients with scale 4 and orientation 6. Wavelet coefficients convolved with even symmetric filter to obtain real part while imaginary part can be obtained by convolution with odd symmetric filter. Using real and imaginary components phase component has been obtained. Further these components are mapped in four levels employing the Daugman method [19-20]. We have obtained 2-bit code for each pixel from fingerprint ROI by using each filter. Hamming distance based classifier has been used to determine dissimilarity between query and stored templates.

Proposed research work performs feature extraction of face biometric using an algorithm based on discrete wavelet transform designed by Joshi, and Kumar 2014 [38]. Multiresolution Detail subband images resulting after 5 level dwt represented in the form of binary form have been used as face feature vector. These feature classified as a genuine or imposter using Hamming distance. According to score generated by classifier further decision regarding acceptance or rejection is taken.

III. SCORE LEVEL FUSION

For Biometrics system scores are derived from matchers at matching stage. These score are real numbers which acts as indication for degree of closeness between query features and features stored in database. Implementing score level fusion can be defined as determining an efficient method to combine these numbers. As scores obtained carries sufficient information to differentiate in between genuine and imposter. Due to this it is one of choice of multimodal system designers. Because of feasibility and practicality of score level fusion is becoming common approach for information fusion. Scores obtained from matchers of individual biometric traits may give similarity or dissimilarity in the form of number. These scores must be mapped to either similarity score or dissimilarity score. Proposed research is aiming at design of score fusion method combining the matching scores efficiently and enhances the performance.

There are various difficulties involved in design of score level fusion based multimodal biometrics system. Scores obtained from matcher may be nonhomogeneous. Further it may be happen that scores generated from matchers of different modalities may be in different range. Score normalization must be used for conversion of raw scores obtained from various modalities to common range. Also some matchers may give similarity score while some may give dissimilarity. Match scores are related to probability distribution function of genuine and imposter scores. Probability distribution function of genuine and imposter scores may be varying for different matchers. For designing efficient multimodal system, Modeling of probability distribution is very challenging. Probability density functions (PDFs) can also be employed which doesn't need normalization methods. Figure 1 shows block diagram of match score level fusion considering normalization.

There are three approaches transformation-based, classifier-based and density-based to achieve fusion of [23, 25]. There are various normalization techniques which are summarized in following table 1. One of simplest method is Min-max. This normalization is appropriate in case of availability of maximum and minimum values of scores. Here minimum and maximum value of score can mapped to 0 and 1 with vary less effort. Decimal scaling based normalization can be used for scores on logarithmic scale. Z-score normalization employs arithmetic mean and standard deviation of scores for normalization. This method is commonly used. Normalized scores doesn't have any specific common range. The median and Median Absolute Deviation (MAD) statistics are more robust as they are less sensitive to the outliers and the points in the extreme tails of the distribution [10, 21].

Score distribution is not maintained by this method. Also it does not convert the scores into a common numerical range. Shape of original score distribution is not maintained in case of double sigmoid normalization but converted into common numerical range [0, 1]. Tanh-estimators based normalization [24] is both efficient and robust. Equation is given as follows

$$S_k^{'} = \frac{1}{2}\left(tanh\left(0.01\left(\frac{S_k-\mu_{GH}}{\sigma_{GH}}\right)\right)+1\right) \quad (1)$$

In this equation k is factor which obtains distribution of normalized genuine scores and its value can be determined by standard deviation of input genuine score for each modality.

Selection of normalization for a particular biometrics system depends on various factors such as modalities involved, score distribution, score range etc. It is very crucial step to design efficient normalization method in fusion to achieve the best performance for proposed fusion problem. In order to achieve optimized fusion performance number of normalization schemes required to be implemented and analyzed. Further we can devise optimal technique for fusion.

Proposed research work performs normalization of scores employing min-max, z-score, tanh normalization [10, 21].

Modified tanh normalization: We have proposed modified tanh normalization method. There is problem in score of multimodal biometrics system for genuine scores with low value and impostor scores with high value. Genuine score can be degraded due to variety reasons which are obtained by a genuine user. While for imposter obtaining high score is very difficult and tedious process. We have considered low genuine score and high imposter scores for corresponding genuine score distribution and imposter score distribution.

Normalization can be achieved using formula given by equation 2:

$$S'_k=0.8*((\tanh\ (0.05*(S_k\text{-min})/(\mu_{GH}\ -\sigma_{GH})\ )\ )+1) \quad (2)$$

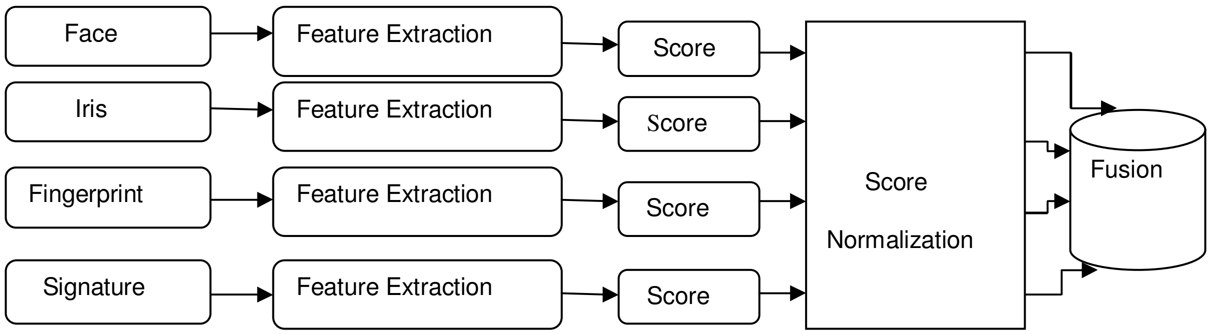

Fig. 1. Match Score Level fusion.

Table 1: Various Normalization techniques [40].

Normalization technique	Robustness	Efficiency
Min-max	No	N/A
Decimal Scaling	No	N/A
Z-Score	No	High
Median-MAD	Yes	moderate
Double Sigmoid	Yes	High
Tanh	Yes	High

In proposed normalization method difference of the mean of genuine scores distribution and standard deviation has been used. This will result in improvement of genuine score values for score with low values. While at the same time imposter scores with high values are also transformed reducing its effect. For choosing this value as division factor {mean-std} we have performed lot of experimentation and analysis. We have taken various combinations for (k*(Sk-min)/(μGH -σGH) to find more better normalization with improvement in fusion performance. After performing rigorous experimentation for k value we have decided to use 0.05 as k Further analysis has been performed to obtain scaling factor which will result in best normalization and we have chosen scaling factor as 0.8.

Using proposed modified normalization method, fusion performance can be improved as compared to tanh normalization. We have made attempt to increase genuineness of genuine users. So overall improvement in fusion performance has been obtained by using proposed method. There are various algorithms such as from simple addition to very complex like based on svm which can be employed for doing fusion of score. It has been shown that all these methods gives similar performance to weighted sum rule based fusion by some literature works [10, 21, 26]. Proposed research work uses weighted sum rule for fusion of scores.

IV. PROPOSED SCORE LEVEL FUSION APPROACH

A. Weighted sum rule

The weighted sum rule (WSrule) can be given

$$W_S rule=W1*S1+\ W2*S2+\ W3*S3+\ \ldots\ldots+Wn*Sn \quad (3)$$

[40]

In equation 3 W1, W2,…….Wn denotes the weights given for each of the individual biometrics. Scores obtained from individual modalities are denoted as S1, S2.......Weights for every biometrics can be obtained considering various factors such as error rates, distribution of scores [22], quality of the individual biometrics.

B. Match score level fusion

We have presented discussion about feature extraction for every unimodal biometrics in section 2. Here scores has been obtained from matcher for every modality using Hamming algorithm. Further these scores are normalized and fused together using weighted sum rule. We have designed and implemented multimodal biometrics system at score level fusion with an aim to enhance the final recognition performance.

In our work we have designed and implemented modified normalization scheme based on tanh normalization scheme. Proposed normalization is efficient and robust. Weighted sum rule based method has been employed for fusing normalized scores obtained from various modalities. For proposed multimodal system fused score can be represented with following equation 4 as

$$Sfuse=W_I*S_{Iris}+W_{face}*S_{face}+Ws*S_{sig}+Wfing*S_{fing} \quad (4)$$

where WI, Wface, Ws and W finger are weights for iris, face, signature and fingerprint resp., subject to condition that WI+ Wface + Ws+ Wfinger=1. Sfuse represents fused scores, Sface, SIris, Ssig, Sfing represents face, iris, signature, fingerprint scores resp. To find the weights we use an empirical weighting scheme as it is more efficient [21].

V. EXPERIMENTAL RESULTS AND DISCUSSIONS

Results of the implementation of the proposed unimodal and multimodal biometrics system has been presented in this section. We have done implementation of proposed algorithms using Matlab. Proposed multimodal biometrics system integrates information from four biometrics modalities as face, iris, fingerprint, and signature.

A. Unimodal Biometrics system Results

Proposed signature recognition algorithm has been tested by conducting several experiments on two signature databases as Caltech university database [28] and the Universal college of engineering and research (UCOER) database respectively. By employing camera based interface signature images are captured for Caltech [27]. There are two sets in this database. First set consisting of 25 genuine and 9 skilled forged signatures for every person. In First set signatures of 56 subjects are collected. While second set made up of signatures corresponding to 50 persons with 30 signatures for every person in database. Set 1 has been used for conducting experiments. Another database UCOER has been used to perform analysis of proposed system. There are total 150 signatures corresponding to 30 persons with 5 signatures of every person.

Proposed iris recognition algorithm has been evaluated on the Chinese Academy of Sciences—Institute of Automation (CASIA) eye image database version 1.0 [28]. This database consisting of 756 frontal non-ideal iris images of 108 volunteers with 7 images from every person in CASIA iris database.

We have tested and verified proposed face authentication algorithm on four face databases: ORL, JAFFE, IIT female database, Yale B. There are total 400 grayscale face images of size 112 × 92 pixels obtained from 40 subjects in ORL database [30]. Images present in the database are captures in various sessions. By changing the lighting, facial expressions such as open or closed eyes and facial details face image samples are obtained. Also it consists of images which are captured against a dark homogeneous background in an upright, frontal position. JAFFE database [31] is comprised of 213 images. It consists of images of 10 Japanese female subjects with 7 facial expressions. Each image with 6 emotion adjectives has been recorded for 60 Japanese subjects. Indian Face Database [32] is having face samples of 40 male and female subjects collected in February, 2002 in the IIT Kanpur campus. There are total 11 images with size 640 × 480 for every person in an upright and frontal position with bright homogenous background.

This database comprises images with different face orientations such as looking towards right, up, front, left, up towards left, up towards right, down. Also face images are with different emotions as neutral, smile, laughter, sad/disgust. For evaluation of proposed algorithm IIT Female face database is also employed. The Yale B database [33] consists face images with 576 different viewing conditions and 9 different poses It is having total 5760 single light source images. An image with ambient (background) illumination was also taken for each object. Here Out of 9 poses pose 0 represents frontal pose. While 12 degree orientation from pose 0 represented by poses 1, 2, 3, 4, and 5 and 24 degree orientation is shown for poses 6, 7 and 8.

To analyze proposed fingerprint recognition algorithm experiments has been carried out on FVC 2004 database [29]. FVC 2004 database has a total of 110 fingers and 8 impressions per finger (880 impressions). FVC2004 databases are markedly more difficult, due to the perturbations deliberately introduced. Proposed algorithms are tested and analysed for performance measures such as Genuine Acceptance Rate (GAR), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Equal Error Rate (EER). The obtained experimental results for unimodal biometrics system for various performance parameters such as recognition rates, FAR and FRR are here outlined in following Table 2. From Table 2 it can be observed that error rates associated with different unimodal system are significant. Success of biometrics authentication system depends strongly on two parameters i.e. no. of false acceptances and number of false rejects. For ideal identity management system FAR and FRR should be 0. It is necessary to optimize performance of biometrics system with FAR=0% and FRR=some value.

Table 2: Performance Analysis of Unimodal Biometrics System on Ideal and non-ideal databases.

Biometrics System	Database	Size of Database	Feature Vector size	FAR	FRR	EER
Iris	CASIAV1	30	702	2%	10.34%	8.67%
Fingerprint	FVC2004	40	960	2.5%	12.45%	9.34%
Face	ORL	40	666	3%	13%	8%
Face	Yale	39	1008	2%	28%	15%
Face	IIT Database	22	666	3.18%	20.06%	11%
Signature	Caltech	56	144	3%	17%	9%

B. Proposed Score level fusion based multimodal system results

Proposed score level fusion with selected biometrics face, iris, fingerprint and signature needs to be evaluated to determine fusion performance. For this purpose a database is required which consists of scores obtained from selected biometric traits of individual. We have prepared virtual multimodal database due to unavailability of real multimodal database having fingerprint, face, signature, iris scores of same individuals. Here we have performed experiments on a virtual database of virtual persons employing face, iris, and fingerprint and signature sample images taken from four different databases. Proposed fusion approach combines normalized scores obtained from ideal database and non-ideal database for selected modalities. A user from the modality dataset is randomly associated with a user with other modalities dataset, creating a virtual user with face, iris, fingerprint and signature. We have conducted six experiments with combination of different modalities on six chimeric databases considering random 30 individuals as shown

in Table 3. In these experiments we have performed combination of Casia database, FVC2004 database with signature databases as ucoer, Caltech database and face databases as ORL, Yale , IIT Female database. During these experiments we have selected 4 images for training samples and 3 images for testing samples for Experiment no. 1 to 3. While in case of experiments where ucoer database is combined with other databases 3 training and 2 testing images are taken. Results obtained after experimentation on proposed multimodal biometrics system in terms false acceptance rate and genuine acceptance rate has been shown in Table 4 and 5. We have presented experimental result analysis for various normalization techniques as shown in Table 5. Proposed fusion approach performs mapping of score to new range using zscore, tanh, min-max, modified tanh. These normalized scores derived are combined together using weighted sum rule. Results of various normalization scheme, such as min–max, z-score, tanh and modified tanh normalization has been shown in Table 5. It has been observed from experimental analysis that we have got best performance for proposed modified tanh normalization scheme as compared to other normalization technique.
For analysis of false acceptance rate and false rejection rate so as to determine best trade off ROC curve is normally used. FAR and FRR are the most important parameters which plays important role in enhancing robustness and security levels of a recognition approach.

Table 3: Experimental setup.

Experiment No.	Face database	Iris database	Signature database	Fingerprint database	No. of users
1	ORL	CASIA	Caltech	FVC2004	30
2	Yale	CASIA	Caltech	FVC2004	30
3	IIT Female	CASIA	Caltech	FVC2004	30
4	ORL	CASIA	Ucoer	FVC2004	30
5	Yale	CASIA	Ucoer	FVC2004	30
6	IIT Female	CASIA	Ucoer	FVC2004	30

Table 4: Performance Analysis of Proposed Score level fusion methodology.

Experiment No.	FAR	FRR	GAR	EER
1	0%	2.5%	97.50%	0.8%
2	0%	3.33%	96.67%	1.4%
3	0%	2%	98%	0.6%
4	0%	1.66%	98.34%	0.4%
5	0%	3.33%	96.67%	1.8%
6	0%	2.55%	97.45%	1.2%

Table 5: Performance Analysis of Score Normalization.

Experiment No.	Normalization Technique	FAR	FRR	GAR	EER
1	Min-Max	0.1%	10 %	90%	3.33%
	Zscore	0.1%	8.33%	91.70%	2.87%
	Tanh	0.1%	8.33%	91.70%	2.87%
	Proposed new	0%	2.5%	97.50%	0.8%
2	Min-Max	0%	9.22%	90.78%	4.00%
	Zscore	0.1%	6.11%	93.89%	3.88%
	Tanh	0%	6.66%	93.34%	3%
	Proposed new	0%	3.33%	96.67%	1.4%
3	Min-Max	0%	9.23%	90.07%	3.14%
	Zscore	0%	9 %	91%	4.16%
	Tanh	0%	6.22%	93.78%	2.22%
	Proposed new	0%	2%	98%	0.6%
4	Min-Max	0%	6.66%	93.34%	2.34%
	Zscore	0%	8.33%	91.67%	3.33%
	Tanh	0%	8.33%	91.67%	4%
	Proposed new	0%	1.66%	98.34%	0.4%
5	Min-Max	0%	7.77%	92.23%	3.50%
	Zscore	0%	9.23%	90.77%	5%
	Tanh	0%	10.41%	89.57%	5.45%
	Proposed new	0%	3.33%	96.67%	1.8%
6	Min-Max	0%	5%	95%	2.3%
	Zscore	0%	5.83%	94.17%	2.93%
	Tanh	0%	7.64%	92.36%	7.82%
	Proposed new	0%	2.55%	97.45%	1.2%

Receiver operating characteristics of score level multimodal system for various normalization techniques are as shown in figure 2a to 2f for all six experiments. The best performance is noted for score level fusion based on our proposed normalization as FAR=0% and FRR=1.66% with EER=0.4%. A novel multimodal biometrics system has been designed and implemented at score level. Proposed multimodal biometrics integrates four biometric modalities face, iris, fingerprint and offline signature. Distinct and significant features of all biometric modalities are extracted using the DWT based algorithm. Detail coefficients has been used for face, iris and signature modalities while approximation coefficients has been used for fingerprint modality which results into efficient representation. Using hamming classifier we have obtained scores from all four modalities. From ROC characteristics it has been proved that we have achieved significant improvement in performance of system in case of proposed normalization algorithm as compared to min-max, tanh and zscore normalization.

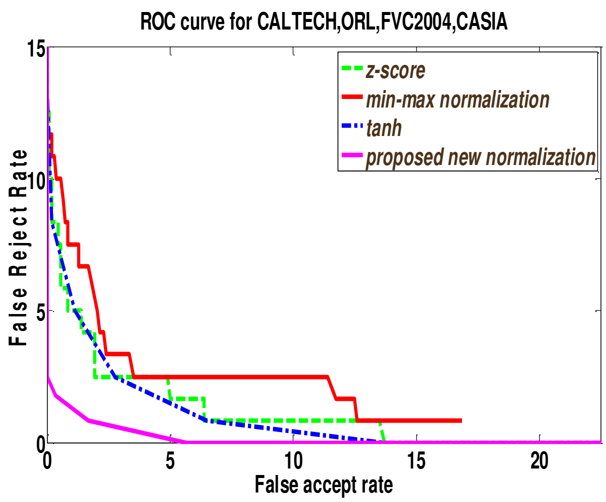

Fig. 2a.

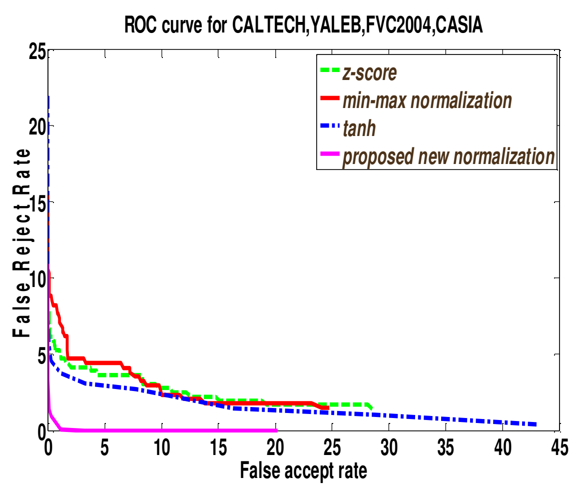

Fig. 2b.

Proposed score level fusion method outperforms unimodal biometrics system. We have presented results of unimodal system and multimodal system as shown in Table 2 and 4. Proposed modified tanh normalization alongwith fusion of scores using sum rule for design of multimodal system results into a considerable improvement in multimodal system performance compared to each unimodal system in case of all experiments. With proposed score level fusion algorithm implementation we have got significant reduction in error rates. We have achieved interesting to point work with multimodal system as FAR=0% and FRR=1.66% in case of experiment 4. It proves in presence of ideal images and non-ideal images we have got superior performance for proposed score level algorithm.

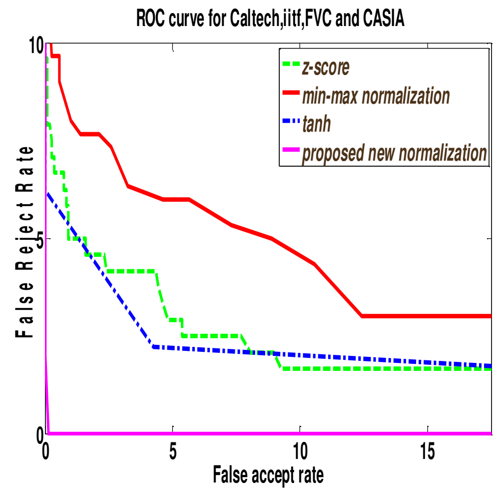

Fig. 2c.

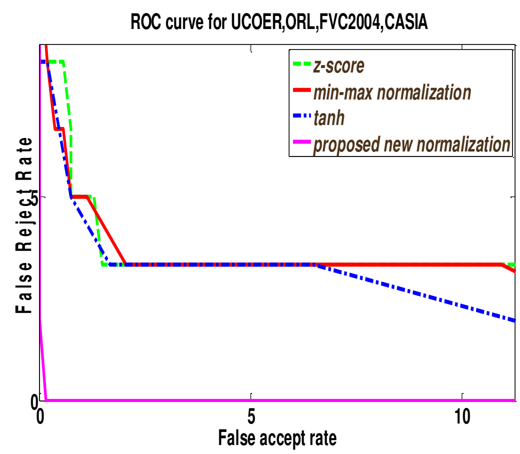

Fig. 2d.

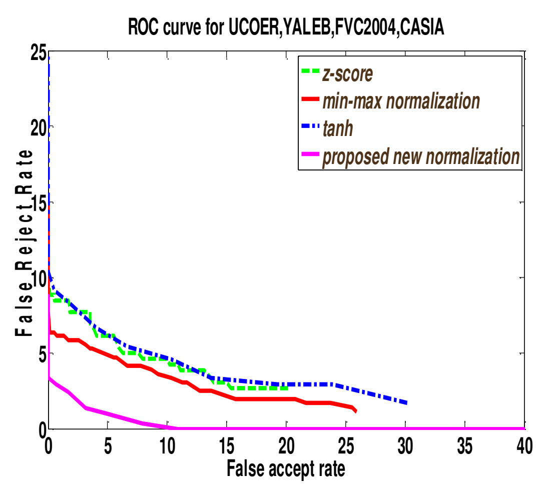

Fig. 2e.

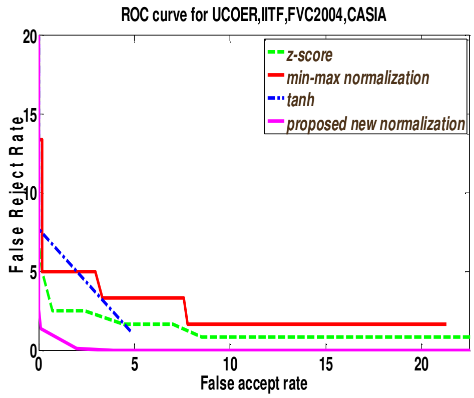

Fig. 2e.

C. Comparison of our approach with literature work

Multimodal biometric identification systems combines biometric data obtained from two or more physical or behavioral traits for optimizing various error rates which will result in performance improvement. Several researchers have carried out their work to design score level based biometrics system. Proposed score level multimodal biometrics system is novel as compared to literature approaches.

We have combined four biometric modalities face, iris, fingerprint and signature, which are very commonly used. Proposed approach extracts wavelet based feature vector and further they are encoded in binary form. Proposed methodology achieves significant reduction in feature vector size and hence resulting into faster recogintion. We have presented a modified tanh normalization technique based on tanh normalization. Table 6 presents a comparison of the different score level methods proposed and implemented in the current literature in terms parameters such as different error rates, genuine accept rate, matching time.

It has been observed that our proposed score level fusion approach has obtained better improved performance as compared to some of prior work based on score level fusion reported by Arun and Anil (2003) [4], Mehrotra, Rattani, and Gupta (2006) [34] , Mingxing *et al.* (2010) [35] and Sim Hiew (2014) [36], Walia *et al.,* (2019) [42], Kamel Aizi (2019) [43] in the overall performance. We see that our proposed method is the better in terms of error rates than the other presented systems.

Table 6: Comparative performance analysis of Proposed algorithm with other literature approaches.

Author	Database	Feature	FAR	FRR	GAR	EER	Matching Time
Arun *et al.*, [4]	Self acquired Database	face, fingerprints, hand geometry	0.03%	1.78%	NA	NA	NA
Mehrotra *et al.*, [34]	Self Prepared Database	Iris and fingerprints	1.58%	6.34%	96.04%	NA	NA
Mingxing *et al.*, [35]	NIST-multimodal	fingerprint, face, finger vein	0.996%	0.00005%	99.40%	NA	NA
Sim *et al.,* [36]	UBIRIS v.2 and ORL	Face and iris	0.09%	0.01%	99.40%	NA	NA
Walia *et al.,* [42]	IITD PolyU Iris database, VERA finger vein database, FVC 2006 fingerprint CASIA fingerprint database	Fingerprint, Fingervein, iris	NA	NA	NA	1.57	NA
Kamel Aizi *et al.*, [43]	CASIA-IrisV4,CASIA-FingerprintV5	Fingerprint and Iris	1.50%	3.89%	95	1,11	NA
Proposed Method	ORL, CASIA, Ucoer, FVC2004	Face, Iris, Signature, fingerprint	0%	1.66%	98.34%	0.4%	0.10

VI. CONCLUSION

Score normalization plays a vital role in design of score level fusion based biometric identification and it has significant impact on performance of multimodal system. This research work has analyzed performance of multimodal system in presence of various score normalization techniques. This research work presented comparative analysis of various normalization techniques for various performance parameters. So Our interest was to find normalization technique which will enhance fusion performance. It has been shown recognition performance of multimodal system enhances due to score normalization. Proposed fusion approach has implemented various normalization techniques such as min-max, z-score, tanh and proposed modified tanh. Normalized scores has been processed using sum rule to obtain fused score. Proposed system has obtained considerable improvement in GAR than unimodal systems. We have presented a modified normalization technique based on tanh normalization. As compared to other normalization techniques proposed normalization method is more robust and efficient. This research work also provides comparative analysis of our results in terms of various error rates with prior work based on score level fusion with other biometric traits. Proposed multimodal system with selected biometric based on fusion of scores provides the highest accuracy in terms of FAR and FRR as compared to prior work. It has been proved that multimodal biometrics system outperforms unimodal system and provides a good solution for security critical applications.

VII. FUTURE SCOPE

In future we can extend our research to handle some open issues related to current system which needs attention. In Most score level fusion system it has been considered that scores from all matching modules are available but it may happen that some scores are missing. In future we can design score level fusion system which can handle missing scores. We can evaluate performance of our proposed system on real time Indian true multimodal database covering huge population.

Conflict of Interest. There is no conflict of interest.

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