Efficient approach to Normalization of Multimodal Biometric Scores

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ABSTRACT
Information fusion at the matching score level is widely used, due to the simplicity in combining the scores generated by different matchers. Since the matching scores output by various modalities are diverse in numerical range, score normalization is needed first, to transform these scores into a common domain. Then score fusion is to be carried out on the normalized scores. In this paper, we have studied the performance of different normalization techniques and fusion rules in the context of a multimodal biometric system based on iris and palm print traits of a user. The conventional normalization techniques used for testing are min-max, median-MAD, double-sigmoid and tanh. These normalized results are combined using tanh, mean, sum, product, min, max and median fusion methods. Also, we propose two novel normalization methods namely modified tanh normalization and max normalization as well as a new modified min-max fusion technique for biometric verification. The experimental results on CASIA iris and palm print databases show that the application of proposed max and modified tanh normalization schemes followed by mean and tanh fusion methods result in better recognition performance compared to all other methods.

General Terms
Pattern Recognition, Security, Biometrics

Keywords
Iris, Multimodal biometrics, Normalization, Palm print, ROC, Score level fusion

1. INTRODUCTION
Biometrics refers to the measurement and analysis of physical and behavioral traits of humans with a goal of verifying or determining the identity of humans. Biometrics provide a more authentic alternative to establish identity as compared to passwords, ID cards, etc. which can be stolen or passed on to others fairly easily. A biometric characteristic should have the following characteristics for it to be truly useful in real scenarios: Universality, Uniqueness, Permanence, Collectability, Acceptability, Difficult to circumvent and Low underlying system errors **[**1]. It may not be possible for a single biometric to have all the above mentioned desirable properties. This has led to the rise of research in multi-biometric systems that rely on fusing information from multiple biometric evidences. Fusion of multiple biometric characteristics has been shown to increase accuracy while decreasing the vulnerability to spoofing [2]**.** In addition, use of multiple biometrics provides a better coverage of population to deal with situations like indistinguishable unimodal biometric characteristics.

In a multimodal recognition system, information can be integrated at various levels: feature extraction level, matching score level and decision level [3]. Fusion at the feature extraction level combines different biometric features in the recognition process. Score fusion matches the individual scores of different recognition systems to obtain a multimodal score. Decision level systems perform logical operations upon the monomodal system decisions to reach a final resolution. In this paper, novel matching score level systems will be presented and compared with the most used conventional ones.

A matching score level fusion system consist of two steps: normalization and fusion [2]. The normalization process converts the scores of different traits to a comparable range of values. Without this step, a biometric with a higher range could eliminate the contribution of another with a lower one. The normalization step is required in the design of a multimodal biometric identification or verification system for the following reasons**.** The matching scores at the output of the individual matchers can be represented in different ways. For example, one matcher may output distances, while the others may output proximities. The matcher outputs can be in different numerical ranges. The genuine and impostor matching scores from different modalities might not follow the same statistical distributions.

2. PREVIOUS WORK
One finds in the literature, multiple techniques for fusing biometric scores. Many researchers have demonstrated that fusion is effective, in the sense that the fused scores provide much better discrimination than the individual scores. Such results have been achieved using a variety of fusion techniques. Several recent papers have compared various techniques on empirical data. Some of the important works are enumerated below:
Authors in [4] evaluated several classifier combination rules on frontal face, face profile, and voice biometrics (using a database of 37 subjects). They found that the "sum of *a posteriori* probabilities" rule outperformed the product, min, max, median, and majority of *a posteriori* probability rules (at EER) due to its resilience to errors in the estimation of the densities. Authors in [5] evaluated five binary classifiers by combining face and voice modalities (database of 295 subjects). They found that SVM and Bayesian classifier achieved almost the same performance and

both outperformed Fisher's linear discriminant, decision tree and a multilayer perceptron methods. Authors of [6] found that SVM outperformed (at EER) the sum of normalized scores when fusing face, fingerprint and signature biometrics (database of 100 subjects and 50 chimeras).
Authors in [7] applied sum of scores, max-score, and min-score fusion methods to normalized scores of face, fingerprint and hand geometry biometrics (database of 100 users, based on a fixed TAR). The normalized scores were obtained by using one of the following techniques: simple distance-to-similarity transformation with no change in scale (STrans), min–max, z-score, median-MAD, double sigmoid, tanh, and Parzen. They found that min–max, z-score, and tanh normalization schemes followed by a simple sum of scores outperformed other methods; tanh is better than min-max and z-score when densities are unknown; optimizing weighting of each biometric on a user-by-user basis outperforms generic weighting of biometrics.

Authors of [8] compared z-score, min-max, tanh and adaptive (two-quadrics, logistic and quadric-line-quadric) normalization methods and sum, min score, max score, matcher weighting and user weighting fusion methods. They found that fusing COTS fingerprint and face biometrics outperformed unimodal COTS systems, but the high performance of unimodal COTS systems limits the magnitude of performance gain; for open-population applications (e.g., airports) with unknown posterior densities, min-max normalization and simple-sum fusion are effective; for closed-population applications (e.g. an office), where repeated user samples and their statistics can be accumulated, QLQ adaptive normalization and user weighting fusion methods are effective. Authors in [9] compared various parametric techniques on the BSSR1 dataset which showed that the best linear technique performed well, in contrast to many alternative parametric techniques, including simple sum of z-scores, Fisher's LDA and sum of probabilities based on normal (Gaussian) assumption.

These studies suffer from the limited availability of data that refers to small datasets used for evaluating the performance. Some of the studies also suffer from problems like usage of simplified assumptions with no investigation into the validity of those assumptions; the results of evaluation may hinge on the validity of assumptions. Thus, despite the progress that has been made in this field, there remains a clear need for large-scale empirical comparison of fusion techniques. There is also a need for guidance on the implementation and selection of techniques.

3. BIOMETRIC VERIFICATION SYSTEM BASED ON FUSION OF PALM PRINT AND IRIS FEATURES

The proposed method is tested on a multimodal biometric verification system based on palm print and iris features.

3.1 Palm print recognition

The palm print recognition system can be divided into three main parts, namely pre-processing, minutiae extraction and minutiae matching [10]. Pre-processing is first carried out to enhance the quality of the input palm print image. Then enhancement of a palm print image is carried out to improve the clarity of images for human viewing. Removal of blur and noise increase the contrast and reveal the finer details on the palm. Ridge direction and frequency estimation are important for minutiae extraction. Initial estimation using a gradient based method estimates the true direction. Ridge frequency is based on the ridge direction. The extracted minutiae have some spurious minutiae due to noise, which needs to be removed. The ridge validation procedure is used to classify ridges as reliable or unreliable and the minutiae associated with unreliable ridges are removed. For each sector, a set of features is computed using the mean ridge direction, mean ridge period and the numbers of neighboring minutiae. The difference between the minutia pairs is used as the matching score between two palm prints.

3.2 Iris Recognition

The process of iris recognition consists of four phases [11]. The iris image is first localized by finding the center of pupil from the image. The outer iris boundary is detected by drawing concentric circles of different radii from the pupil center and intensities lying over the perimeter of the circle are summed up. Among the candidate iris circles, the circle having a maximum change in intensity with respect to the previous drawn circle is the outer iris boundary. The annular region lying between pupil and iris boundary is transformed to polar co-ordinates. Features in iris images are extracted based on the phase of convolution of polarized iris image with mellin operators. The iris code is one for positive phase values and zero for negative phase values. Iris codes thus generated are then matched using Hamming Distance approach.
Since the matching scores generated by the above two methods are not in the same range, score normalization needs to be applied to them. The normalized matching scores from both iris and palm print modules are then combined into unique scores using different fusion methods as given in the next section. Based on this matching score, a suitable threshold is selected and decision about whether to accept or reject a user is made.

4. SCORE NORMALIZATION TECHNIQUES

Score normalization refers to changing the location and scale parameters of the matching score distributions at the outputs of the individual matchers, so that the matching scores of different matchers are transformed into a common domain. For a good normalization scheme, the estimates of the location and scale parameters must be robust and efficient. Robustness refers to insensitivity to the presence of outliers. Efficiency refers to the proximity of the obtained estimate to the optimal estimate when the distribution of the data is known. Although many techniques can be used for score normalization, the challenge lies in identifying a technique that is both robust and efficient. In this section we present some of the well-known normalization techniques used in multimodal biometric systems. Also two new normalization schemes namely modified tanh and max normalization is proposed which is derived from tanh and min-max normalization schemes respectively. In addition, a new fusion method named as modified min-max fusion is proposed. Experiments conducted on the images from iris and palm databases suggest that the proposed schemes lead to consistently high accuracy compared to other score normalization techniques. The following conventional normalization methods [12] are evaluated using the iris and palm print traits.

4.1 Min-max normalization

It is the simplest normalization technique that achieves the common numerical range of the scores [0, 1] and also retains the shapes of the original distributions except for a scaling factor. Let X denotes the set of raw matching scores from a specific matcher. The normalized score of x is then denoted by x'. Given that max(X) and min(X) are the maximum and minimum values of the raw matching scores respectively [12]. The normalized score is then calculated as

$$x' = (x - \min(X))/(\max(X) - \min(X)) \tag{1}$$

This method is highly sensitive to outliers in the data used for estimation**,** therefore it is not robust. The presence of outliers makes most of the data concentrate only in a smaller range.

4.2 Median-MAD normalization

The median-MAD (median absolute deviation) normalization [12] does not guarantee the common numerical range and is insensitive to outliers. The normalization is given as

$$x' = (x - median)/const(median|x - median|) \tag{2}$$

where x is the input score value.

4.3 Double-sigmoid normalization

This normalization scheme provides a linear transformation of the scores in the region of overlap, while the scores outside this region are transformed non-linearly [12].

The double-sigmoid normalization is given as:

$$x' = 1/(1 + (\exp(-2((x-t)/r1))) \quad \text{if } x < t$$

$$x' = 1/(1 + (\exp(-2((x-t)/r2))) \quad \text{if } x \geq t \tag{3}$$

where t is the reference operating point and $r1$ and $r2$ denote the left and right edges of the region in which the function is linear, i.e., the double sigmoid function exhibits linear characteristics in the interval ($t - r1$, $t - r2$). These parameters control the shape of the normalization function on the different segments.

4.4 Tanh-normalization

The normalization based on the tanh-estimators is reported to be robust and highly efficient [12]. This method is not sensitive to outliers. The mean and standard deviation are found out from the genuine score distribution, as given by Hampel estimators**.**

$$s'_k = \frac{1}{2}\{\tanh(0.01(s_k - \mu_{GH})/\sigma_{GH})) + 1\} \tag{4}$$

The results of this normalization technique are quite similar to those produced by the Z-score normalization. The nature of the tanh distribution is such that the genuine score distribution in the transformed domain has a mean of 0.5 and a standard deviation of approximately 0.01. The constant 0.01 in the expression for tanh normalization determines the spread of the normalized genuine scores.

Proposed normalization schemes

4.5 Max normalization

This normalization technique strives to achieve good separation of the genuine and impostor matching-score distributions. We construct the normalization function from the min-max normalization method by making the min value to be zero. It is given by,

$$x' = x/(\max(X) \tag{5}$$

where X denotes the set of raw matching scores from a specific matcher and x is the raw score. These values produce better recognition rates than other normalization methods. Also this method is simpler and faster when compared to that of min-max scheme.

4.6 Modified tanh normalization

This proposed method differs from the tanh approach, in that it does not use Hampel estimators, instead the mean and standard deviation of the scores is considered. Hence the complexity involved in the usage of Hampel estimators is eliminated. Thus it is faster and simpler method. The normalization is represented as,

$$\tanh s' = 0.5[\tanh(0.01(s - \mu)/\sigma) + 1] \tag{6}$$

where mean and standard deviation are computed from the matching scores itself.

5. SCORE LEVEL FUSION TECHNIQUES

Score level fusion is commonly preferred in multimodal biometric systems because matching scores contain sufficient information to make genuine and impostor case distinguishable and they are relatively easy to obtain. Given a number of biometric systems, matching scores for a pre-specified number of users can be generated even with no knowledge of the underlying feature extraction and matching algorithms of each system. Therefore, combining information obtained from individual modalities using score level fusion seems both feasible and practical [12]. In general, score level fusion techniques can be divided into three categories as follows [13], [12]): transformation-based score level fusion (e.g. sum-rule based fusion), classifier-based score level fusion (e.g. SVM based fusion) and density-based score level fusion (e.g. likelihood ratio test with Gaussian Mixture Model). The following conventional fusion methods [14] are evaluated using the iris and palm print traits.

5.1 Mean fusion

The matching scores of the traits palm print and iris are combined by taking their mean value [14]. Thus the final score MS_{Final} is given by,

$$MS_{final} = (axMS_{iris\_R} + bxMS_{palm} + cxMS_{iris\_L})/3 \tag{7}$$

where $MS_{IRIS\text{-}R}$ = matching score of right iris, MS_{PALM} = matching score of palm print, $MS_{Iris\text{-}L}$ = matching score of left iris and a, b, c are the weights assigned to the various traits. Currently, equal weightage is assigned to each trait so the value of (a+b+c) is one. The final matching score (MS_{Final}) is compared against a certain threshold value to recognize the person as genuine or imposter.

5.2 Min fusion

This fusion method chooses the minimum of the different unimodal scores as the multimodal score value [14]. Thus the final score is given by,

$$MS_{final} = \min(MS_{iris\_R}, MS_{palm}, MS_{iris\_L}) \tag{8}$$

5.3 Max fusion

This fusion method chooses the maximum of the different unimodal scores as the multimodal score value [14]. Thus the final score is given by,

$$MS_{final} = \max(MS_{iris\_R}, MS_{palm}, MS_{iris\_L}) \tag{9}$$

5.4 Sum fusion

This rule assumes that the posteriori probabilities computed by the individual classifiers do not deviate much from the prior probabilities. It is applicable when there is a high level of noise leading to ambiguity in the classification problem [14]. The sum of the matching scores of the traits, MS_{Final} is given by,

$$MS_{final} = MS_{iris\_R} + MS_{palm} + MS_{iris\_L} \quad (10)$$

5.5 Product fusion

In general, different biometric traits of an individual are mutually independent. This allows us to make use of the product rule in a multimodal biometric system based on the independence assumption [14]. The product of the matching scores of the traits is given by

$$MS_{final} = MS_{iris\_R} x MS_{palm} x MS_{iris\_L} \quad (11)$$

5.6 Tanh fusion

The traits are combined by taking the tan hyperbolic sum of the matching scores [14]. Thus the final score MS_{Final} is given by,

$$MS_{final} = \tanh(MS_{iris\_R}) + \tanh(MS_{palm}) + \tanh(MS_{iris\_L}) \quad (12)$$

5.7 Median fusion

This fusion method chooses the median value of the different unimodal scores as the multimodal score value [14]. Thus the final score is given by,

$$MS_{final} = median(MS_{iris\_R}, MS_{palm}, MS_{iris\_L}) \quad (13)$$

Proposed fusion scheme

5.8 Modified min-max fusion

This fusion method chooses the minimum of the intra user scores and the maximum of the inter user scores as the multimodal score value. Thus the final score is given by,

$$MS_{final} = \min(genuine(MS_{iris\_R}, MS_{palm}, MS_{iris\_L}))\ AND$$
$$\max(imposter(MS_{iris\_R}, MS_{palm}, MS_{iris\_L})) \quad (14)$$

6. DATABASES USED IN THE EXPERIMENTATION

To evaluate the performance of our multimodal system using the previously described normalization techniques, a database containing palm print and iris samples is required. Hence the CASIA iris and palm image databases are used. A "chimerical" multimodal database is created using pairs of artificially matched palm and face samples.

6.1 CASIA iris database

CASIA-IrisV3 [15] includes three subsets which are labeled as CASIA-IrisV3-Interval, Lamp and Twins. CASIA-IrisV3 contains a total of 22,035 iris images from more than 700 subjects. All iris images are 8 bit gray-level JPEG files, collected under near infrared illumination with a resolution of 320 x 280. Almost all subjects are Chinese except a few in CASIA-Iris V3-Interval. Iris images were captured with self-developed iris camera and most of the images were captured in two sessions, with at least one month interval. It contains 2639 iris images from 249 subjects. From this, a database consisting of 100 subjects was constructed with each 5 samples per user. Thus, 500 (100×5) genuine score vectors and 49,500 (100×5×99) impostor score vectors were obtained from this database.

6.2 CASIA palm print database

CASIA Palm print Image Database [16] contains 5,502 palm print images captured from 312 subjects. For each subject, palm print images from both left and right palms are collected. All palm print images are 8 bit gray-level JPEG files and the samples were collected in one session only. From this, a database consisting of 100 subjects was constructed with each 5 samples per user. The biometric data captured from every user is compared with that of all the users in the database leading to one genuine score vector and 99 impostor score vectors for each distinct input. Thus, 500 (100×5) genuine score vectors and 49,500 (100×5×99) impostor score vectors were obtained from this database.

Assuming the independence of the three modalities, we create 100 "virtual" users by combining the subjects from the two databases. Merging the scores from the above two databases resulted in a database of 100 users with 1000 genuine score vectors and 99,000 impostor score vectors. A score vector is a 3-tuple, corresponding to the matching scores obtained from the left iris, right iris and palm print matchers respectively.

7. EXPERIMENTAL RESULTS AND DISCUSSION

The performance of the proposed multimodal biometric system has been studied under different normalization and fusion techniques. The system can make two types of errors. The first type of error is a False Acceptance Error (FAR), where an impostor is accepted. The second error is a False Rejection (FRR), where a genuine client is rejected. The trade-off between FAR and FRR can be graphically represented by a Receiver Operating Characteristics (ROC) plot [17]. To quantify the performance into a single number, the Equal Error Rate (EER) is often used when FAR is equal to FRR. The distance score 'd' between the stored and test images is computed for each of the trait and is compared with an acceptance threshold '*t'* and if d is greater than or equal to *t*, then the compared samples belong to a different person. Pairs of biometric samples generating scores lower than *t* belongs to a same person. The distribution of scores generated from pairs of samples from different persons is called an impostor distribution, and the score distribution generated from pairs of samples of the same person is called a genuine distribution.

Figure 1 shows the ROC obtained from the multimodal biometric verification system using different normalization techniques and fusion methods. In fig.1.a, the first figure shows the accuracy rate of Max fusion of different normalizations and the second figure shows error rate of the max fusion method. Likewise, the other figures show the performance of the conventional and newly proposed approaches by taking iris and palm print traits.

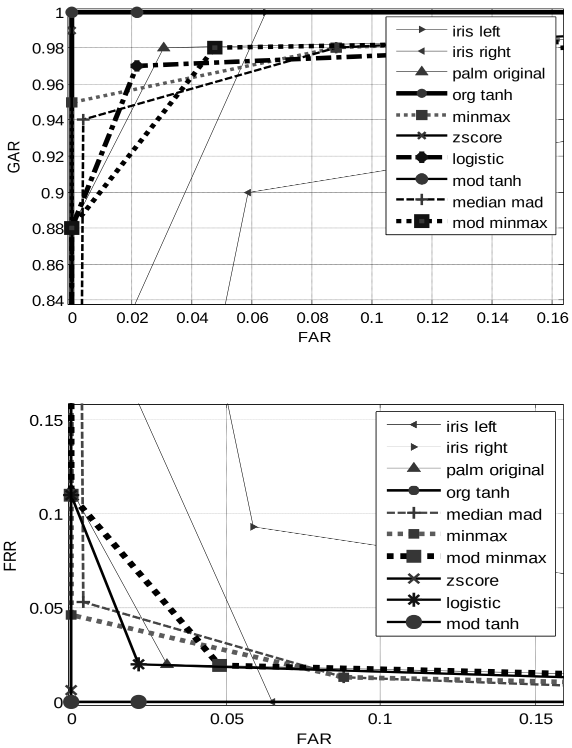

Fig 1.a. Performance graphs obtained for Max fusion of different normalization methods

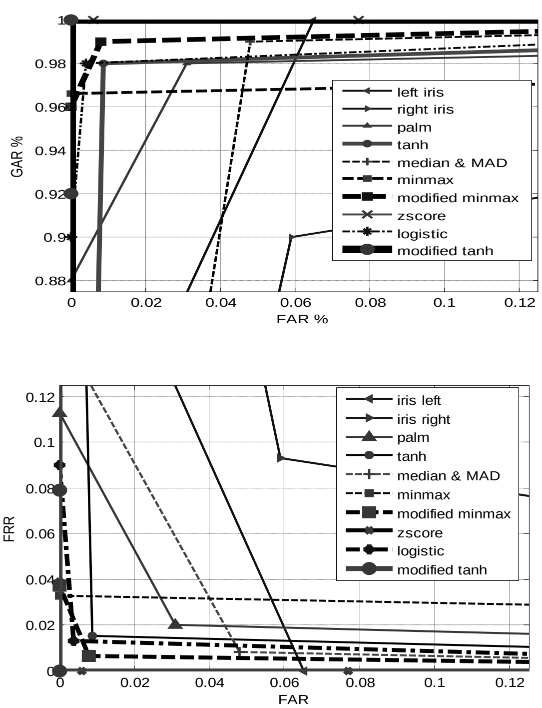

Fig 1.b. Performance graphs obtained for Mean fusion of different normalization methods

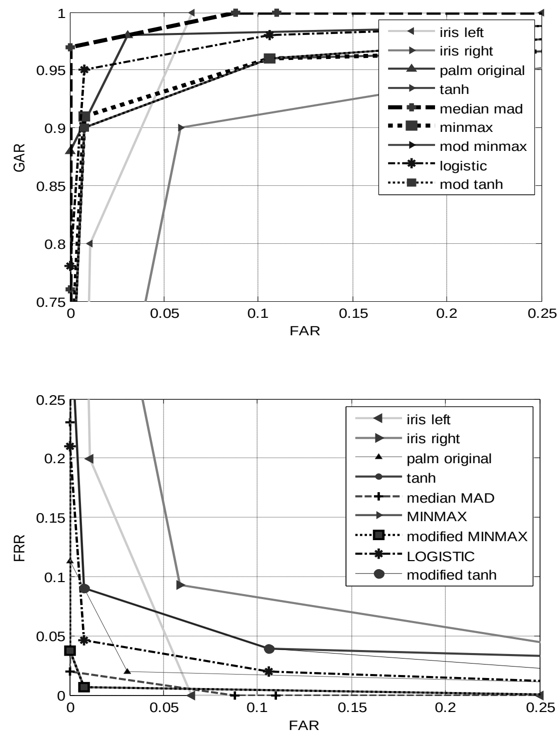

Fig 1.c. Performance graphs obtained for Median fusion of different normalization methods

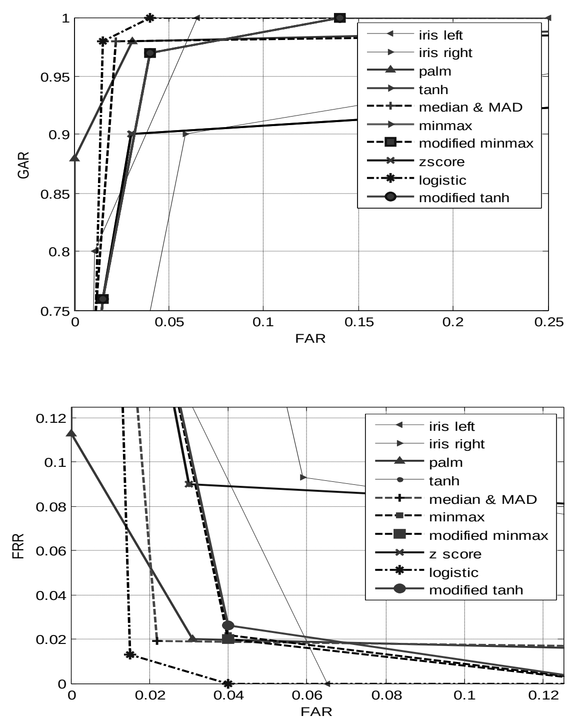

Fig 1.d. Performance graphs obtained for Min fusion of different normalization methods

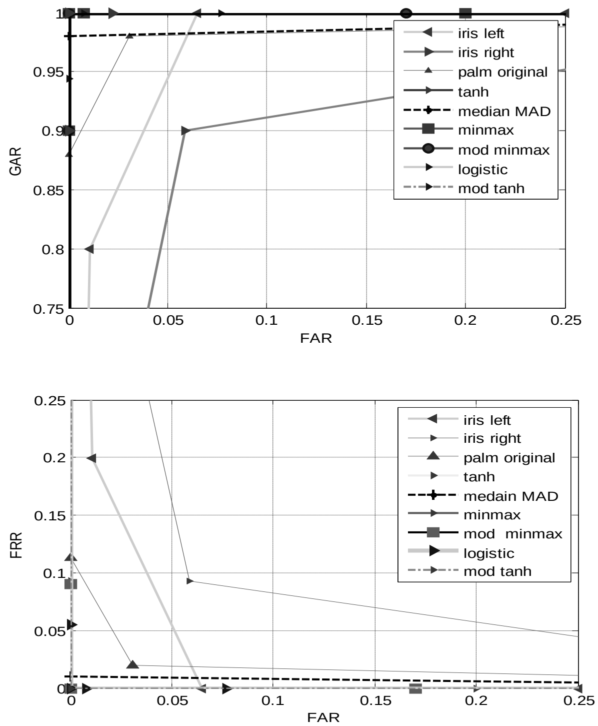

Fig 1.e. Performance graphs obtained for modified Min-max fusion of different normalization methods

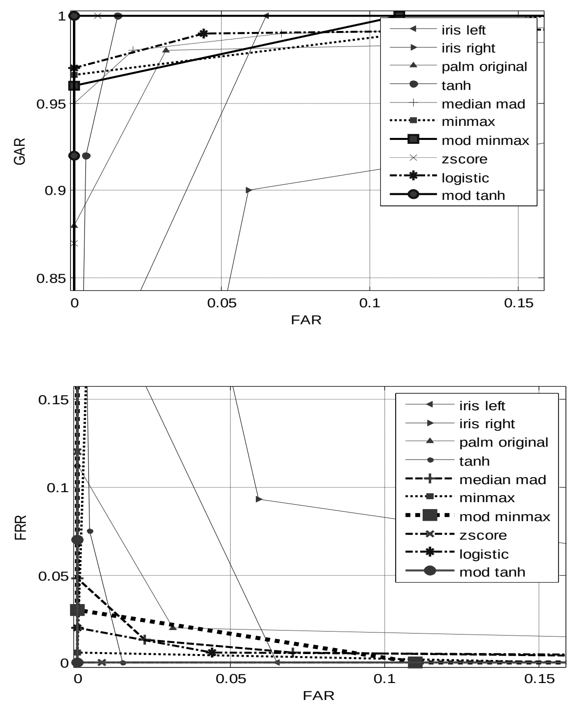

Fig 1.g. Performance graphs obtained for Sum fusion of different normalization methods

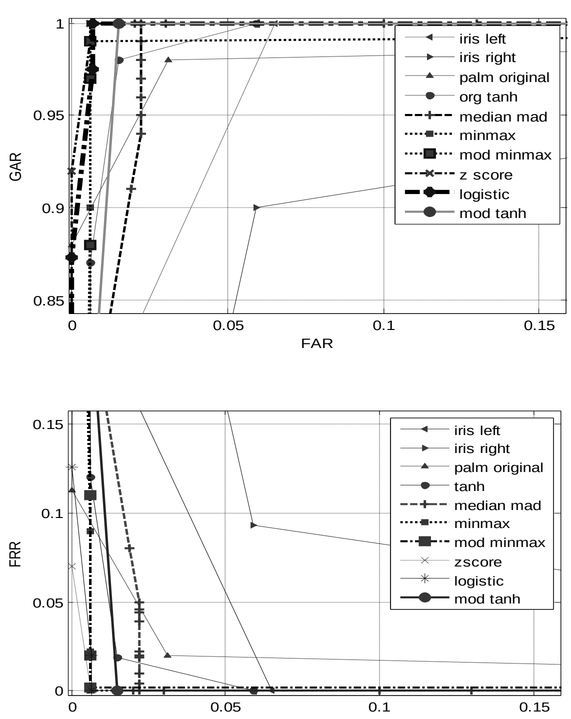

Fig 1.f. Performance graphs obtained for Product fusion of different normalization methods

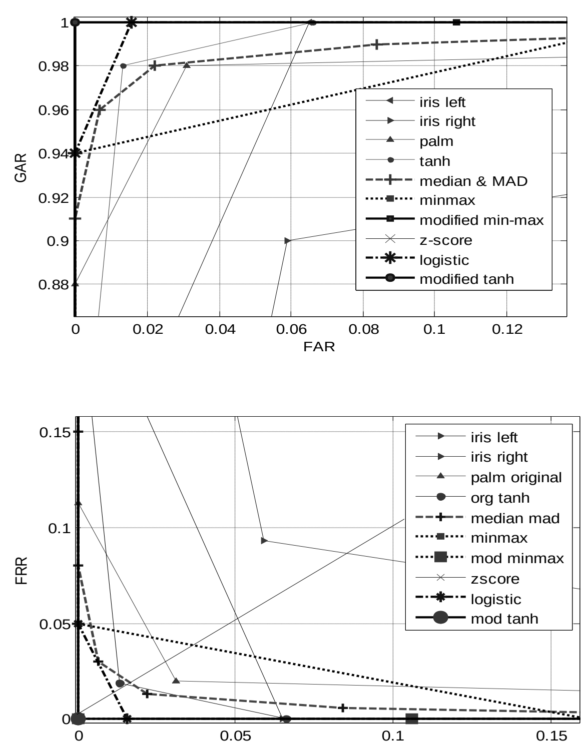

Fig 1.h. Performance graphs obtained for tanh fusion of different normalization methods

Table 1 shows the recognition rates and error rates obtained from the above ROC graphs for different normalization and fusion techniques. Values obtained for the proposed methods are indicated in boldface.

Table 1.a. Recognition rates obtained for fusion of iris (left & right) and palm scores using different Normalization techniques

Normalization Techniques	**Fusion techniques** Tanh sum	Sum	Mean	Product	Min	Max	**Modified min-max**	Median
Tanh	98%	98	98.1	98.2	96.5	100	***100***	*93.5*
Modified tanh	**100%**	**100**	**100**	**98.2**	**96.5**	**100**	***100***	***93.5***
Median & MAD	97.8%	96	95.5	97.4	97.8	95.9	***98.2***	*97.7*
Logistic	98.3%	98	98.1	99.5	98	97.4	***100***	*96*
Min-max	95.8%	97.2	96.6	99.5	95.9	96	***100***	*94*
Max	**100%**	**97.1**	**98.9**	**99.5**	**96.5**	**96.5**	***100***	***93.5***

Table 1.b. Error rates obtained for fusion of iris (left & right) and palm scores using different Normalization techniques

Normalization Technique	Tanh sum	Sum	Mean	Product	Min	Max	**Modified Min-max**	Median
Tanh	1.8%	1.3	1.5	2.3	3.8	0	***0***	*6.2*
Modified tanh	**0**	**0**	**0**	**1**	**3.7**	**0**	***0***	***6.2***
Median & MAD	1.8%	4	3.5	2.5	2	4	***1***	*2*
Logistic	1.2%	2	1.4	0.7	1.8	2	***0***	*4*
Min-max	3.9%	0.8	3.2	0.8	3.8	3.8	***0***	*1*
Max	**0%**	**1.6**	**0.8**	**0.5**	**3.8**	**3.8**	***0***	***1***

As it can be seen from the results, the new modified min max and tanh normalization methods give the best results in terms of the low EER and high recognition rate, when the scores are fed to tanh and mean fusion rules. The modified min max fusion method overrides all other fusion methods and gives the best performance.

8. CONCLUSION

This paper examines the effect of different score normalization techniques and fusion methods on the performance of a multimodal biometric system. We have demonstrated that the proposed max normalization, modified tanh technique and modified min-max fusion methods improve the biometric recognition performance of the multimodal biometric system that uses the iris and palm print traits for user authentication. The modified tanh and max normalization techniques followed by mean and tanh fusion methods result in a superior recognition performance than all the other normalization and fusion techniques as shown in the table.

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