On improving the Performance of Multimodal biometric authentication through Ant colony optimization

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Abstract: - Multimodal biometric authentication systems are now widely used for providing the utmost security owing to its better recognition performance compared to unimodal systems. Multimodal biometric systems are developed by combining the information of individual biometrics. In this paper, a multimodal biometric system is proposed by combining the scores of iris and palm print traits of a person. This information fusion takes place at the matching score level, due to the ease in accessing and combining the scores generated by the two different matchers. Since the matching scores output by the two modalities are heterogeneous, score normalization is needed to transform these scores into a common domain, prior to combining them. The normalized values are then applied to various score fusion methods. The resulting scores are compared to a threshold value for taking a decision of accepting or rejecting the person. The recognition accuracy of fusion methods strongly depend upon the correctness of this threshold value. Hence we propose Ant colony optimization (ACO) technique for selecting the optimal threshold value for each of the fusion method employed. This approach further enhances the accuracy of the system compared to the fusion methods with no optimal threshold. The experimental results obtained using CASIA iris and palm print databases show that the application of ACO results in higher recognition rates and lower error rates. To the best of our knowledge, it is the first work that applies ACO to enhance the accuracy of biometric authentication process.

Key-Words: - ACO, Biometrics, Multimodal, Normalization, Product, Score fusion, Sum

1 Introduction

Biometrics refers to the measurement and analysis of physical and behavioural traits of humans with a goal of verifying or determining the identity of humans. It provides 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 to be truly useful in real scenarios: universality, uniqueness, permanence, collectability, acceptability and difficult to circumvent [1]. It may not be possible for a single biometric to have all the above mentioned desirable properties. This has led to the 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. 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 [2]. 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 unimodal system decisions to reach a final resolution. A matching score level fusion system consist of two steps: normalization and fusion [3]. 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.

Ant colony optimization (ACO) searches for an optimal path in a graph, based on the behavior of ants seeking a path between their colony and a source of food [4]. In the natural world, ants (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail, returning and reinforcing it if they eventually find food. However, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate.

A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones [5]. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads all the ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with simulated ants walking around the graph representing the problem to solve. Thus an ACO is employed to dynamically select the appropriate decision threshold to minimize the error rate and increase the performance compared to fusion results. Here in ACO, ants move continuously to choose the best threshold through the shortest path.

2 Existing work

Many researchers have demonstrated that fusion is effective in the sense that the fused scores provide much better discrimination between the inter and intra classes than the individual scores. Several recent papers have compared various techniques on empirical data. Some of the important works are enumerated below:

In [6] several classifier combination rules were evaluated 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. In [7] they evaluated five binary classifiers on combinations of three face and voice modalities (database of 295 subjects). They found that a support vector machine and Bayesian classifier achieved almost the same performances; and both outperformed Fisher's linear discriminant, a C4.5 decision tree and a multilayer perceptron. [8] found that a support vector machine outperformed (at EER) the sum of normalized scores when fusing face, fingerprint and signature biometrics (database of 100 subjects and 50 chimeras). In [9] the sum of scores, max-score, and min-score fusion methods were applied 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 the 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; and optimizing the weighting of each biometric on a user-by-user basis outperforms generic weightings of biometrics.

Authors in [10] compared combinations of z-score, min-max, tanh and adaptive (two-quadrics, logistic and quadric-line-quadric) normalization methods and simple sum, min score, max score, matcher weighting, and user weighting fusion methods. They found that fusing COTS fingerprint and face biometrics does outperform unimodal COTS systems, but the high performance of unimodal COTS systems limits the magnitude of the 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. [11] compared various parametric techniques on the BSSR1 dataset. That study showed that the Best Linear technique performed consistently well, in sharp contrast to many alternative parametric techniques, including simple sum of z-scores, Fisher's linear discriminant analysis, and an implementation of sum of probabilities based on a normal (Gaussian) assumption. [4] published the first ant colony algorithm to solve the well-known traveling salesman problem. [12] recently presented an ant-based algorithm for obtaining a degree-constrained minimum spanning tree. Their algorithm consists of two stages, exploration and construction. In the exploration stage, each node is assigned an ant, and all ants move around to discover low-cost edges. Low-cost edges thus receive intensive visits and high pheromone levels. In the construction stage, a number of high-pheromone edges are picked out and sorted in ascending order of edge cost. A degree-constrained minimum spanning tree is then constructed from the selected edges using a version of the Kruskal's algorithm.

3 Normalization of Palm print Iris and distance scores

The proposed method is tested on a multimodal biometric verification system based on palm print and iris scores. The palm print recognition system can be divided into three main parts, namely pre-processing, minutiae extraction and minutiae matching [13]. 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 details on the palm. Ridge direction and frequency estimation is very important for minutiae extraction. Ridge direction field estimation consists of two steps. 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.

The process of iris recognition consists of four phases [14]. 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. We have considered both irises of a user for performing authentication. Hence the matching distances obtained from the left and irises are combined using fusion methods employed in section 4.

However, the distance scores generated by palm print are not in the range of 0 to 1. Hence score normalization needs to be applied to that. 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 [15]. 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 [15] and two new normalization methods that are implemented in our multimodal system.

(i) Min-max normalization technique achieves the common numerical range of the scores [0, 1] and also retains the shapes of the original distributions except for a scaling factor. But this method is highly sensitive to outliers in the data used for estimation and it is not robust. Presence of outliers makes most of the data concentrate only in a smaller range.

(ii) Modified Min-max normalization technique is proposed in which the minimum value is taken to be zero. This modification is done on the original min-max normalization method and is found to be better as shown by the results. It achieves good separation of the genuine and impostor matching-score distributions and this method is simpler and faster when compared to that of min-max scheme.

(iii) Median-MAD (Median Absolute Deviation) normalization does not guarantee the common numerical range and is insensitive to outliers.

(iv) Double-sigmoid normalization scheme provides a linear transformation of the scores in the region of overlap, while the scores outside this region are transformed non-linearly.

(v) Tanh normalization based on the tanh-estimators is reported to be robust and highly efficient. 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. 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.

(vi) The modified tanh method differs from the tanh approach, in that it does not use Hampel estimators, instead the mean and standard deviation of the raw scores is considered. Hence the complexity involved in the usage of Hampel estimators is eliminated. Thus it is faster and simpler method.

The normalized matching scores from both palm print and iris modules are then combined into a unique score using different fusion methods as given in the section 4. Based on this matching score, a suitable threshold is selected and decision about whether to accept or reject a user is made.

4 Score level fusion methods adopted in our system

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. Therefore, combining information obtained from individual modalities using score level fusion seems both feasible and practical [15]. In general, score level fusion techniques can be divided into three categories as follows [16], [17]: 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 fusion methods [15] are evaluated using the iris and palm print traits.

4.1 Mean fusion

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

$$S_{Final}=(a*S_{IRIS-R}+b*S_{PALM}+c*S_{IRIS-L})/3 \qquad (1)$$

where S_{IRIS-R} = matching score of right iris, S_{PALM} = matching score of palm print, S_{IRIS-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 that the value of (a+b+c) is one. The final matching score (S_{Final}) is compared against a certain threshold value to recognize the person as genuine or imposter.

4.2 Min fusion

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

$$S_{Final} = \min (S_{IRIS-R}, S_{PALM}, S_{IRIS-L}) \qquad (2)$$

4.3 Max fusion

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

$$S_{Final} = \max (S_{IRIS-R}, S_{PALM}, S_{IRIS-L}) \qquad (3)$$

4.4 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. The sum of the matching scores of the traits, MS_{Final} is given by,

$$S_{Final} = S_{IRIS-R} + S_{PALM} + S_{IRIS-L} \qquad (4)$$

4.5 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. The product of the matching scores of the traits is given by

$$S_{Final} = S_{IRIS-R} * S_{PALM} * S_{IRIS-L} \qquad (5)$$

4.6 Tanh fusion

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

$$S_{Final}= tanh (S_{IRIS-R})+tanh(S_{PALM})+tanh(S_{IRIS-L}) \qquad (6)$$

4.7 Median fusion

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

$$S_{Final} = \text{median} (S_{IRIS-R}, S_{PALM}, S_{IRIS-L}) \qquad (7)$$

5 Ant Colony Optimization

The main aim of an optimization technique is to obtain an optimal result, either to maximize or to minimize a function by systematically choosing values within an allowed given set. Ant colony optimization mimics the behaviour of ants that deposit pheromones along the paths in which they move when foraging [18]. The pheromone level deposited on a particular path rises with the number of ants passing through that path. Ants adopt pheromones to communicate and cooperate with each another to identify shorter paths to the food source. Ants select the next node to visit using a combination of heuristic and pheromone information.

Based on the fused score of iris and palm print, an optimal threshold value is found out dynamically using ACO. This decision threshold is then used for obtaining the recognition rate and error rate. It is found that ACO minimizes the error rate and increase the performance compared to the ordinary fusion methods.

Let q_0 is an predetermined parameter in [0, 1] and if a random number $q \leq q_0$, then an ant at node v_r selects its next node v_s. The pheromone level on edge (r,s) is given by,

$$\tau_{rs}(\eta_{rs})^{\beta} = \max\{ \tau_{rj}(\eta_{rj})^{\beta}\} \quad (8)$$

where η_{rj} is a heuristic function defined as the reciprocal of the cost c_{ij} associated with the edge (i, j); J_i denotes the set of nodes that remain to be visited by the ant at node mi; β denotes the relative importance between the pheromone level and the edge cost, and q_0 represents the relative significance of exploitation and exploration. A greater value of q_0 means that the system performed more exploitation and less exploration. If $q > q_0$, then v_s is randomly selected from Jr according to the probability distribution given by

$$p_{rk} = \Sigma\, \tau_{rk}(\eta_{rk})^{\beta} / \tau_{rj}(\eta_{rj})^{\beta}, \quad \text{if } v_k \in j_r \quad (9)$$
$$= 0, \quad \text{otherwise}$$

After an ant has completed its tour, the pheromones on the edges of that tour are updated by the local updating rule to prevent succeeding ants from searching in the neighborhood of the currently best tour. The rule for this operation is defined as

$$\tau_{rj} \leftarrow (1\text{-}\rho)\, \tau_{rj} + \Delta\rho\tau \quad (10)$$

where $0 < \rho < 1$ is a parameter representing the local pheromone evaporation rate, and Δτ represents the variation in pheromone, which is set to be the initial pheromone level τ_0. Once all ants have completed their tours, the pheromones on all edges of the graph are updated by the global updating rule to accelerate searching the best solution. The global updating rule enhances the edges involved in the globally best tour, and is defined as

$$\tau_{rj} \leftarrow (1\text{-}\ \alpha)\, \tau_{rj} + \alpha\tau_{gb} \quad (11)$$

where $0 < \alpha < 1$ denotes the global pheromone evaporation rate. This ACO mechanism is now applied to fusion algorithms in order to find the optimal threshold value. It is the value at which the genuine acceptance rate (GAR) is the maximum and false rejection rate (FRR) is the minimum. Hence the proposed method gives the best solution for our multimodal biometric system.

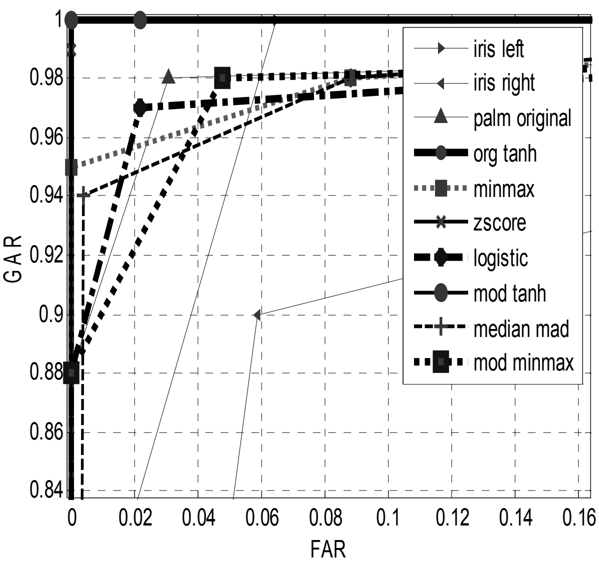
6 Databases used in the experimentation

Database containing palm print and iris samples is required to evaluate the performance of our multimodal system. Hence CASIA iris and palm print image databases are used. A "chimerical" multimodal database is created using pairs of artificially matched palm and iris samples. CASIA IrisV3 [19] database includes three subsets which are labelled 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.

CASIA Palm print Image Database [20] 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 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

Performance of the proposed multimodal biometric system has been studied under different normalization and fusion techniques. Any system can make two types of errors. The first type of error is false acceptance where an impostor is accepted wrongly. The second error is false rejection where a genuine client is wrongly rejected. The trade-off between these error rates namely, FAR and FRR can be graphically represented by a Receiver Operating Characteristics (ROC) plot [21]. To quantify the performance into a single number, Equal Error Rate (EER) is often used which represents the error rate when FAR is equal to FRR. The distance score 'd' between the stored template and test image 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 the same person. Thus 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 three ROC graphs obtained from the above multimodal biometric verification system using different normalization techniques and fusion methods. Table 1 shows the recognition rates and error rates obtained from all the normalization and fusion techniques employed in this work. The table also shows the optimal threshold values obtained for different fusion methods by using ACO. These threshold values enhance the accuracy of the system very well as shown in the last column of the table.



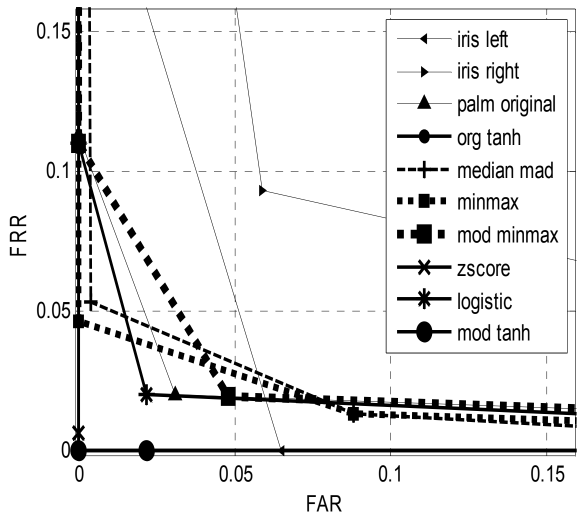


Fig. 1(a) Max fusion

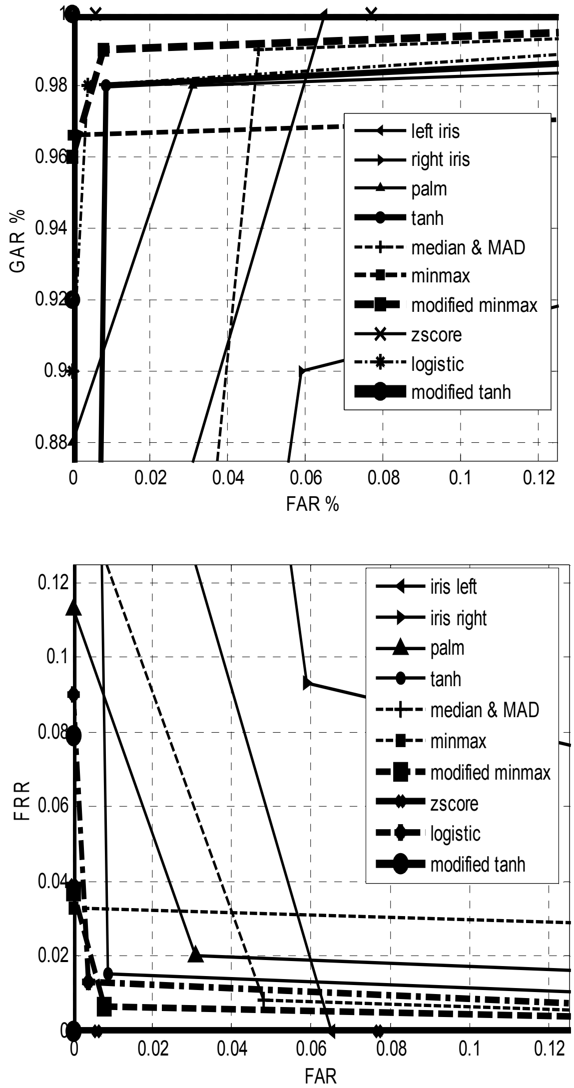


Fig. 1(b) Mean fusion

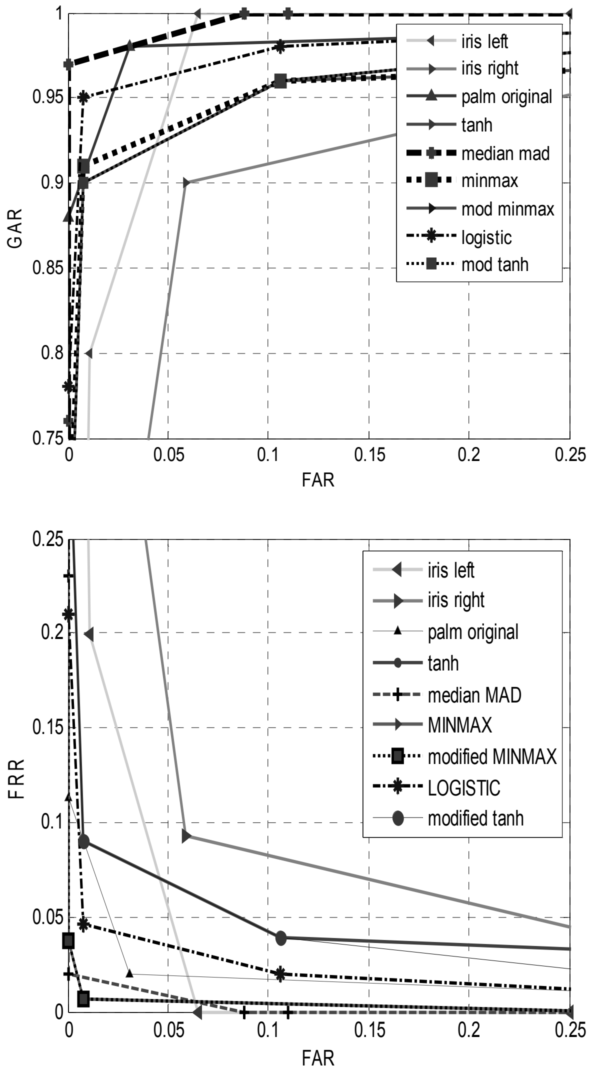
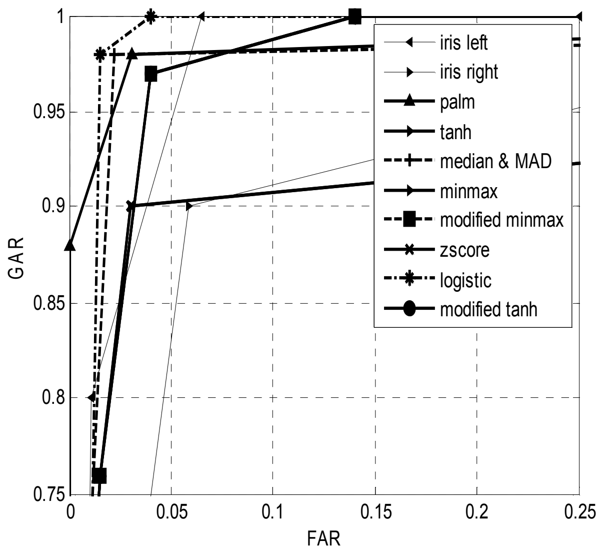


Fig. 1(c) Median & MAD fusion



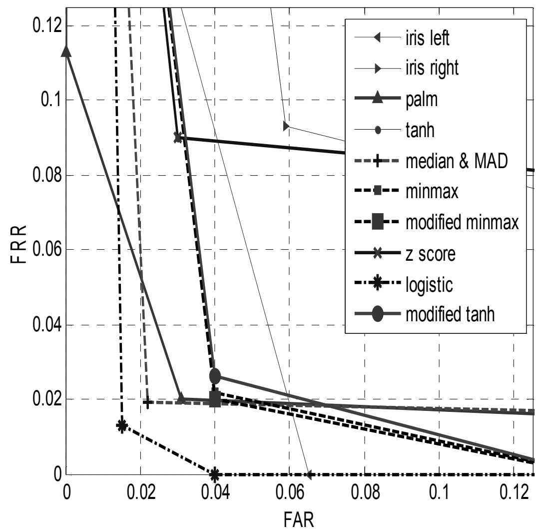


Fig. 1(d) Min fusion

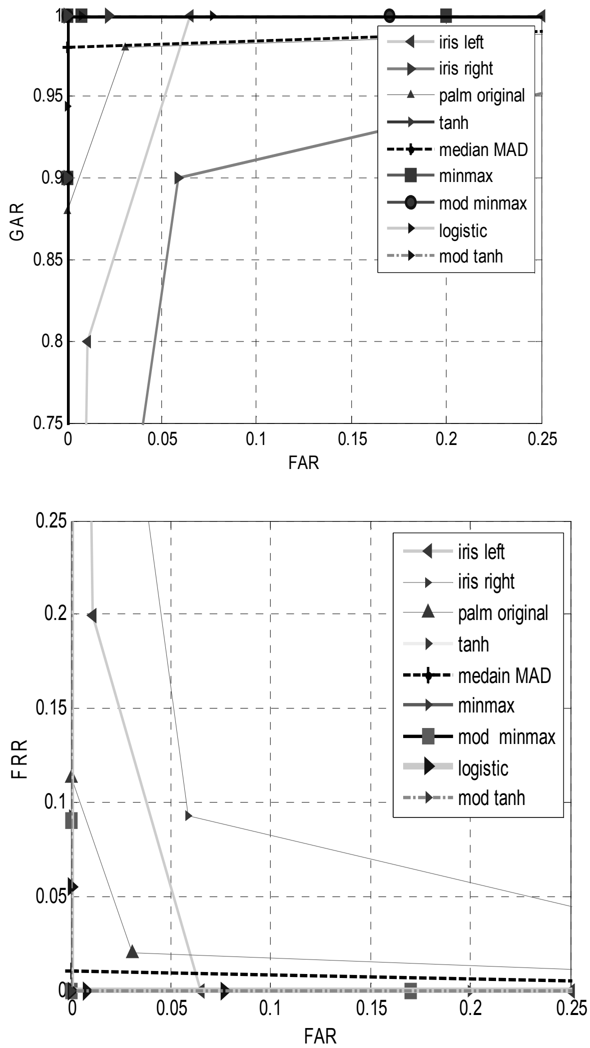
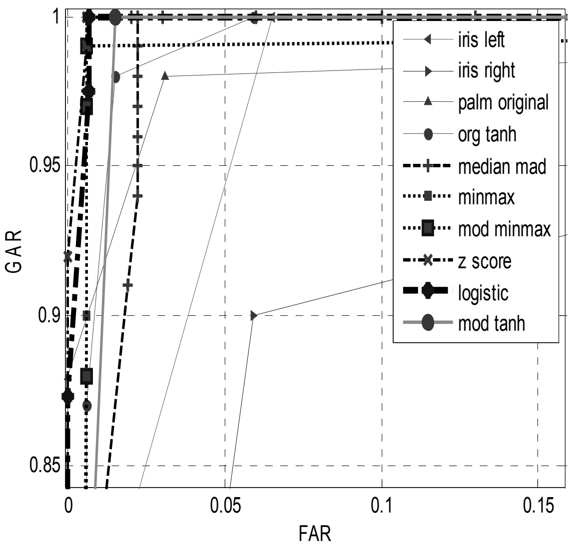


Fig. 1(e) Modified max fusion



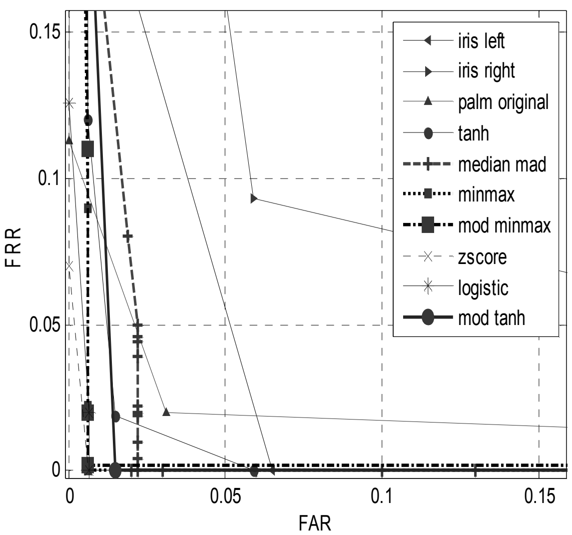
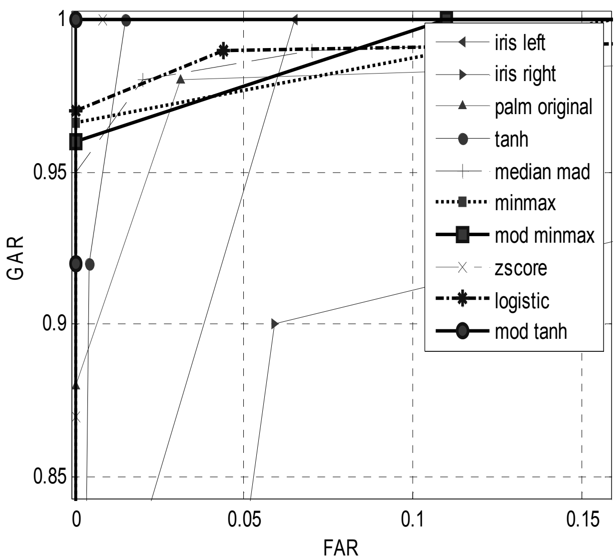


Fig. 1(f) Product fusion



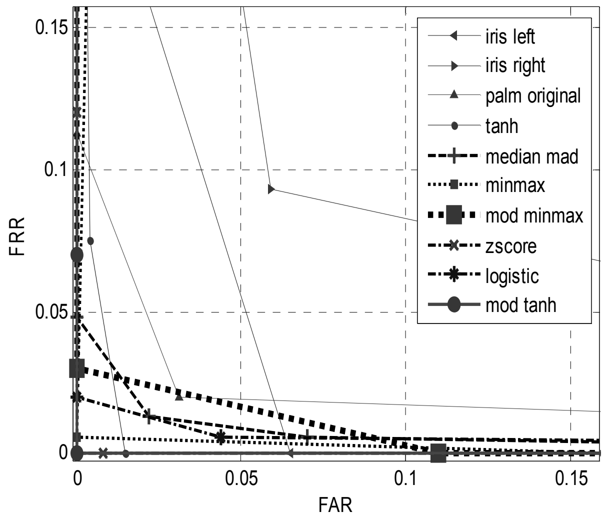
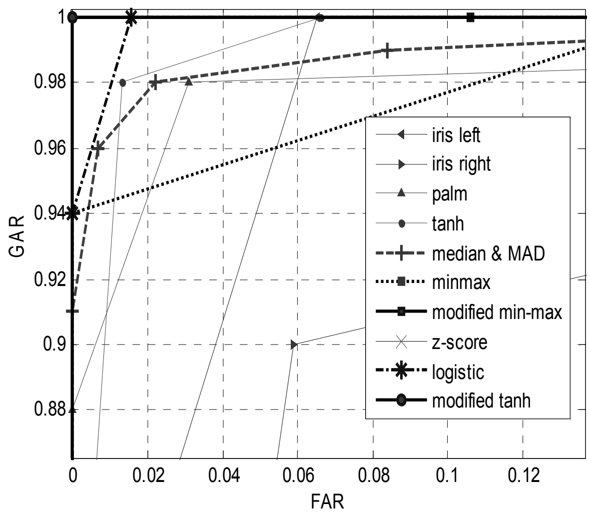


Fig. 1(g) Sum fusion



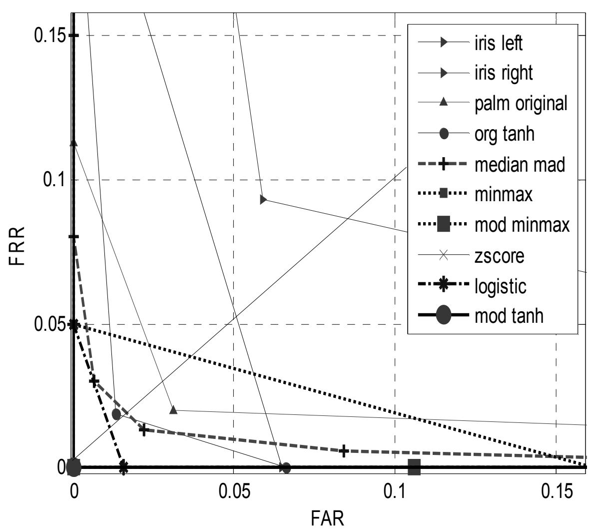


Fig. 1(h) Tanh fusion

Table 1 Comparison of the performance obtained before and after applying ACO to the system

Fusion rule applied	Normalization scheme employed	GAR and EER obtained	Optimal threshold obtained by ACO	GAR and EER obtained by ACO
Product	Logistic	99.3% & 0.7%	0.0071	99.32% & 0.64%
	Median & MAD	97.4% & 2.5%	0.0101	97.76% & 2.1%
	Tanh	98.2% & 2.3%	0.0125	98.25% & 1.77%
	Minmax	99.5% & 0.8%	0.0203	99.4% & 0.58%
	Modified minmax	99.5% & 0.5%	0.0308	99% & 0.3%
	Modified tanh	98.2% & 2%	0.0238	97% & 2.9%
Max	Logistic	97.4% & 2%	0.7978	97.45% & 2.14%
	Median & MAD	95.9% & 4%	0.4910	96% & 8.1%
	Tanh	100% & 0	0.5742	100% & 0
	Minmax	96% & 3.8%	0.8704	96.27% & 3.3%
	Modified minmax	96.5% & 3.8%	0.8819	95.57% & 3.31%
	Modified tanh	100% & 0	1.1690	100% & 0
Median	Logistic	96% & 4%	0.1672	96% & 3.8%
	Median & MAD	97.7% & 2%	0.1527	97.76% & 1.6%
	Tanh	93.5% & 6.2%	0.1665	93.58% & 6.16%
	Minmax	94% & 6%	0.1776	94.73% & 6%
	Modified minmax	93.5% & 6.1%	0.1771	93.58% & 6.1%
	Modified tanh	93.5% & 6.2%	0.1683	93.529% & 6.15%
Tanh	Logistic	98.3% & 1.2%	0.6449	99.39% & 0.51%
	Median & MAD	100% & 1.8%	0.2199	98% & 1.6%
	Tanh	98% & 1.8%	0.5509	98.19% & 1.74%
	Minmax	95.8% & 3.9%	0.3359	95.81% & 3.76%
	Modified minmax	100% & 0	0.6753	100% & 0

	Modified tanh	100% & 0	0.8612	100% & 0
Min	**Logistic**	98% & 1.8%	0.0959	98.5% & 1.3%
	Median & MAD	97.8% & 2%	0.1254	97.82% & 2.1%
	Tanh	96.5% & 3.8%	0.1210	96.6% & 3.5%
	Minmax	95.9% & 3.8%	0.1280	96.06% & 3.68%
	Modified minmax	96.5% & 3.8%	0.0176	96.56% & 3.6%
	Modified tanh	96.5% & 3.7%	0.0310	96.55% & 3.66%
Sum	Logistic	98% & 2%	0.6837	98.32% & 1.19%
	Median & MAD	96% & 4%	0.2639	98% & 1.5%
	Tanh	98% & 1.3%	0.5509	98.5% 7& 1.44%
	Minmax	97.2% & 0.8%	0.3670	97.4% & 2.72%
	Modified minmax	97.1% & 1.6%	0.1690	99% & 1.57%
	Modified tanh	100% & 0	0.2471	100% & 0
Mean	Logistic	98.1% & 1.4%	0.187	99.7% & 02%
	Median & MAD	95.5% & 3.5%	0.9418	96.1% & 2.95%
	Tanh	98.1% & 1.5%	0.5215	99.6% & 03%
	Minmax	96.6% & 3.2%	0.3610	96.5% & 3.2%
	Modified minmax	98.9% & 0.8%	0.8846	99.6% & 0.3%
	Modified tanh	100% & 0	0.7910	100% & 0

As it can be seen from the results, the threshold optimization carried out by using ACO gives a very good improvement in the performance of the system. Max, sum and mean fusion methods give the best results in terms of the low EER and high recognition rate compared to other fusion methods. The normalization method that gives the maximum recognition accuracy and minimum error are highlighted in the table shown above.

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 normalization and fusion methods optimized by employing ACO technique improve the biometric recognition performance. The multimodal biometric system was constructed using the iris and palm print traits. Selection of thresholds play a crucial role in any biometric authentication system as it directly affects the system performance. Hence an optimization approach based on Ant colony system is proposed for proper selection of the threshold values for each of the fusion method adopted in this work. The experimental results obtained using CASIA iris and palm print databases show that the application of ACO for threshold optimization improves the accuracy of the system enormously. In particular max, sum and mean fusion methods give the best results in terms of the low EER and high recognition rate compared to other fusion methods.

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