# IRIS BASED Authentication Using Ant Colony Optimization

**D.Thamaraiselvi**
Department of Computer Engineering
SCSVMV

***Abstract-*** *Multimodal biometric authentication systems are now widely used for providing the utmost security owing to its better recognition performance compared to unimodal systems. Biometric systems are developed by combining the information of individual biometrics. In this paper, IRIS based (biometric) authentication is proposed. 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 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.*

***Keywords***- iris ,ACO, Biometrics, Normalization, Authentication

## I. 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.

## II. 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.

## III. IRIS RECOGNITION

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.

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

## V. 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 q0 is an predetermined parameter in [0, 1] and if a random number $q \leq q0$, then an ant at node vr selects its next node vs. The pheromone level on

edge (r,s) is given by,

$$\tau rs(\eta rs)\beta = \max\{ \tau rj(\eta rj)\beta\} \qquad (8)$$

where ηrj is a heuristic function defined as the reciprocal of the cost cij associated with the edge (i, j); Ji 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 q0 represents the relative significance of exploitation and exploration. A greater value of q0 means that the system performed more exploitation and less exploration. If $q > q0$, then vs is randomly selected from Jr according to the probability distribution given by

$$prk = \Sigma\ \tau rk(\eta rk)\beta \,/\, \tau rj(\eta rj)\beta,\ \text{if } vk \in jr \qquad (9)$$
$$= 0,\ \text{otherwise}$$

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

$$\tau rj \leftarrow (1-\rho)\, \tau rj + \Delta\rho\tau \qquad (10)$$

where $0 < \rho < 1$ is a parameter representing the local pheromone evaporation rate, and $\Delta\tau$ represents the variation in pheromone, which is set to be the initial pheromone level $\tau 0$. 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

$$\tau rj \leftarrow (1-\alpha)\, \tau rj + \alpha\tau gb \qquad (11)$$

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.

## V. DATABASES USED IN THE EXPERIMENTATION

Database containing iris samples is required to evaluate the performance of biometric authentication. Hence CASIA iris image databases are used. 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.

## VI. 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 Antcolony 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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