EFFICIENT AUTHENTICATION METHOD USING SCORE LEVEL FUSION AND PARTICLE SWARM OPTIMIZATION (PSO) OF MULTIMODAL BIOMETRICS

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***Abstract*—A multimodal biometric system aims at combined information from various single modality systems. In this paper various normalization and fusion techniques are examined by using the three modalities namely fingerprint, retina and ear. The performance of score level fusion preceded by the different normalization schemes show the improved recognition rates compared to the fusion of original scores. The results are experimentally verified and the performance graphs are plotted.**

Keywords— Multimodal biometrics, score level fusion, authentication, normalization.

I. INTRODUCTION

Identifying a person is becoming critical in our society. The need for reliable, legitimate method for determining an individual's identity technique is essential to increase security level in the area where reliable authentication is needed. Biometric authentication is being utilized widely as an inherently more convenient and reliable way to authenticate a user over the traditional knowledge based or token-based approaches. Biometric authentication employs unique combinations of measurable physical and biological characteristics that cannot be readily forged by others [1]. Unimodal biometric suffers from a variety of problems such as (i) noisy data (due to dirty sensor or environment poorly illuminated) (ii) Intra-class variations (due to incorrect interaction with sensor i.e. incorrect facial pose). (iii) Inter-class similarities (due to overlap i.e. in a biometric system comprising of a large number of users, there may be inter-class similarities). (iv)Non-Universality (due to incorrect data i.e. the biometric system may not be able to acquire meaningful biometric data). (v) Spoof attacks- this type of attack is especially relevant when behavioral traits such as signature or voice are used [2]. In this paper limitations imposed by unimodal biometric system is overcome by multimodal systems. Multimodal biometrics system refers to the combination of two or more biometric modalities in a single combination and it is more reliable compared to unimodal biometric system [3]. A biometric authentication system operates in two approaches: Enrollment and Authentication. During enrollment user's biometric data are acquired using a biometric read and stored in a database. The stored biometric template is tagged with a user identity to facilitate authentication. In the authentication phase, a user's biometric data is once again acquired and the system uses it to either verify the claimed identity of the user or identify who the user is. While verification involves comparing the acquired biometric information with only those templates corresponding to the claimed identity, identification involve comparing the acquired biometric information. In this paper the scenario for integrating ear, retina and fingerprint using Score level fusion is examined. The evidence provided by the FRR & FAR minimizes the error rate and proven that the system performance is more reliable for future authentication.

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II. SCORE NORMALIZATION

Normalization is a method of transforming the scores in the range of some common domain. 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 [4]. The matching scores generated from different verifiers are heterogeneous because they are not on the same numerical range, which may negatively affect fusion results. For a good normalization scheme, the estimates of the location and scale parameters of the matching score distribution 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 this both robust and efficient. In this paper, four well- known normalization methods are considered, namely Min-Max(MM) normalization, Two- Quadrics(QQ) normalization, Quadric-Line- Quadric(QLQ) and Double sigmoid normalization.

A. Min-Max normalization

This method maps the raw scores to the [0,1] range. The quantities max(s) and min(s) specify the end points of the score range:

$$n = \{s-\min(s)\}/\{\max(s)-\min(s)\} \qquad ..(1a)$$

B. Two-Quadrics (QQ) normalization

This function is composed of two quadratic segments that change the concavity at c (Fig. 1)

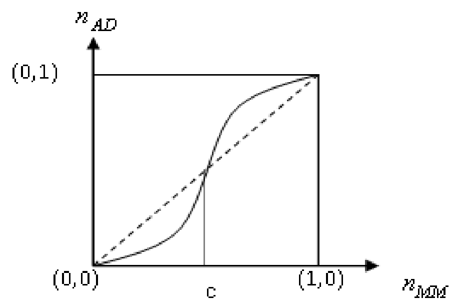

Fig. 1

The formula for Two Quadrics is given by

$$nAD = \begin{cases} (1/c)\, n^2_{MM}, & \text{if } n_{MM} \le c \\ c + \sqrt{(1-c)\,(n_{MM}-c)} & \text{otherwise} \end{cases} \qquad ..(1b)$$

For comparison, the identity function, *nAD nMM* , is also shown by the dashed lines in Fig. 1

C. Quadric-Line-Quadric (QLQ)normalization

The overlap zone, with center *c* and width *w*, is left unchanged while the other regions are mapped with two quadratic function segments (Fig. 2):

$$nAD = (1/(c-(w/2)))\, n^2_{MM} \qquad ..(2)$$

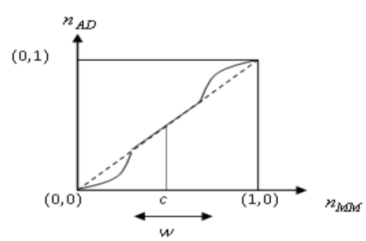

Fig. 2

Equation for Quadric-Line Quadric formula is given below as

D. Double Sigmoidal Normalization

Double sigmoid is used for score normalization and formula for normalization is given by

$$S_k = \begin{cases} 1/(1+\exp(-2((sk-t)/r1))), & \text{if } sk<t \\ 1/(1+\exp(-2((sk-t)/r2))) & \text{otherwise} \end{cases} \qquad ..(3)$$

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 $(t - r1,\ t - r2)$. Fig. 3 given below shows an example of the double sigmoid normalization, where the scores in the [0, 300] range are mapped to the [0, 1] range using $t = 200$, $r1 = 20$ and $r2 = 30$.

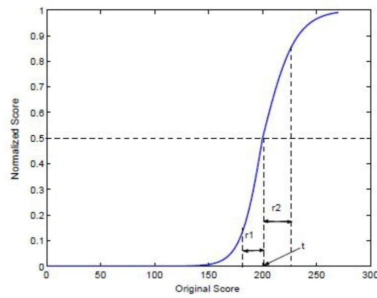

Fig. 3

III. Fusion In Multimodal Biometrics

In multimodal biometrics more than one biometric modality is used. We need to design a mechanism that can combine the classification results from each biometric channel; this is called as biometric fusion. Multimodal biometric fusion combines measurements from different biometric traits to enhance the strengths and diminish the weaknesses of the individual measurements. Fusion in biometric systems falls into two broad categories pre-classification fusion and post-classification fusion. Pre-classification fusion refers to combining information prior to the application of any classifier or matching algorithm. In post-classification fusion, the information is combined after the decisions of the classifiers have been obtained [5], [7].

A. Exponential Sum Fusion

Here the individual scores are multiplied by corresponding weights and then summed up together, after which the exp() function is applied to it. The formula for exponential sum fusion is:

$$s = \sum_{j=1}^{n} exp(s_j) w_j \quad ..(4)$$

where Sj denotes the scores after normalization. After fusion one has decide a threshold value and find FAR, FRR and GAR for the corresponding threshold.

B. Particle Swarm Optimization (PSO):

O is an evolutionary search algorithm motivated from the social behavior of a flock of birds trying to fly to a favorable environment. The PSO is employed to find the solution for the adaptive selection of combination of individual points which are referred to as the particles in multidimensional search space. Each particle (representing a bird in the flock), characterized by its position and velocity, represents the possible solution in the search space. Behavior of the particles in the PSO imitates the way in which birds communicate with each other while flying. During this communication, each bird reviews its new position in the space with respect to the best position it has covered so far. The birds in the flock also identify the bird that has reached the best position/environment. Upon knowing this information, others in the flock update their velocity (that depends on a bird's local best position as well as the position of the best bird in the flock) and fly towards the best bird. The process of regular communication and updating the velocity repeats until the flock finds a favorable position. In a similar manner, the particle in the PSO moves to a new position in multidimensional solution space depending upon the particle's best position [also referred to as local best position (ρ_{ak}) and global best position (ρ_{gk})]. The (ρ_{ak}) and (ρ_{gk}) are updated after each iteration whenever a suitable, i.e., lower cost, solution is located by the particle. The velocity vector of each particle represents/determines the forthcoming motion details. The velocity update equation (5) of particle of the PSO, for instance (t+1), can be represented as follows:

$$\square_{ak}(t+1) = \{\omega \square_{ak}(t) + C_1 R_1 (\rho_{ak}(t) - X_{ak}(t)) + C_2 R_2 (\rho_{ak}(t) - X_{ak}(t)\} \quad ..(5)$$

where ω is the inertia weight between 0 and 1 and provides a balance between global and local search abilities of the algorithm. The accelerator coefficients c_1 and c_2 are positive constants, and r_1 and r_2 are two random numbers in the 0–1 range. The corresponding position vector is updated by

$$X_{ak}(t+1) = X_{ak}(t) + \square_{ak}(t+1) \qquad ..(6)$$

Equation (5) indicates that the new velocity of a particle in each of its dimensions is dependent on the previous velocity and the distances from previously observed best solutions (positions of the particle). The PSO approach detailed above operates on continuous space. However, optimization problems exist where the particles are better represented as discrete binary variables. Such problems require that these binary particles be evolved to obtain an optimal solution. A binary version of the PSO algorithm is also described in reference. The position vector for each particle in binary PSO can have a value of either zero or one on each dimension. The formula for calculating the velocity update in binary PSO remains the same as real valued version, except that ρ_{ak}, x_{ak} and ρ_{gk} in (6) are binary valued. The velocity ν_{ak} for binary PSO represents the probability of bit x_{ak} taking the value 1. A sigmoid function S is employed to limit the value of the probability ν_{ak} to the range [0,1]. Therefore, the position vector of a particle in binary PSO is updated as follows:

$$X_{ak}(t+1) = \{\ 1, \text{ for } r_3 < S(vak(\ t+1)) \quad 0, \text{ otherwise }\} \qquad ..(7)$$

where S(νak(t+1)) = 1/(1+exp (-(νak(t+1)) and r3 is a random number in the interval [0, 1] with uniform distribution. The PSO is employed to dynamically select the appropriate decision threshold and the weights (wj) to minimize the fitness function, from each of the possible score-level combinations. In our implementation, each particle is characterized by three continuous variables; the parameters of score-level fusion rule w1 and w2, decision threshold, and a two bit discrete binary variable representing four different score-level fusion rules. Therefore, a hybrid PSO with real valued and binary versions of the algorithm to determine the optimal fusion strategy and the corresponding fusion parameters is employed.

IV. EXPERIMENTAL RESULTS

The multimodal database used in our experiment was a combination of 450 fingerprint, 464 retina and 450 ear templates obtained from different scanners at different time periods. The database had 450 genuine and 450 imposter scores of all the metrics used. In the case of all metrics, since the scores were much larger than 1, scores had to be normalized using various techniques. After normalization was performed, both the metrics were combined together and fusion rules were applied to calculate GAR % of different normalization and fusion techniques at the 0.1% false acceptance rate (FAR) [6], [8].

A. Performance Results without Optimization

The performance of the multimodal biometric system has been studied under different normalization and fusion techniques. The exponential sum fusion methods were applied on the normalized scores. The normalized scores were obtained by using the following techniques Min-Max(MM) normalization, Two-Quadrics(QQ) normalization, Quadric-Line- Quadric(QLQ) normalization, Double Sigmoid normalization [10], [11].

Fig. 4.1 shows the FAR-GAR performance graphs of ear, retina and fingerprint for exponential sum fusion for min-max and Fig. 4.2 shows the FAR-FRR performance graph of exponential sum fusion for min-max methods.

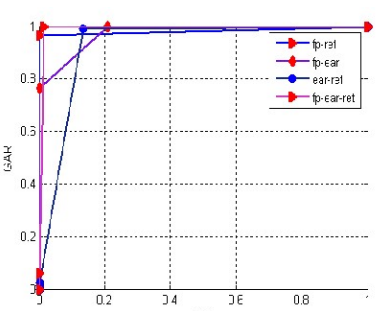

Fig. 4.1 Performance gain obtained by exponential sum fusion of min-max (FAR vs GAR)

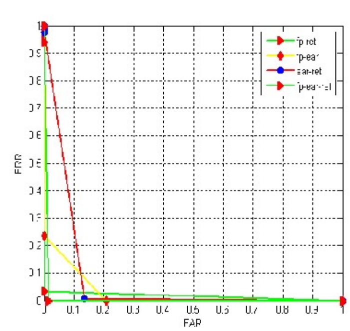

Fig. 4.2 Performance gain obtained by exponential sum fusion of min-max (FAR vs FRR)

Fig. 4.3 shows the FAR-GAR performance graphs of ear, retina and fingerprint for exponential sum fusion for double sigmoid. Fig 4.4 shows the FAR-FRR performance graph of exponential sum fusion for double sigmoid.

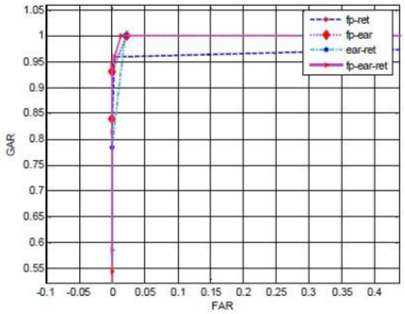

Fig 4.3 Performance gain obtained by exponential sum fusion of double sigmoid (FAR vs GAR)

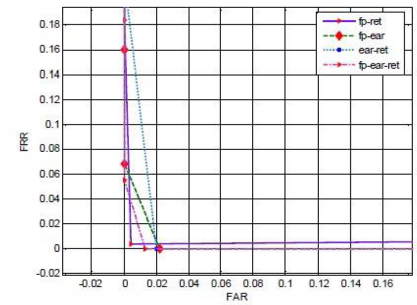

Fig 4.4 Performance gain obtained by exponential sum fusion of double sigmoid (FAR vs FRR)

Fig. 4.5 shows the FAR-GAR performance graphs of ear, retina and fingerprint for exponential sum fusion for quadric line quadric and Fig. 4.6 shows the FAR-FRR performance graph of exponential sum fusion for quadric line quadric.

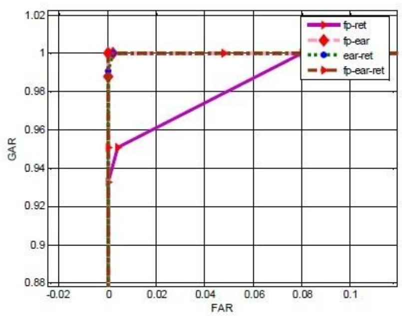

Fig 4.5 Performance gain obtained by exponential sum fusion of quadric line quadric (FAR vs GAR)

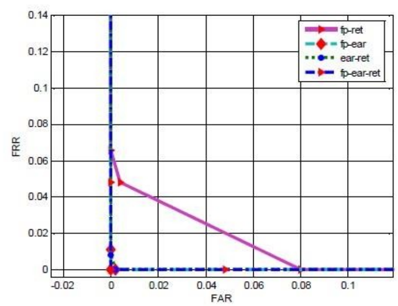

Fig 4.6 Performance gain obtained by exponential sum fusion of quadric line quadric (FAR vs FRR)

Fig. 4.7 and Fig. 4.8 show the FAR-GAR-FRR performance graphs of ear, retina and fingerprint for exponential sum fusion for two quadrics normalization method

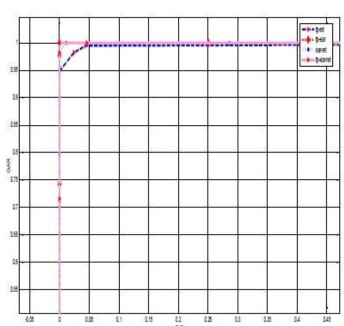

Fig 4.7 Performance gain obtained by exponential sum fusion of two quadric (FAR vs GAR)

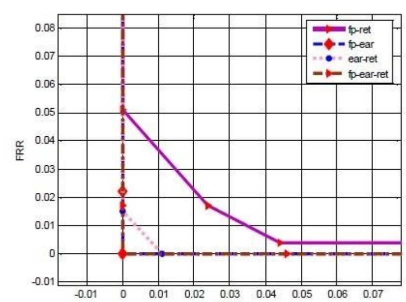

Fig 4.8 Performance gain obtained by exponential sum fusion of two quadric (FAR vs FRR)

B. Performance results after optimization

The performance of the multimodal biometric system has been studied under different normalization and fusion techniques after optimization and the results are displayed.

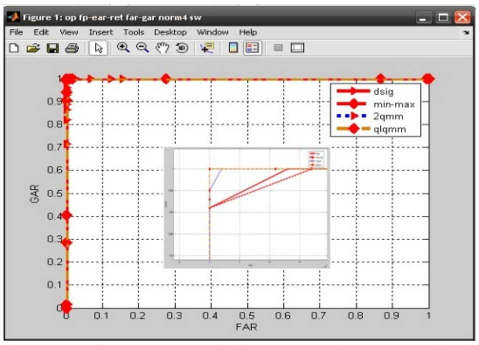

Fig 4.9 Performance graph for FAR against GAR obtained by weighted sum fusion after optimization

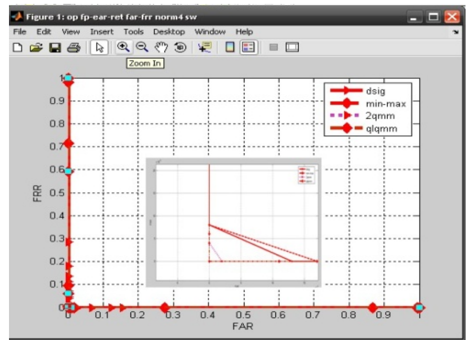

Fig 4.10 Performance graph for FAR against FRR obtained by weighted sum fusion after optimization

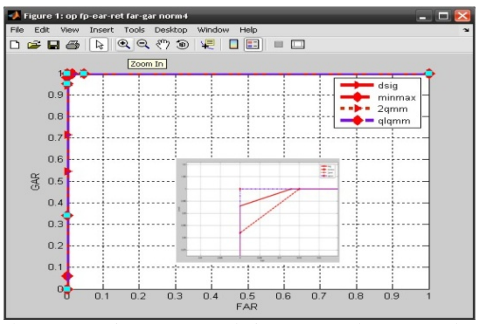

Fig. 4.11 Performance graph for FAR against GAR obtained exponential sum fusion after optimization

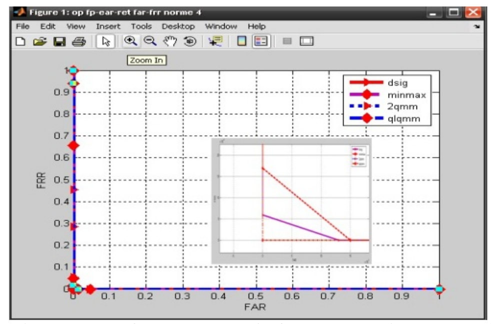

Fig. 4.12 Performance graph for FAR against FRR obtained by by exponential sum fusion after optimization

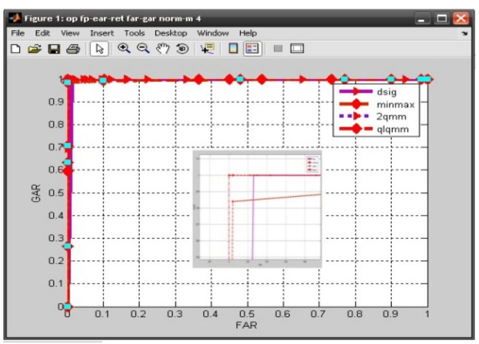

Fig. 4.13 Performance graph for FAR vs GAR obtained by Max fusion after optimization

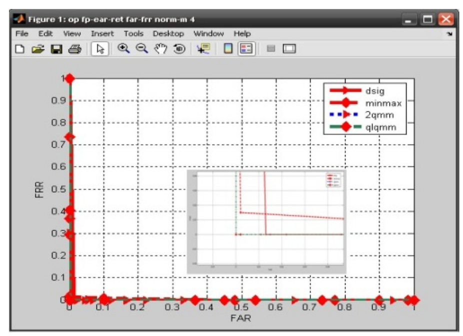

Fig. 4.14 Performance graph for FAR vs FRR obtained by Max fusion after optimization

V. CONCLUSION

This project paper examines the effect of different score normalization techniques and fusion rules on the performance of a multimodal biometric system. It demonstrates that different fusion techniques on normalized scores improve the recognition performance of a multimodal biometric system that uses the finger print, ear and retina for user authentication. The experimental results suggests that the dynamic selection of fusion rules and their parameters using the hybrid Particle Swarm Optimization (PSO) based approach can offer better performance. Thus after particle swarm optimization, this analysis conclude that the Quadric-Line-Quadric normalization techniques followed by a weighted sum of scores fusion method result in a superior GAR than all the other normalization and fusion techniques. It is also decided to employ significantly larger multimodal databases. From the real biometric samples, and generate a more reliable estimate on the performance improvement. The future efforts should be focused to develop algorithms that can adaptively select the best set of biometric modalities from the available set to ensure the desired level of security.

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BIOGRAPHY

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