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A New Approach for Hybrid BF-pfPSO Technique for Face and Fingerprint Multimodal Biometric System

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Abstract

In the recent developments in technologies, security is the main aspect to provide the better confidentiality and integrity to the system. Generally, the biometric system is the important authentication mechanism which provides to protect from any misleading action. It has to validate and verify a person based on unique features of an individual. Basically, biometrics system has two broad areas namely unimodal and multimodal biometric system. Multimodal biometrics is a more secure way of authentication for the identity of a person than unimodal biometrics. Because unimodal biometrics has its own limitations like non-universality, vulnerability to spoofing attacks, noisy data, less robustness. In this paper, we proposed a multimodal biometrics system for face and fingerprint recognition using weighted sum score level fusion. In addition to that, the Hybrid Bacterial Foraging with parameter free Particle Swarm Optimization BF-pfPSO algorithm is used to optimize the weights assigned to face and fingerprint modalities at the score level fusion which attains good optimality and showing faster convergence than other hybrid algorithms. Feature extraction of the face is done by using PCA (Principal Component Analysis) whereas the feature extraction of the fingerprint is done by using minutiae matching. The matching scores of each modality are fused after normalization using weighted sum score level fusion technique and finally, the result is compared with the Equal error rate and RoC curve for the performance measure.

Keywords: Multimodal biometrics, Principal component analysis, minutiae extraction, Score level fusion, BF-pfPSO.

INTRODUCTION

Multimodal biometrics involves with more than one modality than Unimodal biometrics leads to more advantages like noisy data resistance, universality, and no intra class variations, no inter class similarities, robustness, anti-spoofing attacks and so on. Face and fingerprint is the common and very familiar biometrics other than palm print, finger vein, hand geometry, iris, finger knuckle print, voice, gait and signature and so on. It is commonly used in various engineering applications, border security and immigration purposes and financial applications like ATM withdrawal and fund transfer [1]. In future, it would be implemented in all the banks and ATMs for the security purposes as well as money transactions. Meanwhile, it would be more convenient rather than carrying debit /credit cards and remembering passwords at ATM transactions.

The structure of the paper is formatted as: section II deals with the related works of multimodal biometrics using heuristic or hybrid heuristic algorithms. Section III discusses the design methodology of the proposed system. Section IV deals with the implementation techniques with the results & discussions with the experimental results for the fusion of face and fingerprint modalities with EER value and ROC curves for ascertaining the performance measure. The conclusion is defined as the next section V.

RELATED WORKS

There are many works have been done so far in the field of the multimodal biometric system using face, fingerprint recognition. Especially related to this proposed work, using of Meta heuristic optimization techniques, as well as hybrid Meta-heuristic optimization algorithms for the various modalities are discussed below.

Cefiri et al., [2] proposed the score level fusion of Hybrid GA-PSO optimization for the multimodal biometric database which containing face and fingerprint, face and speech respectively. He is not tested with the combined modalities. The limitation of this work has been noted as when using Hybrid GA-PSO algorithm, it got stuck up when it reaches the local optimum.

Aniesha et al., [3] proposed GEC based multi biometric fusion. In this work, they implemented weighted sum score level fusion and the Genetic and Evolutionary Computation is used to optimize the weights assigned to the biometric modalities for score level fusion. They used Face and particular biometrics as the modalities and attained the accuracy level to 95.24%.

M.Hanmandlu et al., [7] proposed a fusion of hand based biometrics like palm print and hand geometry using hybrid PSO with decision level fusion. The sensor points and fusion rules as given as the input to the algorithm.

A.Muthukumar et al., [4] proposed PSO optimization for fingerprint and iris. Here the PSO is employed for the adaptive selection of fusion rule and decision threshold corresponding to the desired security level in terms of Bayesian cost.

S.Arivalagan et al., [5] proposed the face recognition using Hybrid GA-BFO algorithm. Here the Hybrid GA-BFO is used to select the best feature vector which increases the classification accuracy.

Karthikeyan S et al., [1] reviewed Multimodal biometrics using heuristic optimization technique at the feature selection level for getting an optimized feature vector to enhance the classifier accuracy.

PROPOSED METHODOLOGY

This section provides the proposed system of multimodal biometrics using face and fingerprint recognition, the face and fingerprint images are extracted from the respective sensor and then the feature extraction of the face is done by using principal component analysis(PCA) whereas the fingerprint feature extraction is done by using the minutiae matching [16]. Then the respective image is stored as a template in the face and fingerprint databases respectively. Later on, the scores of face and fingerprint is generated and normalized and fused with weighted sum score fusion technique at score level fusion.

Here the hybrid BF-pfPSO algorithm is used to optimize the weights assigned to these modalities. The best fitness value is defined as the minimum EER ratio which defined as the performance measure of the multimodal biometric system.

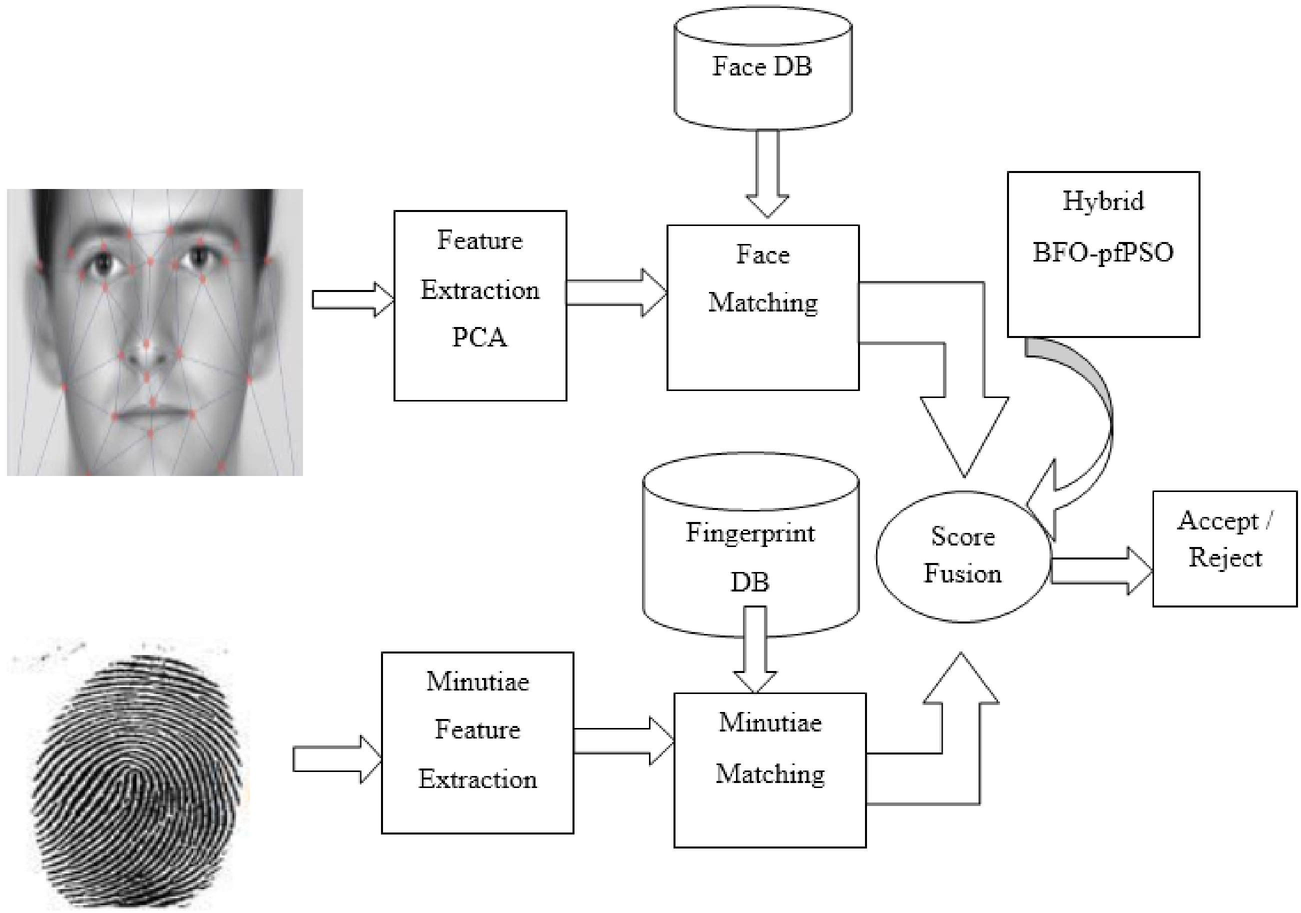

Figure 1. Proposed Methodology Flow Diagram

Face recognition

Face recognition is majorly used biometric for human identification. In this paper, we implemented Principal component analysis (PCA) for feature extraction and Euclidean distance for matching. PCA is used for dimension reduction. The face image is obtained by projecting it to the coordinate system defined by the principal components. With the help of Eigen values and Eigen vectors, the co-variance matrix is computed [6]. The feature vector represents the matrices of the image. Euclidean distance of the image is computed for the classification. The image is identified as the one which gives the least distance with the image to recognize. These features are then used to calculate the genuine and imposter scores using similarity measure [7], after that the normalization of face scores (Sface) using score level fusion is done.

Finger print Recognition

Fingerprint recognition is done by using minutiae extraction which is based on the frequency and orientation of the local ridges and thereby extracting correct minutiae points. Minutiae are the combination of ridge ending and ridge bifurcation in the fingerprint image. After extracting the image in the sensor, the preprocessing of the fingerprint image is done. The preprocessing has various stages like image enhancement; binarization and spur removal by the filter and so on. After that, in the minutiae extraction stage, thinning and minutiae detection is done. In the post processing stage, the false minutiae will be removed. Then the matching is done by using Euclidean distance matcher [8].

$$sd = \sqrt{(x_j^{'} - x_i)^2 + (y_j^{'} - y_i)^2} \leq r_0$$

$$dd = \min(|\,\theta_j^{'} - \theta_i\,|, 360 - |\,\theta_j^{'} - \theta_i\,|) \leq \theta_0$$

Finally, the pairing which generates the similarity scores (Sfinger) which are given to the score level fusion.

Score Level Fusion

In this paper, we proposed weighted sum score level fusion for Face and Fingerprint modalities where the fingerprint score is calculated by minutiae matching and the face score is calculated by using PCA and Euclidean distance classifier. Scores generated from individual modalities are combined at [9] matching score level fusion technique using weighted sum score technique. Let Sface and Sfinger be the matching scores obtained from the face and fingerprint modalities.

Score Normalization – It refers to changing the location and scale parameters [8] of the match score distributions at the outputs of the individual matchers, so that the match scores of different matchers are transformed into a common. The tanh normalization method introduced by Hampel et.al in 1986 [15] is robust to outliers than z-score normalization and optimal also.

$$S_i{'} = \frac{1}{2}\left\{tanh\left(0.01\left(\frac{(Si-\mu)}{\sigma}\right)\right) + 1\right\}$$

Where Si –given matching score, μ – mean, σ – standard deviation.

Generation of similarity scores - Before fusion, it is necessary to check the similarity measure to validate the scores of both modalities whether they belong to similar or dissimilar. If not, the respective modality score has to be changed to similarity measure before fusion.

Hybrid BF-pfPSO Optimization

The role of hybrid BF-pfPSO optimization is to search for the optimal set of weights to be used in the weighted sum score fusion for face and fingerprint modalities. The fitness value is defined as the Equal Error Rate. Attaining minimum Equal Error Rate defines the best fitness value using BFpfPSO algorithm. This algorithm Hybrid Bacterial Foraging with parameter free Particle Swarm Optimization (Hybrid BFpfPSO) [9] is used to find the optimality in the multimodal environment which attains good optimality and showing with fast convergence. Normally in PSO algorithms, the parameters are velocity, acceleration coefficients and inertia weights has to be updated but in this parameter free PSO doesn't require any updating of velocity or position equations.

Xi (t+1) = (1-gbest / Xi (t)) * r1 * gbest + (gbest / Xi (t)) * r2 * pbest(i)

Where t- current iteration, i – particle number, X-position of particle,r1,r2 – random values [01], pbest – local best, gbest – global best. In Bacterial Foraging Optimization algorithm, chemo taxis process is used for local search, reproduction process is used for speed up the convergence whereas elimination and dispersal processes preventing from premature convergence and leads the search towards global optima. The mutation operator helps to avoid premature convergence by getting stuck up with some local minima. It is overcome due to diversity in population method induced by mutation.

Hybrid BF-pfPSO algorithm steps

Step 1: Initialize the parameters S- no.of bacteria in thepopulation, Nc – Number of chemo taxis steps, Ns- No.of swimming steps, Nre – Number of reproduction steps, C(i) – step size specified by tumble, Jbest(j,k) – fitness value of local, Jglobal – fitness value global.

Step 2: Update the parameters. Jbest(j,k), Jglobal=Jbest(j,k)

Step 3: Reproduction loop : k=k+1

Step 4: Chemo taxis loop : j=j+1

Compute fitness function. J(I,j,k) = 1 to S

Update Jbest(j,k), θpbest(j,k)

Tumble: generate random number.

Compute θ for I = 1 to S.

Swim i) let m=0

While m<Ns

Let m = m+1

Compute fitness function J(i,j,k) for I = 1 to S

Update Jbest(j+1,k)

If Jbest(j+1,k)<Jbest(j,k)

Jbest(j,k) = Jbest(j+1,k)

θpbest = θpbest(j+1,k)

Compute θ for I = 1 to S

θ(i,j+1,k) = θ(i,j,k)+c(i)(Δi/√(ΔT(i)Δ(i)))

Use this θ (I,j+1,k) to compute the new j(I,j+1,k)

Else Let m=Ns

Mutation: change the position of bacteria by mutation.

Step 5: if j <Ne , go to step 4.continue chemo taxis till the end of the bacteria life.

Step 6: Sr=S/2 bacteria with the highest cost function (J) value die and other Sr bacteria with the best values split.

Update Jglobal &θglobal

Step 7: If K <Nre, go to step 3 otherwise end.

RESULTS AND DISCUSSIONS

In our work, we used Biometric Scores Set - Release 1 (BSSR1) database. It is a set of raw output of similarity scores from two 2002 face recognition systems and 2004 fingerprint system respectively, [10] operating on frontal faces, and left and right index live-scan fingerprints, respectively. The database includes true multimodal score data, similarity scores from comparisons of faces and fingerprints of the same people.

The data set is comprised of face and fingerprint scores from the same set of 517 individuals. For each individual, [11] the set contains one score from the comparison of two right index fingerprints, one score from the comparison of two left index fingerprints, and two scores (from two separate matchers) from the comparison of two frontal faces. The fingerprint images and the face images from which these scores were computed are from the same person at the same time. There are 517 genuine scores and (516*517) 2,66,772 impostor scores for each user. The learning set consists of 200 users, [12] which are used to compute the verification parameters. The evaluation set consists of 317 users, which is used to assess the verification parameters learnt from the training set. The matching scores from 200 users of the testing set is computed as: {Genuine = 200 (200 × 1) and Imposter = 23,800 (200 × 119)} while second set of 317 users indicates: {Genuine = 317,(317 × 1) and Imposter = 100172 (317 × 316)}.

In our experiment, the hybrid BF-pfPSO used to get the optimal fitness value. The fitness value is defined as Equal Error rate [15]. Our aim is to minimize the EER for better results. The best fitness value is the one which has minimum EER Value. Performance of the multimodal biometric system is defined by analyzing ROC curves and Minimum EER Values. \

Table 1. EER (%) for the various fusion techniques

Fusion Techniques	NIST BSSRI	
	FaG-FiR	**FaC-FiL**
Min	5.78	6.92
Max	5.38	4.62
Sum	1.5	0.8
Weighted sum using GA-PSO (Existing)	0.45	0.75
Weighted sum using BF-pfPSO (Proposed)	0.38	0.62

The above table shows the performance comparison of EER(%) with various fusion techniques. The weighted sum fusion using Hybrid BF-pfPSO shows the optimal result over other fusion techniques. This fusion has less computational time with fast convergence for the minimum no. of iterations affiliation (e.g., if there are five affiliations, place your cursor at end of fourth affiliation). Drag the cursor up to highlight all of the above author and affiliation lines. Go to Column icon and select "2 Columns". If you have an odd number of affiliations, the final affiliation will be centered on the page; all previous will be in two columns.

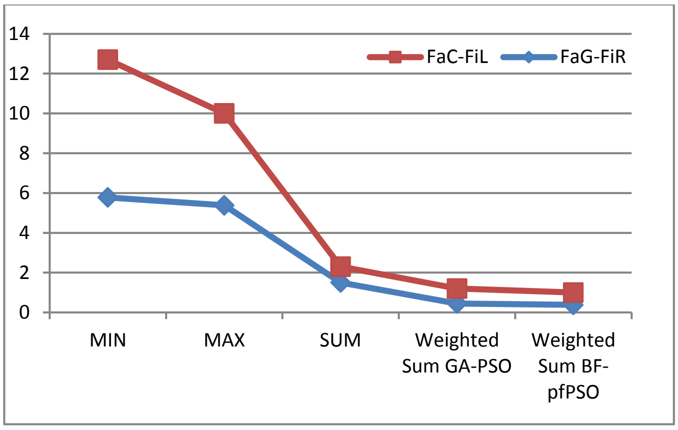

Figure 2. EER(%) value for various fusion techniques

The above figure shows the value of EER (%) for various fusion method like min, max, sum and weighted sum fusion score methods. Finally displays the value of the proposed system using

Hybrid Bacterial foraging –parameters free particle swarm optimization algorithm.

CONCLUSION

In this paper, we implemented multimodal biometric authentication for face and fingerprint recognition using the fusion of Weighted sum score techniques along with the hybrid BF-pfPSO algorithm for finding the optimal weights for the face and fingerprint modalities at the score level fusion. The features are extracted from the pre-processed images of face and fingerprint. These features of a query image are compared with those of a database image to obtain matching scores. The individual scores of each modality is generated .Then it is passed to the fusion module. In this module, generation of scores and Tanh normalization and fusion of weighted scores is done by using hybrid BF-pfPSO. The Equal error rate (EER) ratio and ROC curve which decides the performance measures of the proposed system. The final score is then used to declare the person as genuine or an impostor. The system is tested on NIST BSSR1 database for 2068 samples of fingerprint and 1034 samples of face and gives an overall accuracy of 0.38 and 0.62 EER (%). In future, the comparison has to be done by changing the modalities and using of various data bases for further results.

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