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A Natural Optimization Algorithm to Fuse Scores for Multimodal Biometric Recognition

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Abstract

Multimodal biometrics has become an interest of areas for researches in the recent past as it provides more reliability and accuracy. In this work, we have performed multimodal biometric score fusion with the help of neural networks. The two traits that have been selected for fusion are fingerprint and iris due to their effectiveness and good resistance to spoofing. The type of fusion employed in the system is score level fusion. The neural network classifier approach is chosen to take advantage of its good learning efficiency. The system trains the neural network using a recently developed evolutionary algorithm, the Cuckoo Search Algorithm. The experimental results shown that the proposed fusion system can provide us low FAR, FRR and maximum accuracy of 98.78%.

Keywords: *Artificial Neural Network (ANN), Cuckoo Search (CS), Particle Swarm Optimization (PSO), Back Propagation (BP), Multi-layer Perceptrons (MLP), Multimodal biometrics, Score fusion.*

1. Introduction

Biometrics is the use of physiological or biological traits to identify an individual. With rapid advancements in technology, security has become of prime importance. The use of PIN numbers and passwords as safeguards is not fool proof as it is easy for the intruders to gain access to this knowledge based information. Since the physiological or biological traits of a person are unique, a biometric system enhances security. Unimodal biometric systems use a single biometric characteristic to authenticate a user. Multimodal biometric systems integrate more than one physiological or biological trait. Thus, the presence of multiple independent pieces of data and the use of more than one source to validate an identity makes multimodal biometrics more reliable.

A biometric authentication system can perform both verification and identification tasks. In a verification task the user claims to be a person and a one-to-one matching is performed to validate his or her claim, whereas in an identification task, there is no such claim and thus the matching is done with all the samples of the database (one-to-n), to find out if it is an authorized access. The ultimate aim of a biometric system is to have low error rates.

Various studies and experiments performed thus far show that fingerprint and iris are two most powerful traits. In a multimodal biometric system, the information obtained from individual modalities is fused at different levels [2], [3]. For example sensor, feature, matching score and decision level. Score level fusion is done by combining matching scores provided by different unimodal classifiers [1]. Classifier fusion is one of the best fusion strategies to achieve an improved performance. This paper deals with multimodal biometric fusion with fingerprint and iris as the two biometric modalities. The use of artificial intelligence techniques such as the evolutionary algorithms to train the system is a happening field. Thus, the use of the newly developed algorithms such as the Cuckoo Search Algorithm (CS) in the field of biometrics is a promising area of research.

2. Literature Review

More number of techniques can be found for fusing multimodal biometric scores from different biometric modalities. Kein Nguyen et al. [4] have proposed multibiometric score fusion based on dempster-shafer theory by incorporating uncertainty factors. The system performance accuracy is reducing by uncertainty factors. These factors have been incorporated by weighted combination of score quality metrics and performance of the classifier. The experiments were done using biosecure DS2 database and the proposed system achieved higher performance with low EER.

Rupali L.Telged et al. [5] have proposed a sum rule based score level fusion for multi-biometric system by using face and fingerprint traits. The fingerprint features were extracted by minutiae matching algorithm and face features were extracted by principle component analysis algorithm. From the extracted features, score values are computed and the match scores are normalized and fused using sum rule based fusion techniques.

Wei-yang Lin et al. [6] have proposed a score level fusion for multi–biometric recognition based on Adaboost algorithm. Fusion performances have been increased by introducing a two stage design where any score-level fusion technique can be used at the first stage. The performance of fusion can be increased by allowing different users to continue appending score fusers at the second stage. The experiments were tested by using FRGC database samples.

Md.Maruf et al. [7] they have proposed a novel fuzzy fusion algorithm by adding three physiological traits such as fingerprint, ear and iris and three soft biometric modalities such as gender, eye-colour and ethnicity. The performance accuracy has increased by optimum weight scheme based on the discriminative features of physiological and soft biometrics modalities.

F.Wang et al. [8] Proposed multimodal score fusion using support vector machine. Face and iris traits were chosen as input to the system. Corresponding features are extracted from both the traits and two matching scores from face and iris recognizer were generated. By using SVM based fusion the two score vectors was combined to generate a single score vector which is easy to make the final decision.

3. Proposed Methodology

The work aims at developing a multimodal biometric system that uses the Cuckoo Search Algorithm (CS). The score level fusion strategy is used to integrate the two biometric modalities i.e. fingerprint and iris. The system uses an Artificial Neural Network (ANN) to train the biometric system to perform the tasks of verification or identification. The work aims at providing an enhanced performance as compared to that achieved using several other fusion strategies and algorithms. The System consists of two stages namely extraction of features stage and fusion of score stage. The Proposed system is shown in the below block diagram as shown in figure 1.

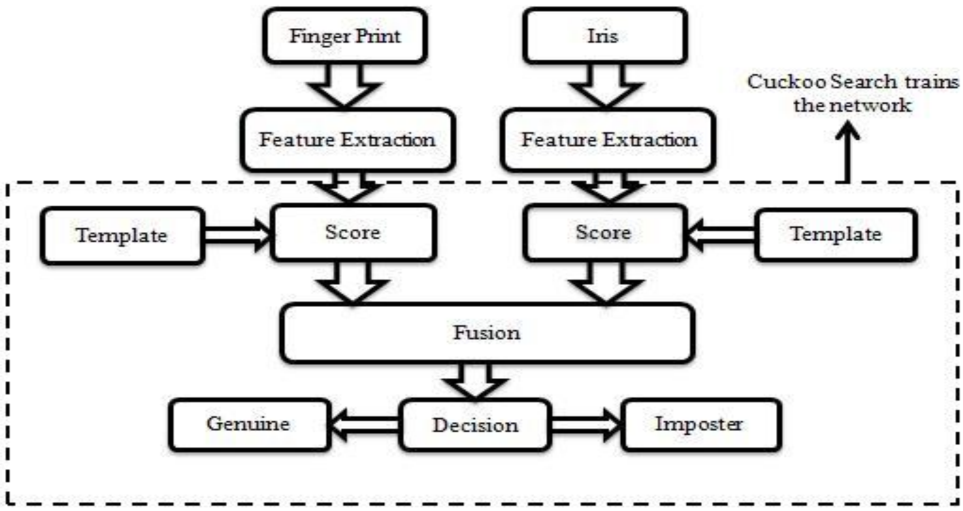


Figure 1: Block diagram of the proposed multimodal biometric system using Cuckoo Search (CS) algorithm.

3.1 Feature Extraction Phase

Feature extraction is selecting or enhancing the key features of a biometric sample. Then the sample is normalized, i.e. the quality is improved by eliminating noisy components and correcting deformations. These features are then encoded for further analysis.

3.1.1 Fingerprint Minutiae

The features extracted from the fingerprint image are the minutiae points: the ridge endings and ridge bifurcations. The image is binarized to get a grey-scale image and thinning operation is performed to limit the ridge thickness to one pixel wide. The Crossing Number Method is used to perform Minutiae Extraction. The features are then used to derive individual scores that are stored in the vector form as shown:

$$FP = \{f_1, f_2, f_3, \dots, f_n\} \quad (1)$$

3.1.2 Iris Extraction

The iris detection is performed using the method of Hough Transform and Canny edge detection. The varying levels of intensity in the iris and pupil are employed and the centre coordinates of iris, pupil and their corresponding radii are determined. The image undergoes normalization as well. This information is then used to obtain the features in the form of template and noise parameters. The individual scores are then obtained and stored in the vector form as shown:

$$Iris = \{i_1, i_2, i_3, \dots, i_n\} \quad (2)$$

3.2 Score Computation Phase

3.2.1 Fingerprint

The features from the fingerprint image are extracted and stored in the form of matrices. The Euclidean distance between the two minutiae matrices (i.e. from the two templates that are being compared) is computed. The similarity index is then determined.

3.2.2 Iris

The template and mask features that are obtained from the iris image are combined and then the Euclidean distance is computed between the features of the two templates being compared.

$$Euclidean\ distance, d = \sqrt{(dx^2 + dy^2)}, \quad (3)$$

where dx and dy are the differences between the two elements. Thus, the scores are generated. These two scores, one from the fingerprint image and other from the iris image are then given as the two inputs to the neural network. The integrated score vector is then obtained as shown below,

$$Score = \{s_1, s_2, s_3, \dots, s_n\} \quad (4)$$

where s_n is the fused FP and Iris score of n^{th} template

3.3 Neural Network Phase

A Neural Network (NN) is a simplified model of the brain that comprises of a large number of units (analogous to neurons) along with weights that measure the strengths of the connections between units [9]-[10]. A Neural Network consists of several layers of neurons: an input neuron layer, an output layer and more number of hidden layers which perform all the computations required and send the final output to the output layer. The flowchart diagram of the Cuckoo Search algorithm based on neural network platform is shown in Figure 2

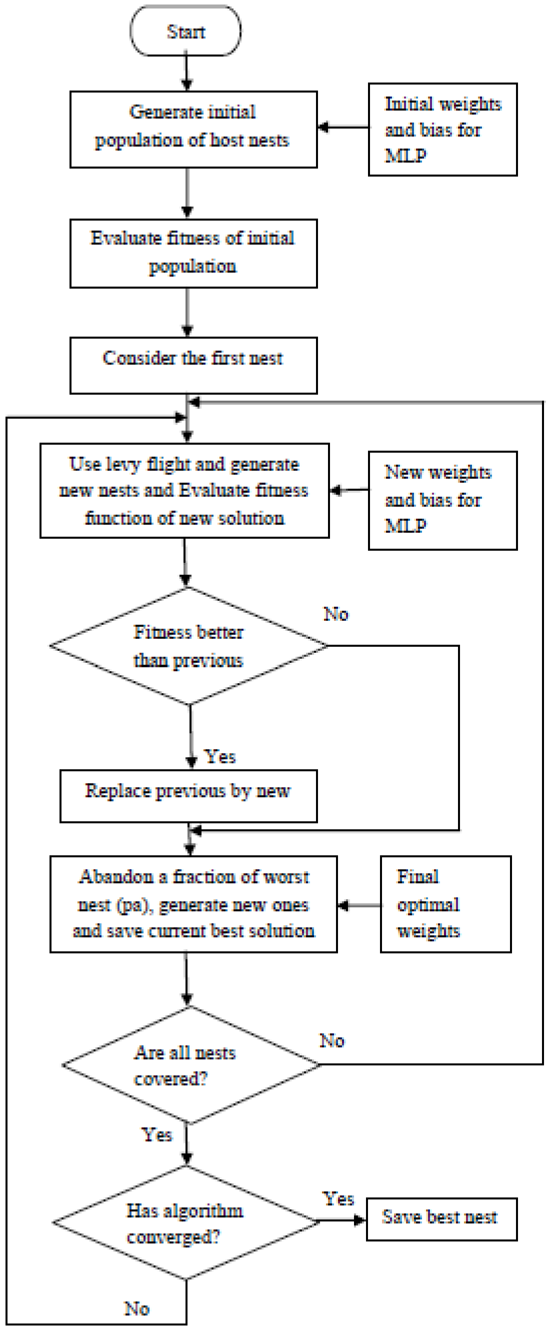


Figure 2: Flowchart for CS algorithm to train MLP.

3.3.1 Cuckoo Search as learning algorithm for Neural Network

The change of weights in a neural network forms the most important part of training [11]. Evolutionary Algorithms are computationally inexpensive and are easy to implement as well. The system trains the neural network using an algorithm called the Cuckoo Search Algorithm (CS), a recent metaheuristic algorithm developed by Yang and Deb in 2009 [12],[13], [14] and [15]. It is based on three principles:

a) Each cuckoo lays one egg at a time, and dumps it in a randomly chosen nest;
b) The best nests with high quality of eggs (solutions) will carry over to the next generations;
c) The number of available host nests is fixed, and a host can discover an alien egg with a probability pa ε [0, 1]. In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

When generating new solutions, x (t+1) for a cuckoo, a levy flight is performed:

$$x_i\,(t+1) = x_i\,(t) + \alpha \oplus \text{levy}\,(\lambda), \qquad (5)$$

where $\alpha > 0$ is the step size.

The Cuckoo Search provides better accuracy and takes lesser number of evaluations as compared to PSO and Genetic Algorithm (GA) [12].

4. Experimental Results and Discussion

4.1 Database Description

The database used for collecting fingerprint samples is FVC2002 Database [18]. Samples of 100 individuals were taken with 5 images per person. The iris samples were collected from the CASIA Iris Database. Samples of 100 persons were taken with 5 images per person [19].

4.2 Evaluation Metrics

The following parameters are used to analyze a biometric system.

False Acceptance Rate:

$$FAR(\%) = \frac{no.of\ false\ acceptance}{no.of\ total\ imposter\ attempts}\,x100 \qquad (6)$$

False Rejection Rate:

$$FRR(\%) = \frac{no.of\ false\ rejection}{no.of\ total\ authentic\ user\ attempts}\,x100\ (7)$$

Accuracy:

$$Accuracy\,(\%) = \left(1 - \frac{(FAR+FRR)}{2}\right) x100 \qquad (8)$$

Total Error Rate:

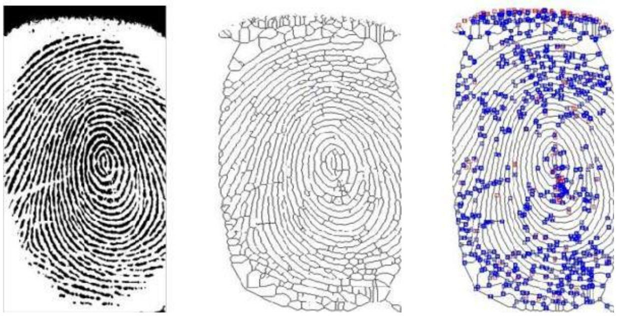
$$TER\,(\%) = FAR\,(\%) + FRR\,(\%) \qquad (9)$$

Genuine Acceptance Rate:

$$GAR = 1 - FRR \qquad (10)$$

4.3 Experimental Results

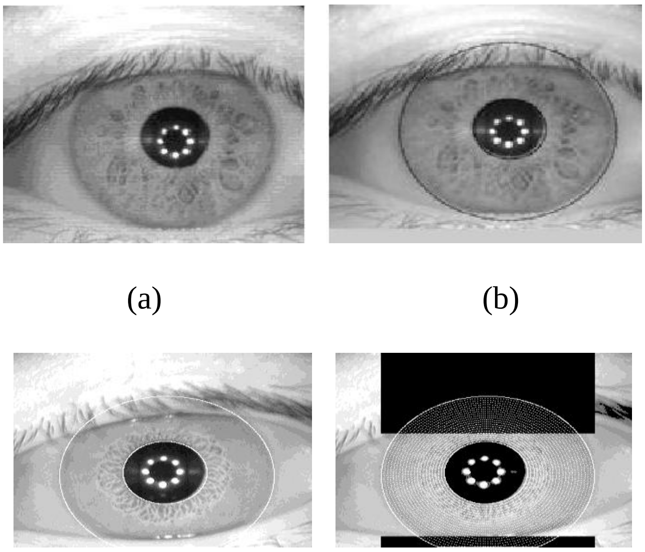
For the finger print feature extraction, the input finger print image has to be binarized and thinned to obtain the Ridges and Bifurcations. The spurious signals that hide the region of interest of the image are removed and the ROI is obtained. The image results for one sample of finger print are shown here.



(a) (b) (c)

Figure 3: (a) Image of the fingerprint sample (b) Thinned image (c) Image with the minutiae marked.

Similarly for the iris, image enhancement is followed by normalization and feature extraction. The images below show the isolated noise regions and iris and pupil edges.



(a) (b)

(c) (d)

Figure 4: (a) Image of the iris sample (b) Image with the iris boundary marked (c) Segmented image (d) Normalised image.

The post processing results are evaluated with the help of evaluation metrics. The necessary graphs are listed below. The FAR and FRR values are plotted against the threshold values. The EER and the threshold are obtained from the intersection of the FRR and FAR curves. At the resulting threshold value the system accuracy is calculated. The system performance is also compared based on different training algorithms like Back propagation and PSO.

4.3.1 Performance Analysis for CS Algorithm

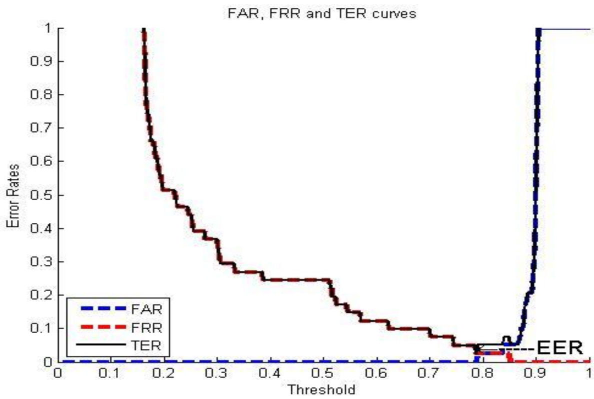


Figure 5: Relation between FAR, FRR and TER

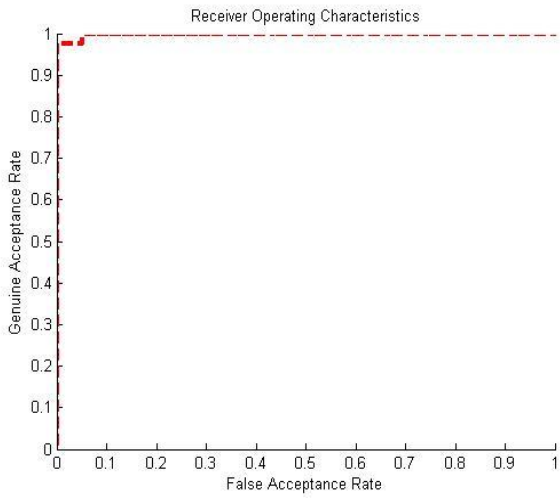


Figure 6: Receiver Operating Characteristics

4.3.2 Performance Analysis for BP Algorithm

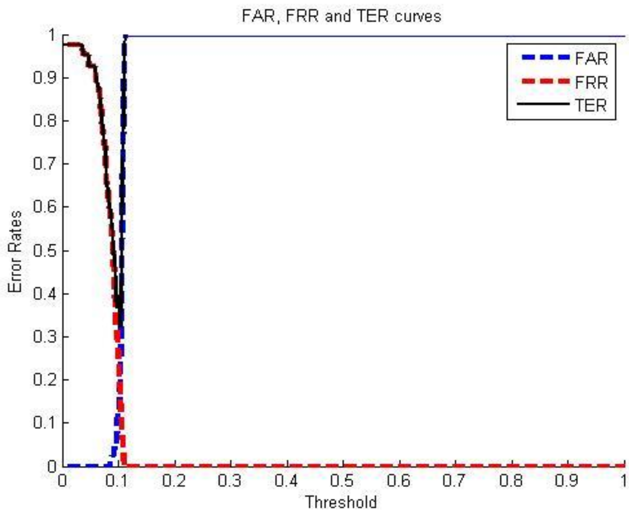


Figure 7: Relation between FAR, FRR and TER

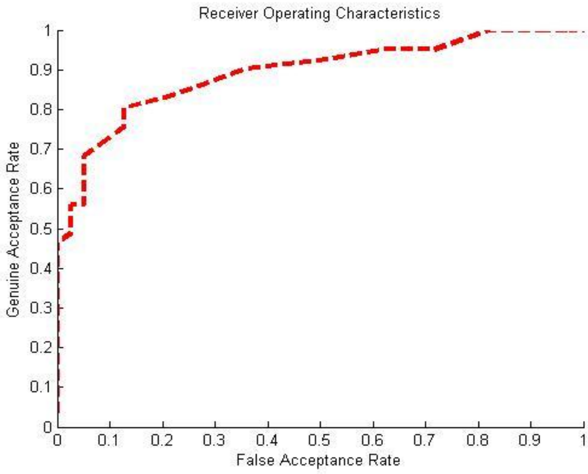


Figure 8: Receiver Operating Characteristics

4.3.3 Performance Analysis for PSO Algorithm

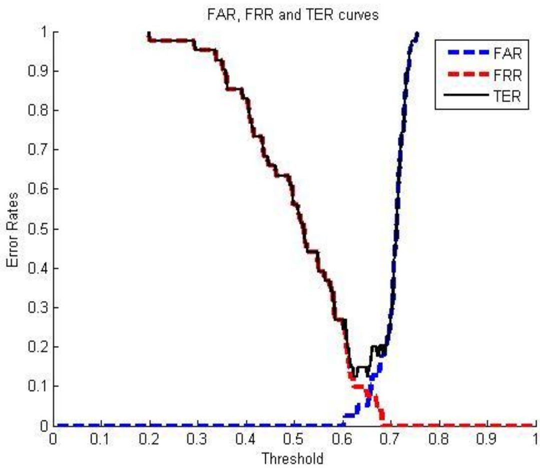


Figure 9: Relation between FAR, FRR and TER

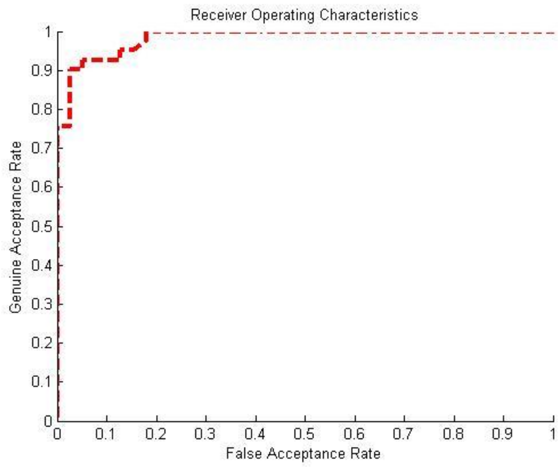


Figure 10: Receiver Operating Characteristics

4.3.4 Performance Comparison for CS, BP and PSO algorithms

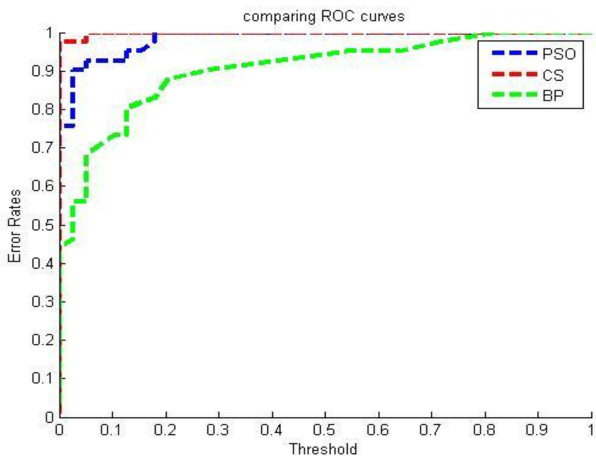


Figure 11: Graph comparing ROC curves

Performance graphs are plotted using the results obtained during the testing phase. At the resulting threshold value the system achieves an accuracy of 98.78%.Error rates obtained from these graphs are tabulated as shown in Table 1.

Table 1: Evaluation Metrics for different training algorithms

	CS Algorithm (%)	BP Algorithm (%)	PSO Algorithm (%)
FRR	2.44	7.32	17.07
FAR	0	7.69	17.95
ACCURACY	98.78	92.5	82.49

5. Conclusion

The multimodal biometric system proposed implements the training of the weights of a neural network by the CS algorithm – an efficient population based nature-inspired algorithm that provides good accuracy. The choice of traits such that they provide good resistance to spoofing and the score level fusion strategy present good system performance. The evaluation metrics yield an accuracy of 98.78% was obtained when the network is trained using cuckoo search. Comparisons with that achieved using algorithms such as back-propagation and particle swarm optimization show that accuracies of 92.5 % and 82.49% were obtained respectively. The receiver operating characteristics showed promising results with the cuckoo-search trained neural network. The success of cuckoo search algorithm can be attributed to its parameter independency and robust nature. The neural network structure optimization and study of various other algorithms can help improve the performance of the biometric system in future.

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