Score Level Fusion Techniques in Multimodal Biometric System Using CBO-ANN

Rajesh S.[1]* and Selvarajan S.[2]
1. Department of Computer Science and Engineering, Paavai Engineering college, Namakkal, INDIA
2. Muthayammal College of Engineering, Rasipuram, Namakkal, INDIA
*softrajeshs@gmail.com, rajeshsantharampec@paavai.edu.in

Abstract
In case of a multimodal biometric system, the method of fusion that is effective is required for the information fusion from different distinct modality systems. The fusion is an approach that is promising that can increase the systems accuracy. Here in this kind of work, the sum rule based score level fusion and its performance and the Artificial Neural Network (ANN) that is based on the score level fusion which is examined. There are three biometric traits that are regarded for this which are the fingerprint, the face and the vein. There was also a proposal for a robust normalization scheme (that leads to the reduction of the high scores which are the effect of normalization) that is derived from any min-max scheme of normalization. The features are extracted through the Discrete Cosine Transform (DCT) and the Gabor filters. The ANN that is Structure optimized like the Colliding Bodies Optimization (CBO). This CBO makes use of the simple formulation that finds either the least or the greatest of the functions and is not dependant on other internal parameters. The experiments made on four different databases that are multimodal have suggested that the presented system if integrated in the sum rule based fusion and the ANN and lastly the CBO-ANN based function which leads to a better accuracy.

Keywords: Multimodal Biometric System, Score Level Fusion, Artificial Neural Network (ANN), Gabor Filters, Discrete Cosine Transform (DCT) and Colliding Bodies Optimization (CBO).

Introduction

The multimodal biometrics refers to using the combination of more than two modalities of biometrics in either a verification or an identification system. The identification that is on the basis of different biometrics shows an up-and-coming development. The main reason for the combination of various modalities is for improving the rate of recognition. This may be carried out once the biometrics features are independent arithmetically. There are various causes for this combination. One is that the modalities of biometrics may be appropriate for other applications. Another reason may be preferences of the consumer.[1]

The International Committee for Information Technology Standards (INCITS) and their Technical Committee M1, their biometrics, and their researchers have been describing systems for the performance of the fusion of multi-biometrics. Generally, the usage of these terms whether multi-modal or multi-biometric shows the availability of the use of some biometric aspects like the sensor, the algorithm, the modality and the instance in certain forms of mixed use to make certain particular decisions of confirmation or recognition.

In environments that are highly sensitive one initial authentication may not be enough for guarantee of security. The combining of evidence that is obtained from various sources by using a fusion scheme may improve significantly the biometric system's overall accuracy. Such systems may demonstrate all significant improvement over the other biometric systems in case of higher accuracy as well as spoofing of high resistance (which is a type of spam that tries gaining access into the system of the user or the information by a pretence of being the user. The Multi-biometric system is being deployed in many applications that are large-scale as they have many advantages like low rate of errors, coverage of larger population in comparison to the uni-biometric systems. But the multi biometric systems need the storage of templates of multiple biometrics (like the fingerprint, the iris and the face) for every user that may result in a higher risk to the privacy of the user and the security of the system [2]

The main objective of the multi biometrics is the reduction of one or more of: the False Accept Rate (FAR), the False Reject Rate (FRR), the Failure to Enroll Rate (FTE) and the Susceptibility to mimics or artefacts. The multi modal biometric systems obtain input from one or more sensors that measure two or more biometric characteristics modalities. For instance, a system that has either a fingerprint and a face recognition is regarded as multimodal when the OR rule is exerted and thereby permitting the users to be verified [3, 4].

The biometric systems that are multi algorithmic tend to take one sample from one sensor and procedure it with more than two algorithms. The multi-instance biometric systems make use of one sensor or sometimes more for capturing the samples of more than two cases of similar biometric traits. For example multiple fingers capture images.

The biometric systems are multi-sensorial with similar biometric trait cases that have two or more sensors. The processing of many samples may be carried out with a single algorithm of a combination. The face recognition application may be used with a visible light camera that is combined with a particular frequency.

A technique for the integration and the classification of the results of each channel of biometrics is known as the Biometric fusion. The biometric fusion that is multimodal make a combination of different features of biometrics for improving the strengths and bring down the limitations of those aspects that are individual. The fusion scheme's efficiency influences to a great level the accuracy of the of this multimodal biometric system. There are three fusion levels in the multimodal biometrics are the feature level fusion, the matching score level fusion and the decision level fusion. There is a belief that a system which is a combination when applied early on the recognition system is much more effective [5]. There are four modules here which are (1) the sensor module, (2) the feature extraction module, (3) the matching module, and (4) the decision-making module. This fusion can thus take place at the level of the sensor or the feature extraction or the matching score or at the decision level.

Here the matching score level fusion is made use of. In this level, there is a separate generation of fusion level of each of the modalities. The extracted feature vectors are contrasted over the templates that reside in a database that is individual for every trait of biometrics for generating matching scores. On the basis of the accuracy of each of the channels of biometrics the output set of the match scores that have been combined for creating a composite matching score are used. For example, the face as well as the hand modalities and their match score can be combined by using a simple sum rule to get a novel match score that may be sent to the decision module [6]

There are different techniques like the logistic regression, the highest rank, the board count and weighted sum, the Hidden Markov Model (HMM), the K-Nearest Neighbour (KNN) fusion, the Bayes rule the Linear Discriminant Analysis (LDA) and the weighted produce that can be used for combining the match scores. A significant feature is to address in the matching score level which is the score normalization that is taken from modalities that are multiple. The Min-max, the median-MAD, the tan-h, the piecewise linear, the z-score and the double sigmoid are the various techniques of normalization that are used for match scores. The matching score level is probably the widest employed fusion level as its difficulty is much lower. Most researchers have made use of the application of fusion at the matching level score.

Here the ANN is being optimized with the algorithm of CBO that has been proposed. This process of the optimization is that of searching for a vector in a function that may produce an optimal solution. All values that are feasible are the solutions available and the optimal solution is nothing but the extreme value. The approach of ANN has been used to take full advantage of the ability of the Neural network to learn and the membership functions as well as degrees of the network. Whether a particular image fits to the non-face class or the face class on the basis of information given at the time of training is decided by the classifier. It is also important to know the matching score level when the neural network is tested [7].

The Meta-heuristics is a very recent generation of the methods of optimization that have been proposed for solving complex problems [8]. The idea behind such stochastic techniques of search are to simulated any natural phenomena. The Genetic Algorithm (GA) has been inspired by the Darwin's theory on biological evolutions. The Particle Swarm Optimization (PSO) is made to stimulate the social interaction and the behaviour of the fish schooling and the bird flocking. The Ant Colony Optimization (ACO) mimics the manner in which the ant colonies are capable to discover the shortest possible route among the food and themselves. The Harmony Search (HS) algorithm has been conceptualized by means of using a musical process for the searching of a perfect harmony. The Charged System Search (CSS) makes uses of the electric Physics laws and the Newtonian Laws of mechanics as a guide to the Charged Particles (CP). Here a new type of meta-heuristic algorithm, CBO has been presented and been exerted to the structural issues by two pioneers Kaveh and Mahdavi.

A structure optimized ANN like the CBO method has been proposed for the system of multimodal biometrics that uses techniques of score level fusion. The rest of the investigation has been organised as follows. Section 2 talks about the related work in literature. In Section 3 the different methods are explained. In Section 4 the results of the experiment are discussed and the conclusion is shown in Section 5.

Related Works

Telgad et al., [9] made a presentation of the fusion of face and the modalities of fingerprint at the score level fusion. This system extracted features that are employed for matching. The Euclidean distance matcher is made use of for the Face as well as the Finger print modalities. The recognition of fingerprint is performed using Gabor filter and minutiae matching. The features of the face are extracted by using the Principle of Component Analysis (PCA) for the dimensionality reduction. After this is done the match scores are duly normalized and the sum score level fusion is made use of for developing the system. This approach has provided better results. The rate of recognition has increased and the rate of error has been decreased by means of this system.

Perumal & Ramachandran [10] made an extraction of the local convex direction map which was a part of the Finger Knuckle Print (FKP) image. After this the enhanced FKP's local features are extracted by using a Scale Invariant Feature Transform (SIFT), the Frequency Feature and the Speeded Up Robust Features (SURF). The SIFT is created by the local patterns based on the key points from the space of scale decomposed images. The Feature vectors through the SURF are formed by the local patterns around the key-points that are identified by means of using the scaled up filter. The frequency range of the pixel levels in every image is hereby exploited through Empirical Mode Decomposition (EMD). The results of the experiment showed the effectiveness and efficiency of this biometric characteristic.

Trabelsi et al., [11] made a proposal for a texture descriptor that was rotation invariant known as the Circular Difference and also Statistical Directional Patterns (CDSDP) for extracting the patterns of hand vein. The histogram of this is taken to be an attribute vector. This CDSDP is known to be a surrounding circular difference that has weights and one that incorporates the directional information that is statistical from the vessels. The results of the experiment show that the descriptor that is proposed on the basis of the CDSDP performs better than the other descriptors that are used in the Local Binary Patterns (LBP). This method shows an Identification Rate (IR) of 99.8 % and further an Error Equal Rate (EER) of 0.01 %. Also the average time taken to process this proposed method is about 5.2ms for the vein posture of one hand that can satisfy the criterion needed for a real time recognition system of hand vein.

Almaadeed et al., [12] further intended and performed another novel multimodal speaker recognition system that was text independent and based on the neural networks and wavelet analysis. The wavelet analysis includes discrete type of wavelet transform and wavelet packing transform along with wavelet sub-band coding and the Mel-Frequency Cepstral Coefficients (MFCCs). This learning module consists of some generally regressive, normally probabilistic and also the Radial Basis Function Neural Networks (RBFNN), that form the decisions through a huge system of voting. This system has been determined as much competitive and also enhanced identification rate by about 15% when compared to the classical MFCC. Additionally, this further reduced the time of identification by about 40% in comparison with the Gaussian Mixture Model (GMM), the PCA and the Back-Propagation Neural Network (BPNN).

Lathika & Devaraj [13] made a proposal for a multimodal biometric system which is a combination of the face, the ear (physical traits) and the gait biometric (behavioural traits) modalities. The advancements in the sensor knowledge like the accelerometers that are a miniature in the smart phones and the Kinect camera that provides the represents to record as well as analyse the gait data from a novel view point. Here the author employs a wavelet transform for the extraction of feature that defines the ratio that exists among dark and the bright ideas. Here, recognition method can use the ANN to achieve a good rate of recognition in case of wide variations in the face. The samples belonging to the face, the ear and the gait datasets have to be normalized by using the z-score method for fusion consequences that are better. Furthermore, the match score fusion and their concepts are employed for combining face, the ear and the gait.

Saini & Sinha [14] had to explore various multimodal systems of biometrics on the Gabor–Wigner Transform (GWT) for the subject recognition. This transform gives an analysis of space as well as the components of frequency for a biometric image. The GWT had been proposed initially in this literature for the analysis of signals. He the GWT is used for the feature vector extraction from different modalities of biometrics. A technique for optimization known as PSO is further used for selecting the features that are dominant from that of the feature vectors. This not only improves the system's performance but also brings down the dimension of the feature vectors that are obtained.
2
Mezai & Hachouf [15] made a proposal for an efficient PSO technique which believes the assignments of voice as well as the face classifiers. The assignment of the belief is basically computed from each modality's score ahat uses the Denœux and Appriou models. The weighted belief assignments and their fusion is performed by the Dempster-Shafer (DS) theory and also the Proportional Conflict Redistribution (PCR5) rules of combination. The results have proved that this approach can improve the EER when compared with other well-established methods that are on the Biometric Access control for the Networked and also the E-Commerce Application (BANCA) which is a multimodal database as it holds all the adverse, the controlled and the degraded data.

Methodology

The matching score level fusion is perhaps commonly used and desired methods of fusion like the matching scores which are available easily and have a adequate information amount which helps distinguishing between a case that is genuine and a case on an imposter. Every system give a matching score that indicates the feature vector's proximity with the template vector. Such scores may be fused for the assertion of the claimed identity's veracity. Here the sum rule based fusion which is preceded by the min-max normalization the features are duly extracted by the Gabor filters and the DCT. The ANN is further optimized with the method of CBO and are hereby discussed.

Score Level Fusion: The fusion at the matching level can normalize the score of the matchers and this is done to the same domain that user the mechanisms like the Quadric-Line-Quadric function [16], which tries separating the imposter score from the genuine score distribution of that of the Min-Max that is used here in this work where the map scores values are to [0, 1], that uses (1) as below:

$$N_{s1} = \frac{MS_{s1} - \min_{s1}}{\max_{s1} - \min_{s1}} \tag{1}$$

In which MS_{s1} is a matching score which is obtained the from sample1 modality, respectively the $\min_{s1}$ and the $\max_{s1}$ denote the minimum and the maximum scores for sample1 trait, respectively. After the stage of normalization, these scores are duly fused by means of using the Sum-rule based kind of fusion which is presented by (2):

$$S = \sum_{i}^{M} N_{si} \tag{2}$$

In which S denotes the score of fusion and M denotes the number of scores, in which M = 2 within the two biometrics of the multimodal and M = 3 with the three multimodal biometrics. Lastly, S is compared to a threshold value T for checking if the pattern is a genuine one or an imposter.

Feature Extraction using Gabor Filter and Discrete Cosine Transform (DCT): The Gabor filters are tools that are useful in the processing of image and also has properties of optimal localization in the spatial and the frequency domain. The Gabor function is an oscillator which is harmonic inside a Gaussian envelope and is composed of a Sinusoidal plane wave[17]. A 2-D Gabor filter on the image (x, y) may be defined as (3):

$$G(x,y) = \exp\left(-\frac{(x-x_0)^2}{2\sigma_x^2} - \frac{(y-y_0)^2}{2\sigma_y^2}\right)$$
$$x\ \exp(-2\pi i(u_0(x-x_0)+v_0(y-y_0))) \tag{3}$$

In which

(x_0, y_0) Indicate the location in image,

(u_0, v_0) Indicate the modulation which has a spatial frequency ω_0

$\omega_0 = \sqrt{u_0{}^2 + v_0{}^2}$

θ_0 is the orientation, $\theta_0 = \arctan(v_0 / u_0)$

σ_x *and* σ_y are the standard deviations

The DCT here is a Fourier related transform, that is real valued. This can be implemented by using Discrete Fourier Transform (DFT). This DCT makes a calculation of a truncated Chebyshev series. It expresses the data relating to the sum of the cosine functions. The commonest type of DCT that is used operates in a real sequence x_n of the length N for producing coefficients CK, as (4 & 5):

$$C_k = \frac{2}{N} w(k) \sum_{n=0}^{N-1} x_n \cos\left(\frac{2n+1}{2N}\pi k\right), 0 \le k \le N-1 \tag{4}$$

And

$$x_n = \sum_{K=0}^{N-1} w(k) C_k \cos\left(\frac{2n+1}{2N}\pi k\right), 0 \le n \le N-1 \tag{5}$$

In which

$$w(k) = \sqrt{2}, k = 0\ and\ w(k) = 1,\ 1 \le k \le N\text{-}1$$

DCT has very strong energy compaction properties. Computation techniques that are fast may be applied for the extraction of features and widely used in case of recognition of patterns. This DCT has been used successfully in the face recognition as opposed to the Karhunen-Loeve Transform (KLT), as the DCT is computationally lower in intensity.

ANN Optimized with CBO (CBO-ANN): A mathematical model inspired by many biological neural networks is the ANN. This is a non-linear mapping model which has been applied successfully in many different domains like the prediction of bankruptcy, recognition of handwriting, inspection of product and detection of fault. This is also accepted widely owing to its selection of the fault prediction model. The optimal values may be found for the parameters of the ANN which are the weight values, the activation functions, the hidden neurons, the hidden layers and the number of input neurons [18].

The ANN is an adaptive one as it can make changes to its structure on the basis of the information flow of the network. This feature of adaptability hs been achieved by the ANN's training with that of the known dataset. In a model that is based on ANN the prediction accuracy may be increased by identifying an optimal value of the parameter for the model. By means of adapting a meta-heuristic algorithm like the CBO, for training the ANN it involves some generic steps which are irrespective of the CBO algorithm that has been considered. As the ANN's weights have to be optimized they also have to be tracked as the entity that is fundamental based on the CBO algorithm. This problem space has all combinations of weights for the ANN. It has more or n-dimensions in which the total weights number has to be optimized. This CBO algorithm is further applied and the objective functions of this is based upon the accuracy of prediction of the ANN.

A CBO is a relatively new simple and also efficient meta-heuristic algorithm. In this, every solution candidate X_i which contains a different variables (i.e. $X_i = \{X_{i,j}\}$) are considered to be a Colliding Body (CB). These massed objects consist of two equal groups which are stationary objects and moving objects, in which the moving objects will move and follow the stationary objects and there may be a collision that occurs between the pairs of objects. There are two purposes to this: (i) for improving the positions of the moving objects; (ii) for pushing the stationary objects to better positions. Once the collision takes place other new positions of these colliding bodies are duly updated on the basis of the new velocity by means of using the laws of collision [19].

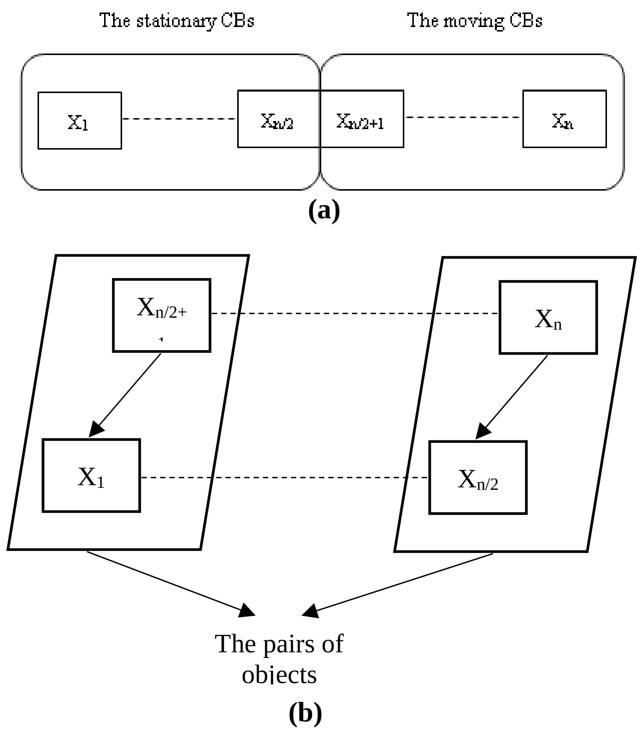

Figure 1: (a) CBs sorted in increasing order; (b) colliding object pairs.

The procedure of CBO procedure is outlined briefly as below:

Step 1: The CBs initial positions are being determined with the random initialization of individual populations in the search space (6):

$$x_i^0 = x_{\min} + rand(x_{\max} - x_{\min}),\ i = 1, 2, ..., n \tag{6}$$

In which, x_i^0 determines initial value vector of i th CB. $x_{\min}$ and $x_{\max}$ denote the minimum and maximum values that are allowable as vectors of the variables; the rand is a random number within the interval [0, 1]; and the n is the actual number of CBs.

Step 2: The body mass and its magnitude for every CB is hereby defined as in (7):

$$m_k = \frac{\frac{1}{fit(k)}}{\sum_{i=1}^{n} \frac{1}{fit(i)}},\ k = 1, 2, ..., n \tag{7}$$

In which fit (i) denotes the objective function and value of the agent i; and n the size of the population. It looks like a CB that has good values may exert a larger mass than that of the bad ones. Also, for the purpose of maximization the objective function which is fit (i) has to be replaced by the 1/fit (i).

Step 3: This arrangement of CBs objective function values has been performed in the ascending order (figure 1a). The sorted CBs are divided equally into two different groups:

- The lower half of the CBs (which are stationary CBs); These are the CBs that are good agents and are stationary with a velocity of these bodies that are before the collision which is zero. So in (8):

$$v_i = 0,\ i = 1, ..., \frac{n}{2} \tag{8}$$

- The upper half of the CBs (which are the moving CBs): Such CBs move towards the other lower half. After this, in accordance to figure 1b, both the better and the worse CBs, i.e. the agents that have upper fitness value, of every group collide together. This change of the position of the body that represents these body's velocity before the collision takes place (9):

$$v_i = x_i - x_{i-\frac{n}{2}},\ i = \frac{n}{2} + 1, ..., n \tag{9}$$

In which, v_i and x_i denote the velocity and the position vector of ith CB in the group; $x_{i-\frac{n}{2}}$ denotes the i th CB pair position of the x_i in the group before this.

Step 4: Once the collision takes place, the colliding bodies and their velocities for each group are duly evaluated by using (10) and (11), and the actual velocity before collision.

$$v_1' = \frac{(m_1 - \varepsilon m_2)v_1 + (m_2 + \varepsilon m_2)v_2}{m_1 + m_2} \tag{10}$$

$$v_2' = \frac{(m_2 - \varepsilon m_1)v_1 + (m_1 + \varepsilon m_1)v_1}{m_1 + m_2} \tag{11}$$

The velocity of each of the moving CBs after collision is beingobtained by (12):

$$v_i' = \frac{\left(m_i - \varepsilon m_{i-\frac{n}{2}}\right)v_i}{m_i + m_{i-\frac{n}{2}}},\ i = \frac{n}{2} + 1, ..., n \tag{12}$$

In which, v_i and v_i' denotes the velocity of the ith moving CB before and after the collision, respectively; m_i is mass of the i th CB; $m_{i-\frac{n}{2}}$ is mass of the i th CB pair [20]. Also, the velocity of each stationary CB after the collision is (13):

$$v_i' = \frac{\left(m_{i+\frac{n}{2}} - \varepsilon m_{i+\frac{n}{2}}\right)v_{i+\frac{n}{2}}}{m_i + m_{i+\frac{n}{2}}},\ i = 1, ..., \frac{n}{2} \tag{13}$$

Where, $v_{i+\frac{n}{2}}$ and $v_i^{'}$ are the velocity of i th moving CB pair before this and i th stationary CB after collision; m_i is the mass of i th CB; $m_{i+\frac{n}{2}}$ denotes the mass of i th moving CB pair; ε the value of COR parameter.

Step 5: The new CB positions have been evaluated by using the velocities that are generated after the collision in place of the CBs that are stationary.
The current positions of each of the moving CBs are (14):

$$x_i^{new} = x_{i-\frac{n}{2}} + rand \circ v_i^{'}, \; i = \frac{n}{2}+1,\dots,n \tag{14}$$

In which, x_i^{new} and $v_i^{'}$ is the current position and its velocity after collision of i th moving CB; $x_{i-\frac{n}{2}}$ denotes the old position of the i th stationary of the CB pair. Further, the new positions of the stationary CBs have been obtained by (15):

$$x_i^{new} = x_i + rand \circ v_i^{'}, \; i = 1,\dots,\frac{n}{2} \tag{15}$$

In which, x_i^{new}, x_i and $v_i^{'}$ is the new position, the old position and velocity after collision of i th stationary CB. $rand$ is the random vector that is uniformly distributed inside the range (−1, 1) and its sign “ $\circ$ ” which denotes a multiplication that is element-by-element.

Step 6: This optimization is now repeated from the step 2 until such time a termination criterion, like the maximum iteration number, is hereby satisfied. The point that has to be noted is that the status of the body whether stationary or moving and their numbering are changed in two iterations subsequent to each other.

Results and Discussion

There are biometric characteristics three in number that are used for this work which are the fingerprint, the face and the finger vein. The fingerprint and the face are the commonest of the traits. But the finger vein is a new characteristic in the biometric integrated systems of authentication. This authentication system that uses finger vein is supposed to have better accuracy in comparison to the fingerprint and the face[21].

Merged database of fingerprint, face, and finger vein: for the evaluation of the multi-biometric system based face, fingerprint and the finger vein modalities and their performance, we need to have a database that has the scores of all the three. But until now there is no database in the public domain that the scores of all the three for the same individual. So it is built on a virtual and multimodal database. Here the features are extracted from the Gabor filters and the DCT. The ANN based score level fusion is being proposed. The Table 1 and figure 2 show the GAR versus GAR by using the CBO-ANN

Table 1
FAR Vs GAR Using CBO-ANN Method

FAR	Fingerprint-Face	Fingerprint-Iris	Fingerprint-Finger Vein	Fingerprint-Finger Vein-Face
0	0.67	0.66	0.65	0.83
0.1	0.67	0.66	0.64	0.86
0.1	0.68	0.64	0.64	0.83
0.1	0.67	0.65	0.62	0.83
0.1	0.66	0.64	0.63	0.85
0.1	0.66	0.65	0.63	0.87
0.1	0.67	0.64	0.64	0.83
0.1	0.68	0.67	0.65	0.85
0.1	0.68	0.66	0.63	0.86
0.1	0.68	0.66	0.63	0.85
0.1	0.67	0.64	0.62	0.84
0.1	0.68	0.64	0.62	0.84
0.1	0.66	0.65	0.62	0.83
0.1	0.68	0.66	0.63	0.83
0.1	0.67	0.64	0.62	0.84
0.1	0.67	0.65	0.63	0.84
0.1	0.66	0.66	0.64	0.85

0.1	0.68	0.66	0.65	0.85
0.1	0.7	0.68	0.66	0.89
0.1	0.71	0.69	0.66	0.9
0.1	0.7	0.67	0.65	0.9
0.1	0.71	0.69	0.68	0.87
0.1	0.74	0.72	0.7	0.94
0.1	0.73	0.7	0.69	0.93
0.1	0.75	0.72	0.69	0.95
0.12	0.74	0.71	0.68	0.9
0.12	0.74	0.71	0.69	0.93
0.12	0.75	0.71	0.71	0.94
0.14	0.74	0.72	0.7	0.93
0.16	0.75	0.72	0.7	0.92
0.18	0.75	0.73	0.71	0.94
0.18	0.77	0.74	0.71	0.93
0.2	0.75	0.71	0.7	0.94
0.24	0.77	0.75	0.73	0.95
0.24	0.77	0.75	0.72	0.95
0.24	0.78	0.75	0.71	0.98
0.26	0.77	0.75	0.72	0.93
0.32	0.77	0.75	0.72	0.96
0.32	0.78	0.75	0.74	0.97
0.32	0.77	0.73	0.71	0.99
0.34	0.79	0.76	0.74	0.96
0.36	0.78	0.77	0.73	0.98
0.36	0.78	0.75	0.73	0.99
0.36	0.78	0.75	0.72	0.99
0.38	0.79	0.76	0.74	0.98
0.4	0.79	0.77	0.75	0.99
0.42	0.81	0.8	0.78	0.99
0.42	0.83	0.8	0.77	0.99
0.44	0.81	0.77	0.75	0.99
0.44	0.82	0.79	0.75	0.99
0.48	0.81	0.79	0.76	0.99
0.5	0.82	0.79	0.76	0.99
0.52	0.79	0.78	0.76	0.99
0.54	0.82	0.78	0.76	0.99
0.56	0.83	0.81	0.79	0.99
0.56	0.83	0.81	0.78	0.99
0.58	0.82	0.8	0.78	0.99
0.6	0.82	0.8	0.79	0.99
0.6	0.83	0.81	0.79	0.99
0.62	0.83	0.79	0.77	0.99
0.64	0.83	0.82	0.79	0.99
0.66	0.85	0.82	0.8	0.99

0.66	0.84	0.83	0.81	0.99
0.68	0.85	0.82	0.79	0.99
0.7	0.85	0.81	0.8	0.99
0.72	0.84	0.82	0.78	0.99
0.72	0.85	0.81	0.78	0.99
0.74	0.85	0.83	0.81	0.99
0.76	0.87	0.84	0.83	0.99
0.78	0.88	0.85	0.82	0.99
0.8	0.86	0.83	0.81	0.99
0.8	0.86	0.83	0.8	0.99
0.82	0.87	0.85	0.83	0.99
0.84	0.87	0.84	0.82	0.99
0.86	0.91	0.87	0.84	0.99
0.88	0.92	0.9	0.86	0.99
0.88	0.9	0.88	0.85	0.99
0.9	0.91	0.9	0.87	0.99
0.92	0.97	0.88	0.86	0.99
1	0.97	0.94	0.87	0.99

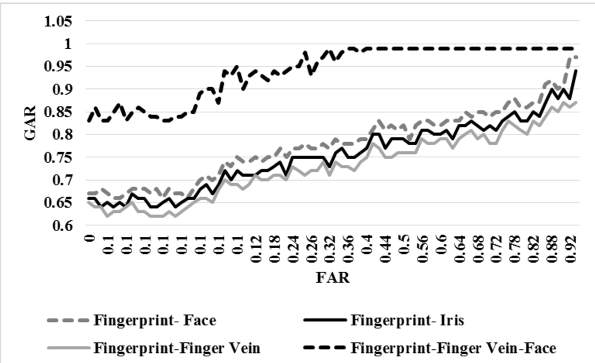

Figure 2: FAR Vs GAR Using CBO-ANN Method

From the figure 2, it can be observed that the fingerprint-finger vein-face has higher average FAR vs GAR using CBO-ANN by 18.91% for fingerprint-face, by 22.19% for fingerprint-iris and by 25.25% for fingerprint-finger vein.

Conclusion

The sum based rule fusion's performance and the CBO-ANN based fusion on the multimodal systems which are based on the fingerprint, the face and the fingerprint have been duly evaluated. If the match scores are combined from various ranges they have to be transformed to one common range before fusion is complete. The ANN is a computational model kind of a structure they belong to the biological NNs. The CBO algorithms are based on the one-dimensional collisions that take place between bodies with every agent solution that is considered as a body with mass or an object. Once the collision of two of the moving bodies takes place they are separated with other velocities. This kind of a collision can cause the agents to move to better positions inside the same search space. The results of the experiments show that the finger print-finger vein and face has a better average FAR versus GAR by using the CBO-ANN by about 18.91% for the fingerprint-face, by 22.19% for the fingerprint-iris and by about 25.25% for the fingerprint-finger vein.

References

1. Mishra, A. (2010). Multimodal biometrics it is: need for future systems. International Journal of Computer Applications, **3(4), 28-33.**

2. Jiwnani, G., & Student, M. Multi-modal Biometric Authentication using Fingerprint and Iris: a Review. International Journal of Computer Science & Communication Networks, **5(2), 115-119.**

3. Sasidhar, K., Kakulapati, V. L., Ramakrishna, K., &KailasaRao, K. (2010). Multimodal biometric systems-study to improve accuracy and performance. arXiv preprint arXiv:1011.6220.

4. Siddiqui, A. M., Telgad, R., &Deshmukh, P. D. (2014). Multimodal Biometric Systems: Study to Improve Accuracy and Performance. International Journal of Current Engineering and Technology, **4(1), 165-171.**

5. Amirthalingam, G., & Radhamani, G. (2013). A multimodal approach for face and ear biometric system. International Journal of Computer Science Issues (IJCSI), **10(5), 234-241.**

6. Sanjekar, P. S., & Patil, J. B. (2013). An overview of multimodal biometrics. Signal & Image Processing, **4(1), 57.**

7. Nayak, P. K., & Narayan, D. (2013). Multimodal Biometric Face and Fingerprint Recognition Using Adaptive principal Component Analysis and Multilayer Perception. IJRCCT, **2(6), 313-321.**

8. Kaveh, A., & Ilchi Ghazaan, M. (2014). Computer codes for colliding bodies optimization and its enhanced version. Int J Optim Civil Eng, **4(3), 321-332.**

9. Telgad, R. L., Deshmukh, P. D., & Siddiqui, A. M. (2014, May). Combination approach to score level fusion for Multimodal Biometric system by using face and fingerprint. In Recent Advances and Innovations in Engineering (ICRAIE), **2014 (pp. 1-8). IEEE.**

10. Perumal, E., & Ramachandran, S. (2015). A multimodal biometric system based on palmprint and finger knuckle print recognition methods. Int. Arab J. Inf. Technol., **12(2), 118-128.**

11. Trabelsi, R. B., Masmoudi, A. D., & Masmoudi, D. S. (2016). Hand vein recognition system with circular difference and statistical directional patterns based on an artificial neural network. Multimedia Tools and Applications, **75(2), 687-707.**

12. Almaadeed, N., Aggoun, A., & Amira, A. (2015). Speaker identification using multimodal neural networks and wavelet analysis. IET Biometrics, **4(1), 18-28.**

13. Lathika, B. A., & Devaraj, D. (2014, July). Artificial neural network based multimodal biometrics recognition system. In Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014 International Conference on (pp. 973-978). IEEE.

14. Saini, N., & Sinha, A. (2015). Face and palmprint multimodal biometric systems using Gabor–Wigner transform as feature extraction. Pattern Analysis and Applications, **18(4), 921-932.**

15. Mezai, L., & Hachouf, F. (2015). Score-level fusion of face and voice using particle swarm optimization and belief functions. IEEE Transactions on Human-Machine Systems, **45(6), 761-772.**

16. Sarhan, S., Alhassan, S., &Elmougy, S. (2016). Multimodal Biometric Systems: A Comparative Study. Arabian Journal for Science and Engineering, **1-15.**

17. Krishneswari, K., & Arumugam, S. (2013). An improved Genetic Optimized neural network for multimodal biometrics. Journal of Scientific & Industrial Research, **72, 23-30.**

18. Kayarvizhy, N., Kanmani, S., &Uthariaraj, R. (2014). ANN models optimized using swarm intelligence algorithms. WSEAS Transactions on Computers, **13(45), 501-519.**

19. Kaveh, A., & Mahdavi, V. R. (2015). Colliding Bodies Optimization Algorithms. In Colliding Bodies Optimization (pp. 11-38). Springer International Publishing.

20. Kaveh, A., & Mahdavi, V. R. (2014). Colliding bodies optimization: a novel meta-heuristic method. Computers & Structures, **139, 18-27.**

21. He, M., Horng, S. J., Fan, P., Run, R. S., Chen, R. J., Lai, J. L., ... &Sentosa, K. O. (2010). Performance evaluation of score level fusion in multimodal biometric systems. Pattern Recognition, **43(5), 1789-1800.**