Fusing Fingerprint and Iris Multimodal Biometrics using Soft Computing Techniques

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Abstract— This paper presents the application of soft computing techniques in multimodal biometrics recognition. The paper investigates the comparative performance of three different approaches: non-optimized neural network trained with unimodal biometrics, non-optimized neural network trained with multimodal fingerprint and iris biometrics and optimized neural network trained with fingerprint and iris biometrics. The experimental results suggest that neural network optimized with genetic algorithm shows better recognition rate as compared to the other two approaches. The performance evaluation of each method is reported in terms of mean square error, percentage error, and accuracy.

Keywords- neural network, genetic algorithm, soft computing, feature level fusion, multimodal biometrics

I. INTRODUCTION

Biometrics has become one of the most promising authentication techniques in the last few years. It has been in big use in large security organizations. Biometrics is a technology for measuring and analyzing human body characteristics for authentication purposes. There are two types of biometrics namely unimodal and multimodal. The increasing attacks and decreasing security in unimodal systems have resulted in designing multimodal biometrics which is created by combining either multiple instances of the same biometric feature or integrating different biometric traits [1]. To make the technology universally acceptable a large number of challenges like higher recognition rates, tolerance for imprecision and uncertainty, fusion levels and cost versus performance tradeoff have to be met [2]. So, a technique is required which is able to address all these issues. Soft computing is increasingly being used in this context in the development of multimodal biometric system [3][4][5][6]. Soft computing is a technique which is characterized by the use of inexact solution for problems which has no known method to compute the exact solution. Within this context fusion of fuzzy logic, evolutionary algorithm and artificial neural network are used to address the accuracy and performance issues in multimodal biometrics [7][8][9][10].

In this paper, multimodal biometric system is designed using two traits i.e. fingerprint and iris. Initially feature extraction for fingerprint is done using gabor filterbank algorithm [11][12][13] and iris feature extraction is done using daugman algorithm[14][15]. The objective of this research is fourfold: first designing and implementing unimodal biometric system using neural network iris and fingerprint recognition. these systems will later be used for comparison; second, designing and implementing multimodal biometric system of combined iris and fingerprint using the neural network; third applying genetic algorithm for optimizing the neural network in order to reduce the mean square error of neural network. At last, a comparative analysis of the achieved results unimodal and multimodal biometric system is done.

The paper is organized as follows: in the next section implication of soft computing techniques in biometrics is discussed; in Section 3 the work methodology along with the database used is presented; in Section 4 the details of the system implementation and experimental results Section 5 presents the performance evaluation and comparison of all the techniques used and Section 6 presents the solution.

II. SOFT COMPUTING IN MULTIMODAL BIOMETRIC

Multimodal biometrics combines two or more physiological or behavioral characteristics of human body for the purpose of authentication. Multiple features from different traits can be combined or fused basically at three different levels i.e. fusion at the feature extraction level, matching score level and the decision level. New requirements over multimodal biometric systems are higher recognition rates, tolerance for imprecision and uncertainty, fusion of heterogeneous features at fusion levels and cost versus performance tradeoff. In this context, soft computing is increasingly being used in the development of multimodal biometric system

[16][17][18]. Soft computing is a technique which is characterized by the use of inexact solution for problems that has no known method to compute the exact solution. The Soft Computing mainly consists of Fuzzy Systems, neural networks and evolutionary algorithm.

III. RESEARCH METHODOLOGY

Research methodology includes different stages involved in the construction of intelligent multimodal biometric recognition system and the overall system design. The main objective of this research work is to integrate various soft computing techniques with multimodal biometric fingerprint and iris system for its intelligent construction. Figure 1 shows the different stages included in our multimodal recognition system and the overall system design shows the following:

- Initially database of iris and fingerprint are acquired for implementing the proposed system. For iris CASIA V4 database is acquired which contains 6 subsets i.e. CASIA-Iris-Interval, CASIA-Iris Lamp, CASIA-Iris-Twins, CASIA-Iris-Distance, CASIA-Iris-Thousand, CASIA-Iris-Syn. For our work, we are using CASIA-Iris-Interval subset. All images are stored as 8-bit gray level JPEG files format with image dimension of 320* 280. For fingerprint FVC 2004 is acquired which contains four distinct databases DB1, DB2, DB3, and DB4. The database contains110 fingers in total and have 8 samples per finger. Each database is partitioned into two disjoint subsets A and B. For our work, we are using subset B database. All images are in TIF, 256 gray-level, uncompressed format.
- Next step is to perform preprocessing on both the iris and fingerprint database. Preprocessing on iris database module include transforming the true color (RGB) image into intensity image. It removes the effect of holes lying on the papillary area. Preprocessing includes binarization, finding the complement of binary image, hole filling using connected approach and complement of hole filled image. Preprocessing on fingerprint database includes transforming the real nature (RGB) image into the grayscale image. After that image enhancement is done to make the image clearer so that the contrast between the ridges and valleys can be increased further for extracting the minutiae. Histogram equalization is used for image enhancement. After that binarization, thinning and spur removal is done.
- After that features are extracted from iris and fingerprint. Feature extraction of iris is done using daugman algorithm. Daugman approach for iris feature extraction includes Iris Localization, Iris Normalization and Feature Encoding. Feature extraction of fingerprint is done using Gabor filter bank algorithm. Gabor filter bank algorithm for fingerprint feature extraction includes finding the core point in the image, tessellation into sectors, normalization and filtering of the normalized sector.
- Combined feature vector for fingerprint and iris is constructed which is used to train the neural network. Feed forward neural network is used for classification.
- Genetic algorithm is applied to reduce the mean square error of neural network for achieving the increased recognition rate.

IV. EXPERIMENTAL RESULTS

The application is divided mainly into three modules.

A. Iris Recognition Module

Neural Network is trained for the feature vectors extracted from the iris database. Figure 2 below present the confusion matrix which contains the information about the actual and predicted classifications done by the feed forward neural network. All confusion matrixes indicate the average of training, validation and testing matrix. It has been derived from the all confusion matrix that 80% of the person is correctly recognized and 20% are recognized incorrectly.

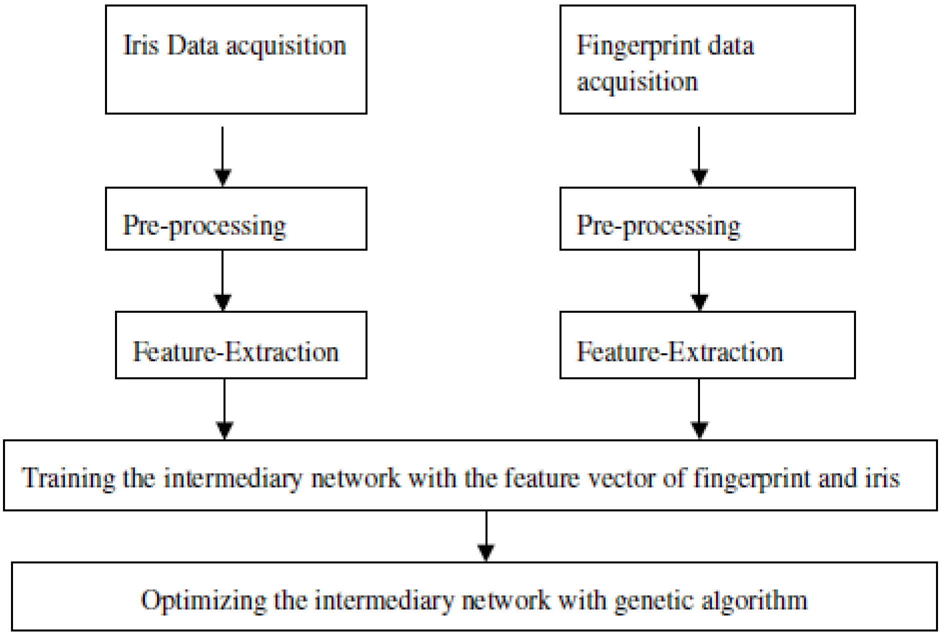

Figure 1. Proposed Model

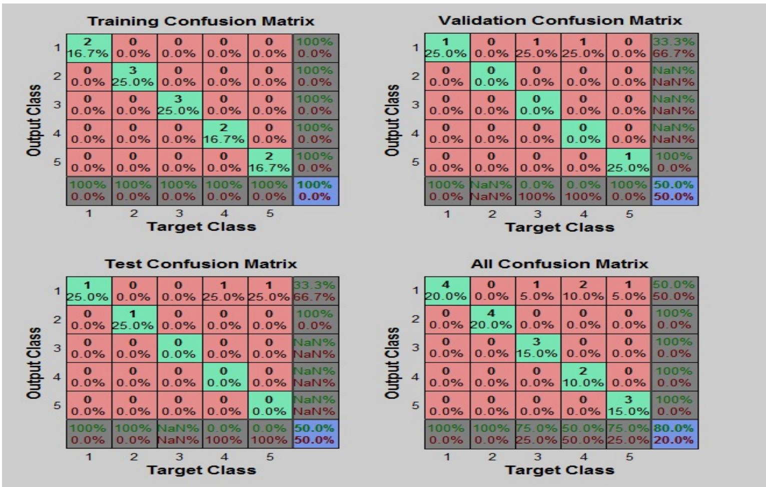

Figure 2 Confusion matrix for iris recognition

B. Fingerprint Recognition Module

Neural Network is trained for the feature vectors extracted from the fingerprint database. Figure 3 below present the confusion matrix which contains the information about the actual and predicted classifications done by the feed forward neural network. All confusion matrixes indicate the average of training, validation and testing matrix. It has been derived from the all confusion matrix that 65% of the person is correctly recognized and 15% are recognized incorrectly.

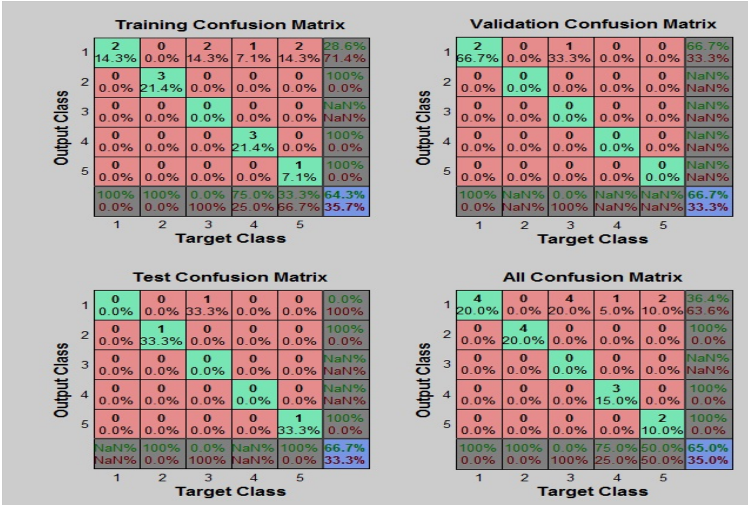

Figure 3 Confusion matrix for fingerprint recognition

C. Combined Iris and Fingerprint Recognition Module

Neural Network is trained for the combined feature vectors of fingerprint and iris. After training the network is validated and tested for calculating the mean square error to determine the network performance. Figure 4 below present the confusion matrices which contains the information about the actual and predicted classifications done by the feed forward neural network. All confusion matrixes indicate the average of training, validation and testing matrix. It has been derived from the all confusion matrix that 85% of the person is correctly recognized and 15% are recognized incorrectly.

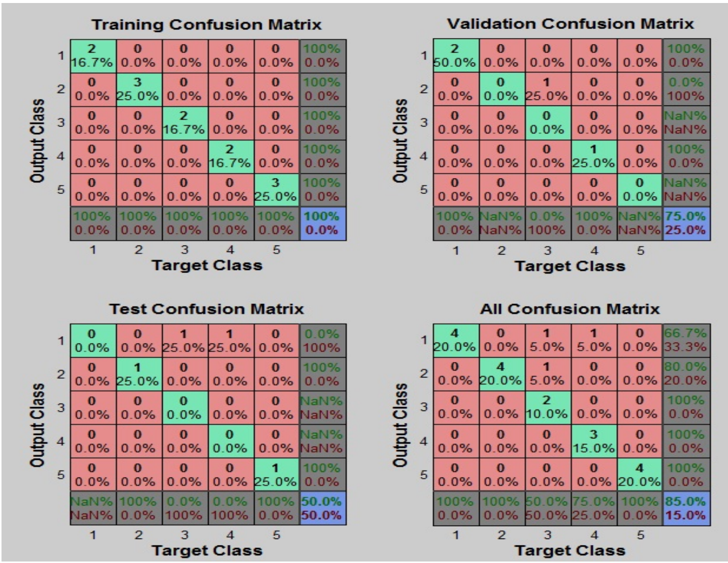

Figure 4 Confusion matrix for iris and fingerprint recognition

D. Optimized Iris and Fingerprint Recognition Module

Trained neural network is optimized using genetic algorithm. Genetic algorithm optimize the number the number of hidden layers, weights, biases and training algorithm of neural network in order to reduce mean square error to minimum. Figure 5 below present the confusion matrices which indicate the increase in recognition rate to 95% as compared to non-optimized neural network.

V. PERFORMANCE EVALUATION AND COMPARISON

In order to test the performance of the proposed schemes for unimodal and multimodal biometric recognition systems and to perform the comparative analysis of both the techniques, following experiments are performed:

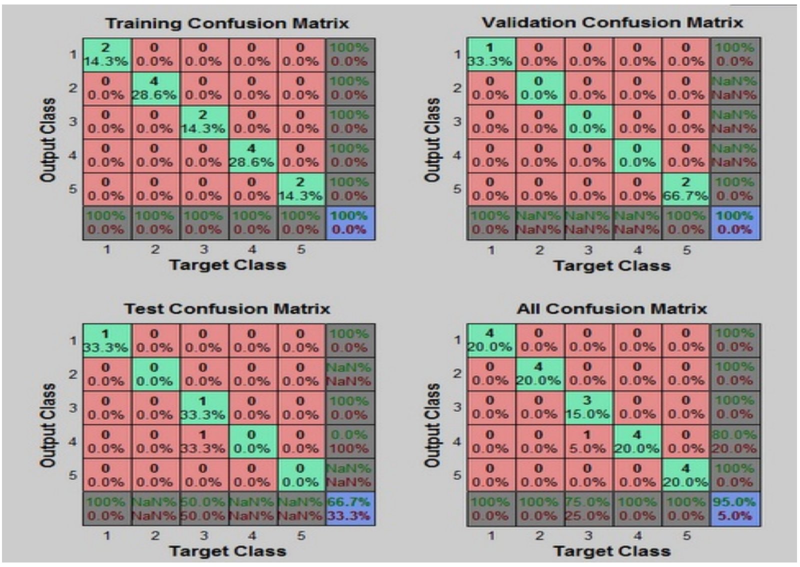

Figure 5 Confusion matrixes for Optimized Iris and Fingerprint Recognition

A. Iris Recognition Module

1. First the database is divided into three parts: 60% of the database is used to train the neural network, 20% is used to validate the network and 20% is used to test the network performance.
2. Genuine recognition attempts (Accuracy): the feature vector of the trained image is given as an input to the neural network and the network will return the index of the person matched. Table I below represent the MSE and %E of the neural trained with iris database.

TABLE I. MSE AND %E FOR IRIS TRAINED NEURAL NETWORK

	Samples (%)	MSE	%E
Training	60	1.31003e-3	2.23e-0
Validation	20	1.25004e-3	22.333e-0
Testing	20	1.50529e-1	50.000e-0

B. Fingerprint Recognition Module

1. First the database is divided into three parts: 60% of the database is used to train the neural network, 20% is used to validate the network and 20% is used to test the network performance.
2. Genuine recognition attempts (Accuracy): the feature vector of the test image is given as an input to the neural network and the network will return the index of the person matched. Table II below represent the MSE and %E of the neural trained with fingerprint database.

TABLE II. MSE AND %E FOR FINGERPRINT TRAINED NEURAL NETWORK

	Samples (%)	MSE	%E
Training	60	1.5871e-1	35.71428e-0
Validation	20	1.4175e-1	33.33e-0
Testing	20	1.847e-1	33.33e-0

C. Combined Iris and Fingerprint Recognition Module

1. First the database is divided into three parts: 60% of the database is used to train the neural network, 20% is used to validate the network and 20% is used to test the network performance.
2. Genuine recognition attempts (Accuracy): the feature vector of the test image is given as an input to the neural network and the network will return the index of the person matched and the network will return

the index of the person matched. Table III below represent the MSE and %E of the neural trained with fingerprint and iris database.

TABLE III. MSE AND %E FOR NEURAL NETWORK TRAINED WITH FUSED FEATURE VECTOR OF FINGERPRINT AND IRIS

	Samples (%)	MSE	%E
Training	60	1.25004e-3	0
Validation	20	1.26110e-1	25.00e-0
Testing	20	1.50529e-1	50.00e-0

D. Optimized Iris and Fingerprint Recognition Module

1. First the database is divided into three parts: 60% of the database is used to train the neural network, 20% is used to validate the network and 20% is used to test the network performance.
2. Genuine recognition attempts (Accuracy): The feature vector of the test image is given as an input to the neural network and the network will be then optimized with genetic algorithm. Optimized network is tested again for performance evaluation. Table IV below represent the MSE and %E of the optimized neural trained with fingerprint and iris database.

TABLE IV. MSE AND %E FOR OPTIMIZED NEURAL NETWORK

	Samples (%)	MSE	%E
Training	60	1.07928e-1	0
Validation	20	1.09606e-1	0
Testing	20	2.07841e-1	33.33e-0

E. Performance of the system in terms of accuracy

A comparative analysis of accuracy of the four systems is given in Figure 6. It has been concluded that the optimized neural network provides better recognition rate and reduced error.

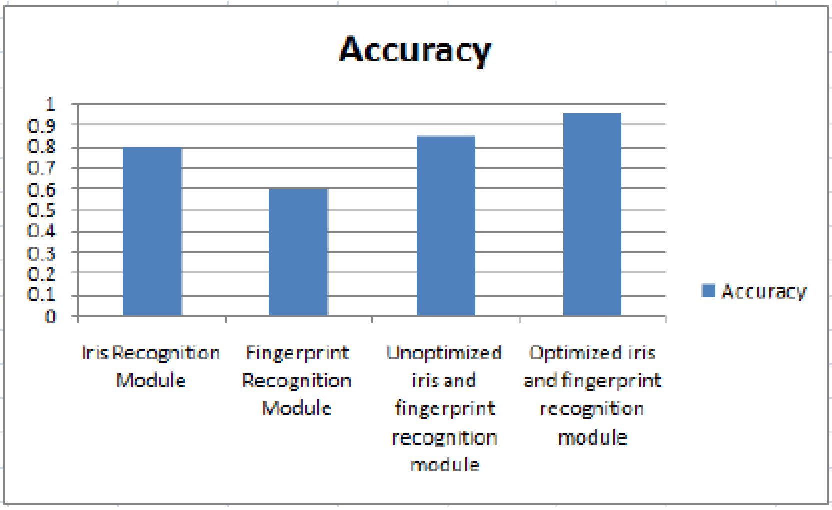

Figure 6 Accuracy graph

VI. CONCLUSION

The objective of this research is to perform feature level fusion and evaluate the performance of the neural network trained with the fused feature vector. It is also concluded that the optimized neural network provides better recognition accuracy as compared to the non-optimized neural network. For future work, it can be suggested that integration of fuzzy logic techniques with the neural network and genetic algorithm can help in increasing the recognition rate to a great extent for biometric modalities.

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