A Hybrid Datamining Technique for Face Recognition System Using Enhanced Independent Component Analysis

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Abstract

Face recognition is one of the most reliable and adaptive systems, which has the benefits of being passive, non –intrusive system for verifying personal identity, and is impossible to deceive as the process involves unique identification methods. The problems in existing technologies are overall accuracy, sensitivity to changes in lighting, camera angle, pose and increased computational time. The proposed Face Recognition system uses a hybrid Data Mining approach which produces promising results for high accuracy as well as reduced computational time. The proposed face recognition system employs hybrid approach with Neural network and Genetic algorithm with an ensemble enhancement of the Independent Component Analysis (EICA). ICA is more adaptive model used for decision making and is insensitivity to large illumination and facial expressions in the recognition process. Genetic algorithm helps to obtain the most optimum value of initial weights and learning rate of the Neural Network. The individual classifier are fused using Radial Basis Function network (RBF), as it requires less training time and has the possibility of learning positive as well as negative samples. Then the Fusion of EICA and Principal Component Analysis(PCA) in combination with RBF network and Genetic algorithm, reduces the computational time and increases the classification accuracy by 2% compared to the individual classifiers PCA and EICA. The proposed Face Recognition system is trained and tested on Bio-ID Face Database taken from the BioID Laboratory, Texas, USA, which consists of 1521 samples for 23 subjects in turn consists of 65 samples per subject.

Keywords: Face Recognition, Independent Component Analysis, Principal Component Analysis, Radial Basis Function and Genetic Algorithm.

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1. Introduction

Personal identification with high reliability is one of the challenging problems in Computer vision in a longer term [3][4]. The need for Automated Face Recognition becomes important in determining personal identity which has shown increased interest in biometrics, various commercial applications such as access of credit card and Automatic Transaction Machines, video surveillance. The existing techniques Principal Component Analysis (PCA)[11] also known as Eigen faces method [11], Linear Discriminant Analysis (LDA) [8], Kernel Direct Discriminant Analysis (KDDA) [9], Line based Techniques[13] leads to difficult situation in learning and practicing the system for appropriate recognition. It consists of classifying highly ambiguous input signals, with multiple dimensions and matching them with the known 'signals'. Though Recent researches Independent Component Analysis [ICA][1], hybrid classifiers[3][12] and Neural Network [16] has focused on diminishing the impact of nuisance factors like sensitivity to higher order image statistics on face recognition, these approaches still face difficulty to separate each class owing to large variation in illumination and facial expression.

The proposed face recognition model with an enhanced version of Independent Component Analysis (EICA) approach regarded as a systematic classification framework leads to the formation of well-separated classes in low dimension subspace. Incorporating Genetic Algorithm [5][6] concepts and a hybrid facial feature extraction recognition approach the fusion of enhanced ICA with PCA classifier leads to the intelligence level of identification of face recognition system. It deals with Illumination, facial expression and pose to ensure higher accuracy and secured recognition.

A fusion approach is developed to overcome the limitation of variation in pose, change of illuminations and the facial expression by implementing the enhanced ICA algorithm with PCA classifier for best classification accuracy. The proposed system architecture model is depicted in Fig 1.

The major stages involved are

- Face Detection stage
- Feature Extraction stage
- Fusion stage
- Classification stage

1.1 Face Detection Stage

The Hausdorff Face Detection method is edge-based and works on grayscale still images. The Hausdorff distance is used as a similarity measure between a general face model and possible instances of the object within the image [13]. The system automatically detects the faces present in a scene and normalizes them with respect to pose, lighting and scale.

1.2 Feature Extraction Stage

The face image of an individual is unique and remains unchanged over the lifetime. Feature Extraction involves extracting the desired facial features from face regions. If the input data to an algorithm is too large to be

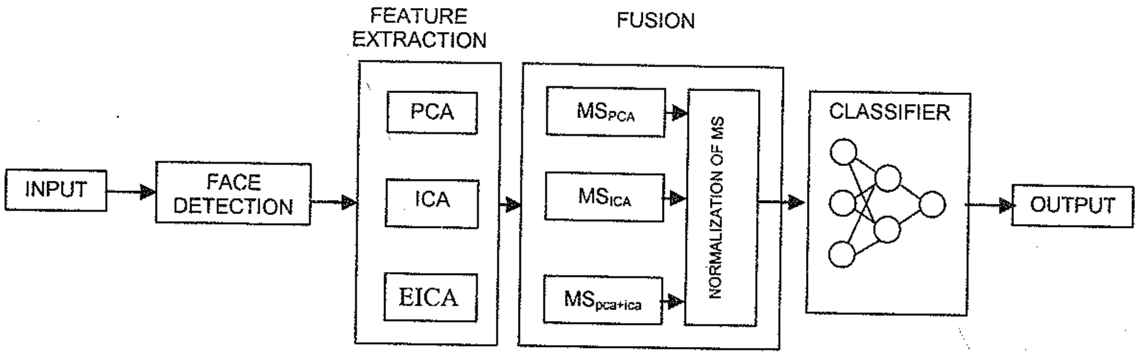

Figure 1 : Architecture of Face Recognition System

processed and is suspected to be notoriously redundant then the input data will be transformed into a reduced representation set of features. Instead of considering the entire input image, the relevant feature sets are carefully extracted from the input image in order to perform the desired task using Feature Extraction process. It reduces the computation time since the unnecessary features will be removed. The algorithms used for feature extraction are Principal Component Analysis (PCA) [11] and Independent Component Analysis (ICA) [1].

1.3 Fusion Stage

The Fusion stage is based on fusion of individual recognizers so that the limitation of single recognizer is overcome and the performance of the overall recognition system is improved. The fusion block combines the feature vectors of the feature extraction algorithms PCA and ICA using Matching Score (MS) process with Radial Basis Function (RBF) Neural network [7]. RBF network is used for training and testing the samples. The hybrid classifiers use the matching score to obtain the feature points which is insensitive to illumination, pose and facial expressions for required classification.

1.4 Classification Stage

A Neural Network is used to Identify face images for the given input, by selecting the images in the database, which better represents an unknown input image where an exact mapping of input-output is easily defined. RBF network is used for classification the face images with the Gaussian function. Genetic algorithm is incorporated to efficiently assign the most optimum initial value for weights and learning rate to the neural network for achieving better recognition rate and reduced computational time.

The paper is organized as follows. In section 2, the details on Hausdorff Face Detection method are presented, In section 3 the feature extraction steps are explained in detail about calculating factors of Eigen faces, PCA and ICA recognizers and Fusion strategy is explained in Section 4, Section 5 describes about Neural network and section 6 gives details about Genetic algorithm. The simulation results are discussed in section 6 and finally section 7 states the conclusion.

2. Face Detection

Face detection block basically involves detecting human facial regions from complex image with background. A model-based approach is implemented to detect facial regions from an image, which works on grayscale still images using "Hausdorff distance (HD)" [13]. It is based on the Hausdorff distance, which are used for other recognitions like iris recognition, fingerprint recognition and speech recognition. This method performs robust and accurate face detection and its efficiency makes it suitable for real-time applications.

The HD is a metric between two point sets. Let A = $\{a_1, \ldots, a_m\}$ and B = $\{b_1, \ldots, b_n\}$ denote two finite point sets. Then the Hausdorff distance is defined by equations (1) and (2).

$$H(A, B) = \max(h(A, B), h(B,A)), \qquad \text{——(1)}$$

$$h(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\| \qquad \text{——(2)}$$

Hereby $h(A, B)$ is called the directed Hausdorff distance from set A to B with some underlying norm $\|\cdot\|$ on the points of A and B. For image processing applications it has proven useful to apply a slightly different measure, the Hausdorff distance, which was introduced by Dubuisson. It is defined in equation (3).

$$h_{mod}(A,B) = \frac{1}{|A|} \sum_{a \in A} \min_{b \in B} \|a - b\| \qquad \text{——(3)}$$

By taking the average of the single point distances, this version decreases the impact of outliers making it more suitable for pattern recognition purposes.

3. Feature Extraction

Feature extraction for face representation is one of central issues to face recognition systems that involve extracting desired facial features from face regions such as eyes, nose and mouth. There are two types of feature extraction 1) Global feature extraction, which takes the entire pixel as the feature 2) Local feature extraction, which takes some special features as eyes, mouth, nose etc. A global feature extraction is used where the whole data are considered as the feature and the process is carried out, whereas local feature are the user defined considering only a few important features of the data. By using the feature templates, all the candidate points within the face region are evaluated based on the feature extraction algorithm. Due to the inclusion of global features the matching of various expression templates will also be evaluated based on the feature extraction algorithm.

An algorithm is proposed for the face recognition problem considering the detected face as input. Two algorithms have been used for feature extraction namely Principal Component Analysis (PCA) [11] and Independent Component Analysis (ICA) [1].

3.1 Eigen Faces

Face images are projected onto a feature space ("face space") that best encodes the variation among known face images. The face space is defined by the "eigen faces" [2][11], which are the eigenvectors of the set of faces they do not necessarily correspond to isolated features such as eyes, nose and mouth.

In mathematical terms, the principal components of the distribution of faces or the eigenvectors of the covariance matrix of the set of face images can be found. These eigenvectors can be thought of as a set of features which together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we can display the eigenvector as a face which are Eigenfaces.

Each face image in the training set can be represented exactly in terms of a linear combination of the Eigenfaces. The number of possible Eigenfaces is equal to the number of face images in the training set. The faces can also be approximated using the "best" Eigenfaces – those that have the largest eigenvalues, and which therefore account for the most variance within the set of face images.

3.2 Principal Component Analysis [PCA]

Principal Component Analysis is a powerful common technique tool used for finding pattern in data such as data reduction and feature extraction in the model based approaches. Model based approaches generally operate directly on images or patterns of face objects and process the images as two-dimensional (2D patterns, to avoid difficulties with three-dimensional (3D) modeling). Principal component analysis is applied to find the aspects of face which are important for identification. Eigenvectors (eigenfaces) are calculated from the initial face image set. New faces are projected onto the face space expanded by eigenfaces and represented by weighted sum of the eigenfaces. These weights are used to identify the faces.

3.3 Enhanced Independent Component Analysis [EICA]

The most popular approaches in the feature extraction process are mainly identified by differentiating the mixture of input representation. The goal of EICA is to recover independent sources observations that are unknown linear mixtures of the unobserved independent source data [10]. In contrast to correlation-based transformations such as Principal Component Analysis (PCA), ICA not only decorrelates the signals (2nd-order statistics) but also reduces higher-order statistical dependencies, attempting to make the data as independent as possible. EICA is a way of finding a linear non-orthogonal co-ordinate system in any multivariate data. The directions of axes of this co-ordinate system are determined by both the second and higher order statistics of the original data. ICA leads to perform the resulting variables of linear transform are statistically independent from other variables and to maximize the mutual information for neural network input-outputs [8]. This is achieved by performing gradient ascent on the entropy of the output with respect to the weight matrix [2]. The metric induced by EICA is superior to PCA in the sense that it may provide a representation more robust to the effect of noise. It is, therefore, possible for ICA to be better than PCA for reconstruction in noisy or limited precision environments due to information maximization algorithm employed [2]. It also assumed that the pixel values in face images were generated from a linear mixing process. However each feature only predict a correct face peripheral better than random vector, the combination of independent feature vectors from a unique face image leads to a high probability of correct facial feature extraction [1].

4. Fusion Stage

The drawbacks of the individual recognizers such as illumination, presence of accessories like sun glasses, beard, and different facial expression are major issues which encourage implementing a Hybrid classifier. The Hybrid classifier consists of the individual classifier, the Principal Component Analysis and Enhanced Independent Component which is fused together using Radial Basis Function network to overcomes these limitations.

The hybrid recognizers is thus capable of considering the problem of dimensionality by eliminating redundant features and reducing the feature space are implemented to consider the problem of dimensionality and to handle variations due to illumination, pose, up to a significant level. The hybrid recognizer overcomes the drawbacks of individual recognizers without any constraints, where PCA approach confers reduced recognition efficiency due to illumination changes and also to image constraints. ICA provide increased recognition efficiency even for higher dimensionality images as well as it is beneficial for imaging constraints like pose and face inclination. The hybrid recognizer can thus overcome the individual drawbacks and increase the performance of the overall recognition system.

4.1 Radial Basis Function Network (RBF)

The feature vectors of images obtained from the feature extraction stage is taken as input to the Neural Network stage. A RBF is a local network that is trained in a supervised manner. RBF performs a local mapping, meaning only inputs near a receptive field produce activation. The RBF are used for classification on both training and testing of images [7]. The feature vector obtained using PCA, and EICA will have maximum feature density. The face images are basically classified on the patterns of features extracted. The eigen values extracted from the images decides the characteristics of face images. The images are classified based on the feature matched for query and the trained images. The parameter values of the RBFN network are estimated and optimized using Genetic algorithm. The purpose of Genetic algorithm is to choose the optimum values of weights. With these values as initial points of Neural Networks, attains the faster convergence of error rate and higher classification rate.

4.2 Genetic Algorithm (GA)

Genetic Algorithm (GA) uses the mechanics of biological evolution such as inheritance, nature selection and recombination or crossover [5]. This algorithm relies on the principles of survival of fittest. In face recognition process, the parametric values such as the weight and learning rate, epochs of the neural network are optimized by Genetic algorithm [6]. The optimization of Neural Network using Genetic algorithm improves the recognition performance of the system to a maximum level. The flowchart of the Genetic algorithm processes are represented in fig 2.

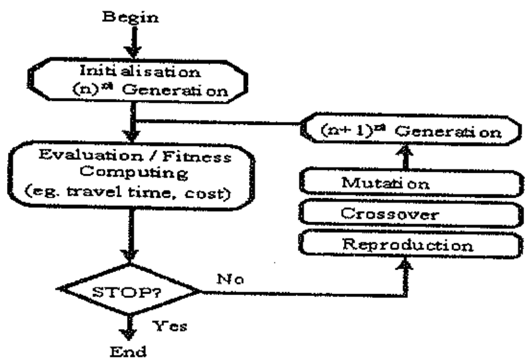

Figure 2 : Block Diagram of Genetic Algorithm

GA's are applied to search for optimum value of weights in solution space (S), a population P is maintained which consist of N elements, where N is the population size. Each element in P is called a chromosome which is composed of a list of genes. The population P will evolve into another population P' by performing the genetic operations. The chromosomes with higher fitness values will have more probability to be kept in the population of the next generation and to propagate their offspring. After a suitable number of generations the mature population will be expected to contain the element with the optimum value of weights. The proposed learning algorithm using genetic algorithm with multilayer Neural Networks for pattern recognition consists of two learning stages. The first learning using Genetic algorithm with the feed-forward step accelerate the whole learning process. The Genetic algorithm performs global search and seeks near-optimal initial point (weight vector) for the second stage, where, each chromosome is used to encode the weights of RBF Neural Network. The detailed Neuro-Genetic algorithm is as follows.

First Learning Stage

Initialize the chromosomes randomly as current generation, initialize working parameters, and set the fitness function.

Start

Step 1: Initialize 'Fitness or Cost value' to zero and 'Child chromosome' as null.

For i=0 to population size

Step 2: Specify the Objective Function and calculate the total fitness by accumulating child chromosome.

For j=1 to Length of chromosomes

Perform RBFN using Gaussian Function.

Next j

Step 3: Calculate Mean, Maximum and Minimum significance level of the chromosomes. Store the best chromosome as Subset chromosome.

Next i

Step 4: Compare the Child chromosome with each other under various steps of genetic operations like Crossover, Mutate and set the best chromosome.

Step 5: For i = 0 to Mean of population, do concurrently:

Select parents' and Child chromosome as null.

For j = 1 to length of chromosome, do sequentially:

Select parent using roulette wheel parent selection.

Apply two-point, multipoint, or uniform crossover and mutation to the parents.

For k = 1 to length of chromosome, do sequentially:

Perform procedure of the RBFN to parent chromosomes.

Calculate the objective function (system error for the Neural Network) for parent chromosomes.

Next k

Calculate the sub_total_fitness by accumulating objective of each chromosome.

Store the best_chromosome as Child chromosome.

Next j.

Replace the old generation by the new generation and name it as best chromosome WHILE (stopping criteria).

Next i.

Second Learning Stage

Step 1: Set the best chromosome as the initial weight vector or learning rate.

Step 2: Compute the actual output of the RBFN neural network.

Step 3: Compute the error and time between desired output and actual output.

Step 4: Update the weights using RBFN algorithm.

End

5. Simulation Results

Face recognition is a multistage process with Face Detection, Feature Extraction, Fusion, and hybrid classifier that are used to quantify the benefits of the recognizers. The optimization of Neural Network parameters are performed using Genetic algorithm. The dataset of face images for recognition are obtained from BioID Laboratory, Texas, USA. It consists of 1521 samples for 23 subjects. The prototype system is implemented in Matlab 7.1 using Pentium 4 (2.4 Mhz and 256 MB RAM) Desktop PC [15].

5.1 Face Detection Module

Face detection implements Hausdorff Distance Face Detection [13] Algorithm to extract the facial regions separately from a given input image.

Total Number of Images=1521

Table 1: Face Detection Results for Various Eye Distances

d_{eye}	Detection Accuracy (%)
0.05	80.2
0.1	91.7
0.15	93.5
0.2	95.4
0.25	97.1
0.3	98.5
0.35	99.3
0.4	100

It is inferred from Table 1 that by employing Hausdorff Distance Face Detection algorithm the detection accuracy shows efficient exposure correctness of face for different distance of human eyes in the input image. Since each input face image will be of different pose, illuminations and facial expressions, the eye distances varies, based on which the detection accuracy can be validated. Face Detection algorithm is used to extract the face portion from the given input images of the database which is represented in fig 3.

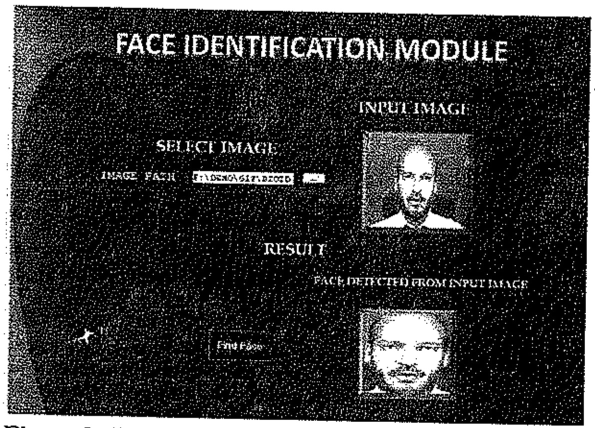

Figure 3 : User Interface for Hausdorff Distance Face detection

5.2 Feature Extraction Module

The feature extraction is the key portion of face recognition system. In feature extraction stage, two recognizers namely Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are implemented. RBF is used for testing and training the images extracted from the above techniques. Genetic algorithm is used to optimize the Neural Network parameters such as learning rate and weight vectors. The results that infer the performance of the individual algorithms are described in the following sections.

Classification of PCA

Principal component analysis is applied to find the aspects of face which are important for identification. PCA is analysed with input parameters such as hidden layers, learning rate and epochs, where the hidden units is set to 50 for better computability, the optimum value of learning rate (α) obtained is 0.56 and the classification rate saturates at 800th epoch.The fig 4 shows the extracted features vectors of the PCA face space projected into the original image.

Comparison of PCA Classification with and without Genetic Algorithm

The recognition rates are evaluated by varying the input parameters like learning rate, epochs and hidden units

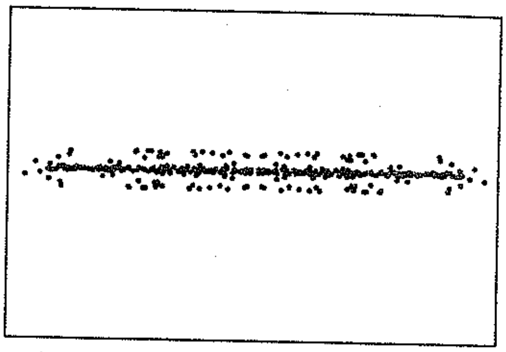

Figure 4: PCA Feature Vectors Superimposed with Original Image

of the Neural Network. The optimal values considered for learning rate is 0.56, epoch is 150 and hidden units are 50. The recognition rate and the computation time calculated for PCA and PCA with Genetic algorithm is shown in Table 2. The GA Parameter chosen are

Total number of samples in database	:1521
Population size	: 600
Mutation Probability Rate	: 0.15
Crossover Probability Rate	: 0.7
Length of Chromosome	: 10304
Number of generations	: 70

The Table 2 shows that PCA with genetic algorithm has increased recognition accuracy by 2%. The computation thus reduces the training time by an average of 2.58 minutes and 1.92 minutes for testing time for the BioID database.

Classification of EICA

The EICA feature extraction is insensitive to facial expressions and pose of human faces. In addition to the input parameters like learning rate, epochs, hidden units, the cosine similarity is applied for feature extraction in ICA. The recognition rate are evaluated with an optimum value of learning rate () obtained as 0.56 and the classification rate saturates at 1000th epoch and the hidden units is set to 50 for better computability. The fig 5 shows the extracted features vectors of the ICA face space projected into the original image.

Table 2: Comparison of PCA without and with Genetic Algorithm

Training Set (%)	Testing Set (%)	PCA without Genetic Algorithm			PCA with Genetic Algorithm		
		Time for Training (Minutes: Seconds)	Time for Testing (Minutes: Seconds)	Recognition Rate (%)	Time for Training (Minutes: Seconds)	Time for Testing (Minutes: Seconds)	Recognition Rate (%)
90	10	42:28	03:40	93.2	38:24	03:24	95.3
70	30	29:19	10:16	87.1	33:04	12:19	90.3
50	50	23:48	24:32	79.2	22:15	25:32	84.1
30	70	15:51	34:18	71.8	12:14	33:24	79.5
10	90	04:24	41:29	66.7	04:52	40:18	73.8

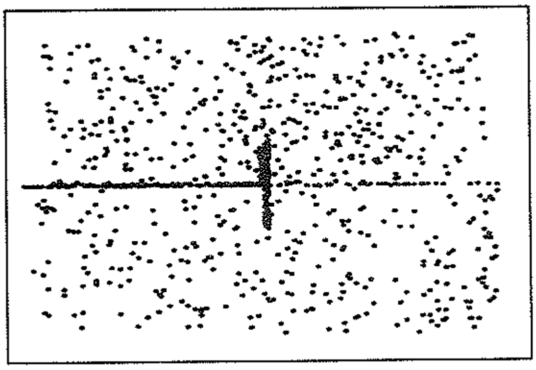

Figure 5 : ICA Feature Vectors Superimposed with Original Image

Comparison of EICA Classification with and without Genetic Algorithm

The computational time and the recognition rate are evaluated for ICA with and without genetic algorithm and are represented in Table 3.

The GA parameters are as follows:

Population size = 600

Mutation Probability Rate = 0.05

Crossover Probability Rate = 0.6

Length of Chromosome = 10304

Number of generations = 50

It is inferred that the computational time is reduced by an average of 3.41 minutes for the training time and the testing time is reduced by 2.3 minutes using GA. Also it shows that ICA with Genetic algorithm has increased recognition rate by 1%.

5.3 Fusion Stage Analysis

The network employed for fusion strategy is Radial Basis Function. The network is trained by average of three input features for target '1'. Each input is tested by the network for minimum error rate. The feature that has minimum error rate is selected as best feature. The limitation of single recognizer is overcome and the performance of the overall recognition system is improved. The fusion block combines the feature

Table 3 : Comparison of EICA without and with Genetic Algorithm

Training Set (%)	Testing Set (%)	EICA without Genetic Algorithm			EICA with Genetic Algorithm		
		Time for Training (Minutes: Seconds)	Time for Testing (Minutes: Seconds)	Recognition Rate (%)	Time for Training (Minutes: Seconds)	Time for Testing (Minutes: Seconds)	Recognition Rate (%)
90	10	45:23	06:41	94.7	43:34	04:31	95.8
70	30	38:39	17:42	89.2	34:25	16:27	91.1
50	50	27:31	28:48	83.8	23:17	26:11	85.7
30	70	20:04	36:36	78.8	14:04	33:05	81.6
10	90	07:45	43:35	71.2	05:24	42:38	75.8

Table 4 : Fusion of PCA + ICA Without and with Genetic Algorithm

Training Set (%)	Testing Set (%)	PCA + ICA Without Genetic Algorithm			PCA + ICA With Genetic Algorithm		
		Time For Training (Minutes: Seconds)	Time For Testing (Minutes: Seconds)	Recognition Rate (%)	Time For Training (Minutes: Seconds)	Time For Testing (Minutes: Seconds)	Recognition Rate (%)
90	10	46:19	05:24	96.1	42:52	04:51	96.7
70	30	37:22	18:36	87.6	35:46	15:43	91.3
50	50	28:36	29:23	80.2	26:29	27:31	85.9
30	70	15:27	39:32	74.4	13:35	37:42	81.4
10	90	04:45	47:43	68.7	05:10	44:20	73.7

vectors of the two feature extraction algorithms PCA and ICA using Matching Score (MS) process with RBF network [7].

Fusion of PCA + EICA

The hybrid recognizer namely PCA+ EICA with Neuro Genetic approaches are applied to the BioID database. The results are evaluated with 1521 samples with the parameter settings, an epoch value of 600, learning rate as 0.5 and hidden units as 50 and the recognition rate for various training and testing time is tabulated in Table 4. The GA parameters are as follows:

Population size	=400
Mutation Probability Rate	=0.5
Crossover Probability Rate	=0.2
Length of Chromosome	=10304

It is inferred that the hybrid recognizer has improved in terms of recognition rate by a factor of 5% and reduces computational training time by 3.83 minutes.

The image output after the fusion of PCA and ICA are illustrated in fig 6. The fig 7 is the user interface describing the output image after the settings of the required parameter options. This clearly shows that the limitation concerning change in illumination and facial expression are overcome by the hybrid recognizer.

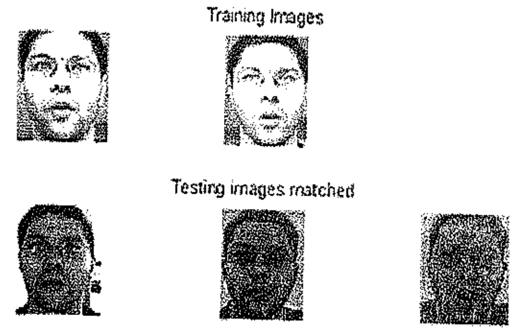

Figure 6 : Output Image of PCA+ICA

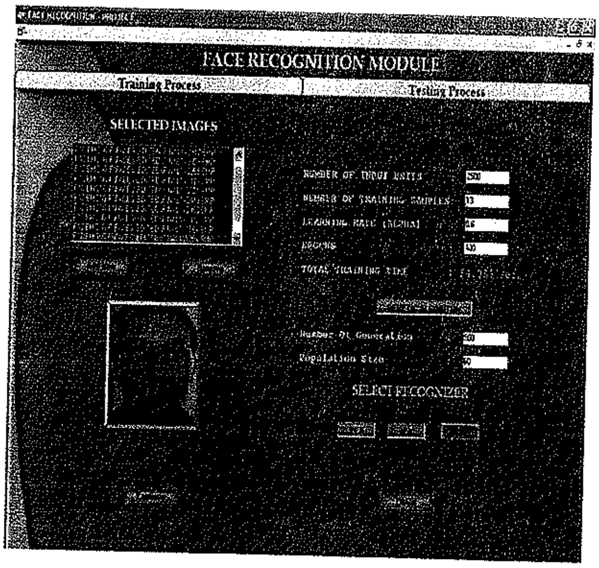

Figure 7 : User Interface Design for Parameter Setting and Output Display

The training image set encloses illuminated images; image set used for testing contains both normalized and illuminated images. GA is incorporated to optimize the learning rate and weight vectors.

The fig 8 and fig 9 illustrates the comparative results of the individual classifiers PCA, EICA and the hybrid classifiers PCA + EICA without Genetic algorithm and with Genetic algorithm respectively.

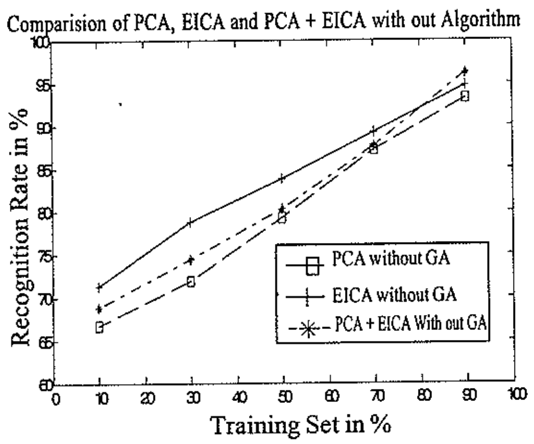

Figure 8 : Comparative Study of the Three Classifiers without GA

The results inferred from fig 8. shows that the classification is high with increasing the percentage of the training set and achieves maximum accuracy with hybrid classifier.

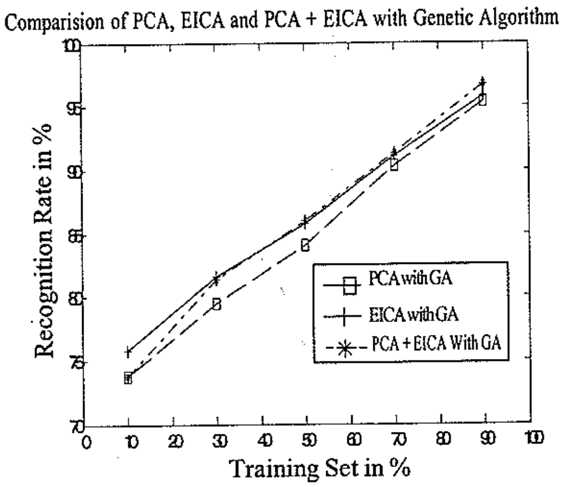

Figure 9 : Comparative Study of the Three Classifiers with GA

The fig 9. represents that the hybrid classifiers outperforms the individual classifier by 2% with Genetic algorithm. But the overall recognition rate increases by a factor of 6% on applying GA to the fusion of the hybrid recognizer PCA+ICA with GA, compared to the individual recognizers PCA and ICA without GA.

8. Conclusion

Biometric facial recognition has the potential to provide significant benefits to society in terms of personal identification. The enhanced ICA Face Recognition method embraces an interesting combination of the ICA class-free technique and benefits from the class-specific information [10].

In face detection stage, a modified Hausdorff distance [13] is implemented for face detection system that works with edge features of grayscale image. The localization results show that the system is robust against different background conditions and changing illumination.

In the feature extraction stage, a combination of algorithms namely, Principal Component Analysis (PCA)[11] and Independent Component Analysis (ICA) [1], is implemented. Each algorithm makes the system immune to any external disturbances such as, illumination effects, imaging constraints like face size, presence of accessories that may be glasses, beard etc.

The fusion of feature extraction algorithms PCA and ICA using Radial Basis Function network [7] is carried out and the Matching Score (MS) obtained from the fusion recognizer overcomes the limitations of individual recognizer.

Genetic algorithm is incorporated to efficiently assign the most optimum initial value for weights to the neural network which improves the processing speed of the overall system by converging the error rate more rapidly with less number of epochs.

The implemented Enhanced hybrid ICA Face Recognition System gives a peak recognition rate of 99.2%, with reduced training time of 4.51 minutes and testing time of 3.19 minutes which outperforms the individual classifiers.

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